FARMERS' SWITCHGRASS ADOPTION DECISION UNDER DIFFERENT MARKET SCENARIOS
-- AN AGENT BASED MODELING APPROACH

By

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ABSTRACT

FARMERS' SWITCHGRASS ADOPTION DECISION UNDER DIFFERENT MARKET SCENARIOS
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The Energy Independence and Security Act of 2007 mandates the production of 36 billion gallons of biofuels per year by the year of 2022, including 21 billion gallons of cellulosic and advanced in addition to 15 billion gallons of conventional (corn) ethanol. It thus becomes important to know the conditions under which farmers are willing to adopt energy crop and which institutional arrangements could facilitate the adoption process.

This paper uses agent based simulation to study farmers' switchgrass adoption decisions under multiple market scenarios using contracts: single-outlet (one biorefinery procures from individual farmers), quasi-multiple outlets (one biorefinery procures from farmers' cooperative) and multiple outlets (several easily accessible market outlets procure switchgrass from individual farmers). The focus of this paper is to model the contract hold-up problem and its influence on farmers' switchgrass adoption decisions under the three market scenarios. The use of an agent based model makes it possible to take multi-level heterogeneity into consideration.

We found that the appearance of an alternative market outlet lowers farmers' perceived risk and drives up their expected switchgrass growing gross margin, leading to a higher switchgrass adoption rate. It is also found that procuring from a farmers' cooperative is an efficient and feasible arrangement. However, commercial operation of a large-scale biorefinery is still not quite feasible in this particular region.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

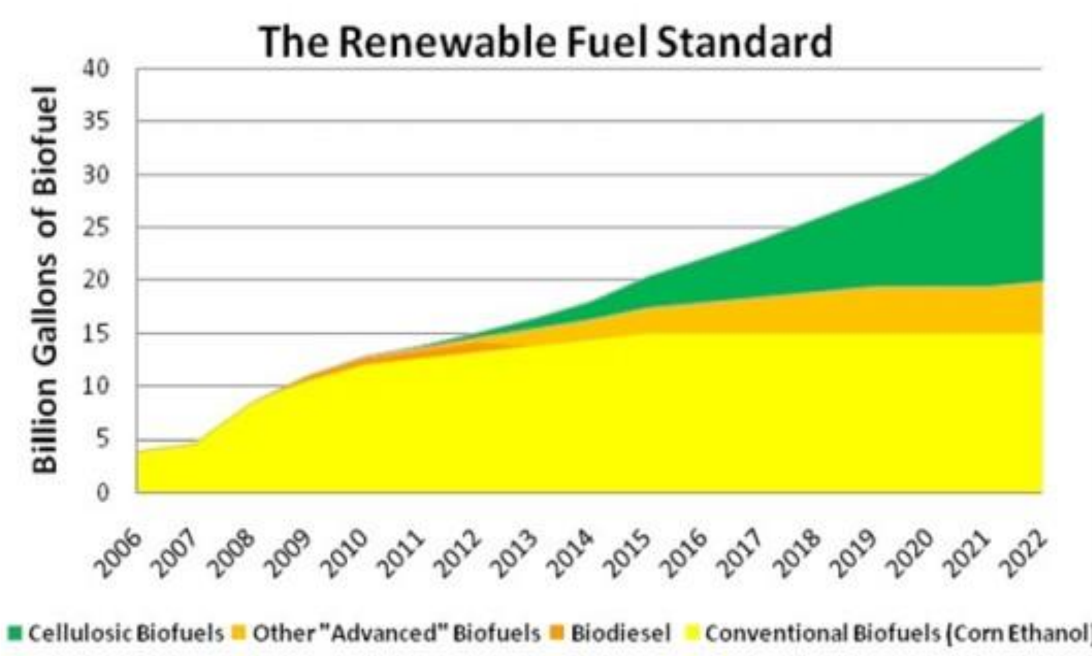
1.1 Background

Renewable Fuel Standard (RFS) provisions of The Energy Independence and Security Act of 2007[1] (EISA) mandates the production of 36 billion gallons of biofuels per year by 2022, including 21 billion gallons of cellulosic and advanced biofuels (increasing from 2 billion gallon per year in 2007), in addition to 15 billion gallons of conventional (corn) ethanol (refer to Figure 1, up). Studies of biomass potential by the USDOE indicated that over a billion tons of biomass feedstocks may be available in the US (Perlack et al. 2005). Furthermore, Epplin.,et al (2007) estimates that a billion tons of cellulosic biomass might be converted to 90 gallons of biofuel under standard conversion technology. This could be used to produce ethanol comprising approximately 26% of the BTUs of the 2005 U.S. net crude oil imports, alleviating the U.S's dependence on foreign oil (Demirbas, 2009). Table 1 reviews the types of biofuel mandated by EISA and the required environmental performance in terms of reductions in life cycle GHG reductions compared with gasoline. It could be seen that cellulosic biofuel is the most environmentally friendly biofuel type – it has the highest GHG reduction among all the categories.

Although corn ethanol production has increased fast enough to keep up with the mandates, the production of cellulosic and advanced biofuels has been well below the targets (the targets for cellulosic and advanced biofuels are shown separately in Figure 1,down) despite significant government support. This has necessitated a downward revision of advanced fuel requirements. The problem seems to be more acute as corn

[1] See http://www1.eere.energy.gov/femp/regulations/eisa.html

ethanol production competes with food markets for corn and has led to increased corn and food prices **(Carter, Rausser & Smith, 2012)**.



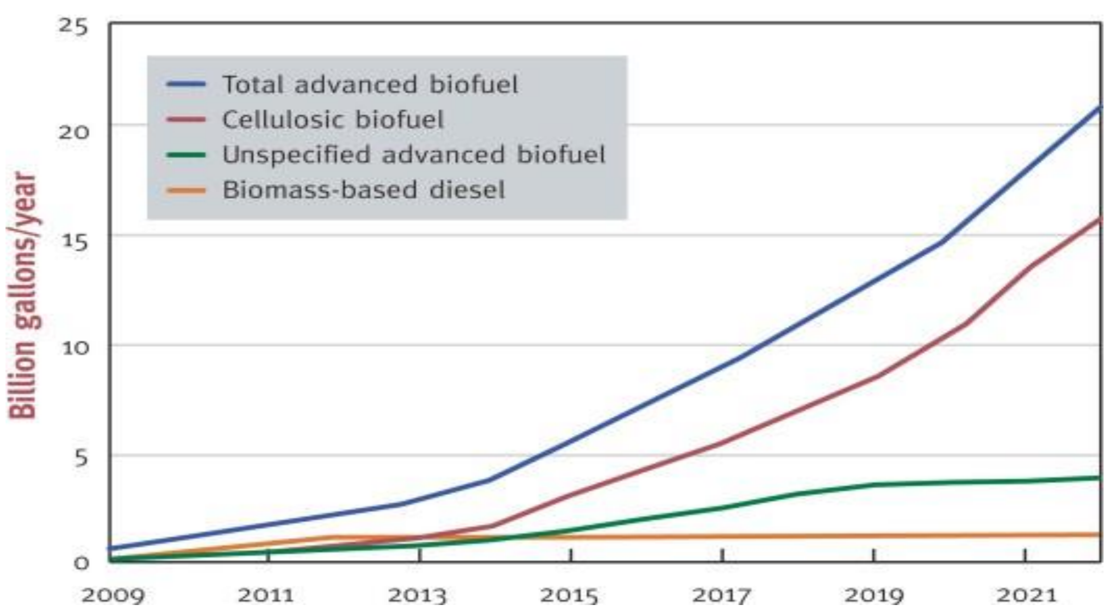


Figure 1 RFS Yearly Biofuel Objective[2]

[2] Source: http://libcloud.s3.amazonaws.com/93/72/c/2270/Issue_Brief_RFS_101.pdf

Table 1 Biofuel Production Mandated by EISA[3]

Fuel	Short Description	Example feedstock	Reduction in GHG emissions	Total gallons mandated by 2022
Conventional Biofuel	Any biofuel-primarily corn ethanol	corn	At least 20% reduction	15 billion
Advanced biofuel	Includes cellulosic, biomass-based diesels, and any other biofuel not made from corn starch	sugarcane	At least 50% reduction	21 billion
Biomass-based Diesel (subset of advanced)	Diesel produced from plant oil or animal fat	soybean, palm, canola	At least 50% reduction	1 billion
Cellulosic Biofuel (subset of advanced)	Fuel derived from the structural tissues of crop residues	switchgrass, algae, Stover, wood	At least 60% reduction	16 billion

Recently, a number of pilot and demonstration scale advanced biofuel facilities like API in Michigan, Genera in Tennessee and Buckeye Technologies in Florida have been established, but commercial scale facilities are yet to become operational. To make informed decisions about this emerging critical industry as well as to ensure a stable feedstock supply, potential biorefinery entrepreneurs and regional policy makers need significant analysis and information on farmers' willingness to adopt these feedstock and how will they switch land into bio-feedstock use. The commonly cited reasons that impede farmers' perennial energy crop adoption include (1) price uncertainty due to the lack of mature market; (2) a high conversion cost; (3) a high sunk cost for long-term commitment and (4) low yield level in the establishing years. Researchers have estimated

[3] Source: http://libcloud.s3.amazonaws.com/93/72/c/2270/Issue_Brief_RFS_101.pdf

that the fraction of farmers willing to adopt switchgrass ranges between 30~70% (Jensen et al., 2007; Wen et al., 2009; Rossi & Hinrichs, 2011**),** varying substantially by regions**.** Hipple & Duffy (2002) also observed a significant "test the water" behavior among farmers. Those findings further warrant a detailed scrutiny of farmers' adaptive behaviors towards perennial energy crops (e.g. switchgrass).

However, many of those uncertainties could be alleviated by contracting between farmers and the biorefinery (e.g. a per ton payment scheme transfer the part of price risk farmers undertake to the biorefinery) (Alexander et al., 2012). But farmers also express their worry on being held-up by the biorefinery (Jensen et al., 2007), which means the refinery would have the potential to default or reduce the payment due to the monopsony power it possesses. In reality, contract is most commonly used in incumbent demonstration biorefineries to procure switchgrass from farmers (e.g. Genera and API biorefinery)[4]. It could also be seen that the strength of the procurer's monopsony power will also affect farmers' adoption decision. As a response, market arrangements should be adjusted to alleviate this concern. Two ways are most commonly considered: (1) introducing competition for procurer, and (2) increase farmers' bargaining power by institutional arrangement.

1.2 Goal of the Thesis

As stated above, market condition plays an important role in influencing farmers' switchgrass adoption decision, so this paper will look into to what extent different market scenarios will impose their influence on farmers based on the data for a North Michigan County. In particular, how different farmers' switchgrass land use will change over time

[4] Genera is a partner of UT Bioenergy Initiative and it currently uses a contract of per acre payment plus per ton payment to procure switchgrass (year1: $450/acre; year2: $250/acre + $40/ton; year3: $150/acre+$50/ton)

under multiple switchgrass outlets market and farmer cooperative market compared with when single procurer purchase switchgrass from individual farmers (more detail in Chapter 2 and 3). To achieve this goal, agent based simulation will be carried out using Repast Simphony toolkit.

Different from traditional economic models, Agent Based Simulation is a widely used bottom-up approach that allows the researchers to specify different attributes and behavioral decision rules for different agents or actors in the model (i.e. capture agent heterogeneity) and then study the interaction of these agents and the consequences of the interactions (Heckbert, Baynes & Reeson, 2010). Therefore, not only the interaction between farmers that emphasizes the social learning process, but also the interaction between farmers and biorefinery that could represents the influence of contract hold-up[5] by biorefinery on farmers, could be modelled.

1.3 Thesis Outline

The thesis is organized as follows: Chapter 2 makes a brief review of the existing literatures; chapter 3 introduces different market scenarios in detail, builds the agent based model framework, and describes agents' decision rules under different market scenarios; chapter 4 introduces the study region, provide detailed reason for choosing this study area and provides a description of data; chapter 5 shows the agent based simulation experiment results; chapter 6 concludes.

[5] We define contract hold-up as the fact that the biorefinery will not pay farmers the full contracted price at the end of some transaction years.

CHAPTER 2: LITERATURE REVIEW

Agricultural Land use decision-making is being analyzed by different disciplines using various methods, either theoretical or empirical. Therefore, this section will summarize some of those studies on modelling farmers' land use decision (including but not limited to energy crop land use) and different methods they use to provide a general background of the ongoing research.

2.1 Agricultural Land use decision studies

In this sub-section, a review on land use decision studies is presented, categorized by the method those studies use with an emphasis on the application of agent based models on land use change.

2.1.1 Optimization-based simulations

Consisting with economic theory, simulations based on mathematical optimization or risk/uncertainty decision rules that apply to representative farms or regional planner is widely used as a method to study land use decision, especially for crops without a mature market. For example, Egbendewe-Mondzozo et al. (2011) simulated biomass supply in southwestern Michigan using detailed production data and showed that the minimum biomass to corn price ratio is in the range of 0.15 to 0.18, varying by energy crops. Larson, English & Lamber (2007) simulated over different contract scenarios (spot market contract, acreage contract, revenue-sharing contract, etc.) on bio-crop land use change in Tennessee's biomass initiative region. Their results showed that spot market price were not high enough to induce biomass production. Khanna et al (2011) also introduced a larger-scale and longer-time math programming model of biomass supply under different yield and price scenarios. They found that besides price, farmers' biomass land use amount also depends heavily on residue collection technology, cost of producing bioenergy crops and land availability.

With regard to risk/uncertainty, Song, Zhao & Swinton (2011) adopted a stochastic process model showing that uncertainty and sunk cost will influence farmers' option value of converting land to switchgrass use (see Corato & Hess, 2013 for another application).

However, though math programming and stochastic programming models are commonly used in land use models, the drawback is the underrepresentation of farm-level heterogeneity and other farmer-level conceptual perceptions for different crops. The two methods below supplement this optimization based models by looking at different aspects of farmers' land use decision process

2.1.2 Willingness to adopt new crop studies

Willingness to adopt studies are also common in the agricultural land use literature. Among the methods used in this subset of studies are focus group talking, discrete choice analysis (e.g. contingent valuation and choice experiment), or the combination of the two. The latter approach is particularly popular with respect to studying the WTP of energy crops. This method provides a way to identify what factors (e.g. demographic characteristics, perceptual concept) other than optimization would influence farmers' land use decisions. Literatures in this way show that among various factors that influence farmers' willingness to adopt switchgrass, the relative newness of switchgrass to farmers are the most frequently mentioned (Jensen et al., 2007; Wen et al., 2009) since it brings farmers a high level of uncertainty.

Other factors such as farms' characteristics (farm head's age, farm size, initial capita), the lack of mature market (if no contract exists), the trust on biorefineries, and even farmers' environment concern will also impose some influence on farmers' adoption decisions (Hipple & Duffy, 2002; Wen et al., 2009; Paulrud & Laitila, 2010; Rossi & Hinrichs, 2011). Researches like Scheffran., et al (2007) and Shastri., et al (2011) show that land opportunity cost and farmers' social networks are important determinants of farmers' Miscanthus adoption rate using agent based modeling approach for a case study in Illinois. Besides the contributing factors to land use change, researchers also estimated that for switchgrass, the fraction of farmers willing to adopt switchgrass is between 30~70% (Jensen et al., 2007; Wen et al., 2009; Rossi & Hinrichs, 2011) varying by regions. Hipple & Duffy (2002) also observed a significant "wait-and-see" behavior among farmers. This finding warrants further investigation of the effect of the adaptive behavior has on adopting switchgrass.

2.1.3 Agent-based land use and land cover change simulations

Agent-based models give every agent a specific decision rule and then study the interaction of these agents in a bottom-up manner (Ross & Westgren, 2009; Heckbert, Baynes & Reeson, 2010; Anderson, 2012). This approach might generate emergent behavior of the system which is hard to predict otherwise (Shastri et al, 2011) due to a lack of interaction and adaptive learning behavior in pure math programming models. Agricultural land use is greatly discussed using agent based modeling method since high-degree heterogeneity among farmers and the environment, high frequency of interaction among farmers and interaction between farmers and environment exist in the real world (Verburg & Overmars, 2009; Shastri et al, 2011; Kelly & Evans, 2011). Kelly & Evans

(2011) successfully modelled and calibrated the impact of farmers' preference on their land use pattern in Indiana Creek Township. Scheffran et al (2007) modeled the spatial dynamics of biofuel crop growth in Illinois by emphasizing the effect of the introducing biomass on the price evolution for both regular crops and biofeedstocks, which was also emphasized by Lundberg (2012), who, after comparing his agent-based modeling result with a similar conceptual model, found out the equilibriums in the two models were similar though using different price determination mechanisms.

However, although agent heterogeneity is fully represented in most agent based land use models, they often ignore various constraints (e.g. capital, labor, etc.) that might greatly influence farmers' decisions. As a response, to incorporate the benefits of optimization in math programming models and agent based modelling's flexibility in representing heterogeneity, another method called mathematical programming based multi-agent system (MP-MAS) has emerged (Schreinemachers, Berger & Aune, 2007; Schreinemachers et al, 2010). This method combines math programming with agent based modeling, thus fills an important gap in literature. By incorporating economic constraints into the model, the simulations are able to address the potential socio-economic feasibilities for different land use patterns (A summary of the mostly often used constraints are listed in Table 2). However, drawbacks also exit: most studies either ignore the learning process (Anderson, 2012) or just incorporate self-learning without learning from others (Schreinemachers, Berger & Aune, 2007). In addition, perceived and real production risk/uncertainty are not adequately modeled in agent's decision process. The reason might be that most studies deal with existing crop systems, where crops and technologies are already familiar to them. However, for a new energy crop, as noted by Hipple & Duffy (2002), farmers will have to learn the real production potential and risk level by observing others and learning from self-experience together.

When detailed existing farmer household data and environmental data are not available, the initialization of land ownership is to random allocates all land parcels (Schreinemachers, Berger & Aune, 2007; Stolniuk, 2008) to different farmers. This willresult in possible rather biased simulated farm land use pattern as the results will be influenced by the random distribution of transportation cost and land quality associated with random farm land location. The generation of farmers conforms to two ways: (1) The first way is to randomly sample farmers and environmental variables, and then populate the rest of farmers in the study area by either replicating the self-conducted survey results to un-surveyed areas and farmers (e.g. Schreinemachers, Berger & Aune, 2007), or populating according to cluster effects among variables in the survey data (Berger & Schreinemachers, 2001). The problems for this method are that without reference like census data (solely relying on survey data), we are not sure if the final result is a representative of the study region; (2) The second way of initializing the model when we do not have detailed farm-level data is to get the farmer household character statistical distributions from census or other related data source and generate synthetic farmers accordingly (Happe, 2004; Stolniuk, 2008; Anderson, 2012). The drawbacks for this method is that completely relying on census data to populate farms might loss specific farm level accuracy though the final farm endowments might conform to the census average.

Table 2 Representative Farm Resource Constraints Included in Existing Literatures

Study	Resource Constraints	Initialization	Initial constraints Sources	Objective function
Schreinemachers et al (2009a) & Schreinemachers et al (2009b)	Land	Artificially located based on qualitative information	Farm household survey data Replicate surveyed household to the rest of the region	**Linear Programming** **Component:** 1. Crop profit 2. Off farm profit **Note:** Off farm incomes comes from other farms who need additional labor
	Labor	Convert Household members to man-day		
	Liquid Cash (other assets not used)	Crop area for different crops * average cash need for each crop		
	Credit availability (Boolean: 0/1)	whether the farmer got loan during the year before survey (yes =1, no = 0)		
	Water (Irrigation, ground)	Assign Survey results to randomly created farmers		
	Green Houses Numbers	Assign Survey results		
Anderson (2012)	Land	1. Divide region into equal size parcels 2. Randomly assign parcel to farmer 3. Land value determined by productivity index	Average data from regional census No individual farmer data	**Mixed Integer Programing** **Component:** 1. Crop profit 2. Net Livestock incomes 3. Off farm income is initially set according to the size of farm and is kept constant during the model run
	Cash	$50*(Total land acres + 4*herd size)		
	Credit (Detail see below)	The ability to borrow is determined by farm debt/asset ratio		
	Debt/Asset Ratio (determine the accessibility to access land market)	**1. Debt:** assigned randomly, referring to a mean value from census record) **2. Asset:** cash, land value, cropping equipment		
	Labor/Machine Package	Random assignment according to distribution data		
Kelly & Evans (2011)	Labor hours	Fixed number for each household	Self-assigned	**Component:** 1. Peculiar utility 2. Farmer Preference

Source: Author self-summarization

Alternatively, if detailed or partially-detailed farmer data and farm land ownership data are available, model validity would be increased (e.g. Kelley & Evans, 2011). For example, if detailed data on a portion of farmers is available, we could populate those real data into the model and then initialize the rest of lands and farmers based on the census data and existing data, which will give a more accurate result.

Due to the significant data requirements of the second model initialization method, the first method is more widely used in the existing literatures. Even if we could get the required data from conducting survey or purchasing, there is also tradeoff between accuracy and cost. Among the agent based land use models, only Evans & Kelly (2004) focused on land-level initialization and showed that a 50m * 50m grid resolution of land might balance model precision and run speed. Further research may be appropriate to compare methods of creating farm households and allocating lands to farms.

2.2 How Economic Agents Learn

2.2.1 General Learning Theory in Economics

Self-learning (learning from one's own experience) and social learning (learning from both others' and the agents' own experience) are two major types of learning models。 The applications of those models are heavily dependent on both how well they represent the real world and the ease of fitting them to the main research method in a study. While self-learning such as adaptive expectation and adaptive risk learning (Nerlove, 1958; Just, 1974) are widely used in econometric analysis due to statistical tractability, social learning models are plentiful in theoretical applications and empirical simulations (e.g. Feder & Mara, 1982) as they do better represent communication in real world.

Brenner (2006) provides a summary of existing learning models and classifies them into different categories from the perspective of who are actually learning and the level to which the learning is rational. Neoclassical economists often assumes that people are fully rational, which leads to the predominance of the Bayesian learning approach (Feder & Mara, 1982; Jordan, 1991; Kalai & Lehrer, 1993). While the strength of Bayesian approach is the mathematical tractability and the ability to incorporate social learning, it is also widely critiqued by its assumption of complete information, fully-rational optimization and ignorance of psychological effects such as the differential effects of recent vs. past experience (Brenner, 2006). Lindner & Gibbs (1990), for example, find that Bayesian learning fails to represent part of the learning phenomena observed in South Australia on farmers' belief about the yield distribution of a new wheat variety.

Besides the Bayesian approach, economists also frequently use two other simple learning models: The first model combines routine-based processes of experimentation, experience collection and communication (Kirchkamp, 2000). In this model, weights are given to different observations in different historical years. The second model is reinforcement learning proposed by searching theory: people make simple adjustments to their previous strategies locally or globally (Ross & Westgren, 2009), depending on the payoff from that strategy. While these two approaches do catch some of observed learning result patterns, they are also criticized by their oversimplification of people's comprehensive learning abilities such as forming probability distributions of the outcome in Bayesian models (Brenner, 2006).

2.2.2 Learning in agent based models

Agent based models assume that people are bounded rational, which means although people are trying to optimize, they still have to learn from experience to update their belief (Kirman, 2010). Depending on study goals and the methods adopted, different agent based models use different learning algorithms.

In agent based models where farm land allocation is studied, farmers' learning is primarily concerned on the parameters of the optimization. For example, in farm land use agent based models (ABMs), adaptive self-learning or Bayesian updating are widely used in farmers' learning on crop gross margin per acre (e.g. Berger & Schreinemachers, 2001) (Exceptions like Freeman, Nolan & Schoney, 2009 doesn't model learning because crops under consideration are quite familiar to farmers).

On the other hand, searching theory (or reinforcement learning) is also used frequently when an explicit searching space (all potential outcomes) is defined (e.g. Kollman, Miller & Page, 2000; Ross & Westgren, 2009). For example, Tesfatsion (2006) proposed a learning algorithm for firms where a finite supply offer options were defined and firms base their choice each year on the success of previous year's strategy as well as its willingness to experiment with new options. This strategy is consistent with the exploration and exploitation approach taken in Chang & Harrington (2003) to avoid being stuck in a local optimum at the early stage.

The main difference in the two learning categories is that the former method is used when the objective people learn is not directly the results of potential strategies – the things they learn are rather something that influences the successfulness of the strategies.

2.3 Effect of risk and transaction cost on transaction parties

2.3.1 Risk and Transaction Cost

Different institutional arrangements (including market structures) often impose different levels of risk and transaction cost (Coase, 1992; Besley, 1995; Dorward, 1999). Here we define market structures as any real-world settings that impose rules to which market parties should conform, which include but not limited to contract regulations, presence of alternative marketing channels and production organization formations.

In economics, risk refers to the variability of outcomes. "Rational people" are always trying to maximize their expected utility taking the risk they are facing into account (Neumann & Morgenstern, 1944). According to expected utility theory, people with high and low level of risk preference will act significantly different when they are facing the same level of risk. With respect to new crop adoption, the more risk averse a farmer is, the more reluctant he will be to adopt a relatively new crop – the unfamiliarity brings a high level of risk. While there might be several drivers of outcome variability, one source is likely related to market arrangement. In order to manage market risk, the common practice is to rearrange risks born by different transaction parties so that entities whose risk tolerance is high could take over some uncertainties facing those who are more risk averse to achieve win-win trade (Kocherlakota, 1996).

Another component of a transaction that may affect transacting parties is the cost of the transaction. As Coase (1937) and Williamson (1996) indicate, costs of participating in a market (or using other transactional mechanisms) exist. Such costs include search costs, negotiating or bargaining costs, contract design costs or monitoring costs . Williamson (1996) further claims that risk and transaction costs might interact: one parties' risk is marked up by the afraid of another parties' opportunistic behaviors caused by the high transaction costs of preventing those actions.

2.3.2 Risk & transaction in agricultural market

Risks farmers face could be categorized into production risk (e.g. yield risk, input price risk), marketing risk (e.g. output price risk) and financial risk (e.g. high leverage). Contracts are commonly used (Key & Runsten, 1999) to alleviate those risks by imposing different compensation mechanisms (Rothschild & Stiglitz, 1976; Alexander et al, 2012) and contracting periods (Jensen et al., 2007; Rossi & Hinrichs, 2011). But farmers might also face the risk of contractual holdup by procurers, in which case their payment might be delayed or be canceled due to various reasons (e.g. quality satisfaction, procurer bankruptcy, procurer market power, high spot market price). The hold-up problem is especially eminent for perennial switchgrass if there is only one buyer in the market. In this case, land devoted to perennial switchgrass may be classified as a relationship-specific asset and provides an opportunity for a opportunistic procurer to extract further rents from the farmer through the threat of contractual holdup (Hipple & Duffy, 2002).

At the same time, the literatures also focus on the difference of market participation among farmers with different size. Janvry, Fafchamps & Sadoulet (1991) and Besley (1994) argue that the high transaction cost brought by high information searching costs, high supervision cost and poor market infrastructure may limit farmers' market participation. Various organization/institutional arrangements have, therefore, emerged overtime to overcome the high transaction cost facing farmers in both input and output market. Cook (1995) found that farmer cooperative could also reduce transaction cost associated with getting loans, designing contracts or searching markets to some extent and brings economic of scale, if properly organized.

2.4 Literature Gaps and Research Questions

By reviewing the above related literatures, this thesis identifies the following literature gaps in modeling farmers' switchgrass land used decision in agent based models:

(1) Optimization based decision rules haven't been incorporate with more realistic social learning models and haven't dealt with risk of farming.

(2) Nearly all existing agent based energy crop adoption models assume that there is aspot energy crop market where farmers could sell all of their energy crops. The effect of major different market scenarios that impose different risk and transaction cost for farmers when no mature spot market exists have not been studied yet.

Therefore, the research question of the thesis examines to what extent farmers' switchgrass adoption decisions and biorefineries' contract hold up decisions will be affected by different market scenarios, particularly when social learning occurs over time. The market scenarios we are looking at include:

1. A biorefinery procures switchgrass from individual farmers.
2. A biorefinery procures switchgrass from a farmer cooperative.
3. Multiple easily accessible market outlets channels procure switchgrass from individual farmers.

CHAPTER 3: THE AGENT BASED MODEL FRAMEWORK

3.1 Basic Farmer Decision Method

Farmers are assumed to be partially-rational individuals who maximize their expected utilities at the beginning of each year based on their current knowledge on crop yield, price and risk.

Following the combination of expected utility theory (EU) in Bocqueho & Jacquet (2010) and Larson, English & Lamber (2007), farmer's problem could be described as a multi-period risk programming:

$$\underset{\boldsymbol{X}}{\text{Max}}\, EU_t(\boldsymbol{X}) \quad \text{s.t. } \boldsymbol{A_t^T X} \le \boldsymbol{b_t} \tag{1}$$

Where $\boldsymbol{X}$ is a vector of land devoted to different cropping activities (corn, soybeans, winter wheat, alfalfa and switchgrass); $\boldsymbol{A_t^T}$ $\boldsymbol{and}$ $\boldsymbol{b_t}$ the resource constraints at time t; $EU_t(\boldsymbol{X})$ the whole farm expected utility at time t. The traditional way of modeling $EU_t(\boldsymbol{X})$ for a farm risk programming is to use a mean-variance formula:

$$EU_t(\boldsymbol{X_t}) = \boldsymbol{EM_t^T X_t} - \frac{\lambda}{2}\boldsymbol{X_t^T}[\boldsymbol{VCV}]\boldsymbol{X_t} \tag{2}$$

Where λ represents the coefficient of absolute risk aversion of a farmer; $\boldsymbol{VCV}$ is the variance-covariance matrix for different cropping activities; $\boldsymbol{EM_t^T}$ is the expected transpose vector of gross margin per acre for crop $\boldsymbol{X}$**.**

However, due to the availability of proper java quadratic risk programming library for the agent based model toolkits[6], this thesis transformed the quadratic risk

[6] Currently only CPLEX solver could handle non-convex quadratic programming in java. However, as the problem under consideration is multi-period and is subjected to a lot of constraints, the solver is quite slow in solving even a single farmer's optimization problem.

programming problem to a linear programming one using MOTAD model proposed by Hazell (1971) as follows[7]:

$$\underset{x_1 \cdots x_n,\, d_1 \cdots d_k}{\boldsymbol{Max}} EU_t(\boldsymbol{X}) = \underset{x_1 \cdots x_n,\, d_1 \cdots d_k}{\boldsymbol{Max}} \left\{ \sum_{i=1}^{n} \sum_{w=1}^{s} EM_{iwt} X_{iwt} - \frac{\lambda}{2} \sum_{j=1}^{k} d_{kt}^{-} \right\} \qquad (3)$$

$$s.t.\ \sum_{i=1}^{n} \sum_{w=i}^{s} a_{mist}\, X_{ist} \leq (or\ =) b_{mit}\ (for\ all\ m - number\ of\ constraints;)$$

$$\sum_{i=1}^{n} \sum_{w=1}^{s} (M_{kiw} - \bar{M}_{iw}) X_{ist} + d_k^{-} \geq 0\ (for\ all\ k)$$

$$x_{iwt},\ d_k^{-}\ \geq 0\ (for\ all\ i, k)$$

Here k denotes the number of historical periods we use to calculate historical gross margin deviations from the mean, s denotes the number of different soil types. In this application, the period's numbers are set to 4 (k = 1, 2, 3 and 4). M_{ki} is the kth historical gross margin for crop i on the most commonly seen soil type in the region (productivity index equal to 10, see section 4 for detail), d_k^- is the absolute value of negative deviation of the k[th] historical year's crop gross margin occurrence from the mean gross margin.

The sum of d_k^-, together with the second constraint, approximate the variance part in the utility function described in equation (1). For simplicity and tractability, it is also assumed here that farmer's subjective deviation of gross margin $(M_{kiw} - \bar{M}_{iw})$ calculated by the historical years doesn't change overtime for traditional crops (for switchgrass, refer to section 3.2 and section 3.4 for detail). The only thing that changes is the expected gross margin for each crop (Hazell & Norton, 1986).

[7] For a detailed description of MOTAD model, please refer to Hazell (1971).

Unlike many other literatures that uses math programming to study land conversion (Berger, 2001; Schreinemachers & Berger, 2006; Anderson, 2012) where lands could only be converted out of perennial crop use until the end of their life cycle, the vector of X not only includes planting crops on currently available lands (lands that are not occupied by perennial crops), but also includes cutting perennial crops and convert the land back to other crops when the perennial crops haven't reached the end of life cycle. This is the first attempt in agent based farm optimization model to allow for converting perennial crop lands back to other uses. It is especially important in analyzing contract hold up issues because farmers are prone to revert to traditional crops when the risk of contract holding up is high. The gross margin and planting cost/conversion cost for perennial grasses are represented by annuity value (Song, Zhao & Swinton, 2011).

Finally, the realized gross margin for traditional crop i (that is, excluding switchgrass) in time t could be expressed as:

$$M_{iPIt} = (P_{it} - C_{vYield})\, Y_{iPIt} - C_{vAcre} \qquad (4)$$

P_{it} is the price of crop i and PI is the soil productivity index. Here we assume out production fixed cost and the variable cost could be decomposed into yield-related variable cost (C_{vYield}) and acre-related variable cost (C_{vAcre}).We also assume that crop yield changes linearly corresponding to soil productivity index:

$$Y_{iPIt} = Y_{i10t}\left(1 + m_i * \frac{PI - 10}{10}\right) \qquad (5)$$

For traditional crops, we assume that Y_{i10t} are continuous, but for switchgrass, we assume that Y_{i10t} has only two states: high yield and low yield year (Kells & Swinton, 2014). Notice that 10 is the dominant PI in the region (i.e. the productivity index that is most commonly seen among soils in this region). m_i is a coefficient representing the crop yield's sensitivity to PI. Therefore, if we know M_{i10t}, we could also know:

$$M_{iPIt} = (M_{i10t} + C_{vAcre})\left(1 + m_i * \frac{PI - 10}{10}\right) - C_{vAcre} \qquad (6)$$

3.2 Market Scenarios for Switchgrass

Contract is a fairly common procurement practice when no mature markets for a commodity exist (Jensen et al., 2007). This also applies to Michigan as the market for switchgrass is negligible. Therefore, contract pricing exists under all market scenarios in this study. Shown in the literature review section, as contract hold-up (delay or reduce payment by the biorefinery) is an eminent risk in contract relationships especially for perennial energy crop, all the market scenarios analysis below will treat it as an important factor.

3.2.1 Single-Outlet (Biorefinery) in the Region Procures from Individual Farmers

As a new energy crop, switchgrass has very few outlets. The most commonly seen outlets are for ethanol production and electricity generation by combustion. However, most of those factories are rather regional and their switchgrass collecting areas do not usually overlap so much. Therefore, if farmers in one region were to sell to an outlet in another region, he had to transport the switchgrass for a long distance. This is difficult as the transportation cost for grass is exhibitive high. In addition, it is also difficult for individual farmers to get enough information for other market outlets far away. All of the above stated facts show that the transaction cost for information searching and trading with those distant outlets is very high. Therefore, for a county under consideration, the usual case is that they are facing a single outlet. As a result, the thesis will study this case first.

Consider a contract with a quantity/yield price ($\emptyset$). The total contracted compensation per acre (P_{iPI}) and gross margin (M_{iPI}) contracted for farmer i could be expressed as:

$$P_{iPI} = \emptyset Y_{iPI} \quad (7)$$

$$M_{iPI} = (\emptyset - C_{vYield})Y_{iPI} * \alpha - C_{vAcre} \quad (8)$$

Here α denotes the percentage payment if contract is held up by the procurer ($0 \leq \alpha \leq 1$), which is assumed to be constant during the simulation period. The smaller α is, the less payment will be received by farmers. In this scenario, farmers and biorefinery act following the flowchart shown in Figure 2.

At the beginning of each year, farmers will get to know the compensation mechanism in the contract and form their expectations on crop gross margins. For traditional crops, the expectations are formed according to Bayesian rule; for switchgrass, farmers observe biorefinery's past hold-up behavior (illustrated in more detail below) and past switchgrass production real cost as well as past ethanol price. That information will be used to determine farmers' expectations of the amount of payment biorefinery will hold up for the coming year. Based on the expectations, farmers will carry out a linear programming optimization that incorporates risk and decide the land allocation for each year. Then biorefinery will be informed how many acres have been allocated to switchgrass use. It will utilize this information and the expectation on the ethanol price to decide the profit gain in this period and the future profit loss if hold up contract. Then the biorefinery decide whether and how much payment to hold up farmers based on the calculation above. Finally, based on biorefinery's hold-up decision, biorefinery's and farmers' profits are realized and the available resources are updated for farmers. The model repeats this behavior for the simulation period (1 year = 1 time step).

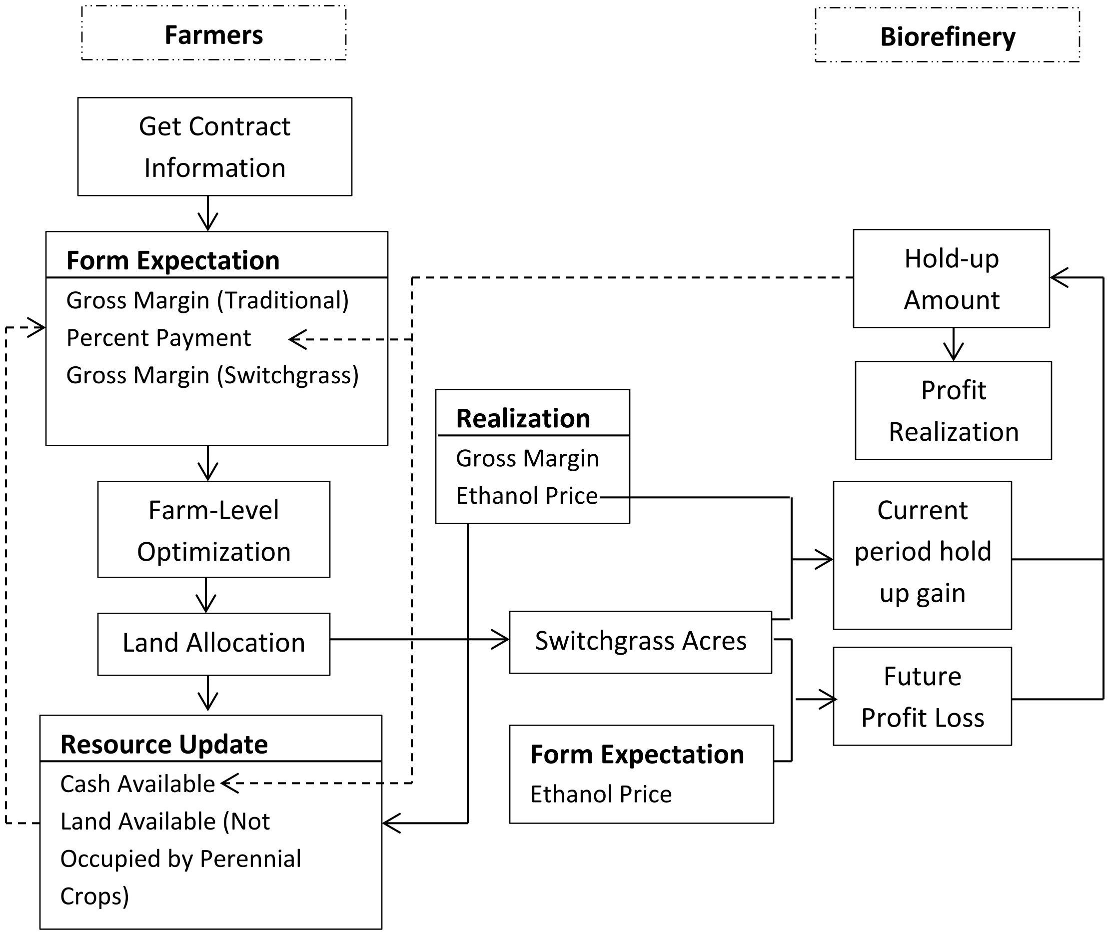


Figure 2 Decision Tree for the Single-Outlet Scenario (Scenario 1)

3.2.2 Quasi-Multiple Outlets – A Biorefinery Procures From a Farmer Cooperative

In the first scenario, we say that for individual farmers, it is usually rather unfeasible to sell their switchgrass to market outlets far away due to the high grass transportation cost and transaction cost of finding another outlet, thus they are in fact facing a single outlet.

However, when farmers form a cooperative, several different things might happen to facilitate the cooperative to find out alternative market outlets -- farmers will indeed gain a much higher bargaining power than when they are operating individually:

First, the cooperative could own a pelletizer, converting switchgrass from grass to pelletize, which saves the transportation cost to a great extent, thus makes relatively long-distance transportation more feasible and extends the potential of multiple outlets appearance.

Second, it is much easier for a cooperative to get necessary information of other market outlets than individual farmers due to more specialized management and more efficient contacting methods, reducing the transaction cost of searching and trading with alternative marketing outlets.

As the alternative switchgrass outlet depends on incurring some extent of transaction cost by the cooperative, this scenario could be regarded as a "quasi-multiple outlets" scenario. The next market scenario would be an ideal (or hypothetical) scenario that assumes there are multiple readily available market outlets.

On the other hand, if farmers want to sell switchgrass via a farmers' cooperative, they need to pay salaries to the management team to guarantee the regular functioning of the cooperative. But it is inferred here that the salary paid is much less than the potential profit gain of the appearance of competition between procures that brought by the alternative outlets found by the biorefinery..

It is expected that under this case, the biorefinery will be more unwilling to hold up contract than the first scenario and the amount of switchgrass land will be higher than in the first scenario: if holding up contract, biorefinery will face the risk of losing a great amount of profit even in the current year.

At the beginning of each year, farmers will form expectation on switchgrass gross margin for continue working with the cooperative and allocate their land. At the end of each year, cooperative collects its farmers' harvested switchgrass, and then the biorefinery decides what percent of the payment it is going to offer this year based on its expectation on current and future loss of paying different percent of the full payment. Next, the cooperative will decide whether to sell switchgrass to biorefinery or sell them to the alternative outlet it could find. Finally, farmers got their payment from the biorefinery and step into the next year's planning.

3.2.3 Multiple Easily Accessible Outlets in the Region for Individual Farmers

Ideally, when multiple switchgrass outlets exist for farmers, the risk of being held up by it transaction partner is relatively lower than single outlet case due to the competition between the two outlets. Biorefinery's capacity will also increase at a faster rate as lower hold-up amount will lead to higher farmers' switchgrass grows margin expectation, making farmers less frequently to convert current switchgrass lands back to other crops. In addition, farmers do not need to incur high transaction cost to find out another outlet, so their switchgrass gross margin expectation is expected to be higher than under the cooperative's "quasi-multiple outlet" situation. In this case, we consider two biorefineries[8] procure switchgrass from individual farmers (the difference between the two biorefineries is discussed in section 3.5.3).

The flowchart in Figure 3 representing the interaction between farmers and biorefinery is quite similar with the single biorefinery & individual farmer case except that farmers need to consider with which biorefinery they sign the contract based on the

[8] This could be easily changed to different sectors procuring switchgrass, such as a biorefinery and a co-firing plant. The only difference is that different sector may have different switchgrass quality standard. Here we consider two biorefineries and we consider it to be a reasonable assumption as it could simplify other factors outside the analysis of hold-up problem.

expected gross margin of contracting (which is determined by the expected payment amount percent probability).

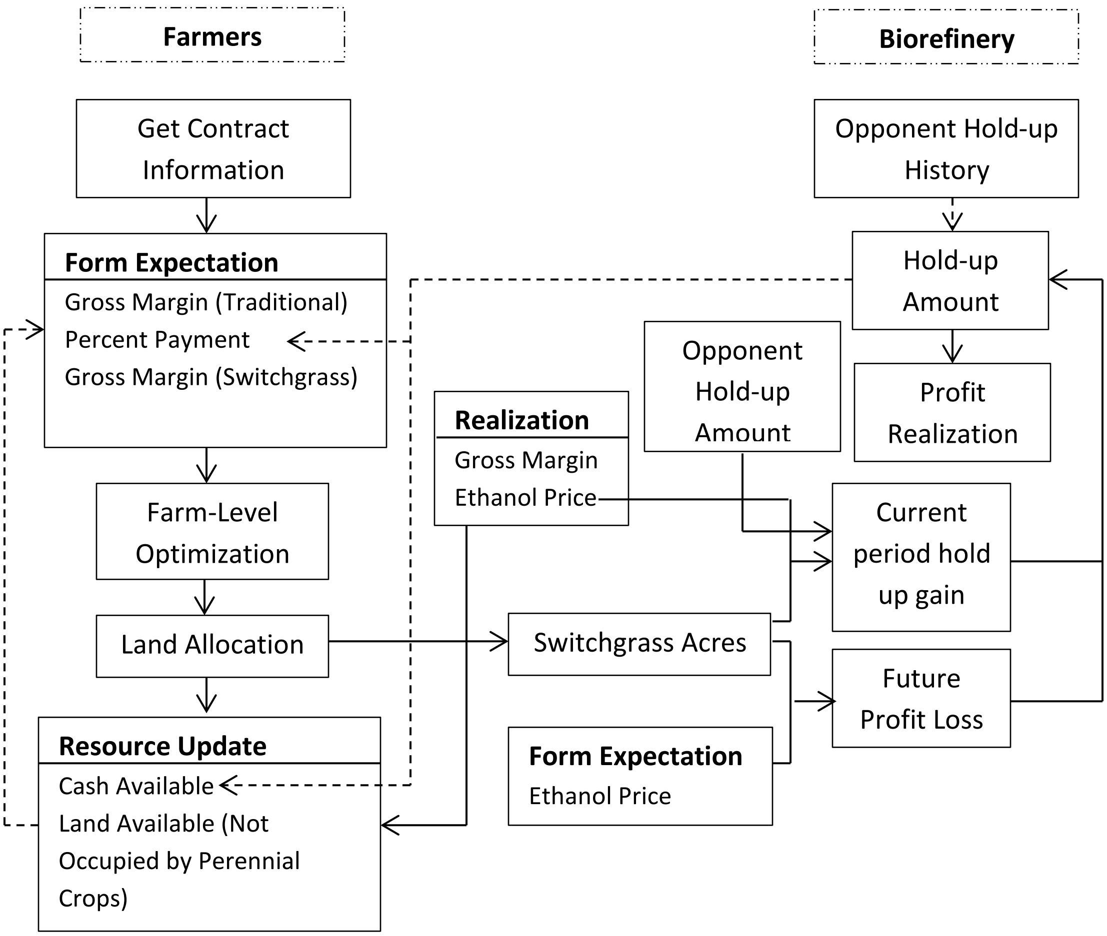


Figure 3 Decision Tree for Multiple-Outlet Scenario (Scenario 3)

Note that in the figure above, opponent's behavior follow the same rule with the biorefinery's strategy.

Biorefineries will also form expectation on each other's hold-up amount. This is done by forming a best response function based on the expected current and future profit loss (gain) if it holds up (doesn't hold up) the contract. By solving the best response function, each biorefinery will set its hold up amount at every simulation tick (More details below).

We have to acknowledge that this scenario is the most unlikely to happen case as it is quite unfeasible that the switchgrass procure areas for two industries overlap. But it is still interesting to compare this results to the cooperative case as that is more realistic to happen and so we want to see how large the difference between the "easy to realize" case and "quite ideal" case will be.

3.3 Farmer's Learning on Crop Gross Margin

For simplicity of the future market scenario analysis[9], this paper uses different learning algorithms for traditional crops (corn, soybean, wheat and hay) and switchgrass.

3.3.1 Learning Traditional Crops' Gross Margin

As the expected gross margin EM_{it} but not M_{it} in equation (4) enters into farmers' linear programming objective function, farmers need to form expectation on the current year's gross margin for each crop at the beginning of each simulation year based on their prior knowledge and new observations utilizing Bayesian learning. We assume that gross margin for farmer i follows a normal distribution[10]:

$$M_{i10} \sim N(\mu, \sigma^2) \ or \ M_{i10} = \mu + \varepsilon_{it} \qquad (9)$$

$$E(\varepsilon_{it}) = 0, \qquad V_{\varepsilon_{it}} = \sigma^2 \qquad (10)$$

A common practice for Bayesian learning is to assume that σ^2 is known to farmers, while μ is unknown and conform to a normal prior distribution $\mu \sim N(m, s^2)$ (Feder & O'Mara, 1982). We update belief for the gross margin of

[9] For detail, refer to section 3.4

[10] The gross margin here excludes transportation costs from farmers' fields to storage and/or to the biorefinery. Later when farmers have formed the expected gross margin for different crops, the transportation cost is then deducted from the gross margin.

traditional crops as a whole, but not form expectation for price and yield separately as we assume that σ^2 is a constant for farmers in the expectation formation process[11].

At the end of the year, crops realize their true gross margin. Notice that in equation (5), price is fixed for each crop in a given year, and crop yield response proportionally to soil productivity. Therefore, farmers could merely update their belief on the gross margin for each crop on the soil type with PI equals to 10. In addition, we assume that the realized gross margins for different farmers are the same in the same year if the soils' PI are the same. Accordingly, if the farmer or his neighbors have grown one crop for a year, the farmer will get the new observation on that crop's realized gross margin, forming his posterior on the mean:

$$f(\mu|G) \propto exp\left\{-\frac{1}{\frac{2\sigma^2 s^2}{\sigma^2+Ns^2}}(\mu-m')^2\right\} \qquad (11)$$

$$m' = \frac{\sigma^2 m}{\sigma^2+Ns^2} + \frac{Ns^2}{\sigma^2+Ns^2}\bar{y}, \quad (s^2)' = \frac{\sigma^2 s^2}{\sigma^2+Ns^2} \quad (12)$$

Here m and s^2 are the prior mean and variance of $\mu. m'$ and $(s^2)'$ are the posterior mean and variance of μ, and $\bar{y}$ is the average of observed gross margin (including own realized gross margin in the last year, if any).N is the total number of observations of crop gross margin. Equation (9) shows the posterior of the distribution of the mean (Lindner & Gibbs, 1990).

More realistically, if we assume that the one farmer's observed gross margin from other farmers may subject to some error, φ, which comes from some farm-specific attributes or communication information distortion, we could make $\varphi \sim N(0, \sigma_\varphi^2)$, which

[11] However, the realized gross margin is calculated using crop price, yield and input cost.

is known to all farmers (Ma & Shi, 2011). Then slightly modify what Ma & Shi (2011) proposed the posterior belief on crop gross margin could be formulated as follows (y_s is the realized own gross margin, while $\bar{y}_o$ is the mean of observed others' gross margin and n is the number of observations from other farmers):

$$m' = \frac{y_s \frac{1}{\sigma^2} + \bar{y}_o \frac{n}{\sigma^2 + \sigma_\varphi^2} + \frac{m}{s^2}}{\frac{1}{s^2} + \frac{Me}{\sigma^2} + \frac{n}{\sigma^2 + \sigma_\varphi^2}}, \qquad (s^2)' = \frac{1}{\frac{1}{s^2} + \frac{Me}{\sigma^2} + \frac{n}{\sigma^2 + \sigma_\varphi^2}} \qquad (13)$$

Here *Me* = 1 if the farmer grew the crop in the last year and equals to 0 if not.

Notice that we treat the gross margin as a whole here (even though the realizations of gross margins are determined by the realization of price and yield) but not separately update the belief for price and yield.

3.3.2 Learning Switchgrass's Gross Margin

As no official record of historical switchgrass yield and gross margin exists, this paper considers two switchgrass yield scenarios according to Kells & Swinton (2014), one high yield (4.7 tons/acre) and one low yield (4.1 tons/acre) and they are randomly assigned to different simulation years. In addition, farmers' expected gross margin is also determined by their expectation of whether the biorefinery will hold up the contract.

At the beginning of every simulation tick (year), farmers will update the expectation of the perceived contract payment percent for the current year E(ρ) and expected yield $E(Y_{iPI})$, following the procedure defined in section 3.5. The expected gross margin for switchgrass is thus:

$$E(M_{iPI}) = \left(\sum\nolimits_{\alpha} [(\emptyset - C_{vYield})E(Y_{iPI})]\alpha * E(\rho)\right) - C_{vAcre} \qquad (14)$$

At the beginning of each simulation tick (year), biorefinery will choose whether to hold up the contract at the current year according to the updating rule in section 3.5.1.

Farmers' learning on switchgrass yield and contract hold up follows a Bayesian procedure for binomial variables. Let's denote the probability of the occurrence of high yield (or contract hold up) by τ. $\tau \in \{high\ Yield, Hold - Up\}$. Following Bolstad (2007), let's set the prior of Bayesian method as $\tau \sim \mathrm{beta}(\alpha, \beta)$. The posterior becomes:

$$\alpha^* = \alpha + s_t, \quad \beta^* = \beta + n_t - s_t \qquad (15)$$

Here n_t denotes the number of observations and s_t the number of realizations of the defined occurrence. Then the new mean and variance of τ are updated as:

$$E(\tau) = \frac{\alpha^*}{\alpha^* + \beta^*} \qquad (16)$$

$$Var(\tau) = \frac{\alpha^* * \beta^*}{(\alpha^* + \beta^*)^2(\alpha^* + \beta^* + 1)} \qquad (17)$$

3.4 Additional Farmer Decision Constraints

In order to prevent the occurrence of unrealistic land allocation results, additional crop rational constraints (maximum proportion of a crop) are imposed on the farm optimization problem following Hazell & Norton (2006) and Anderson (2012). In their model, Kelley & Evans (2011) also impose limitations on farmers' preference for tree and crop, which plays a similar role in the objective function with crop rational constraints.

The rational constraints imposed here include the maximum proportion of perennial grasses/annual crops that could be grown each year on the unused land and the proportion of each annual crop acres (corn, soybean and wheat) to the total annual crop acres. These constraints are chosen based on historical data or calibration process. That is, the set of proportions are chosen so that the simulated crop acre patterns best fit for the observed historical pattern[12]. Table 3 below shows the calibrated crop rational constraint parameters combination.

Table 3 Crop Upper Limit Used in the Model

Crop Type	Parameters	Value	Value Source	Limit
Perennial	Alfalfa/TC*	0.6	Calibration	Max
Perennal	Switchgrass/TC*	0.3	Arbitrarily Choosen	Max
Annual	Corn/Annual	0.5	Historical Data	Max
Annual	Soybean/Annual	0.4	Historical Data	Max
Annual	Wheat/Annual	0.3	Historical Data	Max
Total Annual	Annual/TC*	0.5	Historical Data	Max

* TC: Total Cropland[13]

3.5 Market Scenarios and Agents' Learning on Contract Hold-Up

As we aresaying that the contract prices during all the simulation years are constant, the learning problem for biorefineries is mainly to determine whether to hold up the contracts. We use different learning algorithms to model biorefineries' learning problem under different scenarios.

We are interested in how the land devoted to switchgrass and the possibility that biorefinery might hold-up the contract will evolve overtime, given specific contract compensation. It is also interesting to see how these two trends affect each other. The model framework for contract hold-up presented here is a first attempt to quantify the qualitative assessment used in many literatures (Klein, 1996; Gow, Streeter & Swinnnen, 2001 etc.).

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[12] As switchgrass is historically not presented, it is not included in the calibration process. As a result, no switchgrass maximum proportion is included in the first several years. Switchgrass proportion is set manually based on current literatures after the tick when switchgrass is included in the model.

[13] The use of total croplands could be: grow annual crops, grow perennial crops and left fallow. When there is not enough working capital or the expected gross margin goes to negative, farmers might be prone to left some of their croplands to fallow

3.5.1 Single-Outlet (Biorefinery) in the Region Procures from Individual Farmers

3.5.1.1 Biorefinery's Learning and Decision Process

Biorefinery has Sixteen levels of payment options (hold-up options): Holding up 0%, 5%, 10% ……. 80% of the full payment (paying 100%, 95%, 90% …… 20% of the full payment, respectively). Denote the percent payment by α . $\alpha \in \boldsymbol{\alpha} = \{1,0.95,0.9 \ldots\ldots 0.2\}$. The reason that we cut the payment percent at 20% is to provide a coarse representation of an amount below which farmers are unwilling to give their switchgrass to the biorefinery (e.g., the payment is lower than their switchgrass transportation cost and some other necessary cost of delivering switchgrass to the biorefinery).

Define $q_{\alpha t}$ as the expected utility biorefinery could get by paying α percent of the full payment at year t. The value of $q_{\alpha t}$ is set according to:

$$q_{\alpha t} = Eprofit_{\alpha t} - ELoss_{\alpha t}$$

$$= \sum_j \Big((P_{et} - c) * Y_{jt} * rate - \big(\emptyset Y_{jt}\big) * \alpha \Big) - ELoss_{\alpha t} \qquad (18)$$

Here$Eprofit_{\alpha t}$ is the profit that the biorefinery could gain in the current year by paying α percent of the full contract payment in this year, P_{et} is the price of ethanol at year t stage 0, c is the conversion cost per gallon of ethanol, *rate* is the conversion rate from switchgrass to ethanol, Y_{it} is switchgrass yield for land parcel i in year t, $\emptyset$ is the contracted full payment of switchgrass ($/ton). $ELoss_{\alpha t}$ is the expected potential future profit loss of the currently contracted land for contract hold up (paying α percent of the contract price). The fixed cost of switchgrass to ethanol conversion is converted to the per gallon cost included in c taken from Haque & Epplin (2010). The per gallon cost (*c*) is assumed to be \$1.57/gallon[14] according to their study. The conversion rate (*rate*) of 1 dry ton switchgrass to ethanol is set to 91gallon/dry ton according to Haque & Epplin (2010) and Song, Zhao & Swinton (2011).

$ELoss_{\alpha t}$ is determined by the change of the amount of switchgrass land under contract if α percent of the full payment is paid ($w_{\alpha t}^{b}$) and the expected net present value of current switchgrass land per acre ($\sum_j NPV_{jt}$):

$$ELoss_{\alpha t} = w_{\alpha t}^{b} * \sum_{j} NPV_{jt} \quad (19)$$

$$NPV_{jt} = D\text{is} * \beta * \left((EP_{et} - c) * Y_{jt} * rate\right) \quad (20)$$

$$w_{\alpha t}^{b} = \left(\frac{Max(EGMTradition_{t+1}) - EGMSw_{\alpha(t+1)}}{Max(EGMTradition_{t+1})}\right) \quad (21)$$

$$EGMSw_{\alpha(t+1)} = \sum_{i\in\{1,0.95,0.9......0.2\}} GMSw_{i(t+1)} * ePro_{i\alpha(t+1)} \quad (22)$$

NPV_{jt} is the expected net present value of one acre switchgrass land, $D\text{is} = \frac{\delta}{1-\delta}$ is the discount rate of future value to present value, β is defined as the expected portion of future ethanol production profit to revenue, which is the average of historical profit to revenue. Assuming that biorefinery knows how farmers update their beliefs on switchgrass gross margin (details are in the next sub-section), $EGMSw_{\alpha(t+1)}$ is the biorefinery's expected average farmer switchgrass growing gross margin in the next year for lands under its contract if the biorefinery pays α percent of the full payment this year, $EGMTradition_{t+1}$ is biorefinery's expected average farmer "other crops" growing gross

[14] Different conversion cost is used in different studies. Dipardon (1999) uses \$1.29/gallon in 1998 dollars, McAloon et al., (2000) uses \$1.30 in 1999 dollars, Happe & Epplin (2010) uses \$1.57/gallon in 2010 dollars, and Tao et al., (2013) uses \$1.96/gallon in 2012 dollars. All of these estimates exclude the cost of feedstock. We choose Happe & Epplin (2010)'s estimated cost as the value is neither too high nor too low and year 2010 dollar is also an acceptable measurement.

margin for their lands. $w_{\alpha t}^{b}$ is biorefinery's expected loss coefficient that describes what percent of current land will be converted out of switchgrass use in the current year if the biorefinery pays α percent in this year[15]. $ePro_{i\alpha(t+1)}$ represents biorefinery's expected farmers' perceived payment percent probability ($i \in \{1,0.95,0.9 \dots \dots 0.2\}$) in the beginning of next year if the refinery pays α percent at the end of this tick. $GMSw_{i(t+1)}$ is switchgrass gross margin if the biorefinery pays i percent of the full payment in the next year.

The equation for w_{b1}^{α} says that under most circumstance, the higher the difference between traditional crop and switchgrass profitability is, the higher amount of switchgrass land you will loss. At each time period, the biorefinery will choose the payment rate α that maximizes its utility. That is:

$$\alpha = arg_{\alpha}max\left(\sum_{i}(P_{et} - c) * Y_{it} * rate - (\emptyset Y_{it}) * \alpha - ELoss_{\alpha t}\right) \quad (23)$$

Assuming that biorefinery and farmers know how the other party updates his expectation on contract hold-up probability and how he makes his decision, $ePro_{i\alpha(t+1)}$ and thus $w_{\alpha t}^{b}$ could be calculated according to the next section.

3.5.1.2 Farmers' Learning on Contract Hold-Up Percent Probability

Define farmers expected biorefinery's probability of paying $i \in \{1,0.95,0.9 \dots \dots 0.2\}$ percent this year if it pays α percent of the full payment last year by $ePro_{i\alpha t}^{f}$. It could be expressed as:

[15] It has to be admitted that this is only a rough estimation as the expected loss coefficient depends on farmers' expected profitability of crops in the next period, which depends on quite heterogeneous factors such as soil productivity, farmers' capital available and crop upper limits. Those factors are difficult to tract mathematically, so a rough estimation is used here in the equation. But we do take biorefinery's expected farmer profit expectation in the next period into consideration in the equation for $\mathrm{EGMSw}_{\alpha}^{\mathrm{Me}}$. Thus we say that this approach is valid.

$$ePro_{i\alpha t}^{f} = \Delta_1\, probCal_{it} + \Delta_2 His_{it}(\alpha) \qquad (24)$$

Δ_1 *and* Δ_2 are the weights farmers assign to rational calculated holdup probability ($probCal_{it}$) and historical biorefinery hold up probability ($His_{it}(\alpha)$). A weighted average is used here.

$proCal$ is the expected hold-up possibility in this year calculated by farmers following rational expectations. $probCal_{it}$ could be calculated as:

$$probCal(i) = proCal\left(\mathrm{i} = arg_{\mathrm{i}}max\big(Eq(i,t)\big)\right) = prob\big(Eq_{it} \geq Eq_{\boldsymbol{i_{-1}}t}\big)^{16} \quad (25)$$

$\boldsymbol{i_{-1}}$ is the list of payment percentages that doesn't contain i. We could calculate each $prob\big(Eq_{it} \geq Eq_{\boldsymbol{i_{-1}}t}\big), i_{-1} \in \boldsymbol{i_{-1}}$in the following way:

$$Pr\big(Eq_{it} \geq Eq_{\boldsymbol{i_{-1}}t}\big)$$

$$= Prob\left(\left(w_{it}^{f} - w_{i_{-1}t}^{f}\right) * Dis * CA * \beta * \left((P_{et} - c)\bar{Y} * rate\right) < CA(i_{-1} - i)\emptyset\bar{Y}\right)$$

$$= Prob\left(P_{et} > \frac{(i_{-1} - i) * \emptyset}{\left(w_{it}^{f} - w_{i_{-1}t}^{f}\right) * Dis * \beta * rate} + c\right)^{17} \qquad (26)$$

Therefore, the probability of choosing each level of payment $probCal(i)$ could be expressed as a segment of the ethanol price axis and the probability could be calculated out assuming the ethanol price conforms to a normal distribution.

CA is the current lands under the biorefinery's contract. Given that the ethanol price follows a normal distribution and farmers will update their beliefs on the mean and variance of ethanol price, $proCal$ could be calculated easily.

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16 In the calculation, we could calculate only pairs of $(\mathrm{i}, \mathrm{i}_{-1})$ that $\mathrm{i} > \mathrm{i}_{-1}$. The rest combinations could be calculated based on these results.

17 The final sign of the comparator could be either "greater than" or "less than", depending on the sign of $\mathrm{w}_{\mathrm{it}}^{\mathrm{f}} - \mathrm{w}_{\mathrm{i}_{-1}\mathrm{t}}^{\mathrm{f}}$. It is obvious that if $\mathrm{i} > \mathrm{i}_{-1}$, $\mathrm{w}_{\mathrm{it}}^{\mathrm{f}} < \mathrm{w}_{\mathrm{i}_{-1}\mathrm{t}}^{\mathrm{f}}$

If we apply the same equation of w_{it}^{b} to w_{it}^{f}, the only difference between $ePro_{ki(t+1)}^{f}$ and $ePro_{ki_{-1}(t+1)}^{f}$ (in the equation below) exists in the biorefinery's hold-up history ($His(i)$). Thus $w_{it}^{f} - w_{i_{-1}t}^{f}$ could be expressed as:

$$w_{it}^{f} - w_{i_{-1}t}^{f} = \left(\frac{Max(EGMTradition_{t+1}) - \sum_{k=1}^{16}\left(GMSw_{k(t+1)}\right) * ePro_{ki(t+1)}^{f}}{Max(EGMTradition_{t+1})}\right) - \left(\frac{Max(EGMTradition_{t+1}) - \sum_{k=1}^{16}\left(GMSw_{k(t+1)}\right) * ePro_{ki_{-1}(t+1)}^{f}}{Max(EGMTradition_{t+1})}\right)$$

$$= \Delta_2 * \left(\frac{-GMSw_{i(t+1)} + GMSw_{i_{-1}(t+1)}}{N * Max(EGMTradition_{t+1})}\right) \qquad (27)$$

Therefore, for farmers, $probCal_{it}$ and thus $ePro_{i\alpha t}^{f}$ could be calculated. As biorefinery knows farmers' decision rule (more specifically, it knows the way farmers calculate $w_{it}^{f} - w_{i_{-1}t}^{f}$, it could estimates farmers' perceived $probCal_{it}$ and $His_{it}(\alpha)$, which means $ePro_{i\alpha(t+1)}$ and consequently $w_{\alpha t}^{b}$ in the above section's equations could be estimated.

3.5.2 Quasi-Multiple Outlets – A Biorefinery Procures from a Farmer Cooperative

Under this scenario, after biorefinery announces its payment percent of the full payment, the cooperative will sequentially determine whether to sell the switchgrass of its farmers to the biorefinery or to find out an alternative seller based on the comparison of the real price of the two.

For simplicity, using the same method used in Song, Zhao & Swinton (2011), we assume that the nominal switchgrass price per ton offered by alternative outlet found by the cooperative is determined by ethanol price (P_{et}), conversion cost (*c)* and switchgrass to ethanol conversion rate (*rate*):

$$P_{Swt}^{AN} = (P_{et} - c) * rate \qquad (28)$$

However, the real price of the alternative market scenario facing the cooperative should also take the transaction cost (TC)[18] of trading with the outlet into consideration:

$$P_{Swt}^{A} = P_{Swt}^{AN} - TC = (P_{et} - c) * rate - TC \qquad (29)$$

3.5.2.1 Biorefinery's Learning and Decision Process

As in the first scenario, the biorefinery's expected utility of paying α percent of the full payment at time t to the cooperative is:

$$q_{\alpha t} = Eprofit_{\alpha t} - ELoss_{\alpha t} \qquad (30)$$

$Eprofit_{\alpha t}$ is modified to reflect the effect of the potential cooperative's alternative outlet on the biorefinery's decision:

$$Eprofit_{\alpha t} = \begin{cases} \sum_j \left((P_{et} - c) * Y_{jt} * rate - \alpha\emptyset Y_{jt}\right), & if(\alpha\emptyset \geq P_{Sw}^{A}) \\ 0, & if(\alpha\emptyset < P_{Sw}^{A}) \end{cases} \qquad (31)$$

The equation for $ELoss_{\alpha t}$ is quite similar with that used in the first scenario, except a modification of $w_{\alpha t}^{b}$:

$$w_{\alpha t}^{b} = \left(\frac{Max(EGMOther_{t+1}) - EGMSw_{\alpha(t+1)}}{Max(EGMOther_{t+1})}\right) \qquad (32)$$

Here $EGMOther_{t+1}$ includes not only the expectation for traditional crop's gross margin, but also includes the expectation of farmers' (cooperative's) expectation on its alternative outlet's switchgrass gross margin. $EGMSw_{\alpha(t+1)}$ is the expected gross margin of trading solely with the biorefinery.

[18] Note that here our definition of transaction cost (TC0 is a little different from the traditional way: The traditional definition of TC only include cost such as information searching cost, bargaining cost, contracting cost, etc. Our definition follows the way suggested by Dorward (1999) such that it also includes other quasi transaction cost (e.g. transportation cost)

3.5.2.2 Farmers' Learning on Contract Hold-Up and Cooperative's action

Farmers first form expectation on biorefinery's hold-up probability, and then form the expectation on the probability of cooperative choosing to cooperate with the biorefinery or to sell to the alternative outlet it could find. Everything for farmer is the same as in the first scenario except Eq_{it} used in the calculation of $probCal_{it}$ and the expectation formation formula for switchgrass growing in the linear programming's objective function:

$$Eq_{it} = Eprofit_{it} - ELoss_{it}$$

$$= \begin{cases} \sum_j \left((P_{et} - c) * Y_{jt} * rate - \alpha \emptyset Y_{it}\right) - ELoss_{it}, & if(i\emptyset \geq P^A_{Sw}) \\ 0 - ELoss_{it}, & if(i\emptyset < P^A_{Sw}) \end{cases} \quad (33)$$

Let's set f_i as:

$$f_i = \begin{cases} (P_{et} - c) * rate - i * \emptyset, & if\left(i\emptyset \geq P^A_{Sw}\right) \\ 0, & if\left(i\emptyset < P^A_{Sw}\right) \end{cases} \quad (34)$$

The equation for f_i states that if the price the biorefinery pays in the current year is less than that offered by the alternative outlet, the cooperative could sell the switchgrass to the alternative and the biorefinery would get nothing in the current year. However, it will gain a profit of $(P_{et} - c) * rate - i * \emptyset$ from each acre of contracted switchgrass in the current year if the price it pays is higher than that the alternative outlet.

For any $i > i_{-1}$, there are three possible combinations of f_i and $f_{i_{-1}}$, namely: I. $f_i \neq 0, f_{i_{-1}} = 0$; II. $f_i \neq 0, f_{i_{-1}} \neq 0$; and III. $f_i = 0, f_{i_{-1}} = 0$. The probabilities for the 3 conditions are:

$$\text{I.} \quad \begin{cases} \Pr(i\emptyset \geq (P_{et} - c) * rate - TC) = \Pr\left(P_{et} \leq \frac{i\emptyset + TC}{rate} + c\right) \\ \Pr(i_{-1}\emptyset \leq (P_{et} - c) * rate - TC) = \Pr\left(P_{et} \geq \frac{i_{-1}\emptyset + TC}{rate} + c\right) \end{cases} \quad (35)$$

$$\text{II.} \quad \begin{cases} \Pr(i\emptyset \geq (P_{et} - c) * rate - TC) = \Pr\left(P_{et} \leq \frac{i\emptyset + TC}{rate} + c\right) \\ \Pr(i_{-1}\emptyset \geq (P_{et} - c) * rate - TC) = \Pr\left(P_{et} \leq \frac{i_{-1}\emptyset + TC}{rate} + c\right) \end{cases} \tag{36}$$

$$\text{III.} \quad \begin{cases} \Pr(i\emptyset \leq (P_{et} - c) * rate - TC) = \Pr\left(P_{et} \geq \frac{i\emptyset + TC}{rate} + c\right) \\ \Pr(i_{-1}\emptyset \leq (P_{et} - c) * rate - TC) = \Pr\left(P_{et} \geq \frac{i_{-1}\emptyset + TC}{rate} + c\right) \end{cases} \tag{37}$$

The calculation of each $Pr\left(Eq_{it} \geq Eq_{\boldsymbol{i_{-1}}t}\right), i_{-1} \in \boldsymbol{i_{-1}}$ for the final part under the three combinations becomes:

$$Pr\left(f_i - w_{it}^f * Dis * [(P_{et} - c) * rate - \emptyset] > f_{i_{-1}} - w_{i_{-1}t}^f * Dis * [(P_{et} - c) * rate - \emptyset]\right)$$

$$= \begin{cases} \dfrac{-i\emptyset}{\left[\left(w_{it}^f - w_{i_{-1}t}^f\right) * Dis * \beta - 1\right] * rate} + c & for\ combination\ I \\ \dfrac{(i_{-1} - i)\emptyset}{\left(w_{it}^f - w_{i_{-1}t}^f\right) * Dis * \beta * rate} + c & for\ combination\ II \\ 1 & for\ combination\ III \end{cases} \tag{38}$$

Consequently, $Pr\left(Eq_{it} \geq Eq_{\boldsymbol{i_{-1}}t}\right)$ is calculated as the probability of the intersection of the three conditions. $probCal_{it}$ is then calculated following the method used in the first scenario.

Farmers' perceived probability that biorefinery will hold up i percent of the payment this year after they observed α percent realized hold up amount in the last year could still be calculated by:

$$ePro_{i\alpha t}^f = \Delta_1\, probCal_{it} + \Delta_2 H\mathrm{is}_{it}(\alpha) \tag{39}$$

Also as biorefinery knows farmers' decision rule (more specifically, it knows the way farmers calculate $w_{it}^f - w_{i_{-1}t}^f$, it could estimates farmers' perceived $probCal_{it}$ and $H\mathrm{is}_{it}(\alpha)$, which means $ePro_{\boldsymbol{i\alpha(t+1)}}$ and consequently $w_{\alpha t}^b$ in the above section's equations could be estimated.

Another difference for this scenario compared with the first one exists in the objective function of the linear programming model: when farmers form their gross margin expectations from growing switchgrass in the linear programming's objective function, they consider both (1) the expected payment percent by the biorefinery, and (2) the probability that the cooperative will chose the alternative market outlet for their switchgrass. Therefore, the expectation of the gross margin from growing switchgrass becomes:

$$eGMSw_t = \left(\sum_i GMSw_i * eProb(i, bio)\right) + GMSw_{Alter} * eProb(Alter) \qquad (40)$$

$eProb(i, bio)$ means the probability that the cooperative will continue to cooperate with biorefinery this year and the biorefinery will pay i percent of the full payment. $eProb(Alter)$ is the probability that the cooperative will sell the switchgrass to alternative market this year. $GMSw_i$ is the expected gross margin if the biorefinery pays i percent of the contracted; $GMSw_{Alter}$ is the expected gross margin for the alternative market outlet's switchgrass;

$$eProb(i, bio) = Prob(i\emptyset \geq P_{Sw}^{A}) * ePro_{i\alpha t}^{f} \qquad (41)$$

$ePro_{i\alpha t}^{f}$ is the probability that the biorefinery will choose to pay i percent of the full payment, which is calculated following the method in the beginning of this section.

$$eProb(Alter) = 1 - \sum_{\boldsymbol{i}} eProb(i, bio) \qquad (42)$$

3.5.3 Multiple Easily Accessible Outlets in the Region for Individual Farmers

In this case, two biorefineries compete for the same farmers' switchgrass. Additional assumptions used in this scenario are defined as:

Assumption 1:

The contracts used by the two biorefineries are the same. The only difference regarding the contract between the two refineries is their hold-up amounts in each period.

Assumption 2:

There is no communication between the two biorefineries. That is, no collusion behavior exists.

Assumption 3:

If one biorefinery holds up more payment in one period while the other biorefinery holds up less, the one that holds up more will loss all of its biofeedstock in this period (i.e. farmers can sell all switchgrass to the biorefinery with the higher payment in this tick). However, the expected future switchgrass that could be procured for each biorefinery depends upon the biorefinery's expectation of the farmers' perceived payment amount for each biorefinery in the future.

The assumptions above basically state that there are no differences between the two biorefineries except for the distance to the farmers' land. Although this is a simplification of the problem and it might not be the case in the real world, the essential strategic components between actors have been captured and thus it is believed to adequately demonstrate the effect of multiple outlets on farmers' switchgrass adoption.

3.5.3.1 Biorefinery's Learning and Decision Process

When a biorefinery chooses whether to hold up the contract or how much to hold up, it has to consider: (1) how much profit in this year it will loss (gain) due to the lower (higher) level of hold-up percent used by a competing biorefinery (farmers sell switchgrass that is under contract to a competing biorefinery); (2) how much profit it will loss (gain) in the future due to the lower (higher) level of hold-up percent used by a competing biorefinery (farmers might choose to switch land under contract to a competing biorefinery's contract). Therefore, the formula for $q_{\alpha t}$ in the last section could be modified as below:

$$q_{\alpha t} = Eprofit_{\alpha t}^{A} - EChange_{\alpha t}^{A} \qquad (43)$$

Here $EChange_{\alpha t}^{A}$ represents the expected profit change if the biorefinery pays α percent of the full payment.

If the biorefinery pays less than the competing biorefinery, it will get all the switchgrass from the farmers contracted to the competing biorefinery in the current year (see ***Assumption 3***). Otherwise, it will loss all the switchgrass from contracted farmers in this tick:

$$Eprofit_{\alpha t}^{A} = eProb(\alpha_{At} = \alpha_{Bt}) * Profit_{\alpha t}^{A} + eProb(\alpha_{At} > \alpha_{Bt}) * (profit_{\alpha t}^{A} + Profit_{\alpha t}^{B}) \qquad (44)$$

Here $Profit_{\alpha t}^{B}$ and $profit_{\alpha t}^{A}$ denotes the switchgrass profits for farmers contracted to grow switchgrass for a competing biorefinery (superscript *B*) and for the biorefinery (superscript *A*). The calculation of $Eprofit_{\alpha t}^{A}$ uses a weighted average approach: the first term is the weighted current period profit that the biorefinery could get (profit from own contracted lands) if payment is equal to that of the competing biorefinery ($\alpha_{At} = \alpha_{Bt}$); the second term shows biorefinery's profit (profit from own contracted and competing biorefinery's contracted switchgrass land) if payment is higher than that of the competing biorefinery ($\alpha_{At} > \alpha_{Bt}$); in fact, there should be a term that shows the situation when the payment is less than that of my opponent ($\alpha_{At} < \alpha_{B}$);. However, in this case the profit will be 0 thus it doesn't shown up in the equation.

The formula of $EChange_{\alpha t}^{A}$ is adopted from the first scenario case:

$$EChange_{\alpha t}^{A} = w_{bt}^{\alpha} * \sum_{i} NPV_{it} \qquad (45)$$

However, the formula of w_{b}^{α} is modified so as to include the effect of the competing biorefinery's hold-up strategy on the biorefinery's strategy:

$$w_{bt}^{\alpha} = \left(\frac{Max(EGMOther_{t+1}) - EGMSw_{\alpha(t+1)}^{A}}{Max(EGMOther_{t+1})}\right) \qquad (46)$$

$$Max(EGMOther_{t+1}) = Max(EGMTraditional_{t+1}, EGMSw_{t+1}^{B}) \qquad (47)$$

$$EGMSw_{t+1}^{B} = \sum_{i} GMSw_{i(t+1)}^{B} * ePro_{i(t+1)}^{B} \qquad (48)$$

$EGMSw_{\alpha(t+1)}^{A}$ is calculated the same as in the first scenario.

At each time period, the biorefinery will choose the payment rate α that maximizes its utility:

$$\alpha = arg_{\alpha}max\left(\sum_{i}(P_{et} - c) * Y_{it} * rate - (\emptyset Y_{it}) * \alpha + EChange_{\alpha t}^{A}\right) \qquad (49)$$

3.5.3.2 Farmers' Learning on Contract Hold-Up Percent Probability

The same as in the first scenario, the process for farmers to learn both biorefineries' hold-up probability is formed as the weighted average of a rationally calculated probability and an experience based probability.

The difference exists in the process of calculating the rational probability $probCal_{it}$: In this scenario, farmers need to consider not only biorefinery's future loss from paying a certain amount, but also the current profit loss (gain) from paying the amount, which comes from the probability of the expected hold-up percent of each biorefinery's opponent. It is straightforward to show the equations used for farmers to calculate one biorefinery's hold up probability as below using the equation of $q_{\alpha t}$ defined in the last sub-section; those used for the other biorefinery are exactly the same.

Define$A_i = ePro(i^B = i) * CA^A + ePro(i^B < i) * (CA^B + CA^A)$, then for any $i > i_{-1}$ the calculation of the probability that $q_{it} > q_{i_{-1}t}$could be defined as:

$$Pr\left(q_{it} > q_{i_{-1}t}\right)$$

$$= Pr\Big(A_i[(P_{\text{et}} - c) * rate - i\emptyset] - w_{it}^f * Dis * \beta * [(P_{\text{et}} - c) * rate] * CA^A$$

$$> A_{i_{-1}}[(P_{\text{et}} - c) * rate - i_{-1}\emptyset] - w_{i_{-1}t}^f * Dis * \beta * [(P_{et} - c) * rate] * CA^A\Big)$$

$$= Pr\left(P_{et} > \frac{\emptyset\left(i_{-1}A_{i_{-1}} - iA_i\right)}{\left[\left(A_{i_{-1}} - A_i\right) + \left(w_{it}^f - w_{i_{-1}t}^f\right) * Dis * \beta * CA^A\right] * rate} + c\right) \quad (50)$$

$$w_{it}^f - w_{i_{-1}t}^f = \Delta_2 * \left(\frac{-GMSw_{ki(t+1)}^A + GMSw_{ki_{-1}(t+1)}^A}{N * Max(EGMOther_{t+1})}\right) \quad (51)$$

CA^A is the biorefinery's current contracted farmers' switchgrass land while CA^B is that of its opponent. $ePro(i^B < i)$ means the biorefinery's expected probability that its opponent will pay less than me. It is calculated using the payment history of the biorefinery's opponent[19]. The calculation of $ePro_{i(t+1)}^B$ in biorefinery's problem also follows the same procedure.

3.6 Treat Switchgrass Adoption as Technology Diffusion

As a relatively new crop to be introduced in the area, switchgrass is analogous to a new technology, whose diffusion always empirically follows an "S" shape path such that the diffusion rate is slow at the beginning as only bold farmers will be willing to adopt, but then accelerates due to social learning and finally becomes stable (Alexander et al, 2013).

[19] It should be acknowledged that for a fully rational agent, $\text{ePro}(\alpha^O > \alpha)$ should also be calculated based on its opponent's profit function. However, for a highly heterogeneous environment like this case, that method becomes intractable quickly. Therefore, we consequently loose that requirement and use an algorithm that assembles fictitious play (**Berger, 2007**) to represent the concept.

Therefore, following the method used in Alkemade & Castaldi (2005) and Alexander et al (2013), we first defined each farmers' "willingness to consider" adoption of switchgrass. Farms who are willing to consider the adoption will include switchgrass in the optimization model and subsequently update their beliefs proposed above. Farmers who are not willing to consider switchgrass at the initialization phase will look at their neighbor's adoption. If the percentage of neighbors who have already adopted switchgrass exceeds the farmers' threshold, then the farmer becomes willing to consider planting switchgrass. This approach is also consistent with the use of "social" and "factual" farmers in Shastri et al. (2011). Farmers' thresholds are assigned randomly following a normal distribution (If a farmer's assigned threshold is less than or equal to zero, then the farmer is willing to consider switchgrass in the initialization stage).

CHAPTER 4: DATA, INITIALIZATION AND BASELINE VALIDATION

4.1 Review of the Study Area

Alpena County, located at North Michigan's Lower Peninsula (also the north tier of Michigan), is chosen as the study area of the thesis. The major crops here are alfalfa, corn, winter wheat and soybeans, while the vast majority of live stocks are cattle. Figure 4 below provides a spatially explicit description of Alpena County agricultural zone land cover situation (green color is soybean, yellow color is corn, brown color is wheat and pink color represents alfalfa). Those green colors represent forest, woody wetland and other non-arable lands.

According to NASS Census Statistics 2007[20], there are 573 farms with an average size of 150 acres/farm, covering 85,947 acres of land in total (with 46,450 acres harvested cropland, an approximate of 59577 acres planted cropland).

Figure 4 Alpena County Land Use and Land Cover 2008

The harvested area for hay (alfalfa hay and other hays), corn, winter wheat and soybeans are 25,265 acres (with alfalfa hay for 17,858 acres, taking a share of 71%),

[20] See http://www.nass.usda.gov/Data_and_Statistics/ for detailed information and census statistics

7810 acres, 3695 acres and 2802 acres, respectively[21]. The major crops mentioned account for up to 85% of the total harvested cropland (it ranges from 87% ~ 92% during 2008~2012). Historically, no energy crop like switchgrass or miscanthus has been adopted across the county. The dominance of alfalfa hay is determined by the weather and soil conditions in this region and it becomes one of the reasons that this county is chosen as the study area (i.e. the competition of energy crops vs. food crops are not as fierce as other counties in central and south Michigan).

4.2 Farm Endowment Data and Land Ownership Data

The farm endowment data and land ownership data are required to initialize the model. The data we need comes from three sources:

The first data source is USDA NASS agricultural census data 2007, which contains the average farm characteristics across Alpena County (e.g. farm size, crop composition and net farm income). We also utilized NASS survey data for the historical average crop price and yield of the county.

The second data source is farm land ownership data recorded in Common Land Unit (CLU) data[22] provided by Farm Market Id Company, which is not publicly available. There are totally 4808 CLUs in Alpena County recorded by the company, among which 3481 CLUs have a farmer name (property right) in record, and the percentage of acres covered by CLUs with farmers' name reaches 62% of all the farmlands. This data source

[21] This data only exist for census years, available every fifth year (e.g. 2002, 2007), the CDL data is quite inaccurate in Alfalfa Acres after comparing it with the census data 2007.

[22] According to USDA FSA, A Common Land Unit (CLU) is the smallest unit of land that has a permanent, contiguous boundary, a common land cover and land management, a common owner and a common producer in agricultural land associated with USDA farm programs. The CLUs in Alpena County cover almost all the farm lands in the area.

also includes 178 farmers' records (30% of the total farms in the county) on farm stead location, credit availability and gross farm income for the previous year.

The third data source is Michigan soil productivity index (PI) data produced jointly from NASS SSURGO soil data and USDA forest service by Schaetzl, Krist & Miller (2012). The index ranges from 0 (quite unproductive) to 14 (very productive). Farmers differ in terms of owning different amount of lands with different soil productivity index, which plays an important role in determining crop yield and consequently the gross margin.

The last data source is USDA NASS Cropland Data Layer (CDL), which is a ESRI raster data file that depicts the land cover in the whole Alpena County. The land cover types are further classified into 3 categories in the thesis: croplands, pasture lands and woody wetlands/Forests. Currently in this study, only croplands are available for crop farming. Later researches should include raising livestock on pasture lands.

4.3 Projection of Future Traditional Crop Price and Yield

Crop price is adopted from the USDA prediction for the next decade. The method to project future crop yield is adopted from Richardson, Klose & Gray (2000), simulating a multivariate Empirical (MVE) probability distribution. The multivariate empirical probability distribution is drawn from historical years (1998~2012) for the four traditional crops: alfalfa, corn, soybeans and winter wheat. During the simulation, the inter-temporal and intra-temporal relationships among the four crop yields are captured by an inter- and intra-temporal matrix derived from historical data. Figure 5, and Figure 6 show the final real and projected yields and prices for corn, soybeans, and winter wheat[23]. Figure 7 illustrates the projected ethanol prices from the U.S. Department of Energy for the simulation period (2011-22). Also see Appendix A for projected input cost during the pre-simulation and simulation period. See Appendix B for Crop Budget that adopted from MSU Extension and Kells & Swinton (2014).

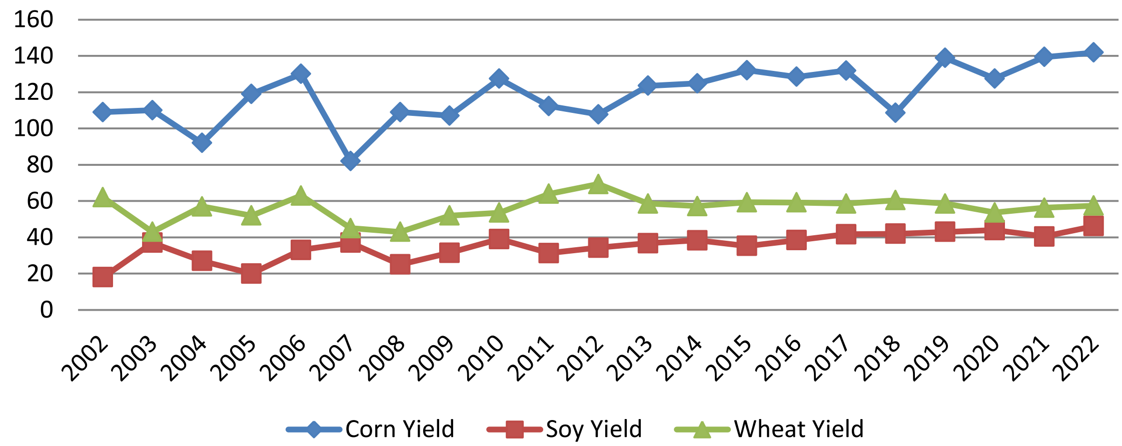

Figure 5 Real (2002~2012) and Projected (2013~2022) Crop Yield (in bushels/acre)

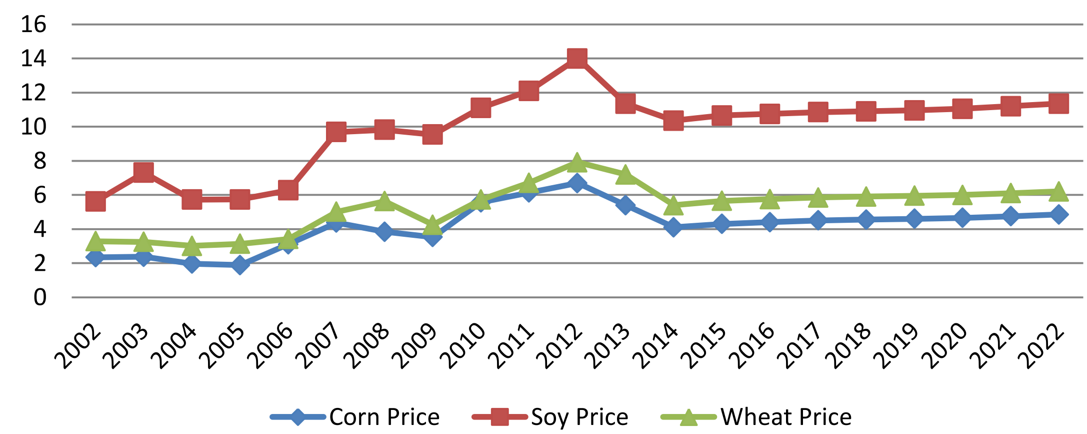

Figure 6 Real (2002~2012) and Projected (2013~2022) Crop Price (in $/bushel)

[23] The projection methods for alfalfa price and yield are the same as for traditional crops. However, as the unit of alfalfa price and yield ($/ton and tons) are different from those of annual crops ($/Bushel and Bushel), the projected alfalfa price and yield are not shown here

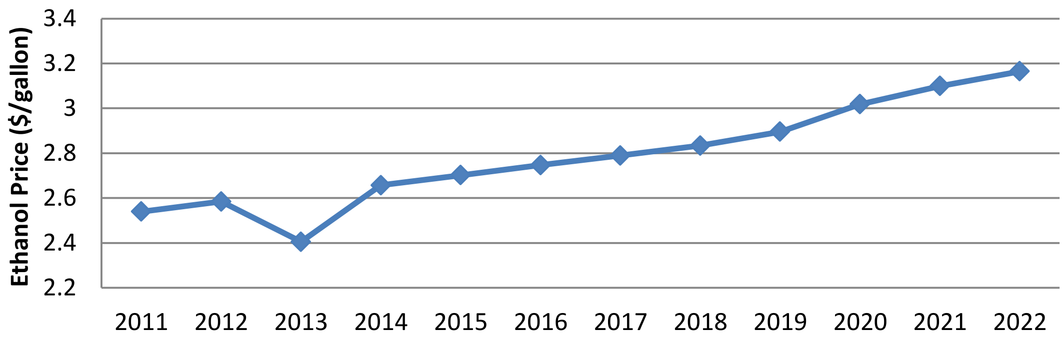

Figure 7 US DOE Predicted Ethanol Price during Simulation Period

4.4 Model Initialization

The model initialization proceeds as follows: First, we initialize the recorded 178 farmers' farm location, farm acres, cropland acres, and net cash income of the last year according to CLU data. Then the rest 395 farmers are initialized according to the census distribution. In addition, to take the possible clustering relationship between these variables into account (Berger & Schreinemachers, 2006), total farm acres is chosen as the clustering reference for farm cropland acres, consistent with NASS census convention (i.e. all other farm resource variables are set referring to farm size if detailed data are not available).

According to the census data, the total farm size in the region is 59577 acres. As we only have harvested acres but not total cropland size in each farm acre level, we make a simple assumption here that the cropland size increases proportionally with harvested acres for farms in each farm size level. Table 4 summarizes some of the census and generated total farm characters.

Farm size is also chosen as the reference for farm income under the assumption that the larger the farm is, the higher income it has (Generated net income distribution for 2007 is shown in Table 5).

Table 4 Total Farm Acres and Farm Cropland Acres

Farm Category by Size		Total Farm Acres		Farm Cropland Acres	
Farm Size (Acres)	Farm Number	Census (Acres)	Generated (Acres)	Census (Acres)	Generated (Acres)
1 ~ 9	16	82	86	21	21
10 ~ 49	195	5,593	5,648	2,044	2,041
50 ~ 69	43	2,515	2,511	1,240	1,244
70 ~ 99	96	7,663	7,667	3,132	3,130
100 ~ 139	63	7,418	7,415	3,739	3,736
140 ~ 179	44	6,946	6,931	2,977	2,980
180 ~ 219	28	5,454	5,453	2,951	2,952
220 ~ 259	10	2,339	2,328	1,933	1,935
260 ~ 499	41	14,314	14,301	10,628	10,629
500 ~ 999	29	20,982	20,968	18,870	18,870
1,000 ~ 1,999	8	12,641	12,639	12,042	12,039
Sum	**573**	**85,947**	**85,947**	**59,577**	**59,577**

Table 5 2007 Farm Income Distribution

Farm Size (Acres)	Generated Data Distribution		
	Min ($)	Mean ($)	Max ($)
1 ~ 9	3,549	5,532	7,266
10 ~ 49	7,611	9,803	12,109
50 ~ 69	12,390	14,593	16,615
70 ~ 99	16,711	19,066	21,221
100 ~ 139	21,522	23,399	25,658
140 ~ 179	25,807	28,158	30,279
180 ~ 219	30,692	32,797	34,769
220 ~ 259	35,142	37,387	38,936
260 ~ 499	39,480	41,580	43,954
500 ~ 999	44,346	46,239	48,142
1,000 ~ 1,999	44,092	45,776	47,835
NASS census (No stratification)	3,020		48,550

4.5 Baseline Validation

As historical Data from 2007 to 2012 regarding the total corn, soybeans and wheat planted acres[24] is available, the simulation is set to start from 2007 using the

[24] Alfalfa acres are not reported in the yearly statistic book, and CDL data that comes from satellite map has a low reliability of distinguishing between grass crops and non-crop pasture. Therefore, historical alfalfa acre is not included in the validation process, but the simulated amount will be included in the later

calibrated parameters in Table 3 and the simulation results are compared to the real data to see whether the simulation produces a similar crop acres pattern with the real world empirical data. Note that during this period, switchgrass is not included in the model as there is historically no switchgrass grown in this region. The figures below show the comparison of the simulated (the value of each year is the average value of 10 simulation runs with different random seed) versus real crop acres in each simulation years.

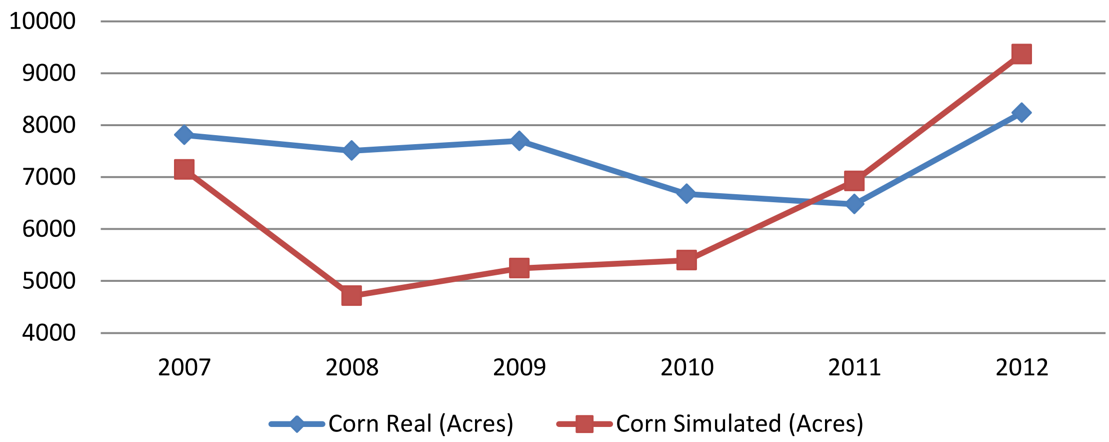

Figure 8 Annual Corn Real Data and Simulated Data 2007 to 2012

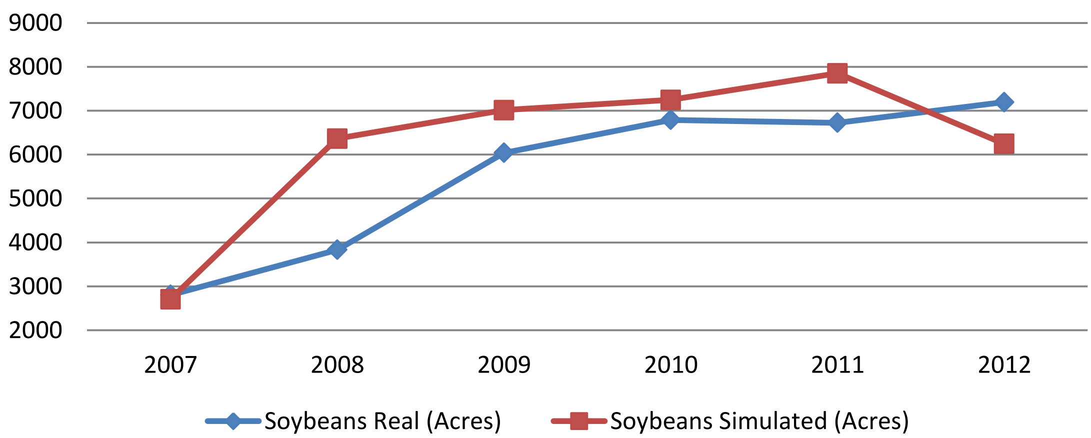

Figure 9 Annual Soybeans Real Data and Simulated Data 2007 to 2012

ABM simulation experiment. Another reason for not including alfalfa acres into the validation is that alfalfa is a perennial grass thus we do not know how many acres have been already allocated to alfalfa and how many acres is about to turn out of alfalfa use in one year.

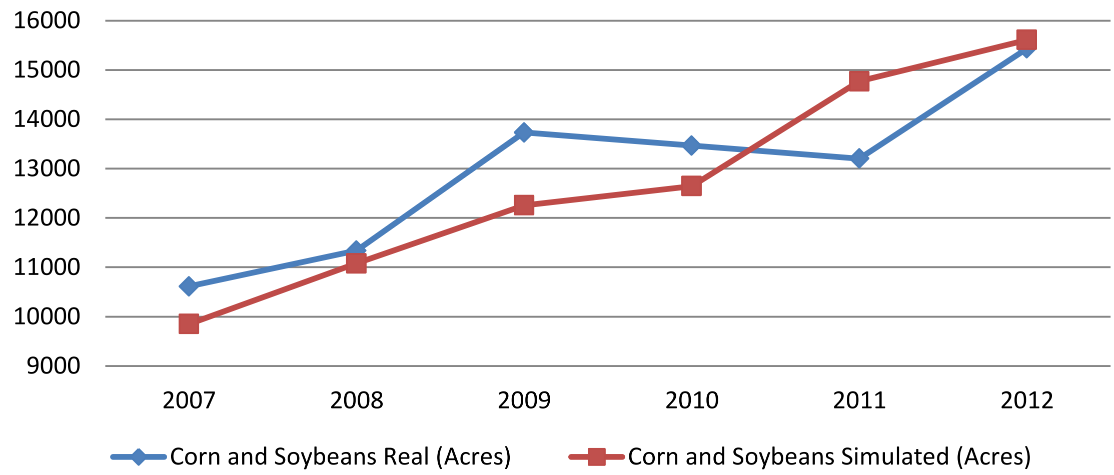

Figure 10 Annual Corn and Soybeans Real Data and Simulated Data 2007 to 2012

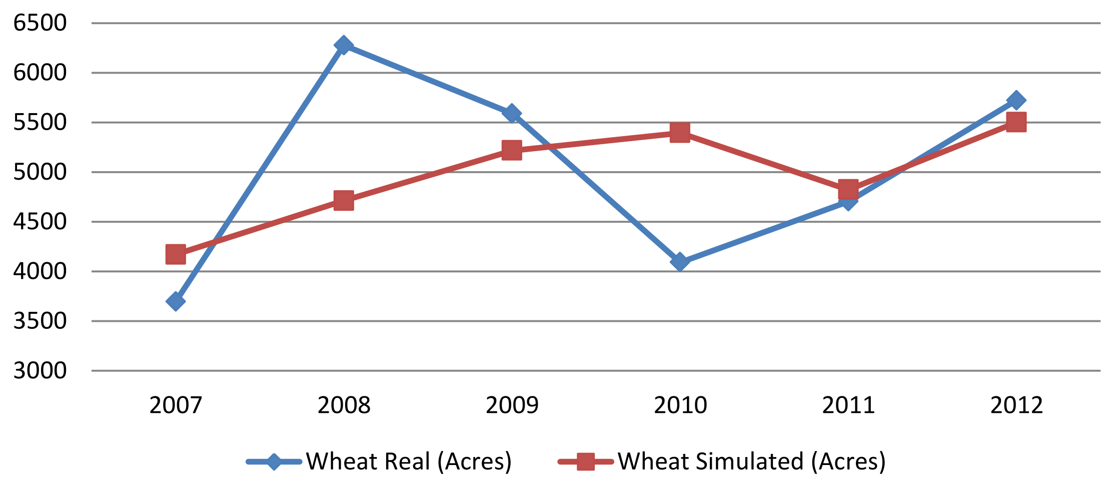

Figure 11 Annual Wheat Real Data and Simulated Data 2007 to 2012

From Figure 8 to Figure 11, we could see that the acres change trends of the simulated results are quite similar with that shown by the real empirical data -- the simulated and real crop acres gradually converge to each other during the last few years. It is reasonable because at the beginning of the simulation, the crop acres for each crop are 0. But as we have perennial alfalfa in this region, the starting point is actually not 0 for alfalfa. As some farmers might be in corn and soybean rotation, the good matching between real and simulated total corn and soybean acres shows that the simulation result is quite satisfactory. After several years' of learning and farming in the simulation, each simulated crop converges to the real data. Therefore, as the overall trend changes and the last few years' simulated acres are quite similar with the real world data, we could say that the calibrated model is validated.

CHAPTER 5: AGENT BASED MODEL RESULTS AND DISCUSSION

In this section, the ABM experiment results are shown and discussed: subsection 5.1 for the first scenario, 5.2 for the second scenario and 5.3 for the third.

5.1 Single-Outlet (Biorefinery) in the Region Procures from Individual Farmers

The results for the scenario where one biorefinery procures from individual farmers (or single outlet scenario) are shown below. The logic of this section could be found at section 3.2.1 and 3.5.1.

5.1.1 Key Parameters Used in the Model

Before running the simulation, the parameters shown in the above sections are parameterized. Table 6 below shows the initialized parameter used in the major runs in this scenario.

Table 6 Single-Outlet Scenario (Scenario 1) Model Parameters

Whose	Parameter	Meaning	Value
Farmer	sw	Switchgrass upper limit	0.3
	$ePro_0(\alpha)$	Initial perceived payment (hold up) percent probability ($\alpha \in \{0,0.05 \dots .1\}$)	0.0625…..0.625
	$E_0(p_{YH})$	Initial perceived probability of high yield	$U(0.3, 0.5)$
	Y_H	High yield of switchgrass	4.7
	Y_L	Low yield of switchgrass	4.1
	Δ_2	Weight on historical hold-up probability	0.5
Refinery	$\emptyset$	Payment per ton	75, 85, 95, 105, 115, 125
	α	Payment percent under consideration	0.2, 0.25, ….., 1

Farmers' expected probability of different payment percent levels are set to be equal. That is, $\sum_{\alpha} ePro_0(\alpha) = 1\ and\ ePro_0(\alpha) = ePro_0(\alpha_{-1})$. s a new crop, the perceived yield by farmers at first is usually low. Therefore, a low range (0.3 to 0.5) is randomly assigned to each farmer on the possibility of high switchgrass yield in a particular year (except the first year in switchgrass's life cycle. In addition, as the switchgrass upper limit is set arbitrarily, a sensitivity analysis regarding this parameter will be conducted at the end of this section.

Shown by Zhou (2013), the contract price for switchgrass in Tennessee needs to go up to $475/acre under acreage contract or $77/ dry ton under tonnage contract. In order to compare with existing contract prices in other researches, we take the payment suggested by Zhou (2013) into consideration when choosing the value for per ton payment. By choosing different values for the per ton payment, it is possible to get a feasible estimation of the payment schedule under which both biorefinery and farmers would be profitable from an ex-post perspective.

5.1.2 Simulation Result for the Single-Outlet Scenario

5.1.2.1 Comparison of Contracts with Different Per-ton Payment

Biorefineries want more land dedicated into switchgrass such that they could procure more switchgrass every year. One way to doing so is to contract for a high price. However, unprofitable results will come if that price level is high, leading to an incentive to hold up contract when its expected ethanol price is low in the future. Consequently, farmers' expectation on contract hold up amount will go higher and devote less land to switchgrass. Therefore, the biorefinery should balance this two factors when determine the price level. Thus different payment schedules are tested to compare potential different contract configuration results.

When comparing the payments, the two criteria used are: (1) biorefinery's net present value (NPV) for the 10 simulation years (from 2013 to 2022); (2) the ability to keep a stable feedstock supply (capacity increases or stabilizes at a certain level after several years).

Table 7 Comparison of Different Contract Configuration in Single-Outlet Scenario

Contract price ($/dry ton)	End Simulation Bio-NPV (1000 $)	Mid (T=2017)	End of Simulation Crop Acres			
		Switchgrass (Acres)	Switchgrass (Acres)	Corn Soybeans (Acres)	Wheat (Acres)	Alfalfa (Acres)
			0 (T=2012)	15,634 (T=2012)	5,447 (T=2012)	32,099 (T=2012)
75	23.846	69	241	20,038	6,674	27,742
85	**108.927**	**232**	**1,582**	**20,267**	**6,868**	**26,691**
95	92.125	772	2,274	9,971	20,287	6,821
105	74.679	105	3,314	20,571	6,761	25,167
115	73.333	60	2,012	20,063	6,670	27,706
125	7.292	165	2,526	20,288	6,814	25,953

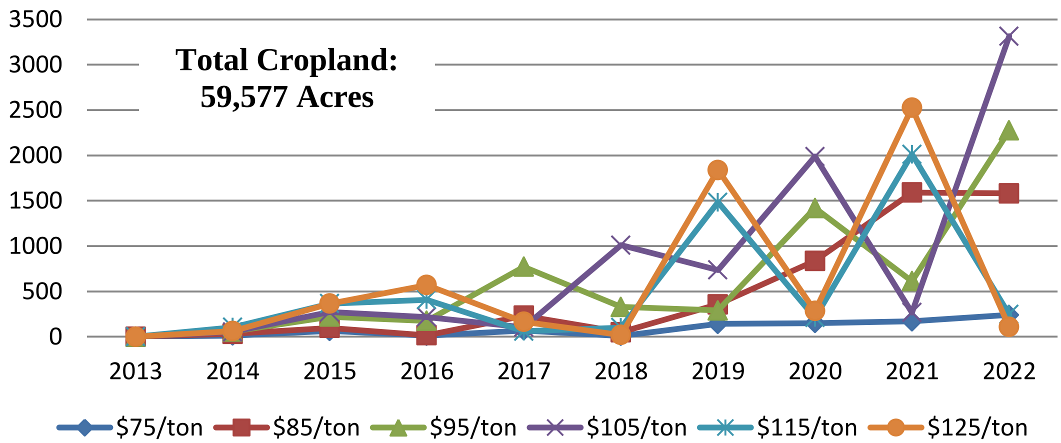

Figure 12 Switchgrass Areas (in Acres) under Different Contract Price

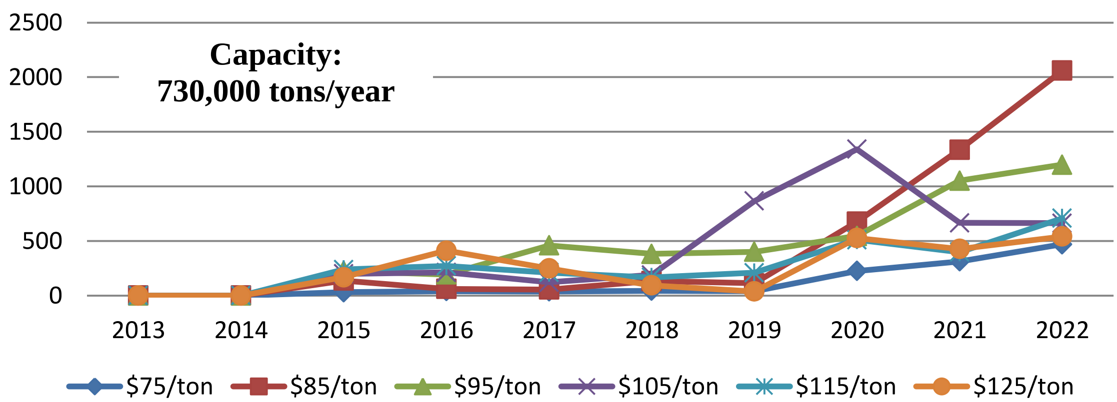

Figure 13 Switchgrass Procured (in tons) under Different Contract Price

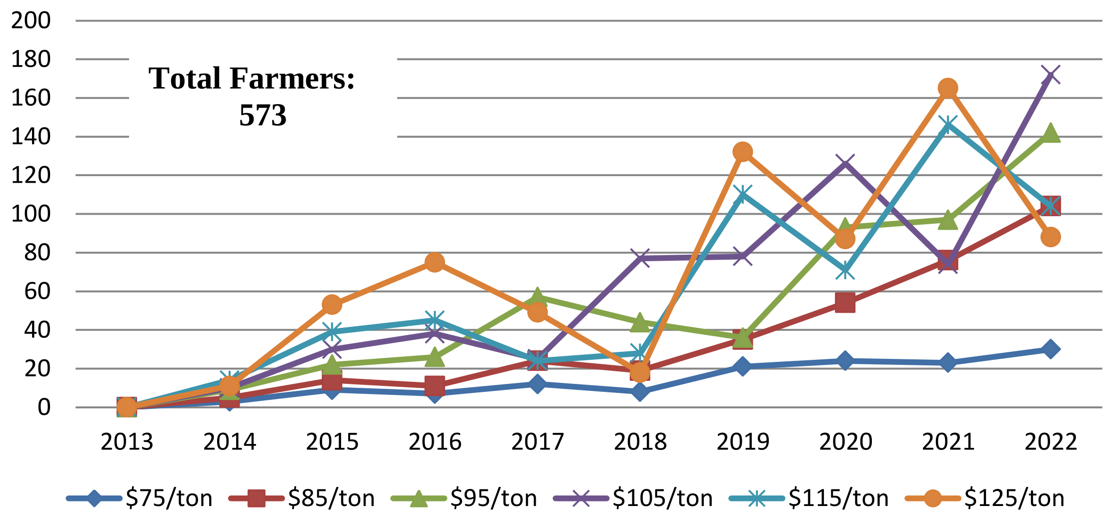

Figure 14 Switchgrass Adopters (in numbers) During Simulation under Different Contract Price

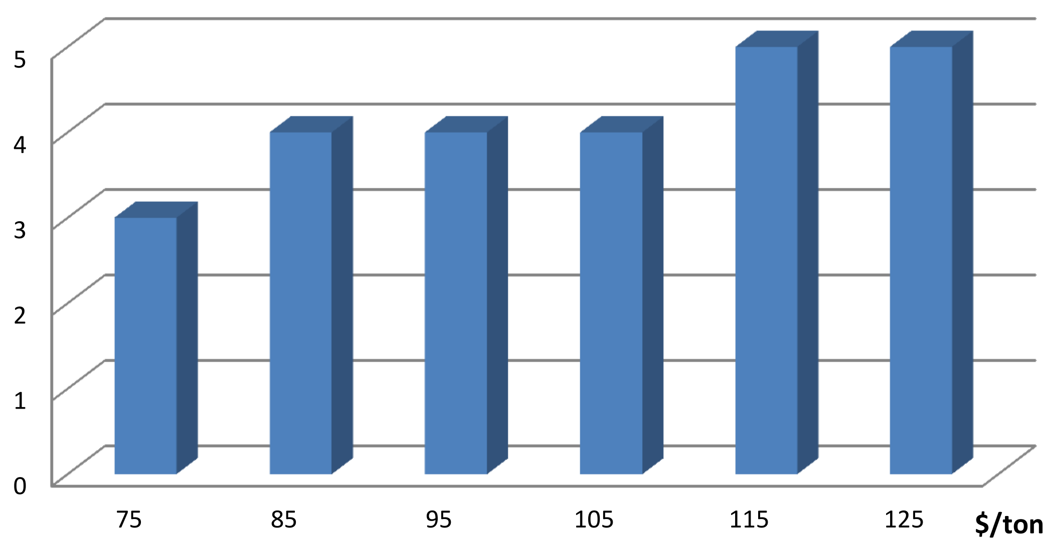

Figure 15 Contract Hold-Up Times (in times) under Different Contract Price

According to Table 7 and Figure 12~15 above, the biorefinery's net present value (NPV) increases when per-ton payment increases before the payment reaches $85/ton. But after the price becomes higher than $85/ton, the biorefinery's NPV decreases. Ideally, the difference of switchgrass area and biorefinery's net present value under different contract price should be quite similar when the refinery could choose the amount to hold up freely (that is, ideally, the real price they pay should be quite similar when using different nominal contract price and thus farmers' expected payment percent should be similar). However, several factors generates the differences among the results: (1) farmers are risk averse: even when the expected payment for farmers in each tick under different contract price might be similar, difference exists in the variance of income; (2) we are saying that at the beginning of the simulation, farmers' perceived possibilities of being held up of different amounts are equally divided. It will take the farmers some time to adjust this perceived probability to the real value. Therefore, under the interaction of farmers and biorefinery, a contracted price of $85/dry ton will be considered the best in the case for the biorefinery.

Compared the results to the $77/ton calculated by Zhou (2013) and $250 + $50/ton that is currently used in the University of Tennessee Biofuel Initiative, the satisfactory price I get is a slightly higher at $85/ton. This is because we take biorefinery's hold up decision into consideration and thus the final price incorporates farmers' risk premium.

5.1.2.2 Contract with $85/dry ton Contracted Payment

In this section, the detailed simulation results for the contract with $85/dry ton contracted price (the most satisfactory contract price we got) is shown and discussed.

Figure 16 to Figure 19 show the traditional crops and switchgrass grown and biorefinery's hold-up probability at each year for the contract with $85/ton payment (the value at each tick is the average value of 10 simulation runs[25]).

[25] Sensitivity analysis is done for the simulation run times and it is found that the difference between 10 runs, 20 runs, 30 runs and 100 runs are quite small. Therefore, to save computational time, 10 runs are used in all analysis.

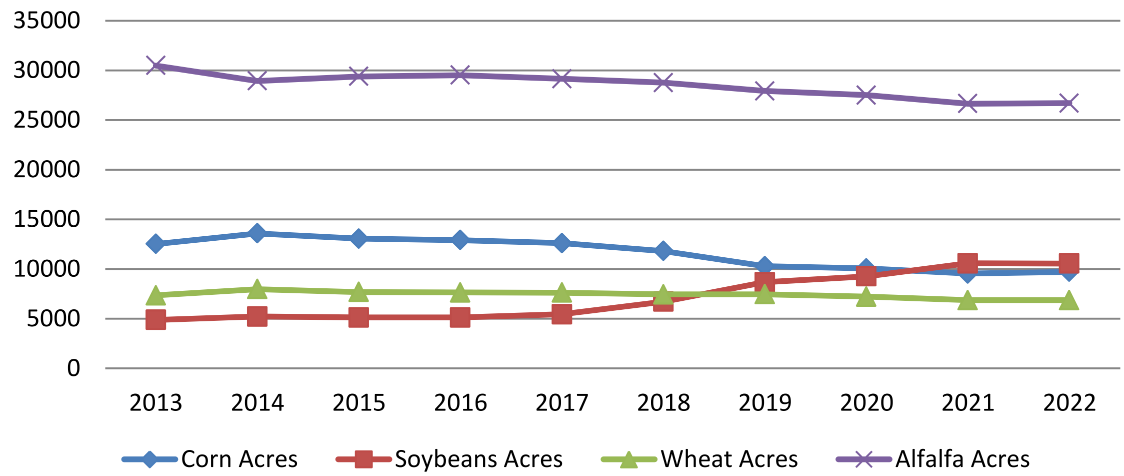

Figure 16 Traditional Crop Areas (in Acres) under Single-Outlet Scenario

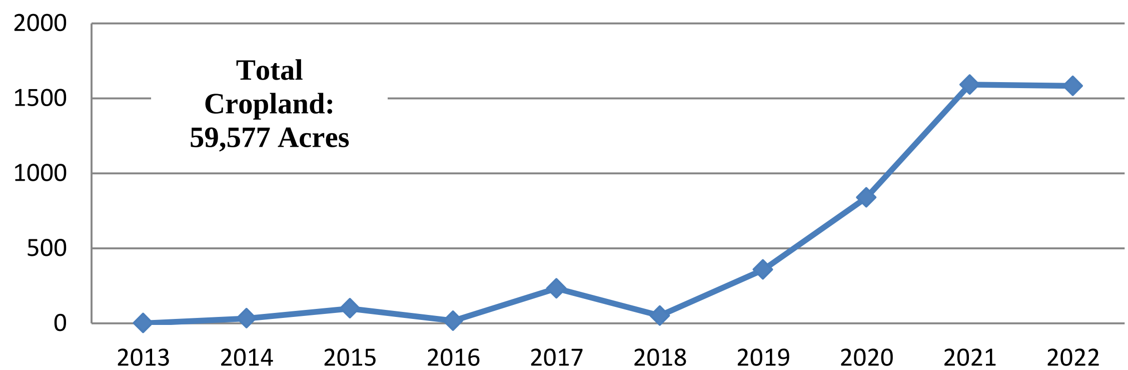

Figure 17 Switchgrass Acres (in Acres) under the Single-Outlet Scenario

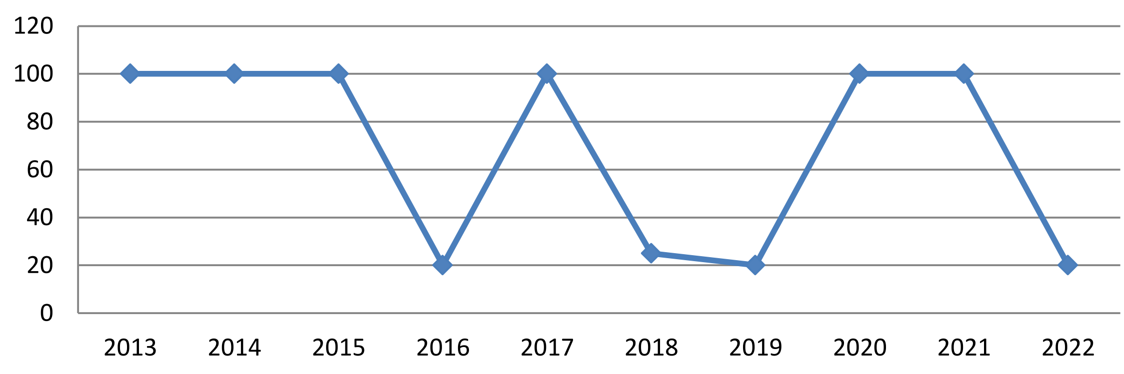

Figure 18 Payment Percent (in %) under the Single-Outlet Scenario[26]

[26] A deviate from 100% payment reflects that the contract is held up

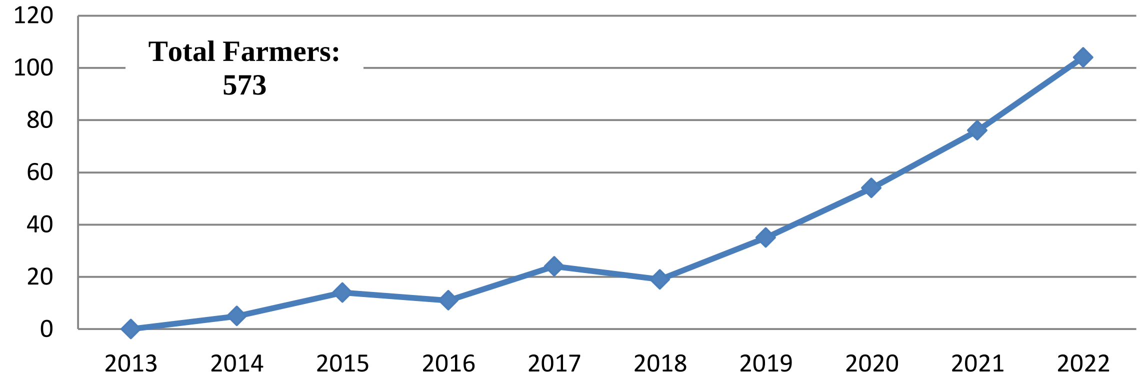

Figure 19 Adopter Number (in numbers) under the Single-Outlet Scenario

The introduction of switchgrass under the single outlet case doesn't significantly alter the agricultural structure in this region. One of the reasons that not so many farmers want to consider switchgrass (and those who consider it won't turn a great amount of land into switchgrass use) is that farmers believe that biorefinery will hold-up the contract. Farmers form their perceived contract payment percent possibility using their rational calculation and the biorefinery's hold-up history (shown in figures above). This argument is supported by many researches on farmers' attitude of biorefinery and switchgrass adoption (e.g. Hipple & Duffy, 2002; Jensen et al., 2007).

5.1.3 Sensitivity Analysis

The sensitivity analysis is conducted for switchgrass upper limit (the max percent that switchgrass could occupy the unused land) as it is imposed arbitrarily in this study and are not subject to any calibration process as no switchgrass is grown in the county historically. The contract price is held constant at $85/ton, while varying the value of the switchgrass limit from 10%, 30% to 100% of the total cropland per year.

Table 8 Sensitivity Analysis on Switchgrass Upper Limit for Single-Outlet Scenario

Switchgrass Limit (Percent)	End Simulation Bio-NPV (1000 $)	Mid Simulation	End of Simulation Crop Acres			
		Switchgrass (Acres)	Switchgrass (Acres)	Corn Soybeans (Acres)	Wheat (Acres)	Alfalfa (Acres)
0.1	48.442	116	834	20,191	6,687	27,401
0.3	**108.927**	**232**	**1,582**	**20,267**	**6,868**	**26,691**
1	106.413	131	1,218	20,193	6,769	26,896

The sensitivity analysis results show that the simulation results are quite insensitive to the switchgrass upper limit we impose, especially when the limit is greater than or equal to 0.3. This result is supported by the fact that farmers are really cautious on perennial energy crops to "test the water", even if they are profitable from farmers' prospective (Hipple & Duffy, 2002). The fact that energy and agriculture are characterized by lock in and resistant to change (Unruh, 2000) could also empirically support this argument. Generally, this is because farmers are uncertain about the new crop's profitability. More specifically, in our study, this uncertainty on profitability is primarily driven by farmers' fear of being held up – the number of years that the biorefinery holds up farmers reaches up to 4 (40% of the total simulation years). Therefore, this study takes an upper limit of 0.3 and believes that it is reasonable.

To test whether the use of different switchgrass upper limit will influence the choice of contract price, an additional sensitivity analysis is also conducted (results not reported here) by testing the 6 price schemes used before under different switchgrass upper limit (0.3 and 0.1). It is found that the choice of switchgrass upper limit doesn't influence the relative merits of different contract price configurations – the price of $85/ton has a higher NPV for the 10 simulation years.

5.2 Quasi-Multiple Outlets – A Biorefinery Procures from a Farmer Cooperative

5.2.1 Parameter Used in the Model

The parameters used in this scenario are listed below in Table 9:

Table 9 Quasi-Multiple Outlets Scenario (Scenario 2) Model Parameters

Whose	Parameter	Meaning	Value
Farmer	sw	Switchgrass upper limit	0.3
	$FePro_0(\alpha)$	Initial perceived payment (hold up) percent probability ($\alpha \in \{0, 0.05 \dots .1\}$)	0.0625…..0.0625
	$E_0(p_{YH})$	Initial perceived probability of high yield	U(0.3, 0.5)
	Y_H	High yield of switchgrass	4.7
	Y_L	Low yield of switchgrass	4.1
Refinery	$\emptyset$	Payment per ton	75, 85, 95, 105, 115, 125
	α	Payment percent under consideration	0.2, 0.25, ….., 1
Cooperative	TC	Transaction Cost of Alternative Outlet	\$10/ton~\$45/ton

5.2.2 Simulation Result for the Quasi-Multiple Outlets Scenario

5.2.2.1 Contract Price Choice under Different Cooperative's Alternative Market Searching Transaction Cost

Through the analysis in section 3, it is straightforward to say that the profitability of the biorefinery depends not only on its own action, but also on how attractive the price of cooperative's alternative outlet is, which relies heavily on the transaction costs of the cooperative to trade with that outlet. Therefore, this study will analysis biorefinery's satisfactory contract price choice among the given 6 contract prices when the cooperative is facing different transaction cost of searching for alternative outlets.

After the simulation, we found that the contract prices that guarantee the highest biorefinery's NPV vary with transaction cost: For transaction cost from \$10/ton to \$35/ton, the chosen contract price is \$125/ton. However, when transaction cost is higher than \$35/ton, the chosen contract price becomes \$105/ton or \$85/ton. Figure 20 and

Figure 21 below shows the biorefinery's net present value and switchgrass acres under contract as a function of the total transaction cost:

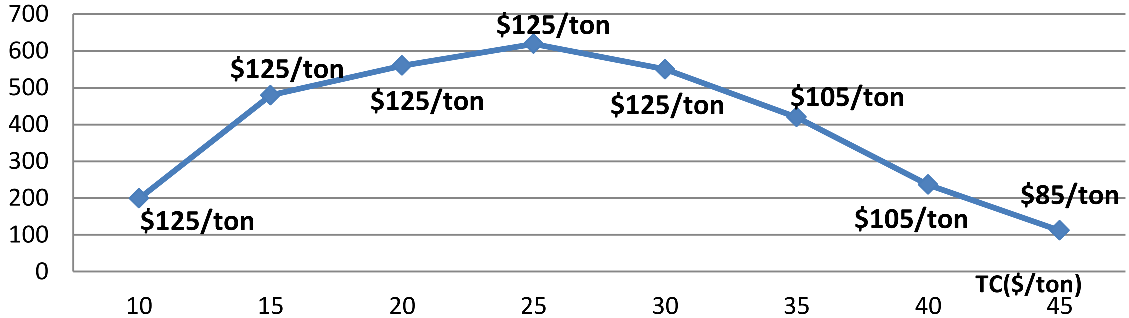

Figure 20 End-Simulation Biorefinery NPV (in 1000 $) under Different Cooperative's Alternative Market Searching Transaction Cost

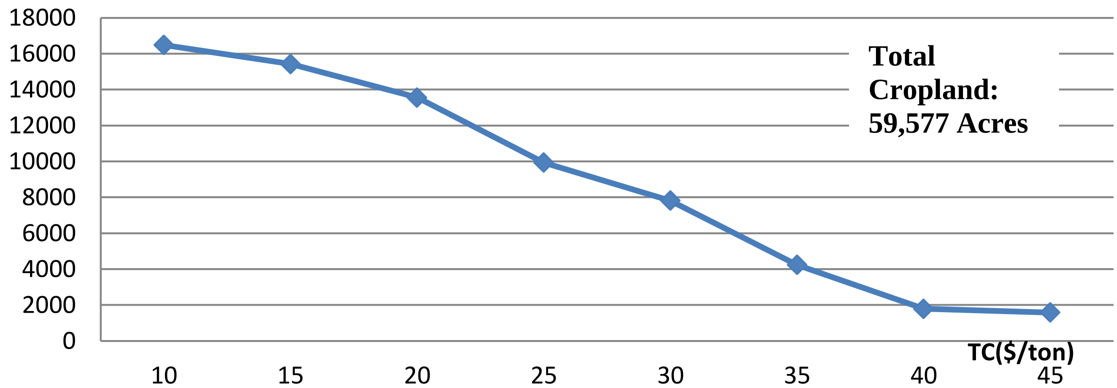

Figure 21 End-Simulation[27] Switchgrass Areas (in Acres) under Different Cooperative's Alternative Market Searching Transaction Cost

From the figures above, some general results could be presented: First, the general trend for switchgrass acres is to decrease as cooperative's transaction cost with alternative outlet increases. The reason is that the higher the transaction cost is, the more difficult the cooperative could find out an economically feasible alternative market outlet

[27] The end of simulation switchgrass acres is used here is because we want the farmers to adjust their expectation on contract hold up for a while.

and thus the biorefinery will possess higher market power, which will drive up farmers' expectation that the biorefinery is prone to hold up a relatively high amount of payment. In fact, the higher the transaction cost is, the situation is more similar with the first scenario where one market outlet (biorefinery) procures switchgrass from individual farmers;

Second, as the cooperative's transaction cost of trading with the alternative outlet increases, the net present value of the biorefinery will first increase and then decrease, reaching the highest point at a transaction cost of ($25/ton) For the biorefinery, the effect of increasing transaction cost could be decomposed into two parts:

(1) The marginal side effect of increasing transaction cost is the decreasing switchgrass lands as its market power goes up.

(2) The marginal benefit of market power is that as the "real switchgrass price" of alternative outlet decrease with higher transaction cost, the amount of payment it could hold up increases.

At first, the marginal side effect of increasing transaction cost does not outweigh the marginal benefit. However, after the transaction cost is higher than $30/ton, the marginal benefit goes below the marginal side effect.

An important implication of Figure 20 and Figure 21 above is that the biorefinery might be willing to encourage other market outlets in some other regions to increase its own profitability, as long as the transaction cost for the cooperative to deal with that market outlet keeps in a reasonable range. By doing so, the refinery could decrease farmers' perceived risk of trading with itself and gain profit by increasing the amount of switchgrass lands contracted.

In the next sub-section, more detailed analysis over the full simulation period will be conducted. To save space and be more specific, it is decided to choose only one transaction cost scenario to conduct the analysis. As the scenario with a transaction cost equals to $25/ton while the chosen contract price equals to $125/ton as it guarantees the highest NPV level for the biorefinery, it is chosen for the detailed analysis.

5.2.2.2 Comparing Results with First Scenario Best Contract Price Case

The results of the best contract price schedule under the two scenarios – (1) $85/ton for the case that one biorefinery procures from individual farmers, and (2) $125/ton with $25/ton transaction cost for the cooperative are compared:

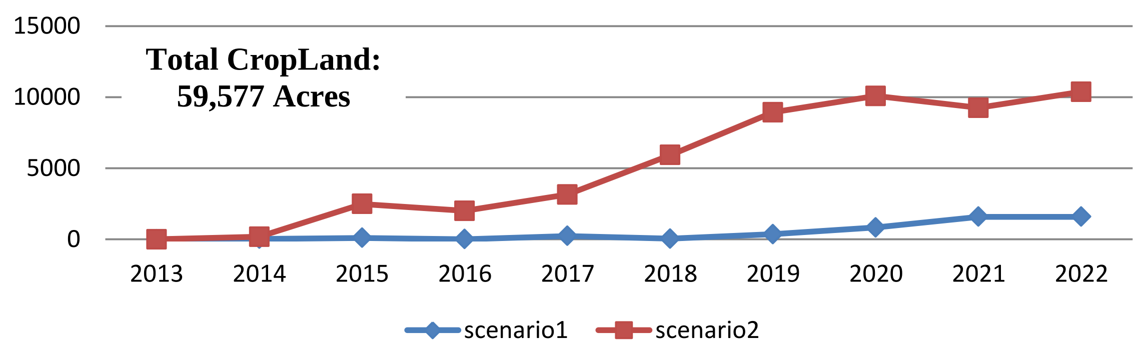

Figure 22 Switchgrass Areas (in Acres) Comparison between the Single-Outlet and Quasi-Multiple Outlets Scenario

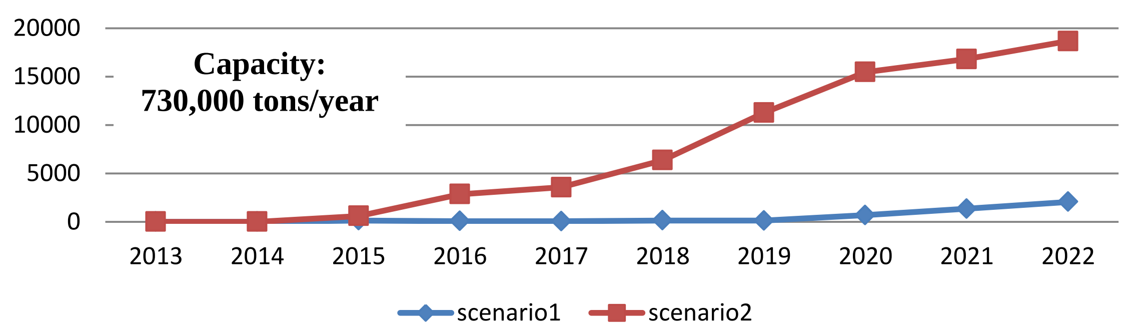

Figure 23 Switchgrass Production (in tons) Comparison between the Single-Outlet and Quasi-Multiple Outlets Scenario

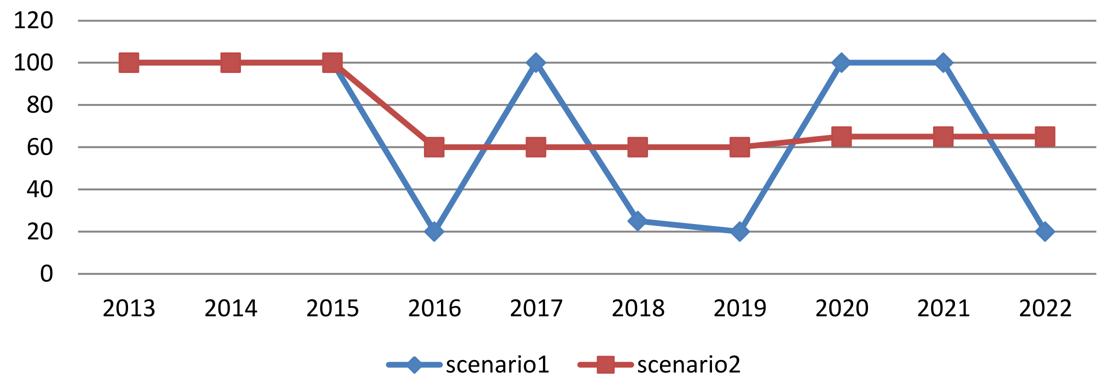

Figure 24 Payment Percent (in %) Comparison between the Single-Outlet and Quasi-Multiple Outlets Scenario

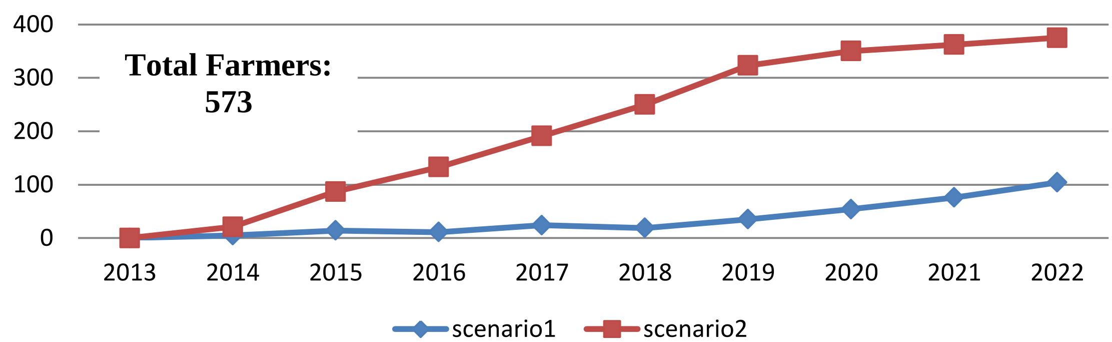

Figure 25 Switchgrass Adopters Comparison between the Single-Outlet and Quasi-Multiple Outlets Scenario

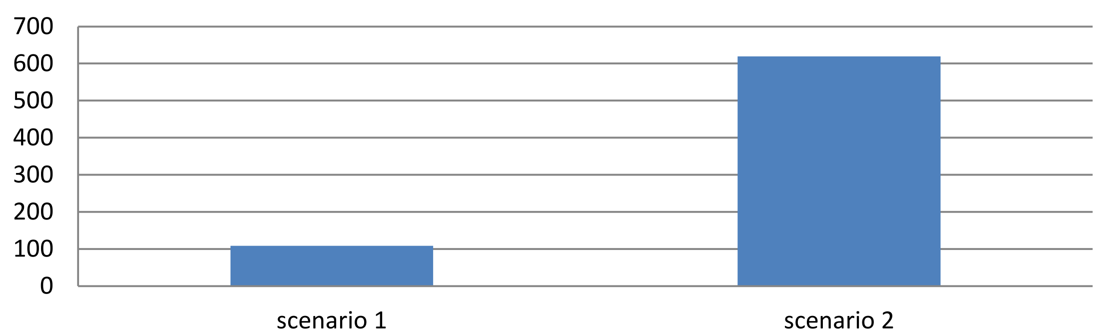

Figure 26 Biorefinery NPV (in 1000$) Comparison between the Single-Outlet and Quasi-Multiple Outlets Scenario

It could be seen that when a farmers' cooperative is introduced, there is a substantial increase in lands that are turned into switchgrass use. The incomplete competition brought by the cooperative's ability to adopt more efficient transportation method (via pelletizing switchgrass) and more efficient information searching of alternative outlets contributes to biorefinery's less contract hold up amount – If the price paid by the biorefinery is lower than the real price of the alternative outlet, the cooperative will sell switchgrass to that alternative outlet, thus farmers would form a higher switchgrass growing gross margin expectation as well as a lower risk level compared with that in the single-outlet scenario as their perceived contract hold-up amount by the biorefinery is low.

We could say that the introduction of farmers' cooperative is a Pareto Improvement -- This arrangement will not only increase farmers' profitability and increases the land areas devoted to switchgrass use (thus moves closer to US DOE's objective), but also increase the long-run profitability of the biorefinery (shown in Figure 26 on biorefinery's end of simulation NPV) .

5.2.3 Sensitivity Analysis

The Sensitivity Analysis for the most artificial parameter – farmers' switchgrass conversion percent per year, sw (sw=0.1, 0.3 and 1), is tested here. As a number of simulation experiments have been conducted with different transaction cost, only the case with $125/ton contract price and $25/ton transaction cost dealing with alternative market outlet is chosen to do the sensitivity analysis for simplicity. The results of the sensitivity analysis are reported in Table 10 below:

Table 10 Sensitivity Analysis on Switchgrass Limit for Quasi-Multi-Outlets Scenario

Switchgrass Limit (Percent)	End Simulation Bio-NPV (1000 $)	Mid Simulation	End of Simulation Crop Acres			
		Switchgrass (Acres)	Switchgrass (Acres)	Corn Soybeans (Acres)	Wheat (Acres)	Alfalfa (Acres)
0.1	117.479	897	4,103	20,431	6,733	25,050
0.3	619.14	3,148	10,372	20,251	6,718	20,115
1	1536.7	5,918	15,794	19,082	6,294	16,673

The sensitivity analysis result shows that the results for this scenario are quite sensitive to the parameters we choose. However, the upper limit that 100% of croplands could be converted to switchgrass is too high and is unlikely to be the true value for a new energy crop (Hipple & Duffy, 2002). Therefore, choosing a number (0.3) between a quite low value 0.1 and a quite high value 1 is still reasonable. To see whether the chosen values for the switchgrass upper limit parameter will affect the contract choice under different transaction cost, an additional sensitivity analysis is conducted -- the results are all the same under different parameter values, which says that the choice of contract price is not sensitive to that parameter (detailed results not shown as the resulting contract price choices are exactly the same).

5.3 Multiple Easily Accessible Outlets in the Region for Individual Farmers

5.3.1 Parameter Used in the Model

The parameters used in this scenario are listed below in Table 11:

Table 11 Multiple-Outlets Scenario (Scenario 3) Model Parameters

Whose	Parameter	Meaning	Value
Farmer	sw	Switchgrass upper limit	0.3
	$FePro_0(\alpha)$	Initial perceived payment (hold up) percent probability ($\alpha \in \{0, 0.05, \dots, 1\}$)	0.0625,…,0.0625
	$E_0(p_{YH})$	Initial perceived probability of high yield	U(0.3, 0.5)

Table 11 (cont'd)

<table>
<tr><td rowspan="2">Farmer</td><td>Y_H</td><td>High yield of switchgrass</td><td>4.7</td></tr>
<tr><td>Y_L</td><td>Low yield of switchgrass</td><td>4.1</td></tr>
<tr><td rowspan="3">Refinery</td><td>$\emptyset$</td><td>Payment per ton</td><td>75, 85, 95, 105, 115, 125</td></tr>
<tr><td>α</td><td>Payment percent under consideration</td><td>0.2,0.25,…,1</td></tr>
<tr><td>$BePro_0(\alpha_{-1})$</td><td>Initial perceived payment (hold up) percent probability ($\alpha \in \{0,0.05,\dots,1\}$) of its opponent refinery</td><td>0.0625,…, 0.0625</td></tr>
</table>

5.3.2 Simulation Result for the Multiple-Outlets Scenario

5.3.2.1 Comparison of Contracts with Different Per-ton Payment

In this scenario, we consider two biorefineries procure switchgrass from individual farmers using the same switchgrass procure contract price[28], guaranteeing multiple (two) relatively easily available switchgrass outlets for individual farmers. One biorefinery is set to be close to most farmers while the other one is set to be relative distant – that is, the difference between the two biorefinery exists in the distance to farmers. Therefore, it could be expected that the closer biorefinery has a much higher procurement amount than the further biorefinery. This difference is made here due to: (1) the two easily available switchgrass outlets needn't to be all the same in every aspect. The difference between them could make some farmers prefer one while others prefer another; (2) It is relatively easy to report results and choose a satisfactory contract if we set one outlet more preferred than the other; (3) Even though one refinery is farther to farmers than the other, the distance difference is not high, thus still guaranteeing easy access for farmers to both outlets, retaining the competition between two easily accessible market outlets.

[28] We consider this assumption to be feasible as when there is direct competition between biorefineries when we assume that no difference exists among farmers' switchgrass, the final contract price should tend to be the same.

Therefore, only the ***closer biorefinery's simulation*** results will be reported in this section. As a first step, different payment schedules are tested to compare potential different contract configuration results using the initial parameters shown above, as what has been done for the first two scenarios.

Table 12 Comparison of Different Contract Configuration for Multi-Outlets Scenario

Contracted Price ($/dry ton)	End Simulation Bio-NPV (1000 $)	Mid Simulation	End of Simulation Crop Acres			
		Switchgrass (Acres)	Switchgrass (Acres)	Corn Soybeans (Acres)	Wheat (Acres)	Alfalfa (Acres)
			0 (T=2012)	15,634 (T=2012)	5,447 (T=2012)	32,099 (T=2012)
75	89.43	4,140	10,591	20,462	6,830	19,259
85	345.21	10,436	12,849	20,558	6,740	19,018
95	438.4	10,556	12,379	20,437	6,700	18,712
105	**639.57**	**12,213**	**14,892**	**20,591**	**6,833**	**18,944**
115	235.45	10,069	7,766	20,473	6,875	22,070
125	65.43	10,499	9,688	20,353	6,758	20,442

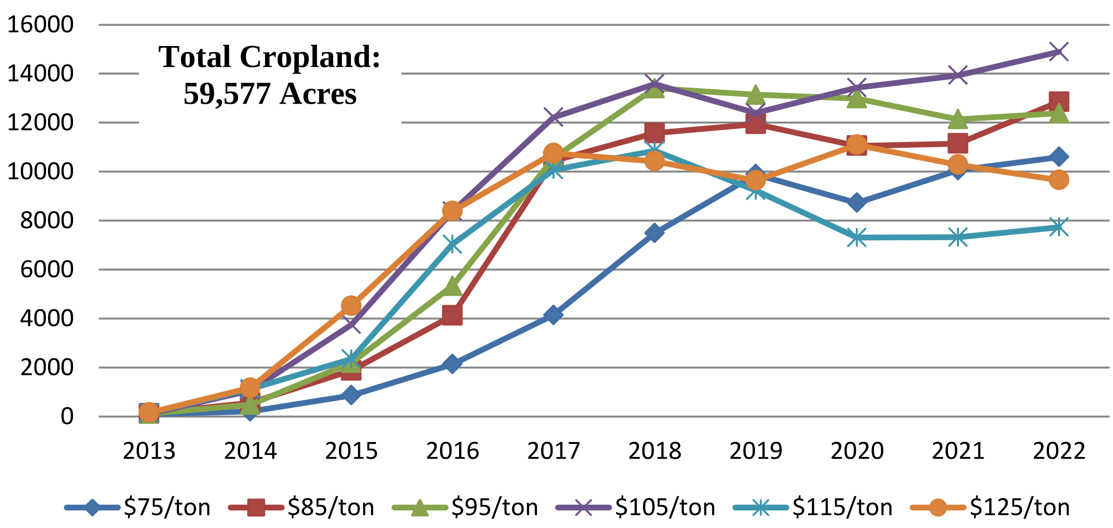

Figure 27 Switchgrass Areas (in Acres) under Different Contract Price in Multiple Outlets Scenario (Main Biorefinery)

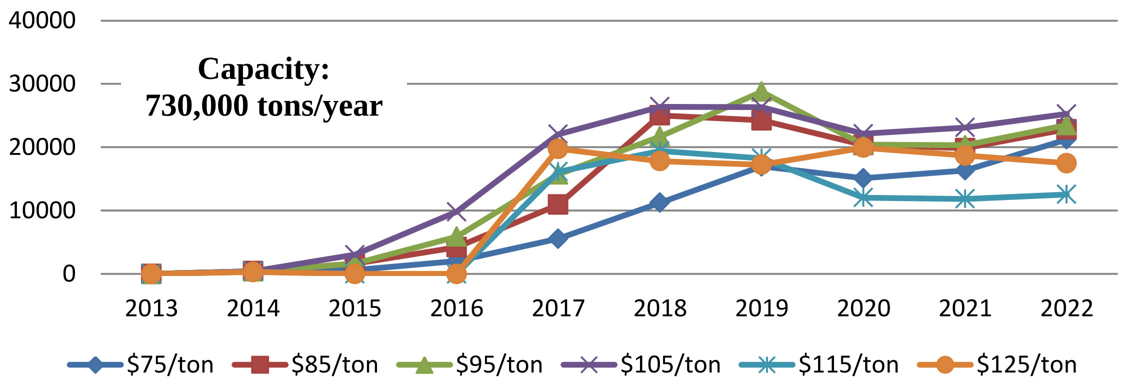

Figure 28 Switchgrass Production (in tons) under Different Contract Price in Multiple Outlets Scenario (Main Biorefinery)

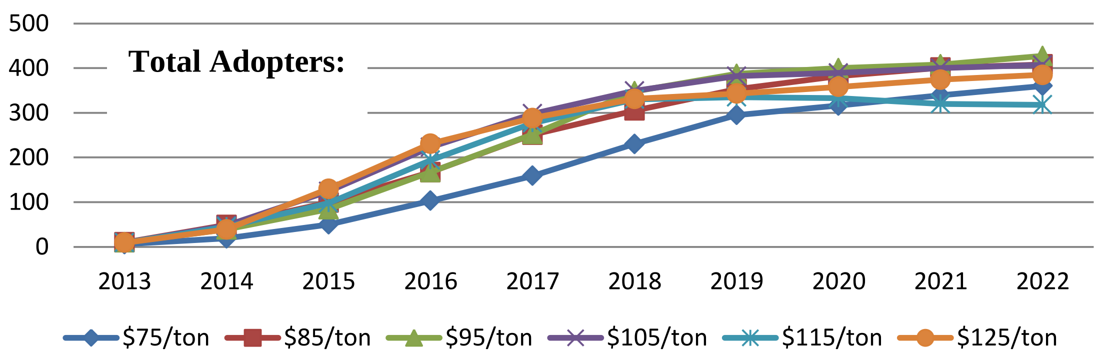

Figure 29 Switchgrass Adopters (in numbers) under Different Contract Price in Multiple Outlets Scenario (Main Biorefinery)

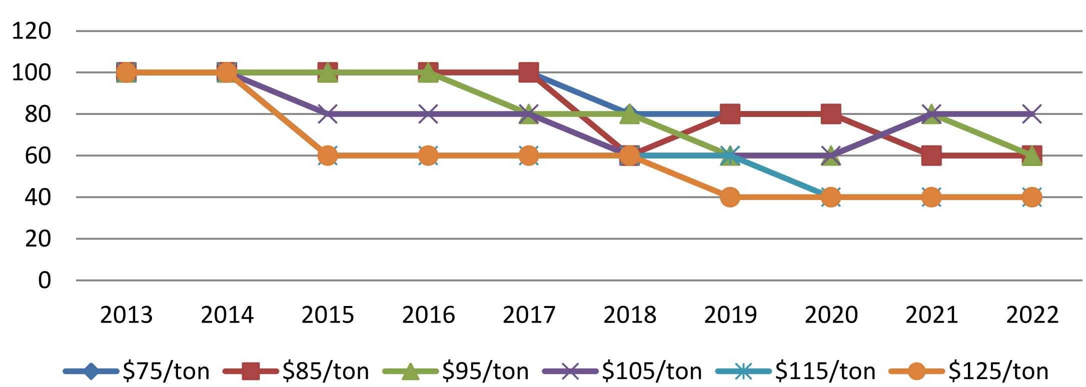

Figure 30 Contract Payment Percent (in %) under Different Contract Price in Multiple Outlets Scenario (Main Biorefinery)

The NPV of the main biorefinery increases at first and then decreases after the contracted payment are higher than $105/ton. Several points need to be noticed:

First, under the competition of another easily accessible switchgrass outlet for farmers, the biorefinery is less willing to hold up a relatively large amount when the ethanol price is in a reasonable range as it will experience not only future loss, but also current loss of switchgrass land.

Second, under almost all feasible and reasonable payment schedule, the switchgrass land devoted to the biorefinery and the refinery's realized capacity (switchgrass tons procured) are higher when there is competition than when only single outlet exists. This is because farmers' expected biorefinery payment percent and thus the expected switchgrass growing gross margin is higher when competition exists. This result is consistent with many others' conclusion that one of the most serious problems for switchgrass adoption is the lack of alternative market for the crop (Hipple & Duffy, 2002; Jensen et al., 2007).

5.3.2.2 Comparing Results of Best Contract Prices under the 3 Scenarios

In this section, the results of the three scenarios are going to be compared simultaneously – (1) single outlet: one biorefinery procures from individual farmers; (2) quasi-multiple outlets: biorefinery procures from farmers' cooperative and (3) multiple outlets: two easily accessible market outlets (biorefineries) procures from individual farmers.

In the quasi-multiple scenario, we say that the appearance of a farmers' cooperative will introduce incomplete competition to the biorefinery as the cooperative has a much higher possibility to find an alternative market outlet as long as it incurs some form of transaction cost. Under this scenario, there are multiple relatively easily available outlet for individual farmers, thus we could provide a brief discussion of how an ideal multiple outlets market could stimulate farmers' switchgrass adoption and compare how large the gap between this case and the "quasi multiple outlets" cooperative case is. The comparisons are shown in Figure 31 to Figure 35:

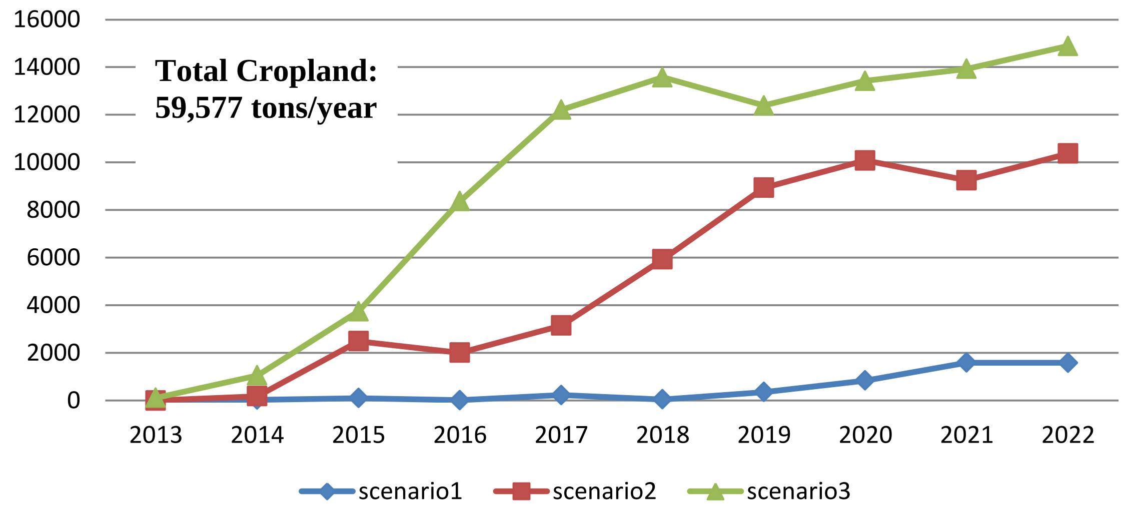

Figure 31 Switchgrass Areas (in Acres) Comparison among All Scenarios

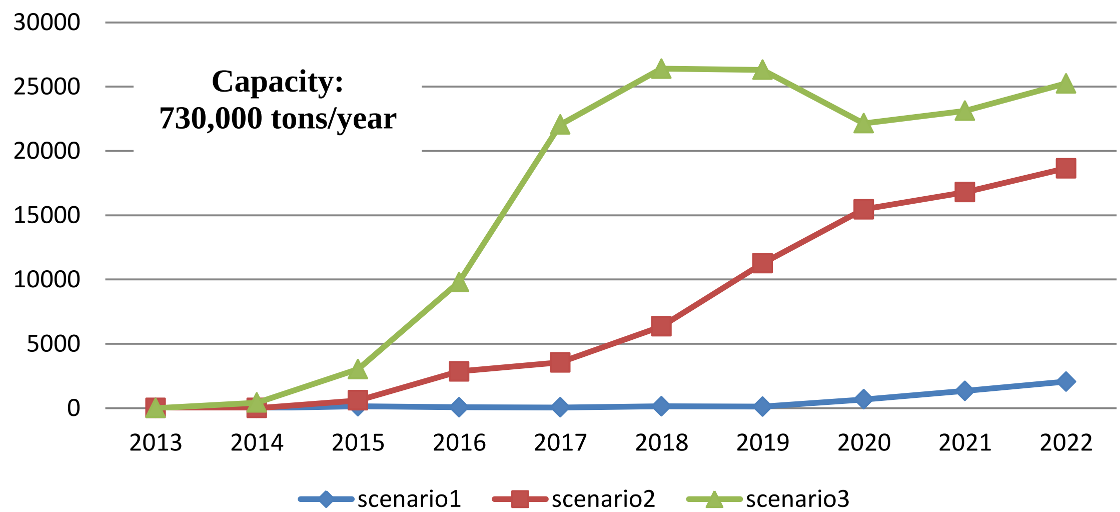

Figure 32 Switchgrass Production (in tons) Comparison among All Scenarios

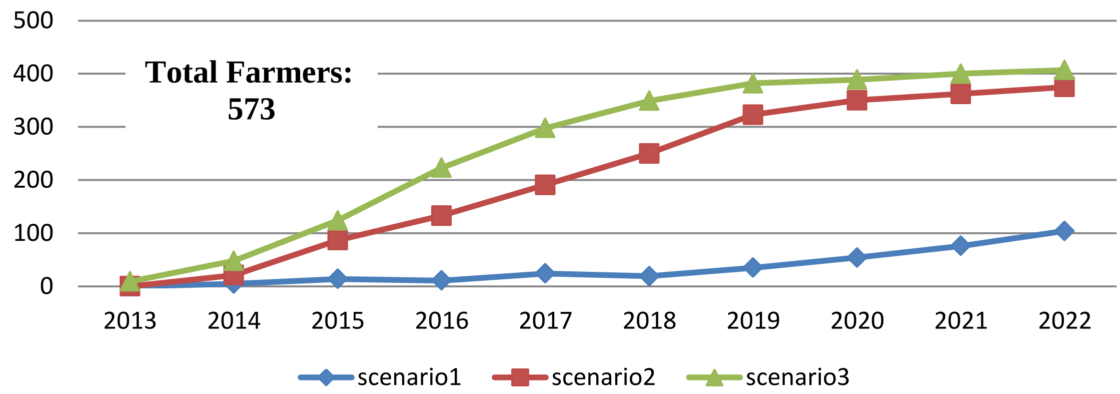

Figure 33 Number of Adopters (in numbers) Comparison among All Scenarios

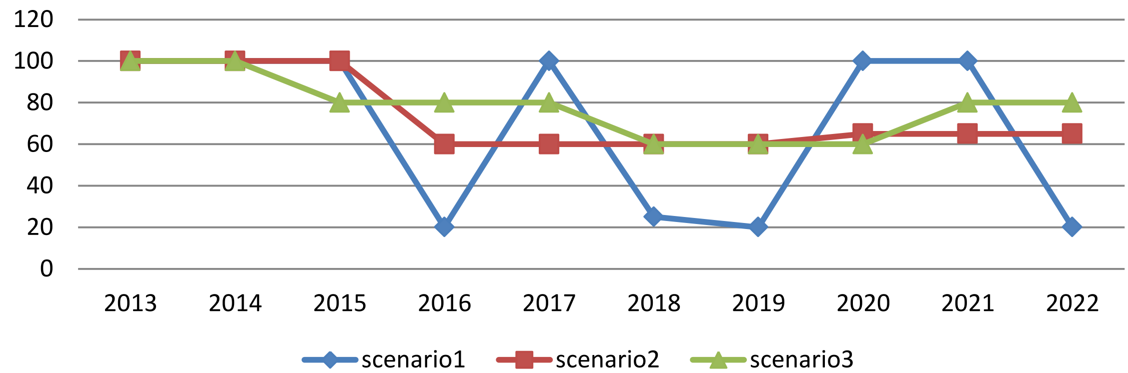

Figure 34 Payment Percent (in %) Comparison among All Scenarios

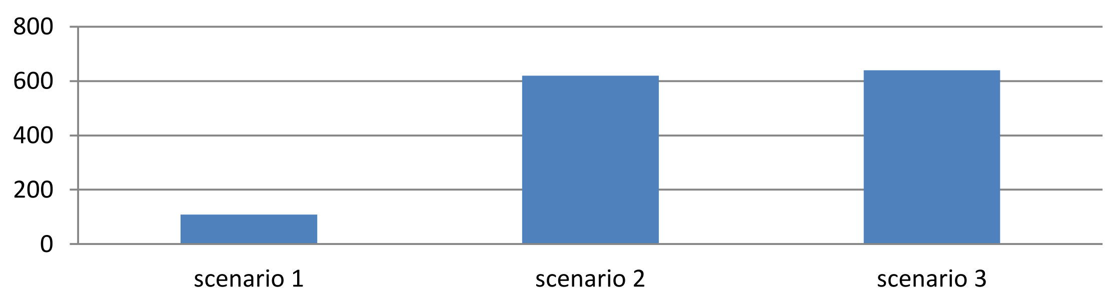

Figure 35 End Simulation Biorefinery NPV (in 1000 \$) Comparison among All Scenarios

It is easy to see that when competition between two easily accessible market outlets exists, switchgrass contracted, adopter number and switchgrass production (biorefinery's realized production capacity) will be higher than those of the quasi-multiple outlet case. The payment percent will be also be higher on average.

However, as discussed above, although we make one biorefinery superior than the other in terms of transportation distance, the switchgrass acres, switchgrass production and biorefinery NPV values are in fact for two biorefineries in the multiple outlets scenario [29]. It could be seen that during early years, both switchgrass acres and switchgrass production (tons) in the third scenario (two easily accessible biorefineries) are more than twice of that in the second scenario (cooperative quasi-multiple outlets scenario). However, as time proceeds, the amount of switchgrass produced under the cooperative scenario goes up gradually and the difference between this amount and the third scenario's amount goes down. As in the cooperative scenario, all realized switchgrass production and biorefinery profit goes to one biorefinery, it becomes more and more efficient overtime than the two biorefinery case from the perspective of switchgrass procurers. However, the fact that switchgrass acre reaches the highest amount in the multiple easily accessible market scenario case shows implicitly that it is still the ideal market condition from the perspective of farmers.

5.3.3 Sensitivity Analysis

Sensitivity analysis for farmers' switchgrass limit is conducted as usual to test whether the parameter value is set to a reasonable level -- the contract price is held constant at $105/ton, while using the value of switchgrass limit by 0.1, 0.3 and 1. The results are shown in Table 13:

[29] The condition is that there exists other difference between the two refineries that make both of them preferred by a portion of farmers

Table 13 Sensitivity Analysis on Switchgrass Limit for Multiple-Outlets Scenario

Switchgrass Limit (Percent)	End Simulation Bio-NPV (million $)	Mid Simulation	End of Simulation Crop Acres			
		Switchgrass (Acres)	Switchgrass (Acres)	Corn Soybeans (Acres)	Wheat (Acres)	Alfalfa (Acres)
0.1	78.215	2,529	3,789	20,520	6,729	25,084
0.3	639.57	12,213	14,892	20,591	6,833	18,944
1	986.43	15,037	17,549	19,287	6,242	14,390

The result is a little sensitive to the switchgrass upper limit parameter that we impose. But the difference is not that high (the results are not that sensitive). Following the same logic of the quasi-multiple outlets scenario's sensitivity analysis, a value of 0.3 for farmers' switchgrass limit is reasonable.

5.4 Large Scale-Commercial Biorefinery?

In the U.S, some small regional trial biorefineries have been set up using government support (e.g. Alpena Biorefinery, UT Biofuel Initiative together with Genera). However, the feasibility of a large scale biorefinery has yet to be scrutinized.

For a commercial biorefinery with a capacity of 2,000 tons of switchgrass per day, the per-year capacity is equivalent to 730,000 tons/year. However, if we use a farmer cooperative procurement method (i.e. the most realistic and efficient procurement method shown by the simulation results), the realized capacity is only about 20,000 tons per year at the 10^{th} year.

This finding does not indicate that a large-scale biorefinery is not feasible for several reasons. First, we could not expect that switchgrass procured from one single county could satisfy the capacity of one commercial biorefinery. Thus for a large-cale bio refinery, we would expect it to procure from multiple counties. According to our results, if there is one switchgrass cooperative in each county, the biorefinery could contract with

36 counties to secure its biomass supply. Second, the county we are studying is in a northern U.S. state where the yield of switchgrass is lower than the in southern U.S. states. If the refinery is set up in a southern U.S. state, a larger portion of the full capacity might be realized. On the other hand, a biorefinery's contracted switchgrass price might be higher in the South as the opportunity cost of land in those regions are higher due to the high gross margin of traditional crops. Furthermore, in our study area, the most affected crop is alfalfa. In southern states, the crops that are most affected would be food related crops such as corn, soybean and wheat (Larson, English & Lamber, 2007) and decision makers would be faced with the food vs. fuel problem. Third, advanced pelletizing techniques could save significant transportation costs and therefore the extent the collecting area for biorefineries. Thus one collecting depot could collect switchgrass from multiple counties. This is consistent with the regional bio-feedstock processing center concept proposed by Carolan, Joshi & Dale (2007). Another way to save transportation costs is to use water transportation. Since Michigan is surrounded by a number of Great Lakes, future studies should examine the feasibility of this transportation method.

CHAPTER 6: CONCLUSIONS, IMPLICATIONS AND LIMITATIONS

6.1 Major Findings

In this thesis, I study farmers' adoption of energy crop production by examining the extent to which farmers will convert land to switchgrass production under different market scenarios. Specifically, three market scenarios are considered: 1) the single outlet case, 2) the "quasi-multiple outlet" case via the introduction of a farmer cooperative, and 3) the multiple outlet case.

There are several major findings from this study. First, compared to studies that consider switchgrass uncertainty that comes mainly from yield uncertainty (Zhou, 2013), or from both yield uncertainty and price uncertainty from ethanol markets (Song, Zhao & Swinton, 2011), we also take into consideration uncertainty related to the contract hold-up problem. This problem exists due to the fact that a mature market for switchgrass does not exist and thus there is an *ex ante* probability that the biorefinery will attempt to extract quasi rents for farmers once a production contract is signed and investments are made into relationship specific assets. We found that accepted switchgrass contract prices range from \$85/ton to \$125/ton under the three scenarios. These prices are higher than the \$77/ton optimal switchgrass price calculated by Zhou, (2013). The difference in prices is primarily due to the farmers' perceived uncertainty related to the potential for contractual hold-up.

The second major finding is that, holding other factors constant, the cooperative procurement method (scenario 2) is the most efficient method to procure switchgrass. After several simulated years, the amount of switchgrass procured under this method approached that of the multiple market outlets scenario (scenario 3, which is a nearly ideal case). In the scenario where one biorefinery procures from a farmers' cooperative, the profitability of the biorefinery depends heavily on the transaction costs related to discovering alternative market outlets. At a transaction cost of around $25/ton, the biorefinery's profit peaks. Therefore, the biorefinery might want to cooperate with other industries to foster an alternative market outlet for farmers. However, the industries the biorefinery is going to coordinate with should be located somewhere far away from the procurement region. This will keep the transaction cost for farmers' cooperative to find out the alternative market outlets in a reasonable range to guarantee the biorefinery itself a high profit.

Third, under all three scenarios, the amount of switchgrass available might not be enough to satisfy the biorefinery's capacity even when efficient procurement organization is used. A maximum of 5%, 16.8% and 25% of total cropland is converted into switchgrass under scenarios 1, 2 and 3, respectively. This land conversion rate is consistent with many other studies of land use change to energy crops (See Table 14).

Table 14 Comparison of Energy Crop Land Conversion in Different Studies

Study	Energy Crop	Focusing Point	Land Conversion Rate
This Study	Switchgrass	Contract Hold Up	5%, 17% and 25% under different market scenarios
Hipple & Duffy (2002)	Switchgrass	Farmer Interview	10% at first and increase slowly overtime
Song, Zhao & Swinton (2011)	Switchgrass	Dynamic Optimization of Payoff Uncertainty	30%
Bocqueho & Jacquet (2010)	Switchgrass Miscanthus	Risk Preference and Liquidity Constraint	20% to 40% under most price volatility and loan scenario
Shastri et al., (2011)	Miscanthus	Bidding	60% in the end

Although existing studies use different methodologies, most of these studies come to a conclusion that the conversion rate from traditional cropland to energy crop use will be around 10% to 30%. This study examines the conversion of land to energy crop production from a perspective that focuses primarily on potential contract hold up problem and its effect on the perceived risk face with respect to the adoption of switchgrass. The results of this study are consistent with previous studies.

6.2 Study Limitations

This study represents an initial attempt to model the contract hold-up problem using an agent-based approach. While the results are encouraging, future work is needed to address the following study limitations:

1. The crop yield data used in this study is not precise. This study uses a relatively crude method to assign crop yields using only crop type and soil productivity index. Though the method is warranted in this case as the major focus point is modeling hold-up problem, results could be more convincing if more realistic crop yield simulation techniques are used.
2. Although switchgrass adoption is a long-term investment decision, this study is limited to short-term decisions. Due to the computational difficulty of dynamic game modeling under highly heterogeneous environments, long-term decision making techniques are not adopted. Instead, each agent is only allowed to look forward for one period on the other player's potential strategy. Future research should think about how to extend the planning periods of both farmers and biorefineries.
3. The levels of heterogeneity included in this model needs to be added. For example, the model assumes that all farms 1) enter the same contracts, 2) have the same hold-up rates, 3) learning using the same methods, 4) are located the

same distance from the biorefinery, and 5) have the same objective functions (i.e. profit maximizing). Future studies should relax these assumptions and this will be discussed in more detail in section 6.4.

6.3 Contributions

This thesis makes several significant conceptual and methodological contributions to the agricultural land use and bioeconomy literature and offers important insights for bioeconomy decision makers. With regards to the conceptual framework adopted and the findings presented, this study offers the following contributions and implications:

1) To the researcher's knowledge, this is the first attempt to emphasize the contract hold-up problem in an agent-based land use model. The results of the study show that farmers' perceived contract hold-up risk should not be ignored when considering contract farming. However, it is a particularly important issue when considering the use contracts to coordinate nascent industries where there may be few alternative markets for production or uses for invested capital (e.g. specific equipment);
2) The form of institutional arrangements greatly influence farmers' perceived risk level and thus influence their willingness to convert land into new energy crops and consequently affect biorefinery's profitability;
3) In some cases, it is mutually beneficial for transacting parties if the party with less bargaining power gains some bargaining power (e.g. the cooperative could find out another outlet with transaction cost, exhibiting higher bargaining power than individual farmers) as it could decrease the perceived risk of trading with its partner;

4) As most pilot biorefineries in the U.S. are now using the most inefficient method (i.e. one biorefinery signs contracts with individual farmers) to procure energy crops, new procurement methods should be initiated (e.g. helping farmers form a cooperative) to meet the renewable fuel standard.

Methodologically, the main contributions of this thesis are twofold:

1) While most literature on agent based agricultural land use models omit the risk level of farming, this study embeds a MOTAD (Minimization of Total Absolute Deviation) risk programming method that includes the farmers' perceived risk level in their farm planning optimization model in the agent based model. This method could be easily generalized into other agent based models as the linearization of a quadratic programming method is easy to implement and makes the model run much faster than a quadratic optimization problem; and
2) This study also provides the first quantitative realization of the contract hold-up framework proposed by the seminal work of Klein (1996) in a simulation model and shows that this framework could be applied to certain empirical applications.

6.4 Directions for Future Research

Using the framework presented in the thesis, there are several future research directions that could be conducted to extend this study. As shown in the empirical literature (Fewell, 2012; Bergtold et al., 2014), heterogeneity among farmers contributes to farmers' having different attitudes towards energy crops. Future research may want to examine how this heterogeneity influences farmer decision making. Furthermore, future research may not only look at aggregate land use patterns, but also study emergent patterns at a disaggregated level. For example, future studies may address the following questions:

1. Is there a difference between the switchgrass adoption rates of large farms and small farms? In particular, future models could capture important heterogeneity at the farm level, including differences in: contract selection, contract hold-up rates, learning methods (i.e. social learning vs. learning from experience), and objective functions (e.g. profit-maximizing vs. satisficing behavior)
2. Is there a difference in adoption rates between farmers located close to the biorefinery and those who are far away from the refinery?
3. If we set a absolute lower limit which requires that if the farm size is less than a certain acres[30], farms will not consider switchgrass, how the land use patterns change?

These questions address the distinctive feature of agent based modeling compared with other modeling frameworks, namely heterogeneity and the high degree of interaction among agents.

Future research may also include additional procurement scenarios. For example, future research may model the farmers' switchgrass adoption decision where there is no risk of contractual hold-up. This scenario is similar to that of the production of corn ethanol where there is a mature spot market (i.e. alternative market) for corn. By comparing the results of that scenario with the current scenarios, we could get an

[30] This is possible because farmers as well as biorefinery will have to consider the economics of scale according to Hayden (2014).

estimation of the amount of social welfare change due to the lack of a mature switchgrass spot market.

APPENDICES

APPENDIX A. Projected Crop Input Cost

Table 15 Projected Input Cost during Pre-simulation and Simulation Period

	Input Price						
Years	Fuel	Corn seed	Soybeans seed	Wheat seed	N	P	K
	$/acre	$/acre	$/acre	$/acre	$/lb	$/lb	$/lb
1998	1.87797	41.4435	20.91185	9.125164	0.149609	0.192546	0.143196
1999	1.83191	37.6409	18.99317	8.287925	0.136635	0.189143	0.141583
2000	2.14484	48.5526	24.49904	10.69049	0.145161	0.17374	0.13597
2001	2.04578	47.1255	23.77893	10.37626	0.181687	0.170837	0.134357
2002	1.91771	45.6984	23.05882	10.06203	0.133713	0.158933	0.127243
2003	2.09465	46.2712	23.34789	10.18817	0.165239	0.16553	0.12363
2004	2.13458	42.8441	21.6186	9.43357	0.169265	0.172627	0.127517
2005	2.73552	51.4170	25.94437	11.32118	0.193791	0.184724	0.155404
2006	2.99545	54.9898	27.74719	12.10786	0.205318	0.192821	0.165291
2007	3.16439	72.5627	36.61424	15.97712	0.247344	0.235418	0.164678
2008	4.22532	81.1356	40.94	17.86472	0.29337	0.422015	0.301065
2009	2.44426	115.708	58.38503	25.4771	0.256896	0.337112	0.442952
2010	3.17719	105.281	53.12363	23.18122	0.234422	0.266709	0.267839
2011	4.08413	100.854	50.88977	22.20644	0.269948	0.325306	0.308726
2012	4.20206	103.427	52.188	22.77294	0.280474	0.336903	0.327613
2013	2.92116	84.5012	42.63908	18.60508	0.230505	0.268459	0.233251
2014	4.75532	81.6408	41.19567	17.97531	0.299172	0.288207	0.244997
2015	5.23753	85.5206	43.15334	18.82957	0.326334	0.294397	0.256743
2016	5.95860	119.066	60.08033	26.21557	0.390152	0.485734	0.390914
2017	4.21154	93.2801	47.06872	20.5381	0.308076	0.383691	0.379093
2018	6.39189	97.1599	49.02637	21.39235	0.38206	0.424979	0.291981
2019	4.50704	119.987	60.545	26.41848	0.354178	0.435799	0.33893
2020	6.82519	151.16	76.27448	33.28199	0.443609	0.622995	0.466636
2021	5.38770	152.307	76.85326	33.5346	0.348889	0.401017	0.442652
2022	5.72974	179.408	90.52858	39.50183	0.392669	0.450216	0.458541

Source: Data from 1998 to 2012 comes from USDA ERS, while data after 2013 are projected by the author.

APPENDIX B. Crop Budgets Used in the Thesis

Table 16 Input needed For Corn, Soybeans and Winter Wheat

Input	Corn	Wheat	Soybeans
Variables whose price changes during simulation			
Nitrogen (lbs)	100	90	0
Phos (lbs)	50	50	60
Potash (lbs)	65	30	90
Fuel & Lube	6	4	5
Drying (tons)	23	20	23
Marketing (tons)	4.5	3	2.63
Trucking	1	1	1
Variables whose price are constant during simulation			
Herbicide ($)	34	5	21
Insects($)	0	20	20
Crop Insurance ($)	0	15	17
Repair($)	29	20.3	20.3
Supplies($)	7.71	7.71	7.71
Utilities($)	27	4.5	4.5
Labor($)	37.8	29.4	26.6

Note: For variables whose price are assumed to be changing during simulation, as the price changes, we list the **input amount** needed for one acre of the crop; However, for variables whose price are assumed to be constant during simulation, we just list the **input cost** needed for one acre of crop.
Source: MSU Extension.

Table 17 Input Amount Needed for Switchgrass

Input	Year1	Year2	Year3 and after
Variables whose price changes during simulation			
Nitrogen (lbs)	0	60	60
Phos (lbs)	3.15	3.15	3.15
Potash (lbs)	13.25	13.25	13.25
Fuel & Lube			
Trucking	0	4	4
Variables whose price are constant during simulation			
Insects($)	27.48	13.74	0
Machine($)	118	111	111

Source: Kells & Swinton (2014)

Table 18 Input Amount Needed for Alfalfa (From Second Year)

Input	**Alfalfa**
Variables whose price changes during simulation	
Nitrogen (lbs)	0
Phos (lbs)	60
Potash (lbs)	235
Fuel & Lube	**7**
Trucking	4
Variables whose price are constant during simulation	
Herbicide ($)	0
Insects($)	6
Repair($)	21.25
Supplies($)	5.1
Utilities($)	7
Labor($)	5.5

Note: The difference between first year and the subsequent years only exists in seeding activity.
Source: MSU Extension.

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