Three Essays on Agribusiness and Food Economics

by

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Abstract

Energy security and food security are global challenges for people across the world. Research examining land use for bioenergy crops is critical because it pertains to issues of food-fuel competition. This dissertation is composed of three chapters; first two chapters focusing on problems of both energy security and food security by doing an economic analysis of scenario where farmers are converting their land from producing conventional crops to adopt bioenergy crops as a new agribusiness opportunity, whereas third chapter focuses on only food security problem by analyzing the impact of smoking on family's food security status. Chapter 1 does a descriptive analysis and an economic analysis for adoption of switchgrass as a bioenergy crop. This study uses real yield data for switchgrass comprising of 21 years of observations from a long-term experiment in Alabama. The results show that adoption of switchgrass as a bioenergy crop can be a viable addition to the crop-mix which can both improve profitability as well as reducing the variability of returns in addition to other important agronomical and environmental benefits. Chapter 2 investigates the economic incentives for loss-averse and present-biased farmers to divert a share of their land to bioenergy crops (namely, miscanthus and switchgrass) by employing an economic model based on prospect theory. Numerical simulation is conducted for 1,919 U.S. counties under a range of behavioral preferences to identify the impact of loss aversion on bioenergy crop adoption and how this impact is influenced by various biomass prices, discount rates, credit constraint scenarios, and policy instruments. Results show that all

else equal; if researchers ignore farmer’s loss aversion then they will over-estimate miscanthus production and under-estimate switchgrass production. We have also expanded our numerical simulation to cover two policy instruments. The aim of Chapter 3 is to see the impact of cigarette smoking on food security. The study has used survey data from National Health and Nutrition Examination Survey (NHANES). The study finds that cigarette smoking is associated with decreased food security and food insecurity worsens due to more smoking.

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1.1 Introduction:

People across the world are seeing biofuels as a potential solution to global challenges: energy security, economic development and mitigation of climate change. Biofuels such as ethanol are renewable fuels and are produced from bio-crops such as corn, sugarcane, miscanthus, and switchgrass. They can be used as a substitute for fossil fuels, which are subject to depletion and contribute significantly to global warming. The U.S. and Brazil are major ethanol producers in the world and account for over 90% of the world's ethanol production (Worldwatch Institute 2006). Ethanol can be broadly classified into two categories based upon the raw material used for its production: grain ethanol and cellulosic ethanol. Grain ethanol is produced from sugar and starch from plants such as corn. On the other hand, cellulosic ethanol is produced from wood, crop residues and grass such as switchgrass. Most of the ethanol production in the USA is from corn. However, there have been concerns as corn grain can be used to feed people or animals. Cellulosic ethanol (such as from switchgrass), on the other hand, does not have a direct influence on food prices and food supply (Runge and Senauer, 2007).

The 2007 Energy Independence and Security Act set a goal of 36 billion gallons of renewable fuel use by 2022. It recommends that 21 billion gallons should be produced from feedstock other than corn. Although cellulosic biomass demand is increasing and switchgrass is one of the promising bio-crops due to its agronomical, environmental, and economic benefits, it is still not adopted by farmers commercially for energy use. One of the reasons for non-adoption can be farmers' lack of information about the two most critical factors in adoption of any new crop, its profitability and riskiness relative to existing crop systems. Switchgrass production may be a profitable alternative, but questions still remain as to its competitiveness with the other enterprise alternatives that farmers can adopt (James et al. 2010). A farmer will adopt production of switchgrass only when it will provide more advantages than conventional options. On the other hand, a farmer may prefer conventional options as associated returns and risks may be better known and understood. This study seeks to provide a better understanding of the potential of switchgrass as a bio-crop using an economic analysis to evaluate profitability and risks associated with switchgrass relative to conventional crops.

Some characteristics of bioenergy perennials make them risky choices. From an economic point of view, most of the previous studies have focused on production cost analyses, such as making enterprise budgets, ascertaining cost of producing ethanol from switchgrass, or ascertaining farmers' willingness to grow switchgrass as a bio-crop. A few studies have calculated the average profitability of different bio-crops (e.g. Heaton et. al.2004). Also, a few studies have calculated the yields and prices at which a producer would cover costs of production (Mooney et al., 2009). Further, a few studies went one step ahead and did comparative breakeven analyses and calculated the yield or price required for a producer to earn profit at least equal to the return on a reference traditional crop (Jain et al., 2010).

All these studies used secondary or simulated data and haven't said much about risk. In the absence of adequate real yield data on bio-crops, studies have relied on general crop growth simulation models (Dolginow et al., 2014). The other approach was to statistically estimate yields of bio-crops across time, using a one-period-lagged, linear and plateau function and using residuals to simulate the probability distribution of random variability around expected yields (Clancy et al., 2012). One study also relied on interview responses and recorded secondary data for short-term empirical distributions of bio-crop yields (Bocqueho & Jacquet, 2010).

There are two novel parts of this paper, first is the use of actual yield data for switchgrass (21 years) from a long-term experiment on switchgrass in south-central Alabama, Macon County. Second is a descriptive analysis to assess and review some of the important factors that help farmers understand the various advantages/disadvantages that may arise from adopting switchgrass as a bio-crop. By doing risk and return analysis using actual yield data and analyzing the information gained from literature, this study offers broad insights by explicitly accounting for risk in addition to relative profitability.

In the section 'Descriptive Analysis', some of the important factors that could be considered by farmers before adopting switchgrass as a bio-crop are discussed. Then a theoretical model is developed in the section on the 'Conceptual Framework.' The 'Methodology and Data' section presents the risk and return analysis. Two hypothetical sample farms of 400 acres each are used, one sample with 200 acres each of two conventional crops, corn and cotton, and, the other with one additional crop of switchgrass taking 5%, 10%, 15%, 20%, and 25% acres away from each conventional crop. A simulation with 1,000 iterations calculates profit/loss and return on investment (ROI) for different options including the case of market failure of switchgrass. Then based on analysis of these sections, this study will offer insights on adoption of switchgrass as an energy crop.

1.2 Descriptive Analysis

To address the question of adoption of switchgrass, economic analysis alone is not sufficient. A farmer may consider some other important factors, which can play an equally important role in deciding on the adoption of switchgrass as a bio-crop. In this section, I will review such factors.

For this, first I will analyze the future of ethanol production in USA, specifically the future of cellulosic ethanol. If the future does not seem good, then there is no point in discussing adoption of switchgrass as a cellulosic biofuel feedstock. Next, I will analyze the potential of switchgrass as a cellulosic bio-crop by evaluating its agronomical, environmental, economic and other benefits. The technical and economic feasibility to convert switchgrass into ethanol will also be carefully analyzed. Lastly, current subsidies and various policy regimes will be studied to throw light on the support program/subsidy for the farmers, which can strongly influence the farmers' decision.

1.2.1 Future of ethanol production in USA

Every year in the last decade ethanol production has increased in the United States. In 2018 the U.S. produced 15.8 billion gallons of ethanol which is a 10.5% increase as compare to 2014 (U.S. EIA, 2018). Ethanol could replace 30% or more of U.S. gasoline demand by 2030 (US Department of Energy, 2009). Several policies to promote the use of renewable sources of energy including cellulosic ethanol have been implemented in the USA (Zegada et al 2013). There is a goal of 36 billion gallons of renewable fuel use by 2022, set by the Energy Independence and Security Act of 2007 (EISA).

The Renewable Fuel Association (2015) has stated that the production of 14.3 billion gallons of ethanol in 2014 had substantial economic impacts including 83,949 direct jobs, 295,265 indirect and induced jobs, $53 billion contribution to GDP, and $27 billion in household. These figures are impressive, and don't yet take into account other potential benefits such as enhanced energy security, improved environmental amenities such as water quality, wildlife habitat, and decreased greenhouse gas emissions. From these facts, future of ethanol production seems promising in USA.

1.2.2 Future of cellulosic ethanol in USA

Ethanol can be broadly classified into two categories based upon the raw material used for its production: grain ethanol (such as from corn) and cellulosic ethanol (such as from switchgrass). Cellulosic ethanol offers an attractive bio-based alternative to conventional gasoline (Ragauskas et al., 2006; Schemer, 2008). Cellulosic ethanol has lower green-house gas emissions and higher energy efficiency as compared to ethanol made from corn grain (Farrell et al., 2006). Using food crops (such as corn) for ethanol production raises concerns of food security (Mitchell, 2008) and environmental degradation (Pimentel and Patzek, 2005). Therefore, the majority of the petroleum importing countries (including U.S.) is interested in utilizing cellulosic biomass as a feedstock for ethanol production. The U.S. has a large cellulosic biomass production base and production of ethanol from cellulosic feedstock and utilizing it as a substitute for gasoline could help in promoting rural development, reducing greenhouse gases, and achieving energy independence (Perlack et al., 2005).

In the USA, the development of cellulosic ethanol is being driven in large part by the Energy Independence and Security Act of 2007 (EISA). The Energy Independence and Security Act set a goal of 21 billion gallons of cellulosic ethanol production by 2022. It is expected that the successful demonstration of at least one conversion technology on a commercial scale will help in increasing the confidence of investors in cellulosic ethanol production and thus, will help in achieving the policy target of producing 21 billion gallons of cellulosic ethanol by the year 2022. These facts clearly state that the biofuels (ethanol) will contribute significantly to future fuel consumption and the government is focusing on cellulosic bio-crops such as switchgrass.

1.2.3 Switchgrass: a potential bio-crop for cellulosic ethanol

Among the many agricultural crops screened as potential biofuels, the herbaceous bio-crop switchgrass has been identified as a promising feedstock for conversion to biofuels (Sanderson et al. 1996; McLaughlin et al. 2002; Parrish and Fike 2005). Switchgrass has been evaluated as a biofuel crop in parts of the USA, Canada and Europe (Adler et al. 2006; Berdahl et al. 2005; Madakadze et al. 1999; Mclaughlin et al. 2002). According to the Parrish and Fike (2005), a number of lowland and upland cultivars of switchgrass are available and cultivars of both ecotypes are being considered for biofuels. Switchgrass can be used to produce biofuel and is viewed as a potential long-term biofuel feedstock to replace corn (Keshwani and Cheng 2009).

The potential of switchgrass as a bio-crop for cellulosic ethanol can be analyzed by understanding the following benefits:

1.2.3.1 Agronomical benefits

Bransby (1998) found that switchgrass is well-adapted to grow in a large portion of the United States with low fertilizer applications and high resistance to naturally-occurring pests and diseases. Switchgrass requires less water than most crops currently cultivated because of a deep and extensive root system (Bransby et al., 1989). Switchgrass requires about 25 inches or less of water per season, compared to 26 inches for corn and 39 inches for cotton (Brouwer and Heibloem, 1986; Stroup et al., 2003; Smith, 2007). Thus, switchgrass is more drought resistant than other crops (Bransby et al., 1989) and may provide higher yields than many annual crops in drought years. In addition, switchgrass requires less pesticides and fertilizers than most crops currently grown in the United States (Bransby et al., 1989; Rinehart, 2006).

Switchgrass has high yields and is tolerant of water deficiency and needs low soil nutrient concentrations (Sanderson et al. 1999). Switchgrass is a high potential bio-crop with advantages such as cost effectiveness, broad adaptability, better tolerance of wet and dry soil, freeze tolerance, efficient use of water and nutrients, and high yields (McLaughlin 2002; Parrish and Fike 2005). Bransby and Huang (2014) determined long term biomass yields of eight switchgrass cultivars in Alabama and evaluated the effects of weather variables on annual yields of switchgrass grown at a single location. They concluded that under similar soil, environmental and management conditions, stands of switchgrass should be productive for 20 years or more. Their results showed that switchgrass is considerably more tolerant of drought than most of the other annual crops. Lots of other research work has also talked about its comparative agronomical benefits as a bio-crop.

1.2.3.2 Environmental benefits

McLaughlin (2005) established that studies of soil carbon storage under switchgrass indicate significant carbon sequestration will occur in soils, improving soil productivity and nutrient cycling and substantially augmenting greenhouse gas reductions. Bai et al. (2010) conducted a study to analyze the environmental sustainability of using the switchgrass plant material as a feed stock for ethanol production. They took air and water emissions into account that are associated with growing, managing, processing and storing switchgrass. They even considered transportation of stored switchgrass to an ethanol plant and found that using switchgrass for ethanol production can reduce the potential of global warming by 5% and 65% for E10 and E85 respectively (E10 and E85 are terms refer to high-level gasoline-ethanol blends containing 10% to 83% ethanol). Ethanol produced from switchgrass, either alone or by co-firing with other fossil fuels has a potential of reducing Green House Gas (GHG) emissions (Tillman 2000). Thus, there are positive environmental impacts from switchgrass production.

1.2.3.3 Economic benefits

Switchgrass has economic advantages due to its features such as being a perennial crop meaning that it does not need to be planted each year and can survive 20 years or more. There is no establishment cost in subsequent years to planting. Unlike many other bio-crops, it can grow on marginal land. Switchgrass has the capability to show high yields on soil that, due to low availability of nutrients or water, would not lend itself to the cultivation of conventional crops (Lewandowski et al. 2003). Thus, for otherwise economically not useful lands, it can prove to be a profitable enterprise. Switchgrass can be high yielding on marginal land (Fuentes &Taliaferro, 2002), so it could potentially be introduced into the feasible product mix by the farmers to increase their overall profitability. Moreover, the establishment cost of switchgrass is very low as compare to most of other perennial energy crops. The establishment cost of switchgrass is approximately 12 times lower than establishment cost of miscanthus (Anand et al. 2017).

1.2.3.4 Other benefits

Farmers can also acquire other benefits such as ecosystem services from the production of switchgrass. These benefits can be in the form of increased soil organic matter that retains moisture and maintains fertility, reduction in soil erosion and fertilizer runoff and provision of wild life habitat. There are some studies that have tried to quantify these benefits. Debnath et al. (2013) estimated that these intangible benefits could raise the value of a switchgrass crop by $13 to $46 per ton relative to intangible benefits from no-till wheat. Liebig et al. (2008) measured increases in soil carbon sequestration under switchgrass and found an average increase of 1.1 Mg C/ha, which at the value the U.S. Environmental Protection Agency places on carbon emission reductions, would be worth $54 per acre (around $15 per ton). These benefits are difficult to quantify but play an important role in decision making.

1.2.4 Feasibility for conversion of switchgrass into ethanol: refineries' perspective

This is really an important aspect for the future of switchgrass as a potential biomass feedstock. In 2014, a genetically altered form of 'bacteriu caldicellulosiruptor bescii' was created which can cheaply and efficiently turn switchgrass into ethanol (Chung, 2014). Without mandates, at current prices for fossil fuels cellulosic ethanol is not competitive with gasoline. Currently the Food, Conservation and Energy Act of 2008 (H.R. 2419) includes a tax credit of US$ 1.01/gallon for cellulosic biofuel refineries (sec 15321), and a cost sharing program matching up to US$ 45/ton for collection, harvest, storage and transportation of biomass crops (section 9011). Yu et al. (2011) evaluated the potential value of including preprocessing in the biomass feedstock supply chain for a bio refinery in East Tennessee using a spatial oriented mixed-integer mathematical programming model. The results showed that stretch-wrap bale reprocessing technology could reduce the total delivered cost of switchgrass for large scale bio refineries.

There is a considerable variability in the expected quantity of ethanol that can be produced from per dry ton of switchgrass. Schmer et al. (2008) used a conversion rate of 91 gallons per dry ton. The USEPA (2010) reports conversion rates of 72 gallons per dry ton (p. 721), 90 gallons per dry ton (p. 285), and 92.3 gallons per dry ton (p. 286), depending on the type and maturity of the system. For a given size of bio-refinery, total feedstock requirements, acres required, transportation distances, and feedstock cost would lead to different conversion rates. Because there is only one commercial-scale cellulosic ethanol plant in operation (in Iowa), it is quite difficult to determine what will be the overall cost of converting switchgrass to ethanol.

Thus, gradual development of technology is bringing the attention of bio refineries towards switchgrass as a potential biomass feed stock.

1.2.5 Subsidies and different policy regimes

It's important to understand all current subsidies and policies in relation to biofuels to analyze whether there is any push from the government to farmers for adoption of switchgrass as a bio-crop. The federal government is subsidizing cellulosic biomass production via a few programs such as the Biomass Crop Assistance Program (BCAP). To illustrate, in BCAP, an establishment cost subsidy to farmers is currently specified to be the lower of 50% of establishment cost or $500 per acre. Tyner (2008) claimed that a boom in the ethanol industry is an unintended consequence of a fixed ethanol subsidy. In future, the policy chosen will be critical in determining the growth of both corn and cellulose ethanol. Using cellulose for ethanol production would reduce the problems associated with using corn —namely, food insecurity, reduced corn exports and higher costs for animal feed. According to Tyner, the government should provide a tax credit to cellulose processors for each dry ton of cellulose converted into fuels in order to assist in launching the cellulose based industry. Babcock et al. (2007) suggested that subsidies should be directly targeted at biomass production rather than ethanol production or biofuels production because new ethanol production subsidies would simply increase the demand for corn, not switchgrass, despite the potentially significant environmental advantages of expanded switchgrass production.

After doing an in-depth literature review in section "Descriptive Analysis", I can say that there are reasonable grounds for promoting more research on switchgrass and taking a first step towards thinking of adoption of switchgrass as a bio-crop more seriously.

After considering all these points, if farmers think about adoption of switchgrass as a bio-crop, then first they will require information about switchgrass profits and risk estimates to compare with of alternative farm enterprises. As mentioned earlier, previous studies doing economic analysis on bio-crops have used secondary data and haven't said much about risk. This study uses actual yield data for switchgrass and offers insights by explicitly accounting for risk in addition to profitability.

1.3 Conceptual framework

Rational economic decision-makers are assumed to make crop production decisions by choosing crop i to maximize their profits in light of their risk preferences. The farm model used in this study is based on a risk-neutral farmer, who is a profit maximizer deciding whether or not to include switchgrass as a bio-crop in his or her crop-mix. The farmer is assumed to grow two traditional crops of corn and cotton and has the choice of replacing a portion of these crops with switchgrass. The farmer's overall objective is to maximize profit, which is the net return from the selected crop-mix. The profit function (π) is represented by:

$$\pi_j = \sum_i [(Y_{ij} \,.\, P_i) - VC_{ij}] \ - FCj \qquad (1)$$

Where π_j represents profit of farm j, Y_{ij} represents yield of crop i on farm j which is stochastic, P_i represents the selling price of crop i which is stochastic except for switchgrass, VC_{ij} represents total variable cost for crop i on farm j and FC_j represents total fixed cost for farm j. Profits will be calculated based on 1,000 draws obtained from the yield-price joint distribution (using 21 years real yield and price data) under stochastic simulation. These profits will be used to analyze the risks and returns for including switchgrass in the crop-mix.

Next, in the 'Methodology and Data' section, as there is still no market for switchgrass, this study will analyze the economic risks and returns at different expected switchgrass prices.

1.4 Methodology and Data

This section describes data used in the study and simultaneously points out all methods and steps undertaken to analyze risks and returns to farmers adopting the switchgrass cultivation as a bio-crop. For this analysis, two hypothetical sample farms, each of 400 acres size, with and without switchgrass are created.

The sample farm 1 (base farm) is created with 200 acres each of two traditional crops i.e. corn and cotton (corn and cotton each take up half the available land because of rotation). The sample farm 2 is created by replacing few acres from each traditional crop with switchgrass i.e. land conversion from traditional crops to bio-crops. This study has considered five different ranges of land conversion and thus second sample farm is created with one additional crop of switchgrass taking 5%, 10%, 15%, 20%, and 25% acres away from each conventional crop. This study has put a maximum cap of 25% on land conversion to perennial grasses of total land availability (Chen et al. 2014).

To analyze the risks and returns for including switchgrass in the crop-mix, I have calculated and compared return on investment (ROI) for both farms (for all five range of land conversion) based on 1,000 draws obtained from yield-price joint distribution. If a farmer, who is growing traditional crops, introduces switchgrass in a crop-mix, then definitely such farmer will like to earn at least the same earlier ROI, and, preferably with reduced profit variability. A critical factor in adopting new crops, such as bio-crops, is their profitability relative to that of existing cropping systems. Most farmers will allocate land to bio-crops only if the economic returns from these crops are at least equal to returns from the most profitable conventional alternatives (Jain et al., 2010).

1.4.1. Data

For this study, yield, price and cost data are required for corn, cotton and switchgrass. This data section will explain the sources of data collection and any processing of data to make it fit for running simulation and for calculating ROI.

1.4.1.1. Yield data

To start with the data collection, first of all data related to yield is collected. For switchgrass yield data, the data used in this study include twenty-one years (during which switchgrass can finish one life cycle) of observations for biomass yields, rainfall and age from a long term experiment on switchgrass. Plots were planted in 1989 at the Auburn University's E.V. Smith Research and Extension Center in south-central Alabama, Macon county, on a Wickham sandy loam (fine-loam, mixed, semi active, thermic Typic Hapludult) soil. Precipitation occurs throughout the year, averaging 1,335 mm on an annual basis. They were planted in a randomized complete block small-plot experiment with four replicates. The plots were 1.5 m wide and 6.0 m long and they were planted with a seed drill with 0.2 m between rows. Nitrogen fertilizer was applied at a rate of 84 kg n ha-1 annually. No P and K fertilizer, irrigation, or herbicides were applied over complete experiment period. Biomass harvested from each plot was weighted immediately after harvesting and subsamples taken out of it were weighted before and after drying to determine dry matter content. Annual yields were determined by harvesting plots twice each year from 1989 to 2009 (Table 1). Average yield for all four replicates are taken as final yield data for the analysis. This study has considered this period as a 21-year framework during which switchgrass can finish one life cycle.

As novel part of this paper is using real yield data for switchgrass in Alabama for 21 years (1989-2009), therefore, yield and price data for corn and cotton is also collected for these same 21 years for the Alabama. The study has chosen corn and cotton specifically because, as per United States Department of Agriculture, corn and cotton are two of the most important and commonly grown field crops in Alabama. Moreover, the major crops of Macon County (place of switchgrass experimental center) by planted acreage are cotton and corn. The study has used state-level yields data for corn and cotton as experimental yield data for corn and cotton is unavailable both at state-level and at county-level. The state data (Alabama data) for yields related to corn and cotton is taken from the database of United States Department of Agriculture (Quick stats, USDA) for same years 1989 to 2009 (Table 2).

Detrending – a statistical or mathematical operation is frequently applied in crop yield risk assessment as risk analysis provides better insight once trend is removed. In yield data, a significant trend is found only with respect to corn. The simplest way to "detrend" a time series would be to fit a straight line through the data, using a least square procedure and then a simple linear trend in mean can be removed by subtracting this least-squares-fit straight line. Application of this approach produced following regression equation which is used to calculate predicted yields for corn (figure 1):

$$y = \underset{(8.28)}{70.271} + \underset{(0.66)}{1.6636}x \qquad (2)$$

These predicted yields are subtracted from actual yield data to get error terms (Table 3 and Figure 1). As no significant trend is found with respect to cotton and switchgrass, a simple mean is found for yield data of cotton and switchgrass and subtracted from actual yield data to get errors around the mean. Thus, error terms for all three yields are calculated to be used in finding correlation matrix later on in order to run simulations. It is important to remove trend, as if one is exploring relationship between two trended time series, then often it will reveal a strong but false relationship. While finding the correlation between two time series, the objective is to know whether variation in one series are correlated with variations in another, and trend blurs the entire vision and should be removed.

1.4.1.2 Price Data

The state data (Alabama data) for prices related to corn and cotton are taken from the database of the United States Department of Agriculture (Quick stats, USDA) for the same years, 1989 to 2009 (Table 2). The crop prices data is indexed with base year 2014 using Producer Price indexes (Table 4). The Producer Price Indexes (PPI) measure the average change in selling prices over time from the perspective of the seller. For further analysis these indexed prices are used everywhere. For prices, after adjusting for inflation, a mean is found and subtracted to get errors around the mean to be used in finding the correlation matrix later on in order to run simulations.

Thus, a set of five error terms (three for yields for corn, cotton, switchgrass and two for prices for corn, cotton) are used to find the correlation matrix. The correlation matrix (Table 5) shows a moderate positive correlation (0.69) between corn and cotton yields. As I cannot have switchgrass yield data for any state other than Alabama (experiment was conducted in south-central Alabama only), I have calculated correlation between corn and cotton yields for Georgia and Texas to do sensitivity analysis. I find a moderate positive correlation i.e. 0.47 and 0.55 for Texas and Georgia respectively. For more sensitivity analysis, complete simulation has also been done for Georgia later in this study.

Due to unavailability of switchgrass market price, it has been taken as $30, $45 and $60 per ton for doing calculations in different scenarios. The U.S. Department of Energy (2011) suggested that a switchgrass price of $60 per ton can attract a sufficient supply of biomass feedstock to replace 30% of transportation fuel use by 2030.

1.4.1.3 Data for Simulations

Data related to five variables i.e. yield data for all three crops and price data for two traditional crops (there is no market price for switchgrass) will be used for this simulation. In this study, simulations are run to obtain 1,000 draws from yield-price joint distribution with the help of Cholesky decomposition which is widely used in generating correlated random numbers (RN). A set of uncorrelated variables can be transformed into variables with given covariance with the help of Cholesky transformation.

Any symmetric positive-definite matrix, K, may be written as:

$$K = U^T D U \tag{3}$$

Where U is an upper triangular matrix and D is a diagonal matrix with positive diagonal elements. Since a variance-covariance matrix Σ is a symmetric positive-definite matrix, therefore one can write:

$$\Sigma = U^T D U \tag{4}$$

$$= \left(U^T . \sqrt{D}\right) \left(\sqrt{D} . U\right) \tag{5}$$

$$= (\sqrt{D} . U)^T \, (\sqrt{D} . U) \tag{6}$$

The matrix $C = \sqrt{D} U$ therefore satisfies $C^T C = \Sigma$.

It is called the Cholesky Decomposition of Σ.

Thus, the Cholesky transformation is represented by a matrix that is square root of the correlation matrix of the actual data. To get the correlated random numbers with the given covariance, a matrix of uncorrelated random numbers is multiplied by the Cholesky matrix.

This study has specifically used this approach as Cholesky decomposition is easier to understand intuitively and has numerical stability as compared to some other methods. It also preserves the variance observed in the data, instead of just the mean value (Table 6). This stochastic approach simply allows calculation of many equally probable situations, which further can be processed to quantify and assess uncertainty. By generating 1,000 iterations for these variables, study has included randomness through properly identified distributions taken directly from actual data.

1.4.1.4 Cost data

Variable costs and fixed costs of producing switchgrass were taken from the Alabama Cooperative Extension System (Table 7). Variable costs and fixed costs of producing corn and cotton were taken from enterprise planning budget summaries – 2015 for Alabama (ACES, 2015). All the costs are adjusted to current levels. Average variable and fixed costs for both sample farms are shown in Table 8. I have considered two scenarios for my analysis i.e. with and without conventional crop insurance. The indemnity payment for crop i for a conventional crop is specified as

$$I_i = \max(\theta_i E(Y_i)E(P_i) - Y_i P_i, 0), \qquad (7)$$

where θ_i is the insurance coverage level for the conventional crop i ; $E(.)$ is the expectation operator; Y_i represents yield of crop i , and P_i represents the selling price of crop i. The insurance premium has been calculated as $E(I_i)$.

In United States, 80% of major crops' acreage is covered under subsidized federal crop insurance (Shields, 2015), so I have also considered further two scenarios for crop insurance i.e. with and without insurance subsidy. Insurance coverage level is taken as 75%, and insurance premium subsidy rate is taken as 55%. I have taken these values as 75% is one of the most common coverage levels and 55% is the corresponding subsidy rate for this coverage level specified by RMA (Shields 2015).

1.4.2 Calculation of risks and returns

By using the costs, yields and prices data of 1,000 draws, first profits/losses for farm 1 are calculated by using equation (1). Then, return on investment (ROI) for farm 1 is calculated with the following equation:

$$ROI = \frac{\pi}{C} * 100 \qquad (8)$$

Where π is the profit function in equation (1) and C is the cost function. The cost function (C) is represented by:

$$C = VC + FC \qquad (9)$$

Where VC is the total variable cost of the farm and FC is the total fixed cost of the farm.

Then in similar way, profits for farm 2 are calculated with three different switchgrass prices i.e. \$30, \$45 and \$60 per ton (for all five range of land conversion). Then, return on investment (ROI) for all cases are calculated. The mean ROI with the standard deviation for each case is calculated along with frequency for different ranges of ROI.

1.5 Results

To see the impact of adoption of switchgrass as a bio-crop on farm profitability, study has analyzed mean ROI, median ROI, and probability of having a positive ROI of two sample farms, with and without switchgrass. From our results, it can be seen that if farmer include switchgrass in the crop-mix, it can improve farm profitability, and also there will be a considerable reduction in risk, measured by the standard deviation, coefficient of variation (CV), and in terms of the probability of a negative ROI.

The results in Table 9 (without conventional crop insurance) show that the sample farm 1 with only corn and cotton provides 4.23% ROI on an average with a standard deviation of 20.66% (CV 4.89%). In the sample farm 2, with switchgrass price at \$30, \$45 and \$60, the mean

ROI is considerable higher than mean ROI for farm 1 in all scenarios of land conversion. For example, mean ROI ranged between 4.37% and 7.93% for 5% land conversion case and ranged between 4.86% and 23.82% for 25% land conversion case. Thus this table shows that on average, a farmer will have higher amount of profits from including switchgrass in the crop-mix.

The median ROI for sample farm 1 is 4.31% and it is really interesting to see that median ROI for farm 2 is higher in all the cases and goes up to 4.70%, 14.28%, and 23.95% for switchgrass prices \$30, \$45 and \$60 respectively (Table 9). Median ROI for farm 2 ranges between 4.32% and 23.95%, which also indicates towards improved profitability.

An important observation regarding reduction in risk is also made from these results with the figures of standard deviation and CV for ROI in all cases. A considerable reduction in risk has been observed in case of farm 2 as compare to farm 1. The results in table 9 shows that the sample farm 1 provides 4.23% return on investment (ROI) on an average with a standard deviation of 20.66% (CV 4.89%), where as in farm 2 mean ROI goes up to 23.82% whereas standard deviation goes down up to 15.49%. The CV in all scenarios of farm 2 is less than the farm 1 indicating reduction in variability in ROIs to the farmer. To illustrate, in scenario of 15% land conversion, the CV of farm 1 is 4.89, whereas CV of farm 2 is only 3.97, 1.76, and 0.72 for switchgrass prices \$30, \$45 and \$60 respectively (Table 9). The lower values of CV indicate towards low riskiness of farm 2.

The results in Table 10 (with conventional crop insurance) show the similar results. In scenario of 15% land conversion, if there is no insurance subsidy, then sample farm 1 with only corn and cotton provides 4.46% ROI on an average with a lower standard deviation of 17.48% (CV 3.92%), as compare to case of without conventional crop insurance. In the sample farm 2, with switchgrass price at \$30, \$45 and \$60, the mean ROI is considerable higher than mean ROI for farm 1. For example, mean ROI ranged between 4.75% and 23.52%. The CV in all scenarios of farm 2 (ranged between 0.63 and 3.28) is less than the CV of farm 1 (3.92) indicating reduction in variability in ROIs to the farmer. Similarly, with 55% insurance subsidy, in the sample farm 2, with switchgrass price at $30, $45 and $60, the mean ROI (ranged between 6.09 and 24.85) is considerable higher than mean ROI for farm 1 (5.95). The CV in all scenarios of farm 2 (ranged between 0.60 and 2.57) is also less than the CV of farm 1 (2.94) indicating reduction in variability in ROIs to the farmer. To do sensitivity analysis, complete above-mentioned analysis has also been done for Georgia State. It can be seen that results of Georgia State (Table 11) are very much similar to earlier results of Alabama (Table 10).

To analyze riskiness in more detail, I have also calculated the probability of having negative ROI. In case of sample farm 1 with only corn and cotton, the farmer expects to incur losses 41% of the time (Table 12). In case of sample farm 2, for switchgrass prices of $45 and $60 per ton, there is a significant reduction in number of years of losses. In these scenarios, farmer expects to incur losses ranging between only 37% and 6% of the time (25% land conversion) and expects to incur losses ranging between 37% and 33% of the time (5% land conversion).

To compare risk for different cases, a chart was created for scenario of 15% land conversion with switchgrass price at $30, $45, and $60 per ton (Figure 2). The frequencies of different ranges of ROI are depicted in this chart. The red and yellow shaded area in each bar represents the frequency of a negative ROI. The green area represents the frequency of a positive ROI. I can see a significant reduction in red and yellow shaded area for the farm with switchgrass, signifying the reduction of risk for the farmer who includes switchgrass as a bio-crop in her crop-mix.

To further account for risk factors of including switchgrass in the crop-mix, I have also analyzed ROI in case of market failure for switchgrass. The case of 15% land conversion is considered for this sensitivity analysis. In the absence of development of biomass market, there is a probability that farmer will not be able to sell the switchgrass production. In our simulation analysis, I have included a range of probability of market failure from 5% to 25% with a step of 5%. Results in Table 13 show that in the sample farm 2, with switchgrass price at $30 per ton, now the mean ROI is considerable lower than mean ROI for farm 1 in all ranges of market failure. But, with switchgrass price at $45 and $60 per ton, still the mean ROI is considerable higher than mean ROI for farm 1 in all ranges of market failure. For example, mean ROI ranged between 5.97% and 9.28% ($45 per ton switchgrass price) and ranged between 15.90% and 21.87% ($60 per ton switchgrass price). Thus, this table shows that even after including the risk of market failure for switchgrass, on average a farmer will have higher amount of profits on including switchgrass in the crop-mix, when switchgrass price is $45 per ton or higher. In case of market failure for switchgrass, as expected, there is an overall decrease in average profitability and a considerable increase in risk (measured by the standard deviation and CV) on including switchgrass in the crop-mix (by comparing Table 13 and third panel of Table 9).

1.6 Conclusions

This study shows that adoption of switchgrass as a bio-crop can be a viable addition to the crop-mix as it can reduce variability of profits and can also improve farm profitability. In addition to risks and returns analysis using stochastic simulation, this paper also provides a valuable overview about some factors influencing switchgrass adoption. By assessing the competitiveness of switchgrass as a bio-crop relative to two common traditional crops i.e. corn and cotton, this study concludes that switchgrass can be a viable addition to the crop-mix which can increase the profitability and can reduce the variability of returns. It will be interesting to consider how much this positive impact can be increased using policies that provide farmers with payments for environmental benefits of switchgrass, as it should be remembered that in addition to economic gains, there are many important agronomical and environmental benefits also. Moreover, the lower corn and cotton yields on poorer soils will definitely increase this advantage gap. At low market prices, switchgrass can turn out to be a poorer investment than corn and cotton, but their lower opportunity cost for marginal lands clearly indicates the potential for comparative advantage at lesser productive sites. Here, one thing is really important to mention that absence of an established market for switchgrass is an important factor affecting variability in profits (i.e. risk), so risk minimization solutions to farmers e.g. by means of contracting, insurance options etc. can really motivate the adoption of switchgrass.

An in-depth literature review of some previous studies has also helped in assessing and reviewing information in order to increase the knowledge concerning the economies of switchgrass adoption and in understanding some of the important decisive factors, which can help farmers to understand various advantages/disadvantages which may arise from adopting switchgrass as a bio-crop. This review has revealed that there are reasonable grounds to consider switchgrass as a potential bio-crop and taking first step towards thinking of adoption of switchgrass as a bio-crop more seriously.

Further research needs to be conducted to explore the feasibility of using switchgrass partly as forage and partly as a biofuel feedstock. As per the news published by Mississippi State University Extension service in August 2008, there is some part (usually first 24 inches of growth) which has high protein and can be harvested for forage. Producers have the option to grow switchgrass as a “dual-purpose” crop. Biomass production will be lower under this scenario, but, due to high forage prices, it can significantly raise the profits of producers.

Further research is needed to find the right mix of crops. Additionally, a deeper investigation of different national and transnational policies promoting different kinds of bio-crops can be conducted to encourage more farmers to adopt switchgrass as a bio-crop. These future research efforts will lead to creation of favorable circumstances for adoption of switchgrass as a bio-crop by the farmers and thus will contribute to meet the cellulosic ethanol targets set by Energy Independence and Security Act.

Table 1. 1 Switchgrass yield (Tons per acre) (Year 1989-2009)

Randomized complete block design with four replications					
Year	Rep 1	Rep 2	Rep 3	Rep 4	Avg. Yield
1989	8.943	9.065	6.091	6.219	7.580
1990	17.170	16.577	14.693	13.292	15.430
1991	15.520	12.418	10.799	11.760	12.620
1992	11.327	11.332	10.002	10.593	10.810
1993	12.152	10.001	7.385	10.905	10.110
1994	12.892	6.769	6.680	8.495	8.710
1995	7.649	7.054	8.101	7.419	7.560
1996	7.784	6.086	6.765	7.535	7.040
1997	6.409	6.854	7.358	6.509	6.780
1998	11.172	8.186	8.753	9.608	9.430
1999	11.240	9.367	9.252	11.662	10.380
2000	12.673	11.381	12.848	16.230	13.280
2001	17.900	10.400	13.108	13.315	13.680
2002	16.393	7.490	10.659	11.730	11.570
2003	10.006	6.780	13.118	13.324	10.810
2004	11.605	5.878	9.909	11.482	9.720
2005	12.146	6.551	11.139	11.556	10.350
2006	13.777	7.076	11.890	12.355	11.270
2007	11.270	3.934	9.596	11.192	8.990
2008	12.066	6.364	8.438	10.207	9.270
2009	15.645	7.314	8.993	12.753	11.180

Note: Real yield data from a long term experiment conducted at Auburn University's E.V. Smith Research and Extension Center, Macon County, Alabama. Average yield for all four replicates are taken as final yield data for analysis.

Table 1. 2 Yield and Price Data for Corn and Cotton (Year: 1989-2009)

Year	Prices		Yields	
	Corn $/BU	Cotton $/LB	Corn BU/Acre	Cotton LB/Acre
1989	2.75	0.637	81	571
1990	2.69	0.69	58	476
1991	2.6	0.566	80	655
1992	2.35	0.562	94	731
1993	2.64	0.571	55	524
1994	2.5	0.691	96	766
1995	3.5	0.729	75	409
1996	3.45	0.709	82	734
1997	2.82	0.673	87	597
1998	2.31	0.606	63	559
1999	2.26	0.478	103	535
2000	2.16	0.528	65	492
2001	2.35	0.277	107	730
2002	2.72	0.435	88	507
2003	2.36	0.596	122	772
2004	2.48	0.406	123	724
2005	2.5	0.487	119	747
2006	2.91	0.446	72	579
2007	4.54	0.597	78	519
2008	5.26	0.449	104	787
2009	3.89	0.657	108	662

Source: United States Department of Agriculture (Quick stats, USDA)

Table 1. 3 Detrending corn yield - Estimation Results

Year	Obs. No.	Actual Yield	Predicted Yield	Error Terms
1989	1	81	71.9346	9.0654
1990	2	58	73.5982	-15.5982
1991	3	80	75.2618	4.7382
1992	4	94	76.9254	17.0746
1993	5	55	78.589	-23.589
1994	6	96	80.2526	15.7474
1995	7	75	81.9162	-6.9162
1996	8	82	83.5798	-1.5798
1997	9	87	85.2434	1.7566
1998	10	63	86.907	-23.907
1999	11	103	88.5706	14.4294
2000	12	65	90.2342	-25.2342
2001	13	107	91.8978	15.1022
2002	14	88	93.5614	-5.5614
2003	15	122	95.225	26.775
2004	16	123	96.8886	26.1114
2005	17	119	98.5522	20.4478
2006	18	72	100.2158	-28.2158
2007	19	78	101.8794	-23.8794
2008	20	104	103.543	0.457
2009	21	108	105.2066	2.7934

Note: Least-squares-fit straight line is used for detrending.

Table 1. 4 Indexed Prices

Year	Corn	Cotton
1989	4.85	1.12
1990	4.52	1.16
1991	4.28	0.93
1992	3.82	0.91
1993	4.24	0.92
1994	3.99	1.10
1995	5.48	1.14
1996	5.27	1.08
1997	4.29	1.02
1998	3.54	0.93
1999	3.41	0.72
2000	3.14	0.77
2001	3.35	0.39
2002	3.92	0.63
2003	3.30	0.83
2004	3.35	0.55
2005	3.22	0.63
2006	3.64	0.56
2007	5.46	0.72
2008	5.95	0.51
2009	4.52	0.76

Note: The crop prices data is indexed with base year 2014 using Producer Price Indexes.

Table 1. 5 Correlation Matrix and Covariance Matrix

Correlation Matrix					
	Corn Yield	Cotton Yield	SG yield	Corn Prices	Cotton Prices
Corn Yield	1.00				
Cotton Yield	0.69	1.00			
SG yield	-0.11	-0.10	1.00		
Corn Prices	-0.26	-0.14	-0.45	1.00	
Cotton Prices	-0.12	-0.30	-0.32	0.33	1.00
Covariance Matrix					
	Corn Yield	Cotton Yield	SG yield	Corn Prices	Cotton Prices
Corn Yield	303.05				
Cotton Yield	1360.07	12804.51			
SG yield	-4.35	-24.79	4.77		
Corn Prices	-3.77	-12.80	-0.80	0.67	
Cotton Prices	-0.46	-7.68	-0.16	0.06	0.05

Table 1. 6 Mean and standard deviations before and after simulations.

	Crop Prices		Crop Yields		
Before (i.e. of actual data)	Corn	Cotton	Corn	Cotton	Switchgrass
Mean	4.17	0.83	105.21	622.67	10.31
S.D.	0.84	0.23	18.30	115.95	2.24
After (i.e. of 1,000 draws)					
Mean	4.15	0.83	105.31	623.79	10.35
S.D.	0.85	0.23	18.76	118.31	2.29

Note: Simulations are run to obtain 1,000 draws from yield-price joint distribution with the help of Cholesky decomposition.

Table 1. 7 Establishment and Maintenance Budget for Switchgrass

Item	Unit	Amt/Acre	Quantity	Price or Cost/Unit	Total Cost
1. Variable costs					
Soil Test	each	0.03	0.0250	7.00	0.1750
Fertilizer					
Nitrogen	lbs.	50.00	50.0	0.58	29.00
Phosphate	lbs.	40.00	40.0	0.43	17.20
Potash	lbs.	40.00	40.0	0.43	$17.20
Interest on op. cap.	dol.		$31.79	5.5%	$1.75
Total variable cost					$65.32
2. Fixed costs					
Estab. cost amort.	dol.		$19.79	1.00	$19.79
General overhead	dol.		$65.32	4.0%	$2.61
Total fixed costs					$22.41
3. Total of all specified costs					$87.73

Harvest & Transport Budget for Switchgrass

Item	Unit	Amt/Acre	Quantity	Price or Cost/Unit	Total Cost
1. Variable costs					
Harvest cost (1 or 2)	acre	1.00	1.0	$59.06	$59.06
Tractor & equipment	acre	1.00	1.0	$65.58	$65.58
Total variable cost					$124.63
2. Fixed costs					
Tractor & equipment	acre	1.00	1.0	$19.45	$19.45
General overhead	dol.		$124.63	4.0%	$4.99
Total fixed costs					$24.43
3. Other costs					
Labor(wages &fringe)	hour	3.80	3.8	$12.50	$47.46

Source: Database of Alabama Cooperative Extension System.

Table 1. 8 Average variable and fixed costs per farm (in $)

	Farm 1	Farm 2
(5% land Conversion i.e. 20 Acres of Switchgrass)		
Average Variable Costs	145200	142860
Average Fixed Costs	36400	35520
(10% land Conversion i.e. 40 Acres of Switchgrass)		
Average Variable Costs	145200	140520
Average Fixed Costs	36400	34640
(15% land Conversion i.e. 60 Acres of Switchgrass)		
Average Variable Costs	145200	138180
Average Fixed Costs	36400	33760
(20% land Conversion i.e. 80 Acres of Switchgrass)		
Average Variable Costs	145200	135840
Average Fixed Costs	36400	32880
(25% land Conversion i.e. 100 Acres of Switchgrass)		
Average Variable Costs	145200	133500
Average Fixed Costs	36400	32000

Source: Enterprise planning budget summaries for Alabama, from the database of Alabama Cooperative Extension System.

Table 1. 9 ROI tables for different cases (in %) (Without conventional crop insurance)

	Farm 1 ROI	Farm 2 ROI (at $30 sg price)	Farm 2 ROI (at $45 sg price)	Farm 2 ROI (at $60 sg price)
(5% land Conversion i.e. 20 Acres of SG)				
Mean	4.23	4.37	6.15	7.93
Standard Deviation	20.66	19.91	19.72	19.53
Median	4.31	4.32	6.20	7.98
CV	4.89	4.56	3.21	2.46
(10% land Conversion i.e. 40 Acres of SG)				
Mean	4.24	4.50	8.11	11.72
Standard Deviation	20.66	19.14	18.77	18.45
Median	4.31	4.44	8.14	11.82
CV	4.88	4.26	2.31	1.57
(15% land Conversion i.e. 60 Acres of SG)				
Mean	4.23	4.62	10.12	23.38
Standard Deviation	20.66	18.34	17.83	16.94
Median	4.31	4.56	10.16	23.65
CV	4.89	3.97	1.76	0.72
(20% land Conversion i.e. 80 Acres of SG)				
Mean	4.24	4.74	12.20	19.66
Standard Deviation	20.66	17.52	16.88	16.42
Median	4.31	4.65	12.27	19.71
CV	4.88	3.69	1.38	0.84
(25% land Conversion i.e. 100 Acres of SG)				
Mean	4.24	4.86	14.34	23.82
Standard Deviation	20.66	16.67	15.94	15.49
Median	4.31	4.70	14.28	23.95
CV	4.88	3.43	1.11	0.65

Table 1. 10 ROI tables for 15% land Conversion case (in %) (with row crop insurance)

(Without insurance subsidy)	Farm 1 ROI	Farm 2 ROI (at 30 sg price)	Farm 2 ROI (at 45 sg price)	Farm 2 ROI (at 60 sg price)
Mean	4.46	4.75	10.26	23.52
Standard Deviation	17.48	15.61	15.25	14.85
CV	3.92	3.28	1.49	0.63
Median	2.81	3.43	8.87	23.17
(With insurance subsidy @ 55%)				
Mean	5.95	6.09	11.59	24.85
Standard Deviation	17.51	15.64	15.29	14.91
CV	2.94	2.57	1.32	0.60
Median	4.37	4.80	10.32	24.53

Table 1. 11 ROI tables for 15% land Conversion case (in %) (with row crop insurance) - Georgia

(Without insurance subsidy)	Farm 1 ROI	Farm 2 ROI (at 30 sg price)	Farm 2 ROI (at 45 sg price)	Farm 2 ROI (at 60 sg price)
Mean	4.79	5.06	10.55	23.78
Standard Deviation	17.80	15.90	15.47	14.84
CV	3.72	3.14	1.47	0.62
Median	3.31	3.59	9.40	22.99
(With insurance subsidy @ 55%)				
Mean	6.46	6.56	12.05	25.27
Standard Deviation	17.80	15.92	15.49	14.88
CV	2.76	2.43	1.29	0.59
Median	4.95	5.18	10.91	24.47

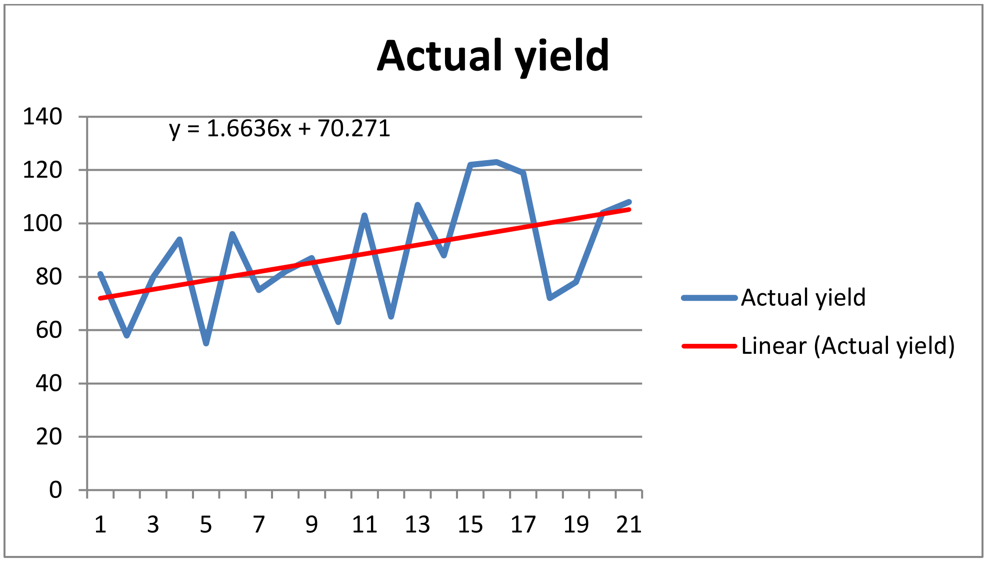
Table 1. 12 Frequency Tables for ROI Percentages

(Out of Total 1,000 cases)				
(5% land Conversion i.e. 20 Acres of SG)	Farm 1 ROI	Farm 2 ROI (at $30 sg)	Farm 2 ROI (at $45 sg)	Farm 2 ROI (at $60 sg)
Losses more than 20%	124	110	95	79
Losses less than 20%	285	297	276	253
Profits up to 20%	373	383	393	408
Profits more than 20%	218	210	236	260
(10% land Conversion i.e. 40 Acres of SG)				
Losses more than 20%	124	102	66	43
Losses less than 20%	285	302	261	212
Profits up to 20%	373	394	422	416
Profits more than 20%	218	202	251	329
(15% land Conversion i.e. 60 Acres of SG)				
Losses more than 20%	124	92	45	8
Losses less than 20%	285	307	240	75
Profits up to 20%	373	405	436	335
Profits more than 20%	218	196	279	582
(20% land Conversion i.e. 80 Acres of SG)				
Losses more than 20%	124	80	30	11
Losses less than 20%	285	310	191	109
Profits up to 20%	373	420	457	388
Profits more than 20%	218	190	322	492
(25% land Conversion i.e. 100 Acres of SG)				
Losses more than 20%	124	66	23	1
Losses less than 20%	285	316	153	63
Profits up to 20%	373	441	463	336
Profits more than 20%	218	177	361	600

Table 1. 13 ROI tables in case of market failure for Switchgrass (in %) (15% land conversion)

(5% Market Failure Probability)	Farm 1 ROI	Farm 2 ROI (at 30 sg price)	Farm 2 ROI (at 45 sg price)	Farm 2 ROI (at 60 sg price)
Mean	4.23	4.06	9.28	21.87
Standard Deviation	20.66	18.64	18.40	18.49
Median	4.31	3.81	9.49	22.52
CV	4.89	4.59	1.98	0.85
(10% Market Failure Probability)				
Mean	4.24	3.52	8.44	20.43
Standard Deviation	20.66	18.85	18.81	19.62
Median	4.31	3.38	8.71	21.33
CV	4.88	5.35	2.23	0.96
(15% Market Failure Probability)				
Mean	4.23	2.99	7.69	19.00
Standard Deviation	20.66	19.04	19.18	20.60
Median	4.31	2.97	8.09	20.67
CV	4.89	6.36	2.50	1.08
(20% Market Failure Probability)				
Mean	4.24	2.41	6.81	17.41
Standard Deviation	20.66	19.29	19.61	21.59
Median	4.31	2.81	7.73	19.69
CV	4.88	8.01	2.88	1.24
(25% Market Failure Probability)				
Mean	4.24	1.85	5.97	15.90
Standard Deviation	20.66	19.47	19.94	22.33
Median	4.31	2.44	7.21	18.78
CV	4.88	10.52	3.34	1.40

Figure 1. 1 Detrending of Corn Yield data



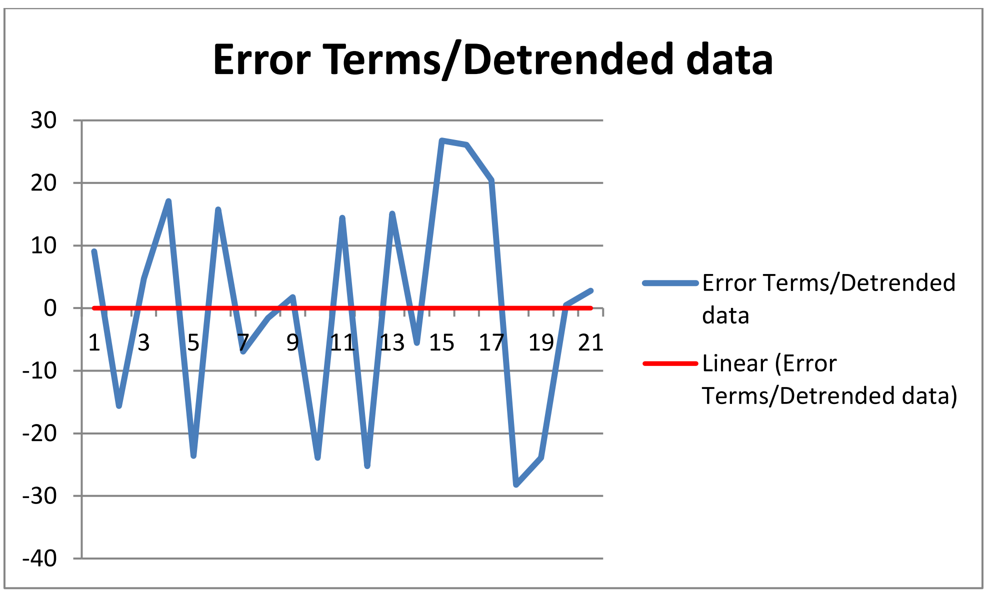
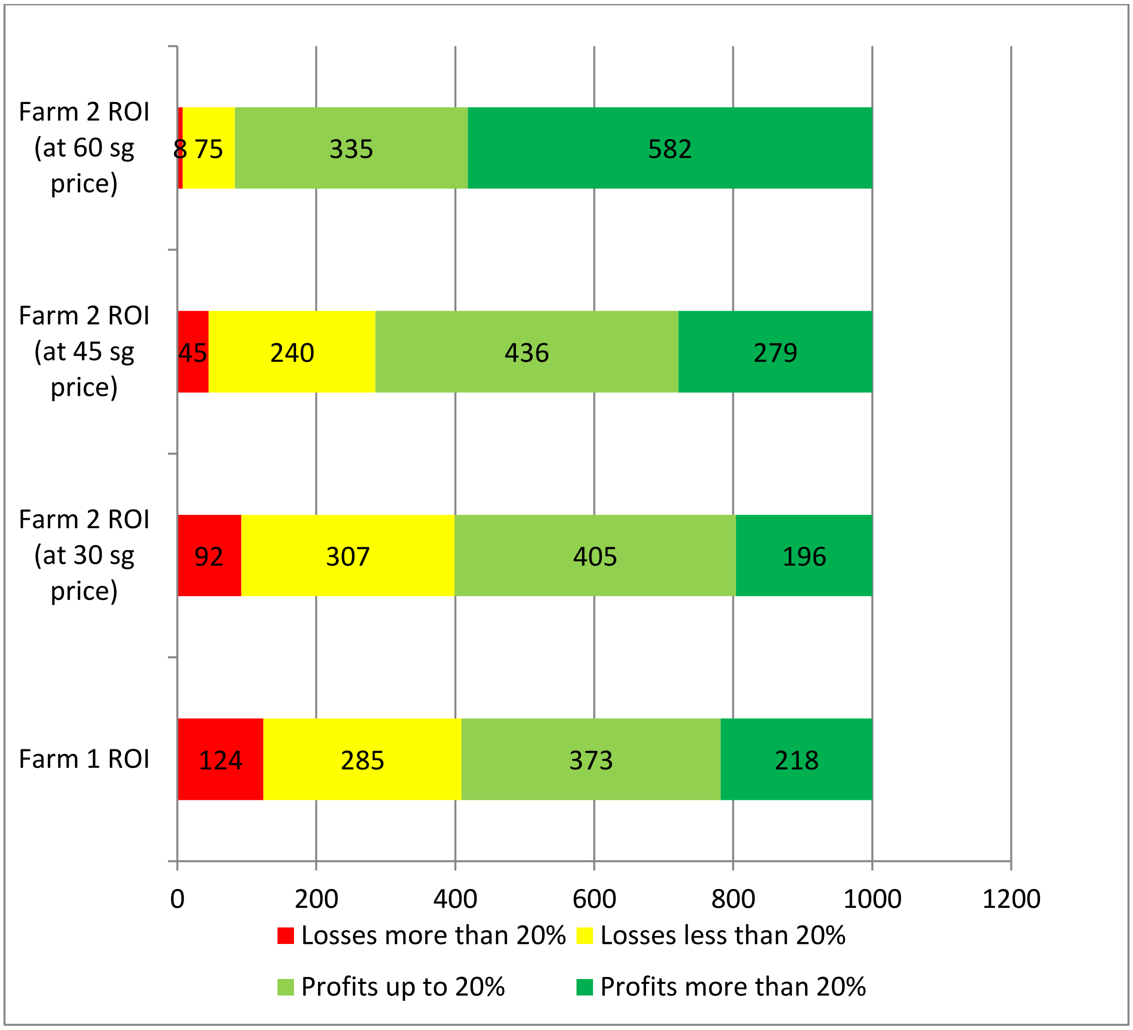


Figure 1. 2 Graph showing frequencies of different ranges of ROI (Case: 15% land conversion, Frequency out of total 1,000 cases)



Chapter 2. Adopting Bioenergy Crops: Does Farmers' Attitude toward Loss Matter?

2.1 Introduction

Perennial bioenergy crops such as miscanthus (Miscanthus × giganteus) and switchgrass (Panicum virgatum) are promising feedstocks for cellulosic biofuels and can provide a range of environmental benefits such as soil carbon sequestration, reduced nitrogen leaching and low carbon fuel (Hudiburg *et al*. 2016). The recent Billion-ton study (USDOE 2016) envisions these two bioenergy crops meeting a dominant share of the billion tons of biomass supply in 2030. The commercial scale production of these perennial bioenergy crops has not commenced yet due to, in part, farmers' lack of information about these crops' profit profiles, particularly in risk dimension (Miao and Khanna 2014, 2017a, b). Several studies have examined the bioenergy crops profitability and the price at which farmers would be willing to produce various types of energy crops, in particular, for cellulosic biofuels in the U.S. (Epplin et al., 2007; Khanna et al., 2011, Anand et al., 2017). A few studies have examined breakeven prices of bioenergy crops against conventional crops as a measure of bioenergy crop profitability (e.g., Miao and Khanna, 2014).

In addition to profitability, few studies have also analyzed the riskiness of bioenergy crop production and the effects of farmer's risk aversion on breakeven price and incentives to produce these crops by using expected utility theory framework. There is however growing evidence that farmers are not only risk averse but also loss averse and that prospect theory can provide a better prediction of individual decision making under risk and uncertainty than expected utility theory (e.g., Kahneman and Tversky, 1979; Tversky and Kahneman, 1992; Barberis, 2013). Bio-energy crop adoption involves a large amount of upfront investment, long-term commitment of land, potential crop failure, variability in yields that is not protected by crop insurance, and risk of biorefinery shutdown which may induce significant losses for farmers (Khanna, Louviere, and Yang, 2017; Smith et al.,2011). Therefore, the attitude toward loss is expected to be an important factor that will influence farmers' decision to grow these perennial bio-energy crops. However, there is a dearth of research in this regard.

In context of risk dimension, there is empirical evidence that farmers typically tend to be averse to risk and use discount rates that are higher than market rates of return in making crop investment decisions (Khanna et al. 2017; Bocquého et al., 2015). Dolginow *et al*. (2014) compare the riskiness of miscanthus, switchgrass, and corn in north-eastern Missouri while Miao and Khanna (2014) do so in the rainfed region of the United States, and Skevas *et al*. (2016) explore the risk of bioenergy crop returns in the southern Great Lakes region. Using expected utility theory, Miao and Khanna (2017a, b) investigate the effects of risk aversion and high discount rates on incentives to produce miscanthus and switchgrass in rainfed regions of the United States and the effectiveness of risk mitigating policy instruments such as insurance for bioenergy crops, establishment cost subsidies, and the Biomass Crop Assistance Program on the production of bioenergy crops. Clancy et al. (2012) and Mathiou *et al.* (2014) examine risk-averse farmers' willingness to produce willow and miscanthus in Ireland and Poland respectively. However, none of these studies account for farmers' loss aversion when examining their adoption decisions. Although loss aversion sounds similar to risk aversion, but it is actually a more complex behavior where people express both risk aversion and risk seeking behavior while decision making under risk and uncertainty. In loss aversion, individual's utility is concave over gains and convex over losses. The present study aims to fill this gap by employing the prospect theory (also known as loss aversion theory) that explicitly incorporates decision makers' loss preferences. While decision making under risk and uncertainty, prospect theory considers individual's reference point rather than utility of wealth and values gains and losses differently.

While prospect theory has been widely applied in various fields of economics (see a comprehensive review by Barberis, 2013) its application to analyze crop adoption choices are few. Among these, Liu (2013) shows that risk or loss averse farmers are more likely to delay adoption of genetically modified cotton while Bocquého et al (2015) survey 102 farmers in eastern France and find that farmers who are more sensitive to losses are less willing to adopt miscanthus. Our study significantly differs from Bocquého, Jacquet, and Reynaud (2015) in terms of both methodology and data. We employ a numerical simulation approach to examine the effect of loss aversion on the share of land that farmers would be willing to convert to energy crop production under various loss preference parameters, credit availability, biomass prices, and discount rates. We simulate the impacts on county-level bioenergy crop production for about 2,000 counties in the rainfed region of United States. We also analyze the impacts of two policy instruments, namely establishment cost subsidy and subsidized energy crop insurance, on bioenergy crop production under various scenarios of farmers' loss preferences.

The purpose of this study is two-fold. First, we examine the impact of loss aversion on the extent to which farmers will allocate land to two alternative energy crops, miscanthus and switchgrass, instead of conventional crops (corn and soybeans in this study) under alternative biomass prices, discount rates and credit constraint scenarios. We first develop a conceptual framework that models a representative farmer's optimal land allocation problem between conventional crops (corn rotated with soybeans) and bioenergy crops (miscanthus and switchgrass) based on prospect theory. We use county-specific simulated yields of miscanthus, switchgrass, corn and soybeans under 27 years of weather conditions to incorporate weather induced temporal variability in yields and then model joint distributions of crop yields and prices. We incorporate spatial heterogeneity in the risk of losses across the 1,919 U.S. counties east of the 100th Meridian rainfed region of the United States and examine the effect of loss and time preferences and credit constraint on the county-specific allocation of land to bioenergy crops at various biomass prices. We develop biomass supply curves to examine the effect of loss aversion on the quantity and mix of biomass feedstocks and the amount of land allocated to energy crops. We also examine the spatial pattern of energy crop production in the rainfed region of the United States under alternative scenarios.

Second, we examine the effectiveness of two types of policy incentives, an establishment cost-share subsidy and subsidized energy crop insurance that can reduce the likelihood of losses from adopting energy crops although in differing ways. While an establishment cost share subsidy reduces the upfront costs of establishing an energy crop and losses in the early years of establishment due to crop failure, subsidized crop insurance reduces losses in post-establishment years due to inter-annual variability in yields and consequently in annual incomes. We choose these two instruments because a) establishment cost subsidy is currently specified in the Biomass Crop Assistance Program (BCAP) that was established in the 2008 Farm Bill and re-authorized in the 2014 Farm Bill; and b) subsidized crop insurance is commonly provided for conventional crops and has been proposed for energy crops to offset the disincentives for switching from conventional crops (Farm Service Agency, 2013).

We compare the implications of an establishment cost subsidy and subsidized energy crop insurance for land allocated to these energy crops. We also examine the effects of these policies on the spatial pattern of energy crop production in the rainfed US. To the best of our knowledge, this is the first study that takes into account farmers' loss preferences when modeling farmers' adoption of bioenergy crops and also the policy analysis in the rainfed region of the United States.

Our results show that ignoring farmer's loss aversion may over-estimate miscanthus production and under-estimate switchgrass production as compared to studies that assume that farmers are risk averse. Our results also indicate that bioenergy crop production on marginal land is relatively less sensitive to accounting for farmers' loss aversion. Therefore, the results lend support to possible policy interventions that encourage biomass production on marginal land, for example, interventions allowing biomass harvesting on land in the Conservation Reserve Program (CRP) without imposing a program payment reduction.[1] We also find that when farmers are credit constrained, biomass production from bioenergy crops is more sensitive to farmers' loss aversion than when farmers are not credit-constrained.[2] This indicates that the availability of credit to farmers mitigates the effect of their loss preferences for bioenergy crop production. Results also show that impact of loss aversion under high discount rate is larger as compared to that under scenario with low discount rate. Moreover, geographical configuration of miscanthus and switchgrass adoption may differ significantly when farmers' loss aversion parameters, credit constraint status, and discount rates change. Policy simulation results show that establishment cost subsidy favors miscanthus production whereas subsidized energy crop insurance program favors switchgrass production. We also find that for the efficacy of these two policy instruments

[1] As of 2017, CRP participants who harvest biomass on CRP land receive a 25% payment reduction. We refer readers to Anderson et al. (2016) for a study regarding using CRP land as a potential source of biomass production.

[2] Credit constraint is relevant to bioenergy crop adoption because the establishment of bioenergy crops will incur large costs and potential adopters may have difficulties to obtain loans to finance such establishment. Kirwan (2014) states that ". . . 6.2% of large commercial farms with over $500,000 in sales reported having been turned down for a loan." Since potential adopters for bioenergy crops are more likely to be young and beginning farmers (Gedikoglu 2015), we expect that credit constraint may be more of an issue for these farmers.

(measured by biomass increased by per dollar of government outlay) depends on farmers' loss aversion parameters and discount rate.

2.2 Conceptual framework

In this section we first discuss the key components of prospect theory and then display a representative farmer's optimal land allocation decision problem under a framework applying prospect theory. In addition to reflecting disutility from income volatility, prospect theory considers a few more features regarding people's preferences toward risky enterprises.

First, unlike expected utility theory, when evaluating returns, prospect theory differentiates gains from losses relative to a reference point of return. Returns higher than the reference point are gains whereas returns lower than the reference point are losses. For a loss averse decision maker, the magnitude of disutility from a certain amount of loss is larger than the magnitude of utility from the same amount of gain. This feature is reflected in prospect theory's value function. Suppose that there are $m+n$ possible realizations for an enterprise's random profit Π_t in year *t* where *m* and *n* are the number of losses and gains, respectively. Let $\pi_{t,k}$ be a realization of Π_t, where $k \in \Omega \equiv \{-m, 1-m, ..., -1, 1, ..., n\}$. We sort the realizations in ascending order so that $\pi_{t,k} \leq \pi_{t,k'}$ if and only if $k \leq k'$. The probability that $\pi_{t,k}$ occurs is $q_{t,k}$. Following Tversky and Kahneman (1992), the value function for a profit realization $\pi_{t,k}$ is specified as

$$v(\pi_{t,k}) = \begin{cases} (\pi_{t,k} - R)^{\alpha} & \text{if } \pi_{t,k} \geq R \\ -\lambda[-(\pi_{t,k} - R)]^{\alpha} & \text{if } \pi_{t,k} < R, \end{cases} \quad (1)$$

where R is the reference point, λ is the loss aversion parameter, and α is the risk aversion parameter. When $\lambda > 1$ (respectively, $\lambda = 1$ or $\lambda < 1$) then the farmer is loss averse (respectively, loss neutral or loss loving). Similarly, when $\alpha < 1$ (respectively, $\alpha = 1$ or $\alpha > 1$) then the farmer is risk averse (respectively, risk neutral or risk loving).

Second, prospect theory accounts for experimental observations that decision makers tend to overweight events with small probabilities but underweight events with large probabilities (Kahneman and Tversky, 1979). This feature is reflected by a probability weighting function. Following Tversky and Kahneman (1992), the probability weighting functions can be specified as:

$$\begin{cases} w^{+}(\phi_{t,k}) = \dfrac{\phi_{t,k}^{\gamma}}{(\phi_{t,k}^{\gamma}+(1-\phi_{t,k})^{\gamma})^{1/\gamma}}, & \text{for gains} \\ w^{-}(\phi_{t,k}) = \dfrac{\phi_{k}^{\delta}}{(\phi_{t,k}^{\delta}+(1-\phi_{t,k})^{\delta})^{1/\delta}}, & \text{for losses,} \end{cases} \tag{2}$$

where $\phi_{t,k}$ is the accumulative probability of profit realization $\pi_{t,k}$; γ and δ are non-stochastic parameters. If $\pi_{t,k} \geq R$ then $\phi_{t,k} = \Pr\{\Pi_t \geq \pi_{t,k}\}$ whereas if $\pi_{t,k} < R$ then $\phi_{t,k} = \Pr\{\Pi_t \leq \pi_{t,k}\}$. It is readily checked that $w^{+}(\cdot)$ and $w^{-}(\cdot)$ are strictly increasing functions with both domain and range as [0, 1], such that $w^{+}(0) = w^{-}(0) = 0$ and $w^{+}(1) = w^{-}(1) = 1$. The decision weight for profit realization $\pi_{t,k}$ is then specified as:

$$d_{t,k} = \begin{cases} w^{+}(q_{t,n}) & \text{if } k = n, \\ w^{+}(\phi_{t,k}) - w^{+}(\phi_{t,k+1}) & \text{if } 1 \leq k < n, \\ w^{-}(\phi_{t,k}) - w^{-}(\phi_{t,k-1}) & \text{if } -m < k \leq -1, \\ w^{-}(q_{t,-m}) & \text{if } k = -m. \end{cases} \tag{3}$$

Unlike the sum of probabilities being equal to 1, sum of decision weights is not necessarily equal to 1 (Tversky and Kahneman 1992). Based on equations (1) and (3), the enterprise's prospective value to the decision maker in year *t* is $\sum_{k \in \Omega} d_{t,k} v(\pi_{t,k})$.

Based on prospect theory, we then consider a representative farmer who optimally allocates a unit of land between conventional crops and a bioenergy crop to maximize her prospective value from her land. It consists of two types of land: high quality land at portion s^h and low quality land at portion $s^l = 1 - s^h$, where superscripts *h* and *l* stand for high and low quality land, respectively. For high quality land, the farmer decides the optimal land division between two uses: growing conventional crops (labeled as *c*) and growing an energy crop (labeled as *e*). For low quality land, the farmer decides the optimal land division among three uses: keeping under original use (labeled as *o*) such as idle or pasture, growing conventional crops, and growing an energy crop.

Let x^{ij} denote land acreage under use $i \in \{c, e, o\}$ and quality type $j \in \{h, l\}$. Clearly, we have $x^{ch} + x^{eh} = s^h$ and $x^{ol} + x^{cl} + x^{el} = s^l$.[3] Furthermore, let π_t^{ij} be the profit per unit of land with use *i* and quality *j* in year *t*. Therefore, for a given set of land-use allocation, x^{ij}, the farmer's profit from her land in year *t* is:

$$\pi_t = \sum_i \sum_j x^{ij} \pi_t^{ij}. \tag{4}$$

Let y_t^{ij} denote the stochastic yield of crop $i \in \{c, e\}$ in year *t* on land with quality type $j \in \{h, l\}$. Price of crop *i* in year *t* is represented by p_t^i. The price of the conventional crop is a stochastic variable, whose distribution is known to the farmer. For bioenergy crops, production is assumed to occur under a long term fixed price contract between the farmer and a biorefinery to ensure certainty of supply of biomass for the biorefinery (Yang, Paulson, and Khanna, 2016).[4] Under such a contract, biomass price is fixed at p_t^e over its lifespan and we assume that this

[3] Based on the land-use assumption on high quality land, we have $x^{oh} = 0$.

[4] For simplicity, the present study focuses on potential for losses on the supply side of biomass market and does not consider demand risk caused by, say, biorefinery shutdown. Including demand risk in the model will further complicate the analysis but will not add much additional insight we seek to provide on the effect of loss aversion on biomass production.

price is the same for miscanthus, switchgrass, and corn stover. The fixed and variable costs of producing crop *i* in year *t* are represented by f_t^i per unit of land and v_t^i per unit of yield, respectively. Because more than 80% of major crops' acreage is covered under highly subsidized federal crop insurance in the United States (Shields, 2015), we include indemnity payments and premium subsidy payment provided by crop insurance in farmer's profits from conventional crops. In this study we consider revenue insurance which is widely used for conventional crops by US farmers (Shields 2015). The indemnity payment per unit land in year *t* and on land type $j \in \{h, l\}$ for a conventional crop is specified as

$$\iota_t^{cj} = \max\{\theta^c \mathrm{E}(y_t^{cj}) \max[p_t^{\mathrm{proj}}, p_t^{\mathrm{harv}}] - p_t^{\mathrm{harv}} y_t^{cj}, 0\}, \tag{5}$$

where θ^c is insurance coverage level for the conventional crop; $\mathrm{E}(\cdot)$ is the expectation operator; p_t^{proj} and p_t^{harv} are respectively projected price and harvest price established by Risk Management Agency (RMA) (2011) of U.S. Department of Agriculture (USDA). The profit per unit of land for the conventional crop in year *t* on land with quality type *j* can then be written as

$$\pi_t^{cj} = (p_t^c - v_t^{cj}) y_t^{cj} - f_t^{cj} + \iota_t^{cj} - (1-\rho^c)\mathrm{E}[\iota_t^{cj}], \tag{6}$$

where ρ^c is insurance premium subsidy rate for the conventional crop.

Yield of a perennial energy crop depends on the crop's age. Assuming a *T*-year lifespan, we define the first $\tau < T$ years in the lifespan as the establishment period and years $\tau + 1$ to *T* is the mature period. Since we are also interested in how credit constraint will affect biomass production, we consider the profit of growing bioenergy crops over the lifespan with and without credit constraint. When there is no credit constraint, then the farmer can obtain a loan to finance the establishment cost of bioenergy crops and then payback the loan in mature years with an annuity. When there is credit constraint, however, then such a loan is not available.

The two policy instruments considered in the analysis, namely establishment cost subsidy and subsidized energy crop insurance, will affect farmers' profits from energy crops if they are implemented. Let *g* denote the one-time establishment cost subsidy per unit of land during a life cycle of an energy crop. When farmers are credit-constrained, the presence of establishment cost subsidy will simply reduce farmers' establishment cost by amount *g*. When farmers are not credit-constrained, however, then the presence of establishment cost subsidy will reduce the amount of loan by *g* and hence reduce annuity payment in mature years repaying the loan. In the case of subsidized energy crop insurance, because biomass price is assumed to be fixed under long-term contracts, revenue insurance is equivalent to yield insurance. Let θ^e be insurance coverage level for energy crops. The energy crop insurance indemnity can be written as,

$$\iota_t^{ej} = p_t^e \max[\phi^e \mathrm{E}(y_t^{ej}) - y_t^{ej},\ 0]. \tag{7}$$

Let ρ^e be the premium subsidy rate of energy crop insurance. Therefore, when subsidized energy crop insurance is in place then its impact on the profit from growing an energy crop is $Z \equiv \iota_t^{ej} - (1-\rho^e)\mathrm{E}[\iota_t^{ej}]$.

To ease exposition of profits from growing an energy crop, we further introduce three indicators, I^{cred}, I^{esta}, and I^{insu}, which equal 1 if there are credit constraint, establishment cost subsidy, and insurance for energy crops, respectively; they equal 0 otherwise. Then, the energy crop's profit in t^{th} year of a lifespan on land with quality type *j* can be specified as

$$\pi_t^{ej} = \begin{cases} (p_t^e - v_t^{ej})y_t^{ej} - \mathrm{I}^{\text{cred}} \cdot (f_t^{ej} - \mathrm{I}^{\text{esta}} g) + \mathrm{I}^{\text{insu}} \cdot Z, & t \in \{1,...,\tau\} \\ (p_t^e - v_t^{ej})y_t^{ej} - f_t^{ej} - (1-\mathrm{I}^{\text{cred}})A(f_1^{ej},..., f_\tau^{ej}, g, \mathrm{I}^{\text{esta}}, r) + \mathrm{I}^{\text{insu}} \cdot Z, & t \in \{\tau+1,...,T\}, \end{cases} \tag{8}$$

where $A(f_1^{ej},..., f_\tau^{ej}, g, \mathrm{I}^{\text{esta}}, r)$ is the annuity the farmer needs to pay back due to the loan for the establishment cost. Note that the annuity is affected by establishment cost subsidy because in the presence of the subsidy the amount of loan needed to cover the establishment cost will be smaller.

Since the farmer's problem is to decide how much land should be allocated to the energy crop, a natural reference point to be used to differentiate gains and losses is the expected profit from original land use when energy crop is absent. Therefore, we set the reference point to be the expected profit from devoting all high-quality land to conventional crop and keeping all low-quality land under its original use such as idle or pasture. That is, we have

$$R = \mathrm{E}(s^h \pi^{ch} + s^l \pi^{ol}). \tag{9}$$

Note that R is constant across time because it is an expected value of returns that have the same distributions across time. By inserting equations (6) and (8) into equation (4) we obtain the total profit the farmer obtains from her land under a given set of land allocation x^{ij}. Based upon the prospect theory we have described above; the farmer's optimization problem can be specified as:

$$\begin{gathered} \max_{x^{ch}, x^{eh}, x^{ol}, x^{cl}, x^{el} \geq 0} \sum_{t=1}^{\Gamma} \beta^{t-1} [\sum_{k \in \Omega_t | x^{ij}} d_{t,k} v(\pi_{kt})] \\ \text{s.t.} \quad x^{ch} + x^{eh} = s^h, \text{ and } x^{ol} + x^{cl} + x^{el} = s^l, \end{gathered} \tag{10}$$

where Γ is the tenure of the land; $\beta \in [0,1]$ is a value discount factor; π_{kt} is profit realization k in year t (see equation (4)) and d_{kt} is the associated decision weight in year t to be determined based on the cumulative probability of an outcome in each year (see equation (3)), and $\Omega_t \,|\, x^{ij}$ is the set Ω in year t for a given set of land allocation, x^{ij}. Recall that $\Omega \equiv \{-m, 1-m, ..., -1, 1, ..., n\}$ where m and n are the number of losses and gains, respectively. Set $\Omega_t \,|\, x^{ij}$ is determined in the following way. First, for a given set of land allocation $\{x^{ch}, x^{eh}, x^{o}, x^{cl}, x^{el}\}$, we obtain N (N=1,000 in this study) realizations of profit from the land. Second, we subtract the reference point profit R from profit under each realization. Finally, we sort these differences ascendingly and identify the number of losses, m, and gains, n, for set $\Omega_t \mid x^{ij}$ (negative differences indicate losses and positive differences indicate gains). Although we consider a Γ-year period in the study, our analysis is basically a static analysis. This is not a dynamic analysis in which new information appears in the future that can lead to a change in land use decisions unlike Song, Zhao, and Swinton (2011). However, unlike their analysis which considers one representative farmer and two return processes (switchgrass and corn-soybean) for a discrete choice between switchgrass and corn-soybean we characterize the spatial and temporal variability in crop yields using DayCent model and estimate the spatial heterogeneity in riskiness and returns to energy crop production across the rainfed region of the United States. Moreover, unlike Song, Zhao and Swinton (2011) that examine the incentives to delay investment in switchgrass production, we are interested in examining the effect of loss and time preferences of landowners, interest rates, land quality and credit availability on the mix of feedstocks that would be produced under various biomass prices, credit constraint and discount rates.

2.3 Simulation Approach and Data

Our simulation includes 1,919 counties in the rainfed region of the United States. For simplicity, each county is assumed to be represented by a farmer who optimally allocates her land among various uses under the aforementioned framework. Following previous literature (e.g., Jain *et al*., 2010; Chen *et al*., 2014; Miao and Khanna, 2017a, b), we assume that the lifespan of miscanthus is 15 years whereas the lifespan of switchgrass is 10 years. We consider a 30-year land tenure framework (i.e., $\Gamma = 30$ in equation (10)) under which miscanthus can finish two lifecycles and switchgrass can finish three in order to avoid accounting for terminal values of standing crop since switchgrass and miscanthus have different lifespans. We assume that low quality land is originally in a low-risk-low-return activity (e.g., enrollment in a conservation program) and, therefore, the profit per unit of low quality land under its original use, π^{ol}, is approximated by land rent payments of the Conservation Reserve Program. We use corn rotated with soybeans to represent conventional crops. Corn stover, as a by-product of corn, may be harvested for biomass. Further, following Miao and Khanna (2017b) we only allow the representative farmer in a county to choose either miscanthus or switchgrass but not both for bioenergy crop adoption.[5] That is, a farmer first chooses the prospective value maximizing land allocation between miscanthus and the conventional crops and then, separately, between switchgrass and the conventional crops. Then the farmer selects the bioenergy crop under which her land generates larger maximum prospect value. The simulation is conducted by using MATLAB®.

For the simulation, we employ a copula approach to estimate a joint yield-price distribution for each county in order to reflect stochastic crop yields, stochastic prices of corn and soybeans, and the correlations among these yields and prices. Copula approach has been utilized to model joint distributions due to its flexibility (Yan, 2007; Du and Hennessy, 2012).[6] A joint yield-price distribution is estimated for each county for up to eight yields and two crop prices. The eight yields are yields of corn grain, corn stover, soybean grain, and miscanthus (or, separately, switchgrass) on both high and low-quality land.[7] The two prices are corn and soybean grain prices. In the simulation we obtain 1,000 draws from the estimated yield-price joint

[5] This is a simplifying assumption which significantly reduces the computational burden.
[6] See Item A in the Supporting Information for details about the copula approach utilized in the analysis.
[7] Not every county has all these eight yields. For example, a county may only have corn and miscanthus yields on high-quality land. We refer readers to Miao and Khanna (2017b) for detailed description regarding the crop yield data availability and for the copula approach employed in this study.

distributions, where each draw is a yield-price vector.[8] Biomass price is not included in the joint yield-price distribution, as it has been assumed to be a constant. In the remaining part of this section we describe data and parameters used in the simulation.

2.3.1 Crop yields

Due to the lack of large scale commercial production, we obtain county-level yield data for both miscanthus and switchgrass on high and low-quality land by using DayCent model. DayCent is the daily time-step version of the CENTURY biogeochemical model that is widely used to simulate plant growth based on information of precipitation, temperature, soil nutrient availability, and land-use practice (Del Grosso *et al.* 2011, 2012; Davis *et al*. 2012).[9] County-level weather information over 1980-2003 assuming a 24-year cycling of weather condition is used as part of the input for the DayCent model simulation that provides us with 27-year annual yield data. Table 1 presents summary statistics of the data simulated by DayCent. We can see that on high and low-quality land, the average yield of miscanthus is 27.2 and 26.8 metric tons per hectare (MT/ha) at 15% moisture and for switchgrass the two corresponding numbers are 14.1 and 12.7 MT/ha, respectively.

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[8] These 1,000 draws for a county are used repeatedly for the county in each year within the 30-year period. In the interest of tractability, we do not obtain a different set of 1,000 draws for each year. We believe this provides a reasonable illustration of the effect of loss aversion as long as the draws appropriately reflect the correlation among crop yields as well as the correlation between yields and prices.

[9] In DayCent model, the high-quality land is approximated by land under crop production whereas the low-quality land is approximated by land under pasture. Together with land management practice and observed daily weather information, properties of dominant soil type of cropland and pasture land in each county are used in input files to simulate crop yields on high quality land and low-quality land, respectively. We refer readers to Miao and Khanna (2017b) for a detailed description about calibration and validation of DayCent yield simulation.

Miscanthus is assumed to have no harvestable yield in the first year of a lifecycle. If the first-year establishment is successful then the farmer will obtain 50% of mature yield in the second year, and full mature yield in the third year and onward within the lifecycle. For miscanthus, we also assume that there is a 10% probability of a complete crop failure in the first year of establishment by following Skevas *et al*. (2016), as extreme cold weather can completely destroy miscanthus rhizomes. In the case of complete crop failure, the grower will have to re-establish in the second year, and therefore she will have no harvest in the second year, 50% of mature yield in the third year, and full mature yield in the fourth year and onward of the lifecycle. Note that there will be establishment cost again in the second year in case of a complete crop failure. For simplicity we assume that the re-establishment will be successful for sure. For switchgrass, we assume that there is no crop failure by following Skevas *et al*. (2016) and the yield reaches its full potential in the first year of a lifecycle.

Although historical yield data for conventional crops are available from National Agricultural Statistics Service (NASS) of USDA, in order to ensure consistency in the methodology underlying yield estimates across all crops considered in this study, we have also utilized DayCent model to obtain simulated yields for corn grain, corn stover, and soybean grain on both high and low-quality land. Use of DayCent-simulated corn and soybean yields provides an additional advantage that we do not need to rely on arbitrary assumptions to obtain corn or soybean yields on low quality land, or to obtain corn stover yield.

Following Miao and Khanna (2017a,b), we assume that corn is grown continuously in those counties that do not have soybean yield data in the DayCent simulated dataset. In counties with soybean data, corn is assumed to be rotated with soybeans. Our data show that corn grain harvested on high and low-quality land are 139.1 bushel/acre and 127.2 bushel/acre, respectively

(Table 1), indicating that on average corn grain yield on low quality land is about 9% lower than that on high quality land. For soybeans, however, the yield difference between low quality land and high-quality land is only about 3%. Yields for corn stover harvested on high and low-quality land are 2.6MT/ha and 2.4MT/ha, respectively. We assume that farmers harvest a fixed portion (30% in this study) of produced stover, as there is no consensus yet on how much corn stover should be left in the field to maintain soil organic carbon and to manage erosion.[10]

2.3.2 Crop Prices

In the simulation, we use three different types of prices of corn and soybeans: received prices, projected futures prices, and harvest futures prices. State-level received prices from NASS are used to calculate realized profits of corn and soybeans, whereas projected futures prices and harvest futures prices are used to calculate crop insurance indemnity for corn and soybeans. These futures prices are determined by following RMA (2011) rules based on Chicago Board of Trade (CBOT) futures prices. We obtain the CBOT futures prices of corn and soybeans over 1980-2010 from Barchart.com. All these prices have been converted to 2010 dollars using the Gross Domestic Product implicit price deflator. Following Miao and Khanna (2017b), prices in each year are assumed to be drawn from the same price-yield joint distribution obtained by using the aforementioned copula approach.[11] As we have discussed above, biomass price is assumed to

[10] Due to lack of knowledge of how advances in technology or crop management will improve energy crop yields, we do not include an upward yield trend for these crops in DayCent simulations. Introducing a yield trend parameter will add another layer of uncertainty to the results. Accordingly, to ensure consistency we do not assume yield trends for conventional crops either.

[11]We do not consider the autocorrelation of prices across years or the possibility that the distribution of conventional crop prices may be affected by land conversion from conventional crop to energy crop production. Taking these factors into account will make the analysis more complex and less transparent without affecting the core insights of the study.

be fixed over the farmer's planning period under a long-term contract, and we have considered farm-gate biomass prices which do not include transportation cost from farms to bio-refineries. To see the impact of different biomass prices on farmers' decisions, we use a range of biomass prices from \$20/MT to \$100/MT with a step of \$10/MT.

2.3.3 Production Costs

The county-specific production costs of the crops considered in this study are basically the same as those used in Chen *et al*. (2014) and Miao and Khanna (2017a,b). The method and assumptions underlying the calculation of these county-specific production costs of miscanthus, switchgrass, corn, and soybeans in the rain-fed region are described in Khanna, Dhungana, and Clifton-Brown (2008), Jain *et al*. (2010), and Chen *et al*. (2014). The only adjustment about the costs that we make is that for miscanthus, if the first-year establishment is successful then we exclude the re-establishment cost in the second year of a lifecycle. We do so because we assume that the first-year establishment is either a complete failure with probability 0.1 or a complete success with probability 0.9.[12] In the first year of establishment, the cost of miscanthus is about \$3,108/ha (Table 1), including expenses on rhizomes, planting machinery, fertilizer, and land preparation. For simplicity we assume that there are no returns to scale for establishment costs. If the first-year establishment is a failure, then the farmer will have to incur the same total establishment cost again in the second year. If the first-year establishment is a success, then in the second year and onward, production costs include expenses on fertilizer, labor, fuel, and machinery for harvesting, baling, transportation, and storage. We divide these costs into variable

[12] Chen *et al*. (2014) and Miao and Khanna (2017a, b), however, assume that the first-year establishment is always successful but 10% replanting rate in the second year is required.

cost and fixed cost. On average the variable cost is $17.2/MT and the fixed cost is $166/ha (Table 1).

For switchgrass, the variable cost is the same as that of miscanthus. The fixed cost, however, differs in the first three years of a lifecycle due to different management in these years. On average the fixed cost of switchgrass is $333/ha, $255/ha, and $252/ha for the first, second, and third year, respectively, within one lifecycle. For conventional crops, the production costs including fertilizer, chemicals, seeds, harvesting, drying, and storage are collected from crop budgets compiled by state extension services (Chen *et al*. 2014). For corn, the average annual fixed and variable costs are $136.5/acre and $1.3/bushel, respectively, whereas for soybeans, the two corresponding costs are $107.4/acre and $1.5/bushel, respectively. For corn stover, the variable cost ($17.5/MT) is close to that of miscanthus and switchgrass while the fixed cost ($48.5/ha) is much lower than that of the two bioenergy crops. We assume that within a county the fixed and variable costs for a crop are the same on low and high-quality land.

2.3.4 Discount Factor, Risk and Loss Aversion Parameters, Land Availability, and Farm Size

The discount factor, β, in equation (10) is calculated by $\beta = 1/(1+r)$, where *r* is discount rate. The discount rate takes two values in our simulation: 2% for low discount rate and 10% for high discount rate. The values for risk and loss aversion parameters are directly obtained from the literature. Tversky and Kahneman (1992) take value of risk aversion parameter at $\alpha = 0.88$ and value of loss aversion parameter at $\lambda = 2.25.$ For the two parameters in probability weighting functions (i.e., γ and δ), they set γ = 0.61 and δ = 0.69. These values are used by Babcock (2015) as well. In the simulation we vary the loss aversion parameters, discount rate, as well as credit constraint status to study how biomass production responds to these variations.

Studies have shown that due to various reasons, farmers' willingness to convert land to biomass production is limited. Skevas, Swinton, and Hayden (2014) document that the loss of amenity value of land is a concern when farmers consider growing bioenergy crops. Based on a survey on 1,124 private landowners, Swinton *et al*. (2017) find that the landowners are only willing to rent up to 23% of their land to bioenergy crop production even the proposed rents are double of market rents. Therefore, for each county we limit the amount of land that can be used for bioenergy crops to no more than 25% of the sum of high and low quality land in the county.[13] The average acreage of high and low quality land per county is 28,841 hectares and 4,507 hectares, respectively, prior to any land availability restriction for perennial energy crops (Table 1). Farm size is one of the factors that determine the magnitudes of losses and gains for a farm. Following Miao and Khanna (2017b), we use data for county-level average farm size from the 2012 Census of Agriculture. The average farm size across counties in our dataset is 139 hectares.

2.4 Profitability and riskiness

Before we discuss the simulation results regarding bioenergy crop adoption, we first examine the profitability and riskiness of the conventional crops and bioenergy crops covered in this study. We use a crop's expected 30-year net present value (NPV) of profits as a measure of the crop's profitability.[14] We do so because crops covered in this study have different lifespans (1 year for the conventional crops, 15 years for miscanthus, and 10 years for switchgrass) and thus the use of expected 30-year NPV of profits makes the profitability comparable across crops. Table SI-1 and Table SI-2 present summary statistics for crop profitability and riskiness when biomass price

[13] We later relax this 25% limit assumption in the sensitivity analysis and find that our major findings carry over.
[14] Following Miao and Khanna (2017b), we assume the interest rate to be 10% for the NPV calculation.

is assumed to be $50/MT or $100/MT. These two prices are chosen because $50/MT (respectively, $100/MT) is a price close to the average breakeven price of biomass grown on marginal land (respectively, cropland) as calculated by Miao and Khanna (2014). When biomass price is $50/MT, then the conventional crops are the most profitable ($6,264/ha and $5,580/ha on high and low-quality land, respectively) and miscanthus is the least profitable ($1,417/ha and $1,304/ha on high and low-quality land, respectively). When biomass price is $100/MT, however, then miscanthus is most profitable and the conventional crops are the least (see Table SI-1). As expected, profitability of a crop on high quality land is higher than that on low quality land. Across the three crops, the difference between high quality land profitability and low-quality land profitability is smallest under miscanthus. For instance, when biomass price is $50/MT, miscanthus' profitability difference between high and low-quality land is only $113/ha ($1,417/ha minus $1,304/ha, an 8% difference). For the conventional crop and switchgrass, the corresponding numbers are $684/ha (an 11% difference) and $433/ha (a 19% difference), respectively.

The four maps in the upper panel of Figure SI-1 depict profitability difference between miscanthus and the conventional crops under two biomass prices ($50/MT and $100/MT) and two land types (high and low quality). The four maps in the lower panel are the counterparts for profitability difference between switchgrass and the conventional crops. We find that the profitability difference between miscanthus and the conventional crops on low quality land is larger than that on high quality land. This is intuitive because the profitability of conventional crops on low quality land is much lower than that on high quality land whereas for miscanthus the profitability on these two types of land is close. Figure SI-1 shows that miscanthus and switchgrass, relative to the conventional crops, are more profitable in the southeastern U.S. and less profitable in the north Great Plains. One possible explanation is that the average yields of miscanthus and switchgrass are highest in the southeastern U.S. but lowest in the north Great Plains (see Figure 1 in Miao and Khanna, 2014).

Regarding crop riskiness we first examine the coefficient of variation (CV) of profits for each crop. The county-level CV of profits from a crop grown on land with a certain quality in each county is calculated based on the 1,000 yield-price draws generated by using the aforementioned copula approach.[15] The CV values associated with profitability in Table SI-1 are averages of county-level CVs across all counties. From Table SI-1 we can see that the average CV is significantly affected by biomass prices. When biomass price is \$50/MT, then miscanthus (with CV around 2) is riskier than the conventional crops (with CV around 0.5) and switchgrass (with CV around 1). When biomass price is \$100/MT, however, the CV of miscanthus' 30-year NPV of profits is the lowest across the three types of crops (see the 3rd panel in Table SI-1).

To explore a crops' loss prospect, we also calculate the probability of having a negative 30-year NPV of profits (within years) for each crop (Table SI-1) and probability of having negative yearly profits (between years) for each crop (Table SI-2). The calculation is conducted for each county on both high and low-quality land under biomass prices \$50/MT and \$100/MT, respectively.[16] Results show that under biomass price at \$50/MT, the average probability of having a negative 30-year NPV of profits from growing miscanthus on high and low quality land

[15] Note that each yield-price draw is corresponding to a realization of profit. Therefore, we obtain 1,000 realizations of profits from the 1,000 yield-price draws. Then the county-level CV of profits is the standard deviation of the 1,000 realizations of profits divided by the mean of these 1,000 realizations of profits.

[16] For a crop grown on a type of land in a county, the probability is calculated by counting number of draws that result in a negative 30-year NPV in the county and then dividing this number by 1,000, which is the total number of draws for each crop, land quality, and county combination. The values presented in Table SI-1 are averages across counties.

is about 28.4% and 29.9%, respectively (see Table SI-1). At the same biomass price, the corresponding numbers for switchgrass is 10.8% and 16.8%, respectively, which are much lower than those of miscanthus. When biomass price is $100/MT then the probability of having a negative 30-year NPV of profits from miscanthus is 2.4% on high quality land and 2.8% on low quality land. For switchgrass, the two corresponding probabilities are 1.1% and 1.9%, respectively.

Maps in Figure SI-2 show the difference in probability of negative 30-year NPV of profits between bioenergy crops and the conventional crops, and maps in Figure SI-3 show the difference in probability of having loss (between years) between bioenergy crops and the conventional crops. We find that when biomass price is $50/MT then for almost every county the probability of having a negative 30-year NPV of profits from growing bioenergy crops is larger than that from growing the conventional crops. However, when biomass price is $100/MT, then for most counties in the Midwest and some counties in the southeastern United States the probability of having negative NPV from growing bioenergy crops is smaller than that from growing conventional crops. In the north Great Plains, growing bioenergy crops endures larger probability of having negative 30-year NPV of profits than does growing the conventional crops under both prices. The geographical patterns of biomass profits and probabilities of having negative NPV will in part determine the geographical configuration of biomass production when farmers' loss aversion is considered. We examine the impact of loss aversion next.

2.5 Simulation Results under *Laissez-faire* Scenarios

We first conduct our simulations for eight scenarios under which policy interventions on biomass production are absent. These eight scenarios are the combinations of two discount rates (2% and 10%), two credit constraint status (credit constrained and not credit constrained), and two loss aversion parameter values ($\lambda = 1$ for loss neutral and $\lambda = 2.25$ for loss averse). Under each of these eight scenarios, we study the representative farmer's optimal land allocation in each county under biomass prices ranging from \$20/MT to \$100/MT with a \$10/MT step. Then we compare simulation results across the eight scenarios to identify the impact of loss aversion on bioenergy crop adoption and how the impact is influenced by discount rate and credit constraint. We use biomass production and land devoted to bioenergy crops as measures of bioenergy crop adoption.

2.5.1 Effect of loss aversion on biomass production

Figure 1 presents simulated biomass supply curves for corn stover, miscanthus, switchgrass, and total biomass grown on both types of land under the eight scenarios.[17] It shows that biomass production from miscanthus and switchgrass commences effectively at biomass price of \$50/MT or higher. From the figure we find that in most cases supply of miscanthus is elastic when biomass price is between \$60/MT and \$80/MT but inelastic when biomass price is larger than \$80/MT. This is because when biomass price rises from \$60/MT to \$80/MT, in many counties miscanthus production just surpasses the margin to be profitable when compared with conventional crops and switchgrass. Therefore, miscanthus production is sensitive to biomass price when the price is in the \$60-80/MT range. When biomass price increases above \$80/MT, however, then acreage for bioenergy crops in many counties reaches the 25% limit of total land and hence becomes less responsive to biomass prices. Supply of switchgrass is inelastic due to its low yield and hence low competitiveness relative to miscanthus. Across the eight scenarios, corn stover production is insensitive to biomass price and may even slightly decrease as biomass price

[17] Figures SI-4 and SI-5 in the online Supporting Information (SI) present the supply curves for biomass produced on high and low-quality land, respectively.

increases from $50/MT to $100/MT. This is because a) profits from corn stover only account for a small portion of total profits from growing corn, hence increase in corn stover profit does not change overall profits from growing corn much; and b) as biomass prices rises to $100/MT, corn acreage faces increasing competition from bioenergy crops.

The four graphs in the upper panel of Figure 1 show that when farmers are credit constrained, then all else equal, miscanthus production under loss averse scenario is much lower than that under loss neutral scenario. The opposite is true for switchgrass, which indicates that when farmers are credit constrained, ignoring loss aversion may overestimate miscanthus production while underestimate switchgrass production. This finding is intuitive because on average miscanthus has the highest probability of having negative 30-year NPV of profits among the crops covered in this study (see Table SI-1). Moreover, when farmers are credit constrained and hence cannot finance miscanthus' high establishment costs by using loans, then high establishment costs and no harvest in the establishment period will result in high losses in that period when compared with only growing the conventional crops. Therefore, for a loss-averse farmer who is credit constrained, miscanthus will be less appealing.

When farmers are not credit constrained, however, accounting for loss aversion has small impacts on biomass production (see supply curves in the four graphs of the lower panel of Figure 1). One explanation is that in the absence of credit constraint, farmers can finance their establishment costs so that the loss in the establishment period is significantly reduced and hence returns across periods become less volatile. Moreover, the low or even negative correlation between miscanthus yield and corn yield (see Table 1 of Miao and Khanna (2014)) provides farmers with diversification benefits from having a mix of the two crops. As the availability of credit reduces the loss in establishment period, this diversification benefits becomes more appealing under the loss aversion scenario when compared with that under the loss neutral scenario. This is because a mix of crops with low or negative yield correlation will make the overall profits less likely to fall below the reference profit.

We can see that the availability of credit to farmers mitigates the effect of the farmers' loss preferences on perennial energy crop production. This finding is consistent with the one in Miao and Khanna (2017b) who find that when farmers are not credit constrained then biomass production is insensitive to changes in risk aversion. Therefore, our results lend support to policy interventions (e.g., the Biomass Crop Assistance Program) that provide establishment cost shares for bioenergy crop growers.

In order to examine the impact of credit constraint, loss aversion, and discount rate on biomass production, we present the optimal biomass production under two scenarios (credit constraint, loss aversion, and high discount rate scenario vs. no credit constraint, loss neutral, and low discount rate scenario) with biomass price being set to be \$50/MT or \$100/MT (see Figure 2).[18] Overall, we find that the impact of loss aversion is the largest in absolute terms when biomass price is high, farmers are credit constrained, and discount rate is high. Figure 2 show that when biomass price increases from \$50/MT to \$100/MT then expansion in miscanthus production mainly occurs at the extensive margin (i.e., new counties commencing miscanthus production). The same pattern holds for switchgrass production (see Figure 2). However, when we shift from the credit constraint, loss aversion, and high discount rate scenario to the no credit constraint, loss neutral, and low discount rate scenario, then the expansion in miscanthus production mainly occurs at the intensive margin (i.e., existing producing counties produce

[18] To save space, we include maps for total biomass production and corn stover production under the same scenarios in the SI (see Figures SI-6 and SI-7).

more). This pattern of expansion is particularly evident when biomass price is $100/MT. When biomass price is $50/MT, however, the pattern of expansion is not quite obvious because the overall miscanthus production is low. For switchgrass, the same scenario change causes the number of producing counties to decrease (see Figure 2). Moreover, when biomass price is $50/MT, then miscanthus and switchgrass production is mainly distributed in counties outside of the central Midwest. However, when biomass price is $100/MT, then miscanthus production mainly occurs in the Midwest while switchgrass production still occurs outside the Midwest. This is because a) miscanthus has relatively high yield and low risk in the Midwest (see Table 1 in Miao and Khanna (2014)); and b) switchgrass cannot compete with corn or miscanthus in this region.

We further explore the impact of loss aversion on biomass production in greater detail, showing the optimal biomass production under four loss-and-time preferences combinations with credit constraint and with biomass price being set to be $50/MT or $100/MT (see Table 2).[19] In Table 2, comparison between columns 1 and 2 (cases of high discount rate) shows that when biomass price is $50/MT then accounting for loss aversion will decrease miscanthus production from 0.4 million MT to almost zero. However, it will increase switchgrass production from 1 million MT to 1.4 million MT. Similar results hold when comparing columns 3 and 4 under the $50/MT biomass price. Overall, when biomass price is as low as $50/MT, the impact of loss aversion is small in absolute terms because at this price bioenergy crops are generally not much viable.

Under the $100/MT price and with high discount rate, when loss aversion is accounted for then miscanthus production on high quality land decreases from 213.3 million MT to 128.8

[19] Table SI-3 includes the counterpart results under scenarios without credit constraint.

million MT (see columns 1 and 2 in Table 2), which is a 40% decrease, whereas miscanthus production on low quality land only decreases by 19%. The reason for the smaller decrease in miscanthus production on low quality land is that, as we have discussed above, the profitability difference between miscanthus and the conventional crops on low quality land is larger than that on high quality land (see the 3rd panel in Table SI-1), which causes miscanthus to be more likely viable on low quality land even when loss aversion is considered. For switchgrass, the comparison between columns 1 and 2 in Table 2 shows that when loss aversion is accounted for then total switchgrass production on high quality land increases from 10.7 million MT to 34.6 million MT, which is a 223% increase, whereas the production on low quality land increases only by 80%. The larger increase in switchgrass production on high quality land is because that switchgrass has much higher profitability and much lower probability of having a negative 30-year NPV on high quality land than on low quality land (see the 3rd and 4th panels in Table SI-1). In sum, we find that for both miscanthus and switchgrass the production on low quality land is less sensitive to loss aversion than production on high quality land is. This finding underscores the importance of marginal land for producing bioenergy crops.

By comparing columns 3 and 4 in Table 2 (cases of low discount rate), we find that at $100/MT biomass price when loss aversion is accounted for then miscanthus production on high and low-quality land decreases only by 5% (from 237.5 million MT to 225.7 million MT) and 4% (from 77.2 million MT to 73.8 million MT), respectively. We can see that the impact of loss aversion is smaller when discount rate is low as compared to when discount rate is high. This is because a lower discount rate implies a larger prospective value discount factor (recall that $\beta = 1/(1+r)$). As a result, returns in mature period of a bioenergy crop will be valued more and losses in the establishing period will account for a smaller portion of a bioenergy crop's overall prospective values. Therefore, impact of losses in the establishing period will be mitigated by a lower discount rate (i.e., a larger discount factor).

Figure SI-6 shows that the Midwest is the major biomass producing region across all scenarios. This is mainly because farmers' risk preferences, discount rate, and credit situation are unlikely to change farmers' decision on whether to provide corn stover in the Midwest (see Figure SI-7) as corn stover is even profitable at $40/MT biomass price and profits from corn stover only accounts for a small portion of total profits from growing corn. Moreover, when biomass price is $100/MT, then the Midwest also becomes the major producing region for miscanthus (see Figure 2).

2.5.2 Land use for miscanthus and switchgrass

Land use for bioenergy crops is critical because it pertains to issues of food-fuel competition and of ecosystem services associated with biomass production. Table 3 presents acreages devoted to miscanthus and switchgrass under four scenarios with credit constraint. By comparing columns 1 and 2 (cases of high discount rate) in the table, we find that acreages on both types of land devoted to miscanthus is lower under loss aversion scenario when compared with those under loss neutral scenario at both price levels. The same conclusion holds when comparing columns 3 and 4 (cases of low discount rate) in Table 3. Specifically, when biomass price is $100/MT, then accounting for loss aversion will decrease use of high quality land for miscanthus from 21,391,023 acres to 12,251,082 acres (a 42% decrease), whereas for low quality land the decrease is only 22%. For switchgrass, however, the comparison of columns 1 and 2 shows that when accounting for loss aversion, then land used for switchgrass increases on both types of land for both biomass prices. Specifically, when the biomass price is $100/MT, then accounting for loss aversion will increase use of high quality land for switchgrass from 1,951,209 acres to

6,278,952 acres, which is a 221% increase, whereas for low quality land the increase is only 71%. Again, this is due to switchgrass' higher profitability and lower probability of having a negative 30-year NPV on high quality land as compared to on low quality land.

By comparing columns 3 and 4 in Table 3 (cases of low discount rate), we find that when discount rate is low and when loss aversion is accounted for then miscanthus acreage on high and low-quality land decreases by only 6.4% and 6.5%, respectively. For switchgrass, however, the acreages on high and low-quality land increases by 169% and 26%, respectively. These results are consistent with the impacts of loss aversion on miscanthus and switchgrass production when discount rate is low. That is, the impact of loss aversion on biomass production is smaller when discount rate is low as compared to when discount rate is high.

When farmers are not credit constrained, then in most cases accounting for loss aversion slightly increases land devoted to miscanthus production (see Table SI-4). The same reasons for why loss aversion slightly increases miscanthus production under scenarios without credit scenarios apply here. For switchgrass, the impact of loss aversion under scenarios without credit constraint depends on biomass price. When biomass price is $50/MT and when discount rate is high, then accounting for loss aversion will increase total land devoted to switchgrass from 114,056 acres to 197,255 acres, a 73% increase (comparing columns 1 and 2 in Table SI-4). At the same biomass price but low discount rate, the increase is much lower, from 65,275 acres to 84,194 acres, a 29% increase (comparing columns 3 and 4 in Table SI-4). When biomass price is $100/MT, however, under scenarios without credit constraint accounting for loss aversion has only negligible impact on land acreage devoted to switchgrass, regardless the discount rate levels. One explanation is that at a high biomass price such as $100/MT, losses from growing bioenergy crops are unlikely and hence loss aversion parameters have no significant impact on bioenergy crop production. Nevertheless, even when biomass price is as high as $100/MT, credit availability and discount rate are still critical in determining biomass production (see Tables 3 and SI-4).

Figure 3 includes maps for county-level land devoted to miscanthus under various scenarios. The counterpart maps for switchgrass are included in Figure SI-8. In Figure 3, we can see that as we move from credit constraint, loss aversion, and high discount rate scenario (maps in the upper panel) to no credit constraint, loss neutral, and low discount rate scenario (maps in the lower panel), miscanthus production expands in both extensive and intensive margins. In contrast, figure SI-8 shows that for switchgrass the same scenario change results in reduced production. When biomass price is $50/MT then land devoted to miscanthus is mainly located outside of the Midwest, regardless land quality; whereas when biomass price is $100/MT then the Midwest becomes the major producing region for the crop (see Figure 3). From Figure SI-8 we can see that both high and low-quality land devoted to switchgrass is located outside of the central Midwest. Particularly, when biomass price is $100/MT then Michigan and Wisconsin can be major producing states of switchgrass, depending on credit availability as well as farmers' loss and time preferences (see Figure SI-8).

2.5.3 Sensitivity Analyses

In this subsection we conduct two sets of sensitivity analyses regarding our simulations under the laissez-faire scenarios. Because under the "no credit constraint" scenarios the effect of loss aversion on biomass production is relatively small, we focus on scenarios with credit constraints hereafter for the sensitivity analyses and for the policy intervention simulations. The first set of sensitivity analyses pertains to relaxing the assumption that farmers can only devote no more than 25% of their total land to energy crop production. In this subsection we completely relax this assumption so that farmers can allocate up to 100% of their land to energy crops. We doing so to explore whether or not the impact of loss aversion on biomass production is significantly influenced by the land availability constraint we have imposed in the simulation. In the second set of sensitivity test we let the farmers evaluate gains or losses based on 30-year net present value of profits, instead of evaluating based on annual profits. By doing so we examine how the effect of loss aversion on biomass production is influenced by the temporal framework by which the farmers evaluate their gains and losses.

Table SI-5 in the SI presents the simulation results when we remove the 25% land limit for energy crop production. We find that although biomass production from the energy crops significantly increased, especially when biomass price is \$100/MT, similar pattern of the impact of loss aversion and discount rate on biomass production exists when compared with results with the 25% land limit. Specifically, everything else equal, loss aversion dis-incentivizes miscanthus production while incentivizes switchgrass production. High discount rate has similar impact. For instance, when biomass price is \$100/MT then under the scenario of loss neutral and high discount rate, total miscanthus production is 1,144.3 million MT and total switchgrass production is 41.5 million MT (see column 1 in Table SI-5). Under the same price but under the scenario of loss averse and high discount rate, however, the two numbers become 307.2 and 337.2, respectively (see column 2 in Table SI-5), indicating that loss aversion disincentives miscanthus production but incentivize switchgrass production.

Table SI-6 includes biomass production when farmers evaluate gains and losses of the 30-year NPV instead of gains and losses at the annual basis. Specifically, we first obtain an empirical distribution of the 30-year NPV for each county based on the 1,000 draws from the copula approach; then we feed this empirical distribution of NPV into equation (10). Note that because the evaluation of gains and losses no longer occurs on an annual basis, Γ in equation (10) now equals 1 and π_{kt} becomes π_k^{NPV}, where π_k^{NPV} is the 30-year NPV of profits from all land uses under land allocation $\{x^{ch}, x^{eh}, x^{ol}, x^{cl}, x^{el}\}$. We find that the simulation results under the 30-year NPV scheme (Table SI-6) are close to the results under scenarios where farmers without credit constraint value gains and losses of profit on an annual basis (Table SI-3). For example, under the 30-year NPV scheme, when biomass price is \$100/MT then under the "loss averse and high discount" scenario, the production of miscanthus and switchgrass is 289.5 and 13.1 million MT, respectively (see column 2 of Table SI-6). Table SI-3 shows that when farmers are not credit constrained and when they evaluate gains and losses on an annual basis, then under the same conditions of biomass price, loss preferences, and discount rate, the production of miscanthus and switchgrass is 300.6 and 8.1 million MT (see column 2 of Table SI-3). When farmers are credit constrained, however, these two numbers become 184.9 and 43.6 (see column 2 of Table 2), which are quite different from the results under the 30-year NPV scheme.

The reason that the results under the 30-year NPV scheme (Table SI-6) are similar to those under the no credit constraint scenarios (Table SI-3) is as follows. Everything else equal, the 30-year NPV of profits is not affected by the farmer's credit constraint status. In other words, obtaining a loan to finance the establishment cost and then paying it back in mature years of an energy crop will not affect the NPV of the profits from growing the energy crop, as long as the discount of the loan is the same as the discount assumed to calculate the NPV. Therefore, the simulation results based on the 30-year NPV of profits being evaluated by the value function are similar to the results under the "no credit constraint" scenario.

2.6 Impact of policy interventions

In this section we examine the effects of two policy interventions, namely establishment cost subsidy and subsidized energy crop insurance, on biomass production under various loss preferences and discount scenarios. In the simulation we set the one-time establishment cost subsidy to be the lower of 50% of establishment cost and $500 per acre, by following the BCAP of the 2014 Farm Bill. We consider establishment cost subsidy only in first year. If a crop failure occurs in the first year, then farmers will have to incur full establishment cost in the second year without receiving any establishment cost subsidy in that year. For energy crop insurance, we assume that the coverage level is 75% of average energy crop yields and the premium subsidy rate is 55%. These two values are chosen because 75% is one of the most popular coverage levels farmers choose for conventional crops and 55% is the corresponding subsidy rate for the 75% coverage level specified by RMA (Shields 2015).

Table 4 presents the impact of the establishment cost subsidy on biomass production under four scenarios with credit constraint as well as various loss preferences and discount rates. To ease exposition in the table we report biomass production changes caused by the establishment cost subsidy. The changes are calculated as by using biomass production with the policy intervention minus the production without the policy intervention (i.e., production in Table 2). For instance, 1.9, the first number in column 1 of Table 4, should be interpreted as when farmers are credit constrained and when biomass price is $50/MT, then under the "loss neutral and high discount" scenario the presence of establishment cost subsidy will increase miscanthus production on high quality land by 1.9 million MT.

From Table 4 we can see that in most cases the presence of establishment cost subsidy increases miscanthus production but decreases switchgrass production. This is because the large difference in establishment costs between these two energy crops results in large difference in establishment cost subsidy received by the two crops. Table 1 shows the average establishment costs for miscanthus and switchgrass are $3,108/ha. and $249.4/ha., respectively. Therefore, based on the rule for establishment cost subsidy (i.e., the lower of 50% of establishment cost and $500/acre), it is readily checked that on average the establishment cost subsidy for miscanthus is about $1,236/ha., whereas the subsidy for switchgrass is only about $127.5/ha. This difference in establishment cost subsidy between miscanthus and switchgrass (almost 10 times) tends to incentivize miscanthus production but dis-incentivize switchgrass production.

Nevertheless, the overall impact of establishment cost subsidy on energy crop production is positive. For example, at biomass price $100, for a loss averse farmer in the case of high discount scenario, there is an increase of 76.2 million MT of biomass production (see column 2 in Table 4). The corresponding annual government outlay is $1,143.56 million.[20] Dividing the biomass increased by subsidy outlay, we can see that when biomass price is $100/MT and when farmers are credit constrained, then under the "loss averse and high discount scenario" one dollar of establishment subsidy will increase energy crop production by 0.07 MT.

The impact of subsidized energy crop insurance on biomass production is presented in Table 5. We find that across all the scenarios presented in Table 5, the presence of subsidized energy crop insurance incentivizes switchgrass production. Regarding miscanthus production, however, when biomass price is $50/MT then the impact of subsidized energy crop insurance is positive but in most cases with a smaller magnitude than that on switchgrass production. When biomass price is $100/MT then in most cases the presence of subsidized energy crop insurance

[20] Note that since biomass production change is measured in an annual basis, to ease exposition we annualize the establishment cost subsidy even though the subsidy occurs only in the first year of the lifecycle of an energy crop.

has negligible or even negative impact on miscanthus production. A possible explanation is that yield risk of switchgrass is much larger than that of miscanthus (see Table 1), which causes insurance premium and hence premium subsidy directed to switchgrass to be larger than those to miscanthus.[21] Therefore, the presence of energy crop insurance incentivizes switchgrass production more than it does to miscanthus production. The difference between the incentivizing effect on switchgrass and that on miscanthus can be large enough to cause a county switch from growing miscanthus to grow switchgrass. This is why in some cases miscanthus production is reduced by the presence of the subsidized energy crop insurance.

Overall, the subsidized energy crop insurance increases the total biomass production from the two energy crops. The magnitude of the increase, however, is smaller than that caused by establishment cost subsidy, especially when biomass price is \$100/MT. This is because, in part, the government outlay under subsidized energy crop insurance is smaller than that under establishment cost subsidy (see Tables 4 and 5). When we compare the amount of biomass production increased per dollar of government outlay, however, we find that when biomass price is \$100/MT, then the subsidized energy crop insurance outperforms the establishment cost subsidy except under the scenario of “loss averse and high discount” (comparing the last row in the panel of “biomass price = \$100/MT” in Tables 4 and 5). This is because when biomass price is \$100/MT and when farmers are credit constrained, loss averse, and face high discount, then the effect of establishment cost subsidy reaches the largest due to the subsidy’s impact on mitigating credit constraint and smoothing utilities across periods.

[21] Table 1 shows that the mean yields of switchgrass are about half of those of miscanthus yields whereas the standard deviation of switchgrass yields are close to those of miscanthus yields. This indicates that the coefficient of variation (CV) of switchgrass yields are about twice as large as the CV of miscanthus yields.

Moreover, we find that increase in biomass production increased by per dollar government outlay is much higher when biomass price is $50/MT than when biomass price is $100/MT. This is because under a price as high as $100/MT, farmers have already found growing energy crops profitable and any further support will not result into additional biomass production.

2.7 Conclusions

By employing prospect theory, we find that farmers' attitude toward loss matters when considering bioenergy crop adoption; but the magnitude depends on credit availability, discount rate, biomass price, and crop types. Our results indicate that if farmers are credit constrained then accounting for loss aversion will decrease miscanthus production but increase switchgrass production. However, corn stover production is insensitive to whether loss aversion is considered. If farmers are not credit constrained then accounting for loss aversion has much smaller impact on bioenergy crop production, indicating that the availability of credit to a farmer mitigates the effect of the farmer's loss preference on perennial energy crop production. Our results show that biomass production on low quality land is less sensitive to farmers' preferences toward losses than production on high quality land is. This finding indicates that policymakers should target those areas where share of low quality land is larger for promoting biomass production. Moreover, results show that impact of loss aversion is larger when discount rate is high as compared to scenario when discount rate is low. Our results also show that accounting for loss aversion, credit constraints, and discount rates may predict different geographical configuration of miscanthus and switchgrass production, indicating the importance of loss preferences, credit availability, and time preferences in determining crop choices.

By comparing the impacts of two policy instruments, we find that BCAP establishment cost subsidy favors miscanthus whereas subsidized energy crop insurance favors switchgrass. We also find that the efficacy (measured by biomass production increased per dollar of government outlay) of policy intervention is much higher when biomass price is at $50/MT than when biomass price is at $100/MT. Whether the efficacy of subsidized energy crop insurance is larger than that of establishment cost subsidy depends on farmers' loss preference, discount rate, and biomass price.

The present paper focuses on the supply side of the biomass market and examines how farmers' preference toward loss affects potential biomass supply. However, the development of biomass markets faces "the chicken or the egg" dilemma in that biorefineries have little demand for energy-crop biomass because they do not see much supply for such kind of biomass and growers have little interest to adopt energy crops because they do not see much demand for these crops (Khanna et al. 2017; Luo and Miller 2017; and Yang et al. 2016). Future research can be directed to understanding the barriers to the biomass market development on the demand side while accounting for farmers' loss preferences in their decision-making. Future research can also be directed to analyze the potential incentives for switching out of energy crops if crop prices were to increase in the future and the timing of the adoption and de-adoption decisions by using a stochastic dynamic programming approach.

Table 2. 1 Summary Statistics of Data Utilized in the Simulation[a]

			Mean	S.D.	Min.	Max.
Yields[b]	miscanthus on high quality land (MT/ha)		27.2	2.9	3.5	48.3
	miscanthus on low quality land (MT/ha)		26.8	2.8	2.8	47.4
	switchgrass on high quality land (MT/ha)		14.1	2.8	0.4	32.1
	switchgrass on low quality land (MT/ha)		12.7	3.3	0.4	31.1
	corn stover on high quality land (MT/ha)		2.6	0.6	0.01	6.9
	corn stover on low quality land (MT/ha)		2.4	0.54	0.02	6.5
	corn grain on high quality land (bu./acre)		139.1	39.2	0.7	304.5
	corn grain on low quality land (bu./acre)		127.2	34	0.5	297.3
	soybeans on high quality land (bu./acre)		42.9	20	1	112.3
	Soybeans on low quality land (bu./acre)		41.5	19.5	0.1	109.2
Costs	miscanthus (Yr 1)	establishment cost ($/ha)	3,108	46.2	3,033.6	3,247.9
	(Yrs 2-15)	variable cost ($/MT)	17.2	2	14.2	19.6
		fixed cost ($/ha)	166	29	113.1	258.7
	switchgrass	variable cost ($/MT)	17.2	2	14.2	19.6
	(Year 1)	fixed cost ($/ha)	332.7	22.8	294	392.9
		establishment cost ($/ha)	249.4	20	223	319
	(Year 2)	fixed cost ($/ha)	254.9	53.9	143.5	368.3
	(Yrs 3-10)	fixed cost ($/ha)	251.6	40.6	169.1	354.1
	corn stover	variable cost ($/MT)	17.5	2.1	12.6	21.7
		fixed cost ($/ha)	48.5	10.9	20.3	75
	corn	variable cost ($/bushel)	1.3	0.4	0.8	2.7
		fixed cost ($/acre)	136.5	28.6	91.4	221.8
	soybeans	variable cost ($/bushel)	1.5	0.3	0.8	1.8
		fixed cost ($/acre)	107.4	45.4	59.4	195.9
Prices[c] ($/bushel)	corn	projected price	4.1	1.2	2.6	7.8
		harvest price	3.8	1.3	2.2	8.1
		received price	4	1.3	1.9	9.1
	soybeans	projected price	9.5	2.9	5.4	17.2
		harvest price	9.3	3	5.4	19.3
		received price	9.2	2.6	5.3	17.3
Acreage (hectare per county)		High quality land	28,841	38,228	202	252,448
		Low quality land	4,507	4,680	0	42,154

Note: [a] Costs and prices are in 2010 dollars; MT refers to metric tons of biomass with 15% moisture content. [b] Corn grain and stover yields are under corn-soybean (CS) rotation. Under corn-corn rotation, yields are assumed to be 12% lower than that under CS rotation. [c] The received price is state-level annual average price while the projected price and harvest price are futures prices calculated following RMA (2011).

Table 2. 2 Biomass Production under different scenarios with credit constraint (Million MT).

Biomass Type	Land Type	Loss Neutral High Discount	Loss Averse High Discount	Loss Neutral Low Discount	Loss Averse Low Discount
		[1]	[2]	[3]	[4]
		When biomass price is $50/MT			
Corn Stover	High Quality	95.8	95.8	95.7	95.7
	Low Quality	13.0	12.9	12.7	12.9
	All land	108.8	108.7	108.4	108.6
Miscanthus	High Quality	0.3	0.0	3.9	0.7
	Low Quality	0.1	0.0	4.4	1.3
	All land	0.4	0.0	8.3	2.0
Switchgrass	High Quality	0.7	1.0	0.3	1.0
	Low Quality	0.3	0.4	0.1	0.3
	All land	1.0	1.4	0.4	1.3
Total Biomass	High Quality	96.8	96.8	99.9	97.4
	Low Quality	13.3	13.3	17.2	14.5
	All land	110.2	110.1	117.1	111.9
		When biomass price is $100/MT			
Corn Stover	High Quality	83.1	87.4	81.7	82.6
	Low Quality	9.0	9.6	8.5	8.7
	All land	92.1	97.0	90.2	91.3
Miscanthus	High Quality	213.3	128.8	237.5	225.7
	Low Quality	69.4	56.1	77.2	73.8
	All land	282.7	184.9	314.7	299.5
Switchgrass	High Quality	10.7	34.6	1.8	4.7
	Low Quality	5.0	9.0	3.2	4.2
	All land	15.7	43.6	5.0	8.9
Total Biomass	High Quality	307.1	250.8	321.0	313.0
	Low Quality	83.3	74.6	88.9	86.6
	All land	390.4	325.5	409.9	399.6

Table 2. 3 Land use under different scenarios with credit constraint (Acres)

Land Type	Loss Neutral High Discount	Loss Averse High Discount	Loss Neutral Low Discount	Loss Averse Low Discount
	[1]	[2]	[3]	[4]
When biomass price is $50/MT				
For Miscanthus				
high quality land	24,368	1,192	358,734	59,574
low quality land	6,748	323	397,726	120,048
total land	31,116	1,514	756,461	179,622
For Switchgrass				
high quality land	123,094	182,235	57,234	186,704
low quality land	51,387	66,197	15,205	58,245
total land	174,481	248,432	72,439	244,949
When biomass price is $100/MT				
For Miscanthus				
high quality land	21,391,023	12,251,082	24,514,886	22,943,734
low quality land	6,749,915	5,259,230	7,859,570	7,345,123
total land	28,140,937	17,510,312	32,374,456	30,288,857
For Switchgrass				
high quality land	1,951,209	6,278,952	333,262	895,990
low quality land	1,003,224	1,713,005	622,258	844,793
total land	2,954,433	7,991,957	955,520	1,740,783

Table 2. 4 Impact on Biomass Production due to BCAP support (with Credit Constraint)

Biomass Type	Land Type	Loss Neutral High Discount	Loss Averse High Discount	Loss Neutral Low Discount	Loss Averse Low Discount
		[1]	**[2]**	**[3]**	**[4]**
When biomass price is $50/MT					
Absolute Change in Biomass Production (Million MT)					
Miscanthus	High Quality	1.9	0.4	9.9	3.9
	Low Quality	2.1	0.6	7.9	5.4
Switchgrass	High Quality	-0.1	0.01	-0.3	-0.2
	Low Quality	-0.01	0.2	0.0	-0.03
Net change in biomass production (Million MT) considering both Miscanthus and Switchgrass together					
	Total land	3.9	1.2	17.5	9.1
Net BCAP support payment (Annuity $ Million) considering both Miscanthus and Switchgrass together					
	Total Land	15.90	5.04	96.91	41.06
Increase in biomass production (Million MT) per Million $ of BCAP support (Annuity)					
	Total Land	0.24	0.24	0.18	0.22
When biomass price is $100/MT					
Absolute Change in Biomass Production (Million MT)					
Miscanthus	High Quality	18.2	90.6	5.0	15.2
	Low Quality	5.7	16.1	1.2	3.8
Switchgrass	High Quality	-6.8	-26.5	-0.7	-3.1
	Low Quality	-1.1	-4.0	-0.1	-1.1
Net change in biomass production (Million MT) considering both Miscanthus and Switchgrass together					
	Total Land	16.0	76.2	5.4	14.8
Net BCAP support payment (Annuity $ Million) considering both Miscanthus and Switchgrass together					
	Total Land	1212.51	1143.56	1291.99	1278.21
Increase in biomass production (Million MT) per Million $ of BCAP support (Annuity)					
	Total Land	0.01	0.07	0.004	0.01

Note: As per BCAP [sec. 9009], one-time establishment cost subsidy is limited to 50% of cost of establishment, not to exceed $500 per acre.

Table 2. 5 Impact on Biomass Production due to subsidized energy crop insurance (with Credit Constraint)

Biomass Type	Land Type	Loss Neutral High Discount	Loss Averse High Discount	Loss Neutral Low Discount	Loss Averse Low Discount
		[1]	[2]	[3]	[4]
When biomass price is $50/MT					
Absolute Change in Biomass Production (Million MT)					
Miscanthus	High Quality	0.1	0.0	0.3	0.2
	Low Quality	0.1	0.1	1.2	0.3
Switchgrass	High Quality	0.3	0.3	0.3	0.3
	Low Quality	0.5	0.5	0.2	0.6
Net change in biomass production (Million MT) considering both Miscanthus and Switchgrass together					
	Total Land	1.0	0.9	2.0	1.4
Net insurance subsidy payment (Annuity $ Million) considering both Miscanthus and Switchgrass together					
	Total Land	4.61	4.72	10.53	6.33
Increase in biomass production (Million MT) per Million $ of insurance subsidy payment (Annuity)					
	Total Land	0.21	0.20	0.19	0.22
When biomass price is $100/MT					
Absolute Change in Biomass Production (Million MT)					
Miscanthus	High Quality	-3.6	-3.5	1.7	-0.4
	Low Quality	0.0	-1.8	0.4	0.3
Switchgrass	High Quality	5.8	8.7	0.9	2.5
	Low Quality	1.5	3.1	0.6	1.0
Net change in biomass production (Million MT) considering both Miscanthus and Switchgrass together					
	Total land	3.7	6.5	3.6	3.4
Net insurance subsidy payment (Annuity $ Million) considering both Miscanthus and Switchgrass together					
	Total Land	166.63	200.45	171.28	164.07
Increase in biomass production (Million MT) per Million $ of insurance subsidy payment (Annuity)					
	Total Land	0.02	0.03	0.02	0.02

Note: Insurance premium subsidy rate is taken as 55%, and insurance coverage level is taken as 75%

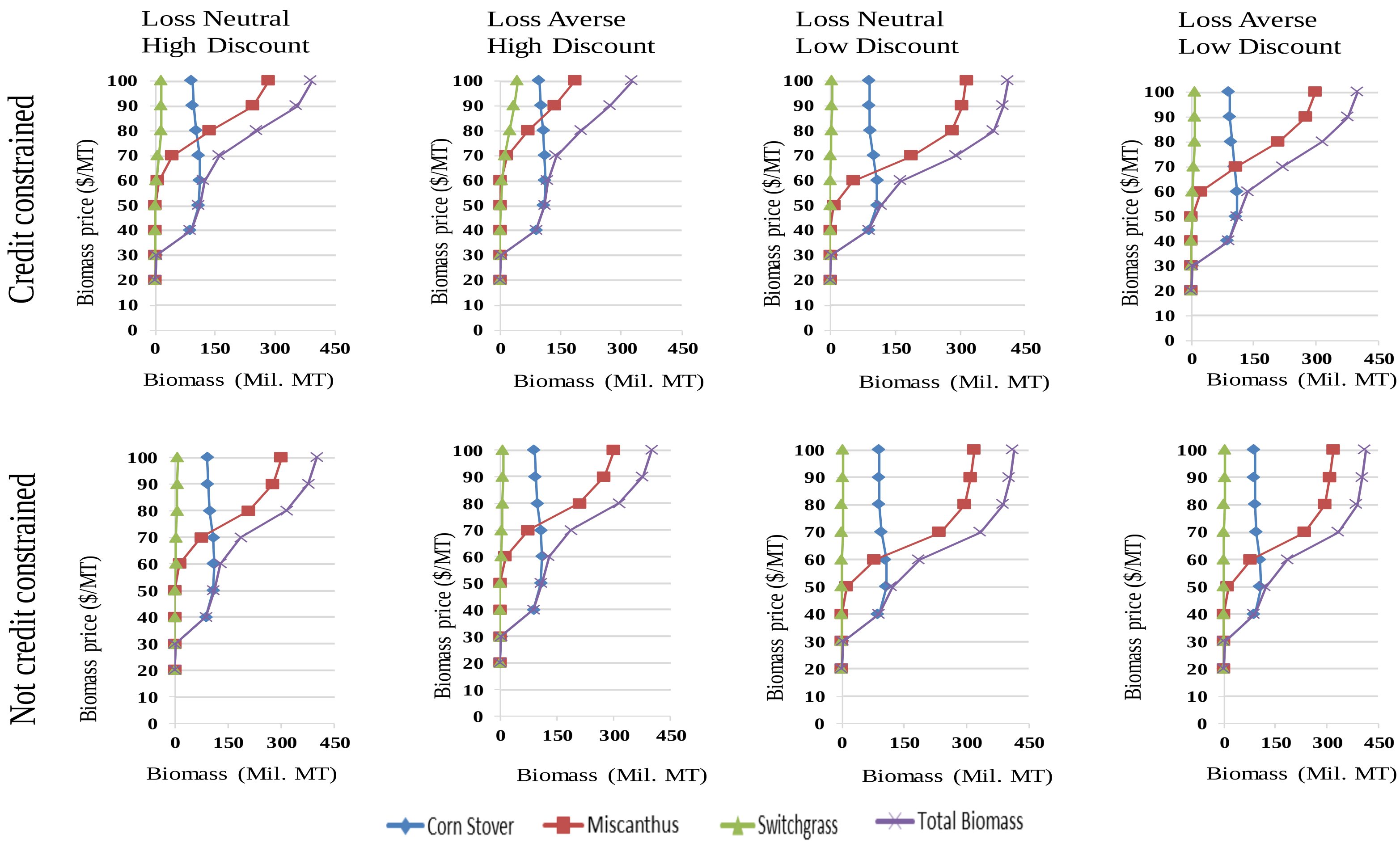

Figure 2. 1 Aggregate Biomass Supply Curves

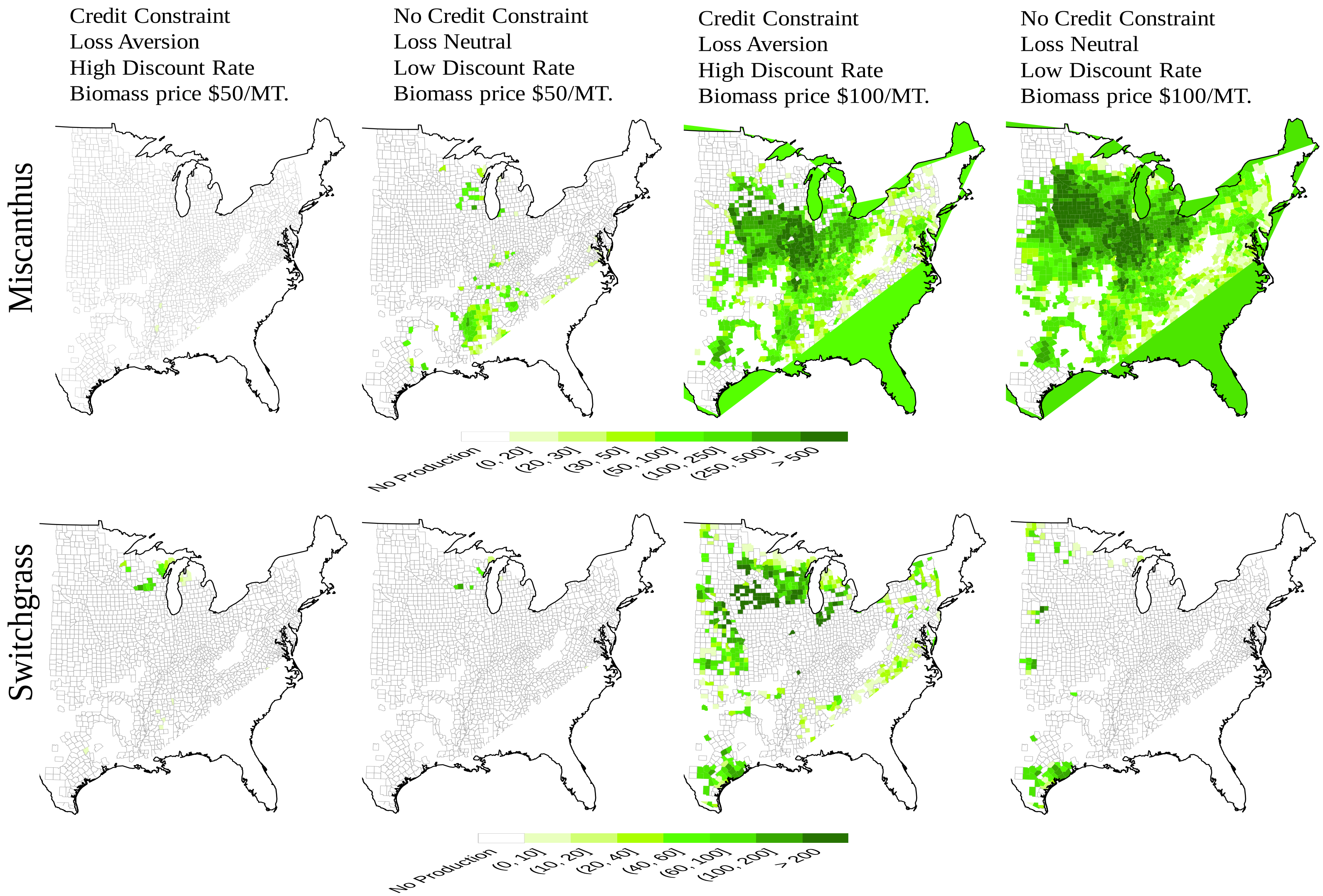

Figure 2. 2 Average County-Level Miscanthus and Switchgrass Production (1,000 MT per year)

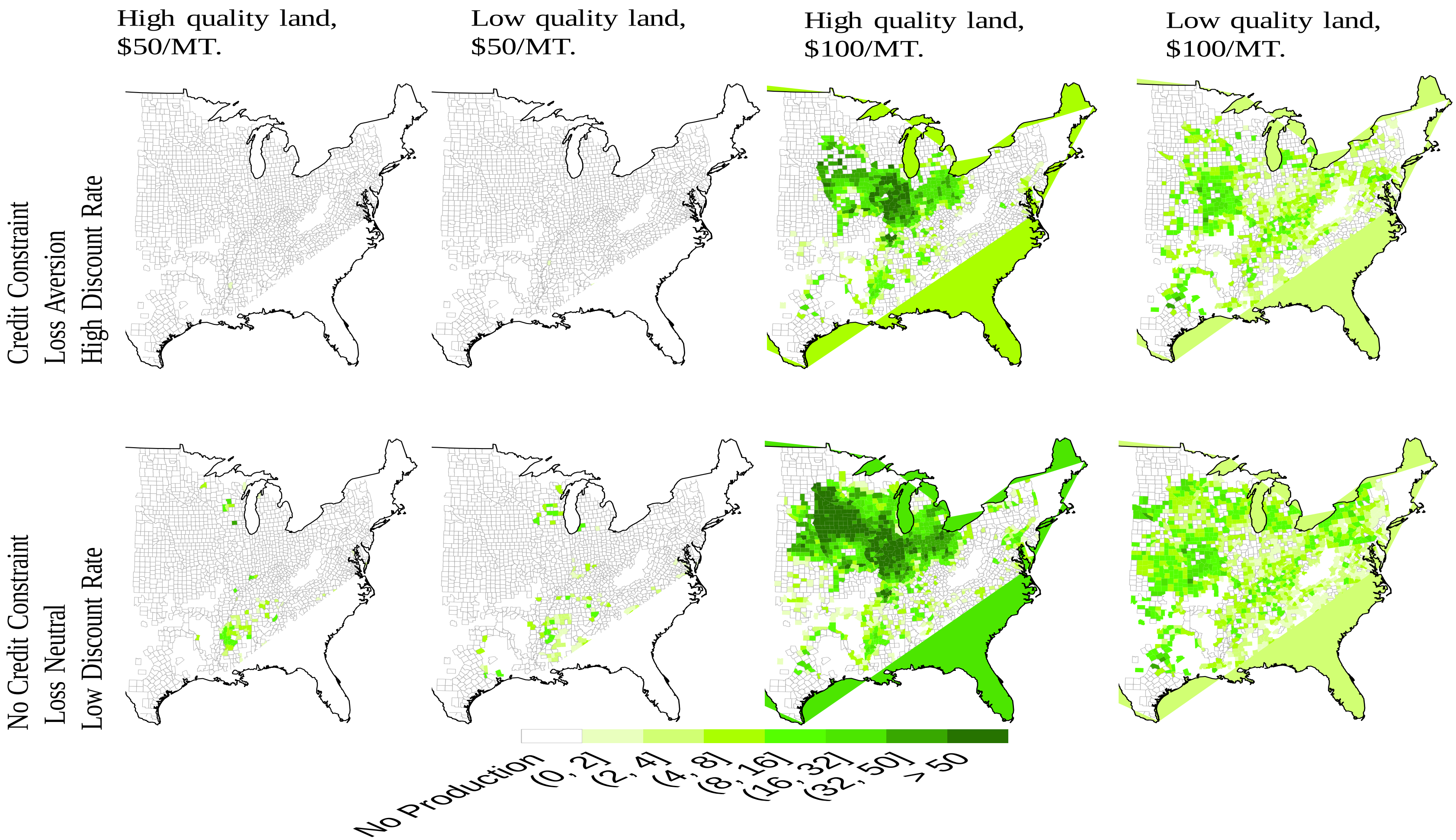

Figure 2. 3 Miscanthus acreage on high and low-quality land (1,000 Acres)

Note: For the first and second maps in the first row, only four and three counties produce miscanthus, respectively. They are all in the southeastern region.

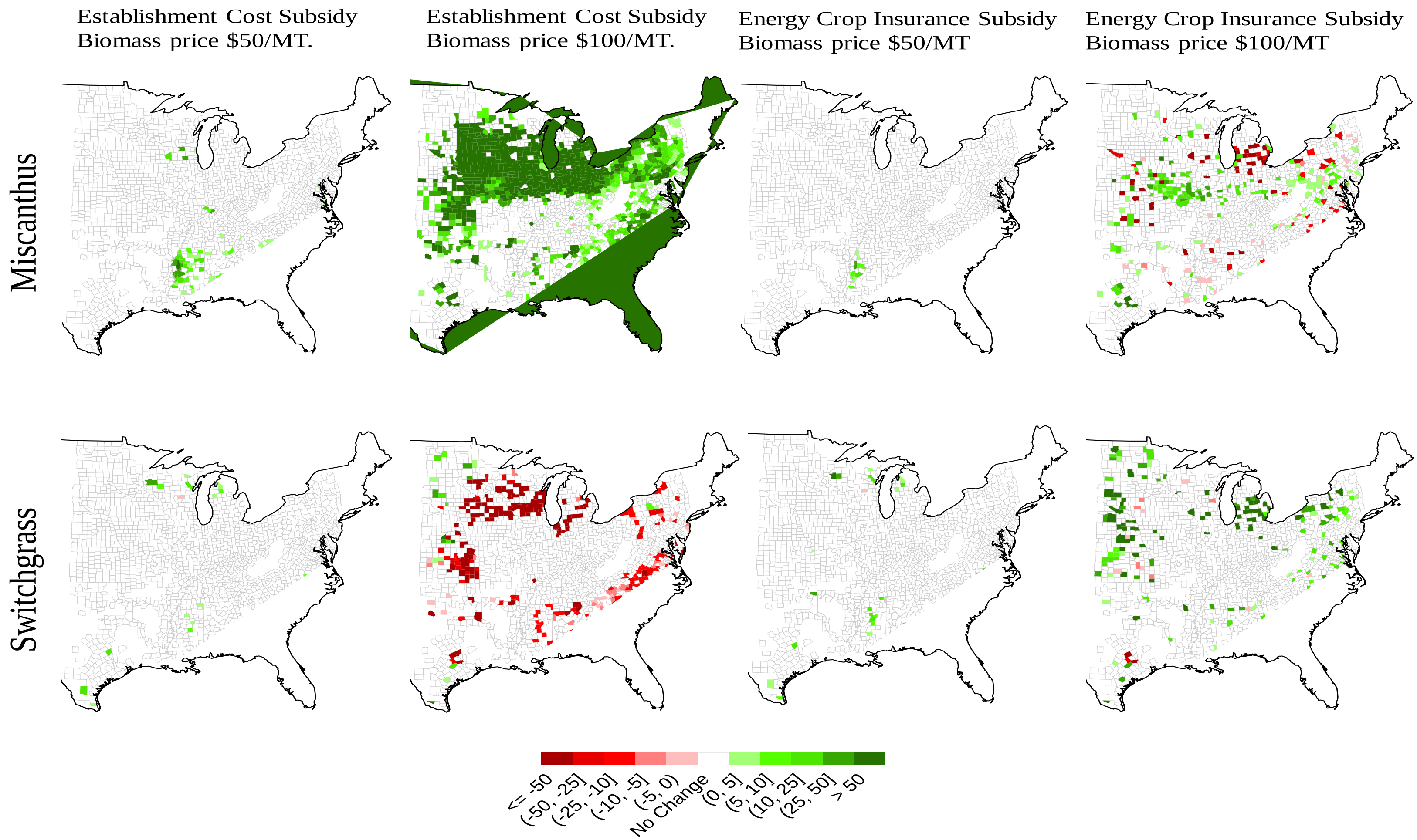

Figure 2. 4 Change in Biomass Production (Million MT) due to policy instruments.

Case: Credit Constraint, Loss Aversion, High Discount Rate

Chapter 3. Does Food Insecurity Worsen due to Smoking?

3.1 Introduction

A household is considered food secure when it has access to nutritionally adequate and safe food at all times to live a healthy life. Even in a developed country like the United States, inadequate access to food remains a serious concern for many people. Concern about food insecurity has great importance because of its relationship with poor mental and physical health (Laraia, 2013). Anderson (1990) has defined food insecurity as "limited or uncertain ability to acquire acceptable foods in socially acceptable ways." As per the recent report from the U.S. Department of Agriculture (USDA) (2018), about 12% of U.S. households were considered food insecure during at least some part of the year in 2017, meaning that these households did not always have access to nutritionally adequate and safe food. Of these food insecure households, more than a third (approximately 4.5% of U.S. households) was among the group having very low food security.

While an inverse relationship between food insecurity and income has been found in the aggregate, not all households below the poverty line are food insecure and not all food insecure households are poor. When Gundersen, Krieder, and Pepper (2011) examined the relationship of food insecurity to household income, they found that some households that were far below the poverty threshold self-reported that they were food secure and some households even at relatively high incomes continued to report food insecurity. These findings make it clear that food insecurity is related to other characteristics of households beyond income alone. To make sound decisions about policies and programs targeted at reducing food insecurity, it is critical to understand these other characteristics.

The level of food insecurity in a household may in part be explained by competing demands, such as expenses related to chronic diseases, high rents, high state and local taxes or money spent on addictions. Kirkpatrick and Tarasuk (2011) found a positive relationship between housing costs and food insecurity in Toronto, Canada. Bartfeld and Dunifon (2006) found that higher median rent is associated with higher food insecurity for households with children in the United States. They also found that a 1% increase in the tax burden was associated with a 1.7% increase in the odds of food insecurity. Out of these competing demands, addiction costs such as smoking, drinking, and gambling should also be considered, as addiction costs, which may be hidden from other household members, may take a major share of income.

One of the most common addictions is cigarette smoking. Smoking may affect food security in a simple way, that is, money spent to purchase cigarettes or other tobacco products is not available for food purchase. In December 2014, the average price per pack of cigarettes in the US was $6.18 (Boonn, 2014). By state, the average price per pack of cigarettes ranged from $5.12 in Missouri to a high of $10.66 in New York, as of November 2016 (Orzechowski and Walker, 2016). A cigarette smoker who smokes only a pack a day can spend roughly $2,500 a year on cigarettes; people with heavy smoking habits can bear costs that reach or exceed about $5,000 to $6,000 per year. Due to addiction, the cigarettes may take precedence over food purchases when income is tightly constrained.

Smoking is more common among low income adults than higher income adults (Jamal et al., 2014), and low-income households have lower disposable income than high income households making even a modest cigarette habit take up a fairly large portion of income. Farrelly et al., (2012) estimated that in New York State, a market where cigarette prices are relatively high, low-income households (income < $30,000 per year), smokers spend roughly

24% of their annual household income on that purchase of cigarettes. The purchase price of cigarettes is not the only cost that smokers incur throughout their lives. Smoking is also related to financial strain through smoking-caused diseases (Brook and Zhang, 2013).

The relationship between smoking and food insecurity has not been widely researched, although a few studies on food insecurity and the food stamp program participation have touched this issue. Armour, Pitts, and Lee first explored this relationship in 2001. They found that smoking among the household heads or spouses is associated with an increase in food insecurity. Another study found that living with an adult smoker is a risk factor for food insecurity among household children (Cutler-Trigges et al., 2008). Mykerezi and Mills (2010) included smoking status of the household head as an independent variable in their model of food insecurity and found it to be significant, although the impact of smoking on food insecurity was not a focus of their study. These studies ignored the possible endogeneity problem, that the stress of food insecurity may increase the likelihood of smoking as has also been hypothesized (Duffy and Zizza, 2016). Thus, to smoke or not to smoke could be a self-selection decision partly caused by food insecurity, leading to a potential problem of endogeneity. Also, previous studies have modeled smoking as a binary variable, ignoring the impact that higher levels of cigarette consumption may have as compared to more moderate smoking.

The aim of this study is to examine the endogeneity problem and also to see the impact of increased smoking on food security. The novel part of this paper is to use quantity of cigarette smoking (average number of cigarettes per day) as an explanatory factor in the food security model to evaluate whether food insecurity worsens due to more smoking.

3.2 Conceptual Framework

There is an imperfect correlation between poverty and food insecurity. Not all households below the poverty line are food insecure, and not all food insecure households are poor. Employing a theoretical model can assist in developing a rationale for the observed discrepancies between food insecurity and poverty. I can say that a household spends its income on two types of commodities i.e. food and an aggregate of all other goods. In the classic utility maximization problem, the household allocates its limited resources between food and other needs to maximize utility, U,

$$U = U\left(F,\ NF\right) \qquad (1)$$

Subject to the budget constraint I,

$$I = P_F . F + P_{NF} . NF \qquad (2)$$

Where F is a composite commodity for all nutritionally adequate and safe food items consumed and NF is a composite commodity for all other goods. P_F and P_{NF} are prices for food and all other goods respectively. The Lagrangian function is thus

$$Max\ U = U\left(F, NF\right) + \lambda\left(I - P_F . F - P_{NF} . NF\right) \qquad (3)$$

Where utility is maximized over F and NF, and λ is taken as the marginal utility of income.

The model shows that the share of income available for nutritionally adequate and safe food (required for food security) will decrease if there is an increased expenditure on other goods. The imperfect correlation between food insecurity and poverty indicates the importance of factors other than income that can affect the budget constraint. Both the relative utility of F and NF and their relative prices will affect the share of income spent on food. One of the competing demands on household income could arise from the costs associated with smoking.

3.3 Data

The study uses survey data from the 2011-2012 and 2013-2014 rounds of the National Health and Nutrition Examination Survey (NHANES). NHANES is designed to assess the health and nutritional status of adults and children in the United States. The survey combines interviews and physical examinations. The Survey examines a nationally representative sample of about 5,000 persons each year. This study collects demographic data, food security data, income data and smoking data, among other things.

The NHANES sample design is a clustered design and incorporates differential probabilities of selection. The NHANES sampling procedure consists of four stages. In stage 1, primary sampling units (PSUs) are selected such as single counties. In stage 2, the PSUs are divided into segments such as city blocks. In stage 3, households within each segment are listed, and a sample is randomly drawn. Then finally in stage 4, individuals are chosen to participate in NHANES from selected households. Typically, individuals within a cluster are more similar to one another than those in other clusters

Food security status is calculated from the 10 core-item food security module of the U.S. Department of Agriculture. For example, one of the question is “'(I/we) couldn’t afford to eat balanced meals.' Was that often, sometimes, or never true for (you/your household) in the last 12 months?” The full text of the questionnaire module can be found in (Coleman-Jensen et al.,2015). Based on the responses of these questions, households are classified either as fully food security, marginally food security, or as having low food security or very low food security. Households having full food security and marginal food security are considered food secure, whereas, household having low food security and very low food security are considered food insecure.

While the NHANES classifies food security/insecurity into four discrete categories, these status levels can reflect meaningful ranges based on an underlying continuous scale. The categorical responses to the food security questions can also be coded into a continuous scale using the Rasch model, which is based on item-response theory. Special software can be used to calculate Rasch scale values; however, when there are only small portions of missing values, a simpler direct imputation method can be employed. Accordingly, for this study, a Rasch scale of food insecurity was developed following the procedures outlined in Bickel et al. (2000). A higher value on this scale indicates worsening food insecurity.

3.4 Methods

Different regression models are used to explore the relationship between food security and smoking, which can be represented by the following general equation:

$$Food\ \mathrm{sec}urity = \beta_0 + \beta_1 Smoking + \beta_2 X + \mathrm{u} \qquad (4)$$

where 'X' is a set of control variables. Control variables included in the model are age of survey participants, family size, poverty income ratio, gender, race, citizenship status, education and marital status. In one approach for our model, the dependent variable i.e. food security status is taken as a binary dependent variable representing food security as '1' and food insecurity as '0'. In a model where the dependent variable is binary, our objective is to find the probability of something happening. Thus, I estimate the probabilities of a household being food secure i.e. $\Pr(Y_i = 1 / X_i) = P_i$. In another approach for our model, the dependent variable i.e. food security status is taken as a continuous variable (using the Rasch model). When the dependent variable is the continuous scale, the model estimates how much each explanatory variable affects the level of food insecurity.

The objective of using different models is to improve the understanding about said relationships, and also to view and analyze these relationships from multiple perspectives. In further sub-sections, I will discuss different models used to explore the relationship between food security and smoking. As discussed earlier that smoking is more common among low income adults than higher income adults, thus, I have also made one subset of data for families within 200% of poverty level i.e. low-income households. Thus, I am using two sets of data for my analysis i.e. data for all households, and data for only low-income households.

3.4.1 Probit Model

The two common approaches to develop a probability model for a binary response variable (food security in this study) are the Logit model and Probit model. In most applications, both models are similar. The main difference is that the logistic distribution has slightly fatter tails, i.e. the conditional probability approaches 0 or 1 at a slower rate in the Logit model than in the Probit model. Therefore, there is no compelling reason to choose one over the other. The Logit model uses the standard logistic distributions, whereas the Probit model uses a standard normal distribution. This study has applied the Probit model to explore the relationship between food security and smoking, which can be represented by the following two regression equations:

$$Food\,security = \beta_0 + \beta_1 FamilySize + \beta_2 PIR + \beta_3 SmokingStatus + \beta_4 Gender + \beta_5 Race + \beta_6 Citizenship + \beta_7 Education + \beta_8 MaritalStatus + \beta_9 \mathrm{Age} + \mathrm{u} \tag{5}$$

$$Food\,security = \beta_0 + \beta_1 FamilySize + \beta_2 PIR + \beta_3 SmkQty + \beta_4 Gender + \beta_5 Race + \beta_6 Citizenship + \beta_7 Education + \beta_8 MaritalStatus + \beta_9 \mathrm{Age} + \mathrm{u} \tag{6}$$

Food security is modeled in both equations as a binary variable (0 for food insecure and 1 for food secure). FamilySize is the total number of people reported in the family. PIR is the ratio of income to the poverty level. Gender is coded as 1 for female, 0 for male. Race is a set of binary variables representing Hispanic, non-Hispanic African American, and non-Hispanic white. (The omitted category is "other," which includes mixed race.) Citizenship status is a binary variable with the value 1 if the respondent is a U.S. citizen, 0 otherwise. Education is also represented by a set of binary variables, for low education (no high school degree), high school education, and college degree or more. (The omitted category for the regression was arbitrarily chosen as high school education.) Marital status takes the value 1 if the respondent is married or living with a partner, and 0 otherwise. Age is reported in years. SmokingStatus, in the first equation, takes the value 1 if the respondent reports currently smoking, in the second equation; smoking is measured by a continuous variable of daily cigarette use.

These equations will help us to know the impact of ‘smoking status’ and ‘smoking quantity’ on food security status individually. The marginal effects of smoking on the probability of food security are calculated after the model is estimated.

3.4.2 Reducing the problem of endogeneity

One aim of this study is to examine the possible endogeneity problem due to the decision to smoke. Before I take care of this particular endogeneity problem, I will also take care of another possible endogeneity problem. As discussed earlier, food insecurity disproportionately affects households near the poverty level i.e. not all households below the poverty line are food insecure, and not all food insecure households are poor. There is a probability that there may be unobserved factors associated with poverty that are also associated with food insecurity. This situation will raise an endogeneity problem.

The most common technique to solve for endogeneity problem is the introduction of an instrument variable in the model. Thus, we need a variable that is correlated with poverty, but not associated with food security. However, it is really very difficult to find such a variable. Thus, to reduce this problem of endogeneity, this study runs models (same as in equation 5 and 6) to explore the relationship between food security and smoking on just households within 200% of the federal poverty level as well as for all households.

3.4.3 Probit Model with survey correction

As NHANES data (used in this study) are not obtained using a simple random sample, thus survey correction must be taken into account. If while calculating variance estimates, one assumes simple random sampling, then the variance estimates are generally too low, and thus significance levels will be overstated, because they do not account for the differential weighting and the correlation among sample persons within a cluster. In complex survey design, independence of observations and equal probabilities of selection may no longer hold. Thus, for survey correction, one must account for the design effects of stratification, design effects of clustering, and should also account for the unequal probability of sampling with the help of weights.

A simple weight is assigned to each sample person, which is a measure of the number of people in the population represented by that sample person. Probit models with survey corrections are run to explore the relationship between food security and smoking to get more precise variance estimates and significance levels. The models in (5) and (6) are run both with and without survey corrections to see the impact of failing to make these corrections on the estimated significance of the explanatory variables.

3.4.4 Endogenous – Treatment regression Model

A second objective of this study is to examine the possible endogeneity problem due to a self-selection decision to smoke. To control for the endogeneity of the treatment, a control-function approach is commonly used. In this approach, residuals from the treatment model are included as a regressor in the models for the potential outcomes.

Thus, two models are run in this Endogenous – Treatment regression model. The first model is a choice model – to see whether the respondent is in a group or not. In this study, if one smokes then he/she will be in the group, otherwise not. A regression for observing a positive outcome of the smoking status is modeled with a Probit Model, which can be represented by the following equation:

$$\begin{aligned} SmkStat = {} & \beta_0 + \beta_1 FamilySize + \beta_2 PIR + \beta_3 \mathrm{Age} + \beta_4 Gender + \beta_5 Race + \\ & \beta_6 Citizenship + \beta_7 Education + \beta_8 MaritalStatus + \mathrm{u} \end{aligned} \qquad (7)$$

The residuals from this first choice regression model are included as a regressor in the second regression model. The second model then examines the effects of independent variables on the outcome, i.e. food security.

I use two approaches here; one using 'Survey Linear Regression with Endogenous Treatment ('etregress' in STATA)', in which the smoking is represented by a binary variable in the second stage regression model. This approach will take care of the possible endogeneity problem due to self-selection decision but will not tell about impact of increased smoking on the food security. This approach also takes care of the survey corrections. In the second approach, by using 'Endogenous – Treatment Regression Model ('Proc Qlim' in SAS)', in which the variable 'smoking quantity' is included in the second regression model. This approach will tell about impact of increased smoking on the food security. However, this approach does not take care of the survey corrections and significance levels will be overstated. This second regression model can be represented by the equation (6).

In SAS PROC QLIM and in STATA ETREGRESS it is possible to estimate a treatment model and outcome model when both dependent variables (treatment and outcome) are binary variables, but in the case of the outcome model, this would be similar to running an Ordinary Least Squares (OLS) on a binary dependent variable. Therefore, for these two approaches, I have coded food security variable into the continuous variable on a 'Rasch' scale.

To test for self-selection bias, the study examines the relationship between the residuals for stage 1 and stage 2. If the unobservables in the treatment model (stage 1) are correlated with the unobservables in the outcome regression model (stage 2), it shows that we have biased estimates without correction. It simply means that unobservables in the choice model of being a smoker are also affecting the outcome regression model.

3.5 Results

Among all households, 17.66% households are food insecure (Table 1), whereas among the low income households (i.e. within 200% of poverty level), roughly 33% households are food insecure (Table 2). For smoking, respondents were asked, "Do you now smoke cigarettes?" and "Average number of cigarettes per day during the past 30 days." Among all households roughly 23% are smokers (on average 13.95 cigarettes per day), whereas in low-income households 31.4% are smokers (on average 13.14 cigarettes per day). The average number of cigarettes per day has been converted to half packs (10 cigarettes). Questions about smoking were asked only of respondents who are 20 years of age or older at the time of the survey. For our analyses, I considered only the domain of respondents aged 20 to 60.

Household income is measured using the ratio of family income to poverty as provided in the NHANES data. Summary statistics for variables used in this study is given in Table 1 (for all households), and in Table 2 (for low-income households). There are a few interesting findings such as, among all households, roughly 39% people are college graduate or above (Table 1), whereas among low income households, only 17% people are college graduates or above (Table 2). Among all households, 10% people didn't finish high school (Table 1), whereas among the low income households, roughly 19% people didn't finish high school (Table 2). Among all households, 17% are Hispanic, whereas among the low income households, roughly 25% are Hispanic. In the case of non-Hispanic African Americans, these figures are 12% and 17% for all households and for low-income households' respectively.

First of all, this study has run the Probit models on all households to find the impact of 'smoking status' and 'smoking quantity' on food security status. Table 3 shows the results of the Probit model on all households for 'smoking status' as one of the explanatory variables. The variable 'smoking status' has a negative sign, which means that households in which the respondent is a smoker are less likely than households where the respondent doesn't smoke to be food secure. The mean value of the marginal effect of 'smoking status' on the probability of food security is 0.0628, which signifies that, if the respondent is a smoker, the household is roughly 6.3% less likely to be food secure. Table 4 shows the results of the Probit model on all households for 'smoking quantity' as one of the explanatory variable. The parameter estimate has a negative sign for the variable 'smoking quantity' which means that for each additional half pack of cigarettes smoked per day, you are less likely to be food secure. Mean value of marginal effect of 'smoking quantity' on the probability of food security is 0.005,which signifies that, for each additional half pack of cigarettes, household is roughly 0.5% less likely to be food secure.

For the reasons discussed earlier in this study (to take care of one type of possible endogeneity in this study), the regression models are also run on families within 200% of the federal poverty level i.e. low-income families. Table 5 shows the results of the Probit model on low-income families for ‘smoking status’ as one of the explanatory variables. In this case also, smoking has a negative sign. Here, the mean value of the marginal effect of ‘smoking status’ on the probability of food security, 0.0856, is higher than for the case of all households (0.0628), which signifies that if a respondent is a smoker in a low-income household, this low-income household is roughly 8.56% less likely to be food secure than households where the respondent doesn't smoke.

Similarly, Table 6 shows the results of the Probit model on low-income families for ‘smoking quantity’ as one of the explanatory variables. In this case also, for each additional half pack of cigarettes, low-income households are less likely to be food secure. The mean value of the marginal effect of ‘smoking quantity’ on the probability of food security is 0.0502,which signifies that, for each additional half pack of cigarettes, a low-income household is roughly 5% less likely to be food secure, which is ten times higher as compared to the case of all households (i.e. 0.5% only).

Table 7 to Table 10 shows the results for the Probit model for the cases whose results are mentioned in Table 3 to Table 6 (impact of ‘smoking status’ and ‘smoking quantity’ with respect to all households and low income households), but with survey corrections. The values of parameter estimates are the same, but larger standard errors result in smaller ‘t-values’. It signifies that ignoring survey corrections will lead to smaller variance estimates, and thus significance levels will be overstated.

Tables 11 and 12 show the results of models with survey correction when food insecurity is taken as a continuous variable for all households and low income households, respectively. Results show a positive sign for the variable 'smoking quantity' which means that for each additional half pack of cigarettes the respondent smokes per day, a household's food insecurity level will increase. For example, in case of low income households, for each additional half pack of cigarettes, food insecurity will increase by roughly 0.07 scale points

Table 13 shows the results for the Endogenous – Treatment regression model without survey corrections for low-income households, which gives a statistically significant positive value of 0.029 for the variable smoking quantity in the second stage model. In this second stage model, the dependent variable is scale of food insecurity, which simply means that, for each additional half pack of cigarettes, food insecurity will increase by roughly 0.03 scale points. To test for self-selection bias (possible endogeneity), I examine the relationship between error terms for two stages involved in this method. 'Rho' in results represents the correlation coefficient between error terms of first and second model. In our results, I have a statistically significant negative value of 0.2777 for 'rho'. If it is not statistically significant, it signifies that there are no effects of self-selection, and if this is significant, then one should use Endogenous – Treatment regression model to correct for possible endogeneity due to self-selection bias.

Table 14 shows the results of linear regression with endogenous treatment with survey corrections, which gives a statistically significant positive value of 1.13 for the variable 'smoking status', when scale of food insecurity is the dependent variable. It signifies that the respondent being a smoker is going to increase household insecurity by 1.13 scale points in comparison to non-smoker. In these results with survey corrections, I don't have a statistically significant value for 'rho'. If it is not statistically significant, it signifies that there are no effects of self-selection. So, in a model with survey corrections, there seems no problem of endogeneity due to self-selection decision problem. Thus with ‘Endogenous – treatment’ models, this study has tried to address the possible problem of endogeneity due to self-selection decision problem. If smoking is not endogenous, it would appear that the observed correlation between smoking and food insecurity may be working through the budget constraint. That is, people aren't smoking because they are food insecure; rather, food insecurity is made worse by smoking.

3.6 Limitations

A limitation of all studies that use the USDA food security model is that the level of food security is self-reported. Households may experience objectively similar food hardship, but one respondent may minimize the problem or be embarrassed to report it. Smoking is also self-reported and people may under-report their actual cigarette use. Further, in the NHANES data, the smoking status is reported only for the respondent. If there are other adults in the household who smoke, their smoking may also reduce the available resources to purchase food, meaning that the effect of household smoking on household food security may be under-estimated in this study.

3.7 Conclusions

Many American households struggle to bring in sufficient income to meet basic needs related to nutritionally adequate and safe food. Due to addiction, expenditures on cigarettes may impose an extra financial strain on these low-income households. The results indicate that cigarette smoking is associated with decreased food security and also food insecurity worsens due to more smoking. The results indicate that in low-income households, if the respondent is a smoker, that household is roughly 8.5% less likely to be food secure and for each additional half pack of cigarettes smoked per day, that low-income household is roughly 5% less likely to be food secure. The results indicate that the smokers may substitute cigarettes for nutritional and safe food, which adversely affects household food security. This assessment can guide Food Assistance and Tobacco Control Programs to work together to formulate effective policies. If successful, households will be able to free up family funds that might be used to reduce food insecurity. In recent years, due to a consistent increase in federal and local tobacco excise taxes, cigarette pack prices have been increasing. From evidence it is clear that higher tobacco prices both encourage users to quit tobacco use and reduce tobacco initiation in young people (Chaloupka et al., 2011). However, an unintended consequence of these increased prices may be to worsen food security in low-income families.

As discussed earlier, one of the aims of this study is to see the impact of increased smoking on food security. Even with the data of only low-income households, this study has found that those who reported smoking more cigarettes per day are more likely to find it difficult to maintain food security for their households. It is critically important to develop policies that encourage smokers to quit which would in turn reduce food insecurity.

Table 3. 1 Summary Statistics for All Households (Respondent Age 20 – 60)

Continuous variables					
Variable	**Label**	**Minimum**	**Maximum**	**Mean**	**SE Mean**
Age	Age in years at screening	20.00	60.00	39.93	0.36
Family Size	Total people in the Household	1.00	7.00	3.32	0.04
PIR	Ratio of family income to poverty	0	5.00	2.87	0.08

Categorical variables					
Variable	**N**	**Mean**	**SE of Mean**	**95% CL for Mean**	
Married	7906	0.60	0.014	0.577	0.634
College graduates	7917	0.39	0.019	0.352	0.431
Didn’t finish High school	7928	0.10	0.008	0.080	0.116
Citizen	7902	0.89	0.009	0.872	0.912
Hispanic	7928	0.17	0.019	0.128	0.206
Non-Hispanic black	7928	0.12	0.014	0.093	0.153
Non-Hispanic white	7928	0.62	0.027	0.568	0.678
Female	7928	0.51	0.005	0.496	0.519
Scale – food insecurity	7786	0.97	0.052	0.864	1.080

Table of smokers					
smoker	**Frequency**	**Wgt Freq**	**SD of Wgt Freq**	**Percent**	**SE Percent**
0	5981	130389836	5853684	77.10	0.97
1	1867	38718754	1969509	22.90	0.97

Table of Food Secure People					
Food security	**Freq**	**Wgt Freq**	**SD of Wgt Freq**	**Percent**	**SE Percent**
0	1738	29859150	1515908	17.66	0.95
1	6110	139249441	6486360	82.34	0.95

Average Cigarettes Per day					
Smokers	**Variable**	**Minimum**	**Maximum**	**Mean**	**SE of Mean**
1	Smoke qty	1.00	999.00	13.95	0.75

Note: The study uses survey data from National Health and Nutrition Examination Survey (NHANES) 2011-12 and 2013-14

Table 3. 2 Summary Statistics for Low-Income Households (Respondent Age 20 – 60)

Continuous variables					
Variable	**Label**	**Minimum**	**Maximum**	**Mean**	**SE Mean**
Age	Age in years at screening	20.00	60.00	37.69	0.48
Family Size	Total people in the Household	1.00	7.00	3.66	0.07
PIR	Ratio of family income to poverty	0	2.00	1.03	0.02

Categorical variables					
Variable	**N**	**Mean**	**Std Error of Mean**	**95% CL for Mean**	
Married	4285	0.51	0.019	0.474	0.554
College graduates	4289	0.17	0.016	0.14	0.208
Didn't finish High school	4296	0.19	0.014	0.159	0.219
Citizen	4272	0.83	0.017	0.794	0.864
Hispanic	4296	0.25	0.028	0.195	0.310
Non-Hispanic black	4296	0.17	0.022	0.126	0.218
Non-Hispanic white	4296	0.50	0.038	0.417	0.575
Female	4296	0.52	0.007	0.505	0.535
Scale – food insecurity	4167	1.80	0.060	1.673	1.920

Table of smokers					
Smoker	**Frequency**	**Wgt Freq**	**SD of Wgt Freq**	**Percent**	**SE of Percent**
0	2908	49087174	2432068	68.59	1.51
1	1310	22480407	1625236	31.41	1.51

Table of Food Secure People					
Food security	**Frequency**	**Wgt Freq**	**SD of Wgt Freq**	**Percent**	**SE of Percent**
0	1454	23466497	1393290	32.79	1.40
1	2764	48101084	2631593	67.21	1.40

Average Cigarettes Per day					
Smokers	**Variable**	**Minimum**	**Maximum**	**Mean**	**SE of Mean**
1	Smoke qty	1.00	999.00	13.14	0.85

Note: The study uses survey data from National Health and Nutrition Examination Survey (NHANES) 2011-12 and 2013-14

Table 3. 3 Probit model - All Households for smoking status (Dependent variable: Food Security)

Parameter Estimates					
Parameter	**DF**	**Estimate**	**SE**	**t Value**	**Pr > |t|**
Intercept	1	-0.0293	0.000776	1421.6749	<.0001
Age at screening	1	0.00743	7.518E-6	977196.074	<.0001
Family Size	1	-0.0338	0.000080	179083.420	<.0001
Ratio of family income to poverty	1	0.3328	0.000098	11448779.6	<.0001
Smoker	1	-0.2828	0.000274	1061446.31	<.0001
Female	1	-0.00060	0.000242	6.1248	0.0133
Hispanic	1	-0.1530	0.000522	85997.7909	<.0001
Non-Hispanic black	1	-0.0704	0.000545	16702.5805	<.0001
Non-Hispanic white	1	0.0711	0.000476	22351.8343	<.0001
Citizen	1	-0.0352	0.000435	6520.2294	<.0001
Didn’t finish High school	1	-0.1249	0.000343	132438.587	<.0001
College graduates	1	0.4241	0.000332	1629902.60	<.0001
Married	1	0.1532	0.000255	360870.746	<.0001

Analysis Variable : Marginal effect of smoker on the probability of Food Security=1	
Mean	**Std Dev**
0.0628016	0.0388241

Classification Table									
Prob Level	**Correct**		**Incorrect**		**Percentages**				
	Event	**Non-Event**	**Event**	**Non-Event**	**Correct**	**Sensi-tivity**	**Speci-ficity**	**False POS**	**False NEG**
0.500	8236	222	1852	238	80.2	97.2	10.7	18.4	51.7

Note: The study uses survey data from National Health and Nutrition Examination Survey (NHANES) 2011-12 and 2013-14

Table 3. 4 Probit model - All Households for smoking quantity (Dependent variable: Food Security)

Parameter Estimates					
Parameter	**DF**	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.1416	0.000768	33995.1462	<.0001
Age at screening	1	0.00818	7.441E-6	1208964.28	<.0001
Family Size	1	-0.0341	0.000080	182694.030	<.0001
Ratio of family income to poverty	1	0.3413	0.000098	12127720.1	<.0001
Cigarette pack (half)	1	-0.0225	0.000054	172225.165	<.0001
Female	1	0.0173	0.000240	5164.1588	<.0001
Hispanic	1	-0.1124	0.000521	46469.4260	<.0001
Non-Hispanic black	1	-0.0620	0.000545	12960.3262	<.0001
Non-Hispanic white	1	0.0636	0.000475	17889.8251	<.0001
Citizen	1	-0.0642	0.000436	21678.4671	<.0001
Didn’t finish High school	1	-0.1404	0.000342	168195.629	<.0001
College graduates	1	0.4692	0.000329	2037595.80	<.0001
Married	1	0.1528	0.000255	359777.698	<.0001

Analysis Variable : Marginal effect of cigarette Pack (half) on the probability of Food Security=1	
Mean	**Std Dev**
0.0050145	0.0030905

Classification Table									
Prob Level	**Correct**		**Incorrect**		**Percentages**				
	Event	**Non-Event**	**Event**	**Non-Event**	**Correct**	**Sensi-tivity**	**Speci-ficity**	**False POS**	**False NEG**
0.500	8262	190	1878	201	80.3	97.6	9.2	18.5	51.4

Note: The study uses survey data from National Health and Nutrition Examination Survey (NHANES) 2011-12 and 2013-14

Table 3. 5 Probit model - Low Income Households for smoking status (Dependent variable: Food Security)

Parameter Estimates					
Parameter	**DF**	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.5265	0.00111	225002.333	<.0001
Age at screening	1	-0.00458	0.000014	103087.453	<.0001
Family Size	1	-0.0275	0.000105	69046.2770	<.0001
Ratio of family income to poverty	1	0.2835	0.000338	703912.287	<.0001
Smoker	1	-0.2373	0.000373	404110.951	<.0001
Female	1	-0.0538	0.000336	25729.5372	<.0001
Hispanic	1	-0.2246	0.000726	95798.8088	<.0001
Non-Hispanic black	1	-0.0268	0.000753	1268.4825	<.0001
Non-Hispanic white	1	-0.0138	0.000682	411.0118	<.0001
Citizen	1	-0.0570	0.000554	10590.9643	<.0001
Didn’t finish High school	1	-0.00770	0.000448	296.1614	<.0001
College graduates	1	0.3500	0.000517	457630.077	<.0001
Married	1	0.0583	0.000354	27066.4753	<.0001

Analysis Variable : Marginal effect of smoker on the probability of Food Security=1	
Mean	**Std Dev**
0.0855856	0.0099446

Classification Table									
Prob Level	**Correct**		**Incorrect**		**Percentages**				
	Event	**Non-Event**	**Event**	**Non-Event**	**Correct**	**Sensi-tivity**	**Speci-ficity**	**False POS**	**False NEG**
0.500	2189	111	1231	107	63.2	95.3	8.3	36.0	49.1

Note: The study uses survey data from National Health and Nutrition Examination Survey (NHANES) 2011-12 and 2013-14

Table 3. 6 Probit model – Low Income Household for smoking quantity (Dependent variable: Food Security)

Parameter Estimates					
Parameter	**DF**	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.4882	0.00111	194137.875	<.0001
Age at screening	1	-0.00410	0.000014	81299.7160	<.0001
Family Size	1	-0.0286	0.000105	74349.3097	<.0001
Ratio of family income to poverty	1	0.2849	0.000338	711658.870	<.0001
Cigarette pack (half)	1	-0.1395	0.000223	389388.944	<.0001
Female	1	-0.0614	0.000337	33179.7570	<.0001
Hispanic	1	-0.2149	0.000727	87477.4072	<.0001
Non-Hispanic black	1	-0.0310	0.000753	1697.8738	<.0001
Non-Hispanic white	1	-0.00021	0.000684	0.0919	0.7617
Citizen	1	-0.0668	0.000554	14570.0577	<.0001
Didn't finish High school	1	-0.00566	0.000449	158.9518	<.0001
College graduates	1	0.3603	0.000514	491317.750	<.0001
Married	1	0.0656	0.000355	34125.5022	<.0001

Analysis Variable : Marginal effect of cigarette Pack (half) on the probability of Food Security=1	
Mean	**Std Dev**
0.0502665	0.0058197

Classification Table									
Prob Level	**Correct**		**Incorrect**		**Percentages**				
	Event	**Non-Event**	**Event**	**Non-Event**	**Correct**	**Sensi-tivity**	**Speci-ficity**	**False POS**	**False NEG**
0.500	2202	104	1234	91	63.5	96.0	7.8	35.9	46.7

Note: The study uses survey data from National Health and Nutrition Examination Survey (NHANES) 2011-12 and 2013-14

Table 3. 7 Probit model with Survey Correction – All Households for smoking status (Dependent variable: Food Security)

Parameter Estimates				
Parameter	**Estimate**	**SE**	**t Value**	**Pr > |t|**
Intercept	-0.0293	0.1698	-0.17	0.8642
Age at screening	0.00743	0.00179	4.16	0.0002
Family Size	-0.0338	0.0280	-1.20	0.2372
Ratio of family income to poverty	0.3328	0.0224	14.89	<.0001
Smoker	-0.2828	0.0615	-4.60	<.0001
Female	-0.00060	0.0402	-0.01	0.9882
Hispanic	-0.1530	0.0973	-1.57	0.1257
Non-Hispanic black	-0.0704	0.0903	-0.78	0.4411
Non-Hispanic white	0.0711	0.0899	0.79	0.4349
Citizen	-0.0352	0.0744	-0.47	0.6396
Didn’t finish High school	-0.1249	0.0626	-2.00	0.0544
College graduates	0.4241	0.0820	5.17	<.0001
Married	0.1532	0.0635	2.41	0.0218

Classification Table									
Prob Level	**Correct**		**Incorrect**		**Percentages**				
	Event	**Non-Event**	**Event**	**Non-Event**	**Correct**	**Sensi-tivity**	**Speci-ficity**	**False POS**	**False NEG**
0.500	8112	1030	1044	364	86.7	95.7	49.7	11.4	26.1

Note: The study uses survey data from National Health and Nutrition Examination Survey (NHANES) 2011-12 and 2013-14

Table 3. 8 Probit model with Survey Correction – All Households for smoking quantity (Dependent variable: Food Security)

Parameter Estimates				
Parameter	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	-0.1416	0.1616	-0.88	0.3876
Age at screening	0.00818	0.00175	4.68	<.0001
Family Size	-0.0341	0.0285	-1.19	0.2412
Ratio of family income to poverty	0.3413	0.0224	15.23	<.0001
Cigarette pack (half)	-0.0225	0.0141	-1.59	0.1216
Female	0.0173	0.0414	0.42	0.6790
Hispanic	-0.1124	0.0990	-1.13	0.2649
Non-Hispanic black	-0.0620	0.0929	-0.67	0.5092
Non-Hispanic white	0.0636	0.0922	0.69	0.4952
Citizen	-0.0642	0.0743	-0.86	0.3936
Didn't finish High school	-0.1404	0.0620	-2.26	0.0305
College graduates	0.4692	0.0797	5.89	<.0001
Married	0.1528	0.0630	2.42	0.0212

Classification Table									
Prob Level	**Correct**		**Incorrect**		**Percentages**				
	Event	**Non-Event**	**Event**	**Non-Event**	**Correct**	**Sensi-tivity**	**Speci-ficity**	**False POS**	**False NEG**
0.500	8150	989	1079	315	86.8	96.3	47.8	11.7	24.2

Note: The study uses survey data from National Health and Nutrition Examination Survey (NHANES) 2011-12 and 2013-14

Table 3. 9 Probit model with Survey Correction – Low Income Households for smoking status (Dependent variable: Food Security)

Parameter Estimates				
Parameter	**Estimate**	**SE**	**t Value**	**Pr > |t|**
Intercept	0.5265	0.2082	2.53	0.0166
Age at screening	-0.00458	0.00331	-1.39	0.1755
Family Size	-0.0275	0.0288	-0.96	0.3464
Ratio of family income to poverty	0.2835	0.0736	3.85	0.0005
Smoker	-0.2373	0.0750	-3.16	0.0034
Female	-0.0538	0.0629	-0.86	0.3982
Hispanic	-0.2246	0.1049	-2.14	0.0399
Non-Hispanic black	-0.0268	0.1087	-0.25	0.8067
Non-Hispanic white	-0.0138	0.1070	-0.13	0.8979
Citizen	-0.0570	0.1006	-0.57	0.5751
Didn’t finish High school	-0.00770	0.0789	-0.10	0.9229
College graduates	0.3500	0.1368	2.56	0.0154
Married	0.0583	0.0781	0.75	0.4607

Classification Table									
Prob Level	**Correct**		**Incorrect**		**Percentages**				
	Event	**Non-Event**	**Event**	**Non-Event**	**Correct**	**Sensi-tivity**	**Speci-ficity**	**False POS**	**False NEG**
0.500	8396	1385	689	80	92.7	99.1	66.8	7.6	5.5

Note: The study uses survey data from National Health and Nutrition Examination Survey (NHANES) 2011-12 and 2013-14

Table 3. 10 Probit model with Survey Correction – Low Income Households for smoking quantity (Dependent variable: Food Security)

Parameter Estimates				
Parameter	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	0.4882	0.2008	2.43	0.0208
Age at screening	-0.00410	0.00320	-1.28	0.2087
Family Size	-0.0286	0.0286	-1.00	0.3242
Ratio of family income to poverty	0.2849	0.0731	3.90	0.0005
Cigarette pack (half)	-0.1395	0.0522	-2.67	0.0118
Female	-0.0614	0.0615	-1.00	0.3258
Hispanic	-0.2149	0.1030	-2.09	0.0449
Non-Hispanic black	-0.0310	0.1053	-0.29	0.7700
Non-Hispanic white	-0.00021	0.1097	-0.00	0.9985
Citizen	-0.0668	0.0972	-0.69	0.4966
Didn’t finish High school	-0.00566	0.0789	-0.07	0.9433
College graduates	0.3603	0.1352	2.67	0.0119
Married	0.0656	0.0773	0.85	0.4022

Classification Table									
Prob Level	**Correct**		**Incorrect**		**Percentages**				
	Event	**Non-Event**	**Event**	**Non-Event**	**Correct**	**Sensi-tivity**	**Speci-ficity**	**False POS**	**False NEG**
0.500	8392	1380	688	73	92.8	99.1	66.7	7.6	5.0

Note: The study uses survey data from National Health and Nutrition Examination Survey (NHANES) 2011-12 and 2013-14

Table 3. 11 Model with Survey Correction – All Households for smoking quantity (Dependent variable: Food Insecurity as a continuous variable)

Parameter Estimates				
Parameter	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	2.3268733	0.15249524	15.26	<.0001
Age at screening	-0.0097271	0.00156820	-6.20	<.0001
Family Size	0.0256760	0.03312601	0.78	0.4440
Ratio of family income to poverty	-0.3438277	0.01788451	-19.22	<.0001
Cigarette pack (half)	0.0379869	0.02147471	1.77	0.0864
Female	-0.0064242	0.03859886	-0.17	0.8689
Hispanic	0.1312978	0.09380042	1.40	0.1712
Non-Hispanic black	0.1911024	0.09131669	2.09	0.0444
Non-Hispanic white	-0.0396458	0.07542839	-0.53	0.6028
Citizen	0.0312538	0.08549097	0.37	0.7171
Didn’t finish High school	0.2129976	0.08948385	2.38	0.0234
College graduates	-0.2916287	0.04986841	-5.85	<.0001
Married	-0.1096995	0.06233108	-1.76	0.0880

Fit Statistics	
R-Square	0.2030
Adjusted R-Square	0.2026
Root MSE	1.5467
Denominator DF	32

Note: The study uses survey data from National Health and Nutrition Examination Survey (NHANES) 2011-12 and 2013-14

Table 3. 12 Model with Survey Correction – Low Income Households for smoking quantity (Dependent variable: Food Insecurity as a continuous variable)

Parameter Estimates				
Parameter	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	2.0202161	0.39093588	5.17	<.0001
Age at screening	0.0106917	0.00534759	2.00	0.0541
Family Size	0.0118047	0.04948918	0.24	0.8130
Ratio of family income to poverty	-0.5846372	0.14155482	-4.13	0.0002
Cigarette pack (half)	0.0759183	0.03170965	2.39	0.0227
Female	0.0807740	0.09588818	0.84	0.4058
Hispanic	0.0625749	0.20417758	0.31	0.7612
Non-Hispanic black	-0.0376362	0.20201903	-0.19	0.8534
Non-Hispanic white	-0.0918149	0.18844213	-0.49	0.6294
Citizen	0.2054359	0.17134641	1.20	0.2394
Didn’t finish High school	-0.0504650	0.14416887	-0.35	0.7286
College graduates	-0.7394652	0.20406480	-3.62	0.0010
Married	-0.0193060	0.12226666	-0.16	0.8755

Fit Statistics	
R-Square	0.1353
Adjusted R-Square	0.1347
Root MSE	1.1145
Denominator DF	32

Note: The study uses survey data from National Health and Nutrition Examination Survey (NHANES) 2011-12 and 2013-14

Table 3. 13 Endogenous – Treatment Regression Model (Low Income Households)

Model 1: Dependent variable: Smoker (Binary variable) Model 2: Dependent variable: Food Insecurity Scale (Continuous variable)					
Parameter	**DF**	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
scale.Intercept	1	2.850884	0.594741	4.79	<.0001
scale.Age	1	0.006088	0.006321	0.96	0.3355
scale.FamilySize	1	0.013809	0.042476	0.33	0.7451
scale.Poverty Income Ratio	1	-0.528034	0.162651	-3.25	0.0012
scale.cigarette pack half	1	0.029865	0.017166	1.74	0.0819
scale.female	1	0.375262	0.164223	2.29	0.0223
scale.hispanic	1	0.489376	0.328792	1.49	0.1366
scale.non-hispanic black	1	0.117246	0.300802	0.39	0.6967
scale.non-hispanic white	1	0.300020	0.323518	0.93	0.3537
scale. Didn’t finish High school	1	0.025849	0.178780	0.14	0.8850
scale. College graduates	1	-0.347845	0.403664	-0.86	0.3888
scale.Married	1	0.114353	0.151173	0.76	0.4494
_Sigma.scale	1	2.501246	0.090602	27.61	<.0001
smoker.Intercept	1	-0.831143	0.124000	-6.70	<.0001
smoker.Age	1	0.005179	0.001906	2.72	0.0066
smoker. Poverty Income Ratio	1	-0.223662	0.046673	-4.79	<.0001
smoker.female	1	-0.296885	0.045721	-6.49	<.0001
smoker.hispanic	1	-0.235302	0.087566	-2.69	0.0072
smoker. non-hispanic black	1	0.097130	0.084665	1.15	0.2513
smoker. non-hispanic white	1	0.486848	0.081057	6.01	<.0001
smoker.citizen	1	0.519014	0.077101	6.73	<.0001
smoker. Didn’t finish High school	1	0.126578	0.059278	2.14	0.0327
smoker. College graduates	1	-0.812581	0.080164	-10.14	<.0001
_Rho	1	-0.277717	0.147392	-1.88	0.0595

Note: The study uses survey data from National Health and Nutrition Examination Survey (NHANES) 2011-12 and 2013-14

Table 3. 14 Linear Regression with endogenous treatment with survey corrections (Low Income Households)

		Estimate	Standard Error	t value	P value
scale					
	age	0.008257	0.0049259	1.68	0.103
	familysize	0.0082411	0.049434	0.17	0.869
	poverty income ratio	-0.4984522	0.1458003	-3.42	0.002
	female	0.1393001	0.1015698	1.37	0.18
	hispanic	0.1917146	0.1992718	0.96	0.343
	non-hispanic black	0.0036583	0.1831286	0.02	0.984
	non-hispanic white	-0.1620763	0.1704827	-0.95	0.349
	didn't finish High school	-0.1299032	0.1418365	-0.92	0.367
	college graduates	-0.4721692	0.2433687	-1.94	0.061
	married	-0.0185092	0.1209067	-0.15	0.879
	1.smoker	1.133934	0.4178292	2.71	0.011
	_cons	1.807839	0.4110875	4.4	0
smoker					
	age	0.0073283	0.0042068	1.74	0.091
	poverty income ratio	-0.2788823	0.0805219	-3.46	0.002
	female	-0.2086832	0.0649422	-3.21	0.003
	hispanic	-0.3771282	0.119786	-3.15	0.004
	non-hispanic black	-0.0887797	0.1544597	-0.57	0.569
	non-hispanic white	0.2521945	0.1590227	1.59	0.123
	citizen	0.5521057	0.0938307	5.88	0
	didn't finish High school	0.1950377	0.0667392	2.92	0.006
	college graduates	-0.9481319	0.1245815	-7.61	0
	_cons	-0.7570052	0.2286479	-3.31	0.002
	/athrho	-0.1523178	0.1027741	-1.48	0.148
	/lnsigma	0.8047527	0.0243073	33.11	0
	rho	-0.1511507	0.1004261		
	sigma	2.236143	0.0543546		
	lambda	-0.3379946	0.2298701		

Note: The study uses survey data from National Health and Nutrition Examination Survey (NHANES) 2011-12 and 2013-14

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Appendix 1: Supporting information (SI) for Chapter 2

Item A. Copula Approach

In this item we briefly discuss the copula approach utilized in our analysis to obtain the joint yield-price distributions. For a more detailed discussion about the approach, its application, and the examination of estimation results, we refer readers to Item 3 of the online supporting information of Miao and Khanna (2017).

Sklar (1959) showed that any continuous *l*-dimensional joint distribution, $F(z_1,...,z_l)$, can be uniquely expressed by *l* marginal distributions and an *l*-dimensional copula function, where the latter is an *l*-dimensional joint distribution with standard uniform marginal distributions. That is,

$$F(z_1,...,z_l) = C(F_1(z_1),...,F_l(z_l)), \tag{SI-1}$$

where $C(\cdot)$ is the copula function; and $F_i(z_i)$ is the marginal distribution of random variable $z_i,\ i \in \{1,...,l\}$. Define $\eta_i \equiv F_i\left(z_i\right),$ then the copula function in equation (SI-1) becomes

$$C(\eta_1,...,\eta_l) = F(F_1^{-1}(\eta_1),...,F_l^{-1}(\eta_l)), \tag{SI-2}$$

where $F_i^{-1}(\cdot),\ i \in \{1,...,l\}$ is the inverse marginal distribution function of random variable z_l. Due to its popularity in risk management, we utilize the Multivariate Gaussian Copula (MGC) in our simulation (Zhu, Ghosh, and Goodwin 2008). The MGC is

$$C(\eta_1,...,\eta_l;\rho) = \Phi_l(\Phi^{-1}(\eta_1),\ ...\ ,\Phi^{-1}(\eta_l);\rho), \tag{SI-3}$$

where ρ is a dependence matrix that captures dependence between the marginal distributions; $\Phi_l(\cdot)$ is the *l*-dimensional multivariate standard normal distribution with mean zero and correlation matrix as ρ, and $\Phi^{-1}(\cdot)$ is the inverse distribution function of the standard one-dimensional normal distribution.

Based on the MGC, once we identify the marginal distributions, $F_i(z_i)$, $i \in \{1,\ldots,l\}$, and the dependence matrix, ρ, then we can obtain the joint distribution, $F(\cdot)$, by equations (SI-1) and (SI-3). In our study, we estimate marginal distributions of crop yields by using the 27-year crop yield data obtained from DayCent model and estimate marginal distributions of crop prices by using futures prices in the same years as those of crop yields. We assume that crop yields have beta distributions and crop prices have log-normal distributions. Once we estimate the marginal distributions, the estimation of the copula is performed by using command "copulafit" of MATLAB®. We refer readers to Miao and Khanna (2017) for details regarding how to obtain random draws from the estimated copula and an evaluation about the copula estimation.

Another approach that is widely used in the literature to obtain joint yield-price distributions is the deviate approach in which correlated price and yield deviates are generated (e.g., Paulson and Babcock 2008; Claassen, Cooper, and Carriazo 2011). It has the advantage of simplicity but lacks solid statistical foundation and flexibility when compared with the copula approach.

Table SI-1. Profitability and Riskiness (Probability of Negative 30-year NPV) of Crops

	Mean	S.D.	Min.	Max.	CV
When biomass price is $50/MT					
Profitability (30-year NPV of profits, $/ha)[a]:					
Conventional crops on high quality land	6,264	2,700	-4,111	36,748	0.4
Conventional crops on low quality land	5,580	2,584	-3,390	37,480	0.5
Miscanthus on high quality land	1,417	2,063	-9,942	12,861	1.7
Miscanthus on low quality land	1,304	2,042	-9,565	11,792	2.1
Switchgrass on high quality land	2,277	1,652	-3,747	13,157	0.9
Switchgrass on low quality land	1,844	1,672	-3,747	11,882	1.0
Probability of having negative yearly profits (%)[b]:					
Conventional crops on high quality land	0.9	4.9	0.0	72	5.5
Conventional crops on low quality land	0.9	4.8	0.0	68	5.4
Miscanthus on high quality land	8.0	2.8	7.3	40	0.3
Miscanthus on low quality land	8.2	3.4	7.3	38	0.4
Switchgrass on high quality land	10.8	9.7	0.0	73	0.9
Switchgrass on low quality land	16.8	11.4	0.0	98	0.7
When biomass price is $100/MT					
Profitability (30-year NPV of profits, $/ha)[a]:					
Conventional crops on high quality land	7,162	2,756	-3,005	38,667	0.4
Conventional crops on low quality land	6,398	2,656	-2,794	38,716	0.4
Miscanthus on high quality land	12,890	4,356	-9,517	40,816	0.3
Miscanthus on low quality land	12,635	4,309	-9,444	38,955	0.3
Switchgrass on high quality land	9,762	4,156	-3,747	36,857	0.4
Switchgrass on low quality land	8,685	4,207	-3,747	34,583	0.5
Probability of having negative yearly profits (%)[b]:					
Conventional crops on high quality land	0.3	2.8	0.0	60	8.1
Conventional crops on low quality land	0.3	2.7	0.0	55	8.5
Miscanthus on high quality land	7.4	0.5	7.3	12	0.1
Miscanthus on low quality land	7.5	0.7	7.3	17	0.1
Switchgrass on high quality land	1.1	1.8	0.0	10	1.7
Switchgrass on low quality land	1.9	2.5	0.0	14	1.3

Note: [a] The county-level CV of profits from a crop grown on land with a certain quality in each county is calculated based on the 1,000 yield-price draws generated by using the copula approach. The CV values presented here are averages of county-level CVs across all counties. [b] The CV values for probability of having negative yearly profits are calculated by using mean and standard deviation values in this table.

Table SI-2. Profitability and Riskiness (Probability of Negative Yearly profits) of Crops

	Mean	S.D.	Min.	Max.	CV
When biomass price is $50/MT					
Profitability (30-year NPV of profits, $/ha)[a]:					
Conventional crops on high quality land	6,264	2,700	-4,111	36,748	0.4
Conventional crops on low quality land	5,580	2,584	-3,390	37,480	0.5
Miscanthus on high quality land	1,417	2,063	-9,942	12,861	1.7
Miscanthus on low quality land	1,304	2,042	-9,565	11,792	2.1
Switchgrass on high quality land	2,277	1,652	-3,747	13,157	0.9
Switchgrass on low quality land	1,844	1,672	-3,747	11,882	1.0
Probability of having negative yearly profits (%)[b]:					
Conventional crops on high quality land	0.9	4.9	0.0	72	5.5
Conventional crops on low quality land	0.9	4.8	0.0	68	5.4
Miscanthus on high quality land	8.0	2.8	7.3	40	0.3
Miscanthus on low quality land	8.2	3.4	7.3	38	0.4
Switchgrass on high quality land	10.8	9.7	0.0	73	0.9
Switchgrass on low quality land	16.8	11.4	0.0	98	0.7
When biomass price is $100/MT					
Profitability (30-year NPV of profits, $/ha)[a]:					
Conventional crops on high quality land	7,162	2,756	-3,005	38,667	0.4
Conventional crops on low quality land	6,398	2,656	-2,794	38,716	0.4
Miscanthus on high quality land	12,890	4,356	-9,517	40,816	0.3
Miscanthus on low quality land	12,635	4,309	-9,444	38,955	0.3
Switchgrass on high quality land	9,762	4,156	-3,747	36,857	0.4
Switchgrass on low quality land	8,685	4,207	-3,747	34,583	0.5
Probability of having negative yearly profits (%)[b]:					
Conventional crops on high quality land	0.3	2.8	0.0	60	8.1
Conventional crops on low quality land	0.3	2.7	0.0	55	8.5
Miscanthus on high quality land	7.4	0.5	7.3	12	0.1
Miscanthus on low quality land	7.5	0.7	7.3	17	0.1
Switchgrass on high quality land	1.1	1.8	0.0	10	1.7
Switchgrass on low quality land	1.9	2.5	0.0	14	1.3

Note: [a] The county-level CV of profits from a crop grown on land with a certain quality in each county is calculated based on the 1,000 yield-price draws generated by using the copula approach. The CV values presented here are averages of county-level CVs across all counties. [b] The CV values for probability of having negative yearly profits are calculated by using mean and standard deviation values in this table.

Table SI-3: Biomass Production without credit constraint (Million MT)

Biomass Type	Land Type	Loss Neutral High Discount	Loss Averse High Discount	Loss Neutral Low Discount	Loss Averse Low Discount
		[1]	[2]	[3]	[4]
When biomass price is $50/MT					
Corn Stover	High Quality	95.8	95.8	95.6	95.6
	Low Quality	13.0	12.9	12.6	12.6
	All land	108.8	108.7	108.2	108.2
Miscanthus	High Quality	0.3	0.4	5.5	5.6
	Low Quality	0.1	0.1	6.7	6.7
	All land	0.4	0.5	12.2	12.3
Switchgrass	High Quality	0.5	0.8	0.3	0.4
	Low Quality	0.1	0.2	0.0	0.1
	All land	0.6	1.0	0.3	0.5
Total Biomass	High Quality	96.7	97.0	101.3	101.5
	Low Quality	13.2	13.3	19.4	19.5
	All land	109.9	110.2	120.7	121.0
When biomass price is $100/MT					
Corn Stover	High Quality	82.4	82.4	81.4	81.4
	Low Quality	8.8	8.8	8.4	8.4
	All land	91.2	91.2	89.8	89.8
Miscanthus	High Quality	227.5	227.5	241.8	241.8
	Low Quality	73.0	73.0	77.63	77.60
	All land	300.6	300.6	319.4	319.4
Switchgrass	High Quality	4.1	4.1	1.0	1.0
	Low Quality	4.0	4.0	2.9	2.9
	All land	8.1	8.1	3.9	3.9
Total Biomass	High Quality	314.1	314.2	324.1	324.2
	Low Quality	85.8	85.8	89.0	88.9
	All land	399.9	399.9	413.1	413.1

Table SI-4: Biomass Production without credit constraint (Million MT)

Biomass Type	Land Type	Loss Neutral High Discount	Loss Averse High Discount	Loss Neutral Low Discount	Loss Averse Low Discount
		[1]	[2]	[3]	[4]
		When biomass price is $50/MT			
Corn Stover	High Quality	95.8	95.8	95.6	95.6
	Low Quality	13.0	12.9	12.6	12.6
	All land	108.8	108.7	108.2	108.2
Miscanthus	High Quality	0.3	0.4	5.5	5.6
	Low Quality	0.1	0.1	6.7	6.7
	All land	0.4	0.5	12.2	12.3
Switchgrass	High Quality	0.5	0.8	0.3	0.4
	Low Quality	0.1	0.2	0.0	0.1
	All land	0.6	1.0	0.3	0.5
Total Biomass	High Quality	96.7	97.0	101.3	101.5
	Low Quality	13.2	13.3	19.4	19.5
	All land	109.9	110.2	120.7	121.0
		When biomass price is $100/MT			
Corn Stover	High Quality	82.4	82.4	81.4	81.4
	Low Quality	8.8	8.8	8.4	8.4
	All land	91.2	91.2	89.8	89.8
Miscanthus	High Quality	227.5	227.5	241.8	241.8
	Low Quality	73.0	73.0	77.63	77.60
	All land	300.6	300.6	319.4	319.4
Switchgrass	High Quality	4.1	4.1	1.0	1.0
	Low Quality	4.0	4.0	2.9	2.9
	All land	8.1	8.1	3.9	3.9
Total Biomass	High Quality	314.1	314.2	324.1	324.2
	Low Quality	85.8	85.8	89.0	88.9
	All land	399.9	399.9	413.1	413.1

Table SI-5. Land use for Miscanthus and Switchgrass without credit constraint (in Acres)

Land Type	Loss Neutral High Discount	Loss Averse High Discount	Loss Neutral Low Discount	Loss Averse Low Discount
	[1]	[2]	[3]	[4]
When biomass price is $50/MT				
For Miscanthus				
high quality land	28,162	29,390	498,700	521,413
low quality land	8,261	8,872	599,368	613,340
total land	36,422	38,261	1,098,068	1,134,753
For Switchgrass				
high quality land	93,724	157,800	55,129	70,818
low quality land	20,332	39,456	10,146	13,376
total land	114,056	197,255	65,275	84,194
When biomass price is $100/MT				
For Miscanthus				
high quality land	23,125,743	23,130,013	25,139,538	25,142,081
low quality land	7,221,634	7,217,365	7,960,891	7,958,347
total land	30,347,378	30,347,378	33,100,428	33,100,428
For Switchgrass				
high quality land	772,027	772,027	183,532	183,532
low quality land	804,824	804,824	565,930	565,930
total land	1,576,851	1,576,851	749,462	749,462

Table SI-6: Biomass Production with credit constraint (Million MT)
Case: - Land conversion limit 100%

Biomass Type	Land Type	Loss Neutral High Discount	Loss Averse High Discount	Loss Neutral Low Discount	Loss Averse Low Discount
		[1]	[2]	[3]	[4]
When biomass price is $50/MT					
Corn Stover	High Quality	95.6	95.6	94.3	95.6
	Low Quality	11.3	11.4	10.2	11.3
	All land	106.9	107.0	104.5	106.9
Miscanthus	High Quality	2.8	0.0	28.0	0.6
	Low Quality	1.1	0.0	24.3	1.0
	All land	4.0	0.0	52.3	1.6
Switchgrass	High Quality	2.7	2.8	0.5	2.9
	Low Quality	0.7	0.7	0.1	0.6
	All land	3.4	3.5	0.6	3.4
Total Biomass	High Quality	101.1	98.5	122.8	99.1
	Low Quality	13.2	12.0	34.6	12.9
	All land	114.3	110.5	157.3	112.0
When biomass price is $100/MT					
Corn Stover	High Quality	14.3	45.7	9.0	17.7
	Low Quality	1.4	2.6	1.0	1.5
	All land	15.7	48.3	10.0	19.2
Miscanthus	High Quality	1001.0	224.4	1071.1	953.9
	Low Quality	143.3	82.8	150.5	139.9
	All land	1144.3	307.2	1221.6	1093.8
Switchgrass	High Quality	28.7	297.5	6.8	38.4
	Low Quality	12.8	39.6	10.2	14.6
	All land	41.5	337.2	17.0	53.1
Total Biomass	High Quality	1043.9	567.7	1086.9	1010.0
	Low Quality	157.5	125.0	161.7	156.1
	All land	1201.5	692.6	1248.6	1166.0

Table SI-7: Biomass Production with credit constraint (Million MT)
Case: - Considering 30-years combine decision weighted utility.

Biomass Type	Land Type	Loss Neutral High Discount	Loss Averse High Discount	Loss Neutral Low Discount	Loss Averse Low Discount
		[1]	[2]	[3]	[4]
When biomass price is $50/MT					
Corn Stover	High Quality	95.8	95.7	95.5	95.4
	Low Quality	13.0	13.0	12.6	12.6
	All land	108.7	108.7	108.1	108.1
Miscanthus	High Quality	1.4	1.5	7.0	7.3
	Low Quality	0.1	0.1	7.0	7.1
	All land	1.5	1.6	14.0	14.4
Switchgrass	High Quality	0.6	0.9	0.3	0.4
	Low Quality	0.3	0.4	0.1	0.2
	All land	0.9	1.3	0.4	0.6
Total Biomass	High Quality	97.8	98.1	102.8	103.2
	Low Quality	13.4	13.5	19.7	19.9
	All land	111.2	111.6	122.5	123.1
When biomass price is $100/MT					
Corn Stover	High Quality	82.6	82.6	81.6	81.6
	Low Quality	8.8	8.8	8.4	8.4
	All land	91.4	91.4	90.1	90.1
Miscanthus	High Quality	216.8	216.8	230.8	230.8
	Low Quality	72.7	72.7	77.4	77.4
	All land	289.5	289.5	308.3	308.3
Switchgrass	High Quality	8.7	8.7	5.1	5.1
	Low Quality	4.3	4.3	2.9	2.9
	All land	13.1	13.1	8.1	8.1
Total Biomass	High Quality	308.2	308.2	317.6	317.6
	Low Quality	85.8	85.8	88.9	88.9
	All land	394.0	394.0	406.4	406.4

Table SI-8: Biomass production (Million MT) on Total Land under different scenarios for a range of biomass prices

	Loss Neutral High Discount				Loss Averse High Discount				Loss Neutral Low Discount				Loss Averse Low Discount			
	Credit Constrained															
Biomass Price	**CS**	**MIS**	**SG**	**Total**	**CS**	**MIS**	**SG**	**Total**	**CS**	**MIS**	**SG**	**Total**	**CS**	**MIS**	**SG**	**Total**
20	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30	2.6	0.0	0.0	2.6	2.6	0.0	0.0	2.6	2.6	0.0	0.0	2.6	2.6	0.0	0.0	2.6
40	89.2	0.0	0.0	89.2	89.2	0.0	0.3	89.5	89.2	0.1	0.0	89.3	89.2	0.0	0.3	89.5
50	108.8	0.4	0.9	110.1	108.7	0.0	1.4	110.1	108.4	8.3	0.4	117.1	108.6	2.0	1.3	111.9
60	111.0	7.7	3.9	122.7	111.2	1.9	4.9	118.0	108.2	53.8	0.6	162.6	110.1	22.9	3.8	136.8
70	109.7	42.3	7.5	159.5	110.9	16.4	12.0	139.3	99.8	187.4	1.5	288.7	105.3	108.7	5.9	219.9
80	103.4	135.8	14.6	253.8	106.8	68.8	24.8	200.4	92.1	281.8	2.9	376.8	97.8	210.1	8.6	316.5
90	95.4	244.0	15.0	354.3	101.7	134.6	34.0	270.3	90.5	304.9	4.2	399.5	93.0	275.7	8.5	377.2
100	92.0	282.7	15.6	390.4	97.0	184.9	43.6	325.5	90.2	314.8	4.9	409.9	91.3	299.5	8.9	399.6
	Not Credit Constrained															
Biomass Price	**CS**	**MIS**	**SG**	**Total**	**CS**	**MIS**	**SG**	**Total**	**CS**	**MIS**	**SG**	**Total**	**CS**	**MIS**	**SG**	**Total**
20	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30	2.6	0.0	0.0	2.6	2.6	0.0	0.0	2.6	2.6	0.0	0.0	2.6	2.6	0.0	0.0	2.6
40	89.2	0.0	0.0	89.2	89.2	0.0	0.1	89.3	89.2	0.1	0.0	89.3	89.2	0.2	0.2	89.6
50	108.8	0.4	0.6	109.9	108.7	0.5	1.0	110.2	108.2	12.1	0.3	120.7	108.2	12.4	0.4	121.0
60	110.7	14.6	3.0	128.3	110.7	14.5	3.2	128.3	106.5	79.7	0.5	186.7	106.5	79.7	0.5	186.7
70	108.0	74.9	4.5	187.3	108.0	74.8	4.6	187.4	95.8	236.6	1.1	333.5	95.8	236.5	1.1	333.4
80	98.4	209.5	6.8	314.6	98.3	209.4	6.9	314.6	90.7	295.1	2.1	388.0	90.7	295.1	2.2	388.0
90	93.2	275.9	7.3	376.4	93.2	275.5	7.6	376.3	90.0	310.3	3.5	403.8	90.0	310.3	3.5	403.8
100	91.2	300.6	8.1	399.9	91.2	300.6	8.1	399.9	89.8	319.4	3.9	413.1	89.8	319.4	3.9	413.1

Note: CS - Corn Stover, MIS - Miscanthus, SG - Switchgrass, Total - Total Biomass

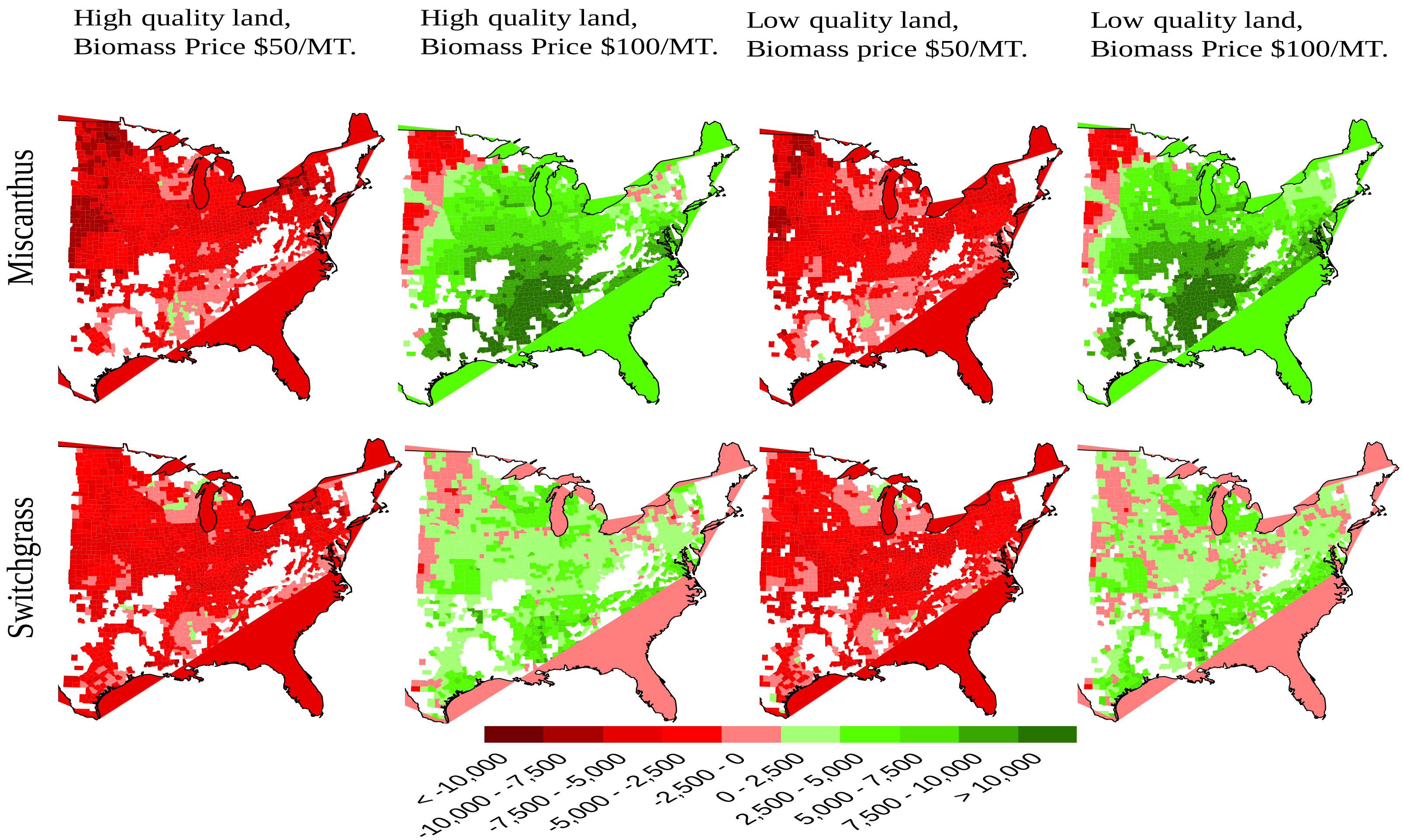


Figure SI-1. Profitability Difference between Bio-energy Crops and the Conventional Crops ($/ha)

Note: Each map depicts the county-level value of the expected 30-year NPV of miscanthus (or switchgrass) profits minus that of conventional crop. So red colors or negative numbers indicate that miscanthus (or switchgrass) has low profitability than does the conventional crops; green colors or positive numbers indicate the opposite.

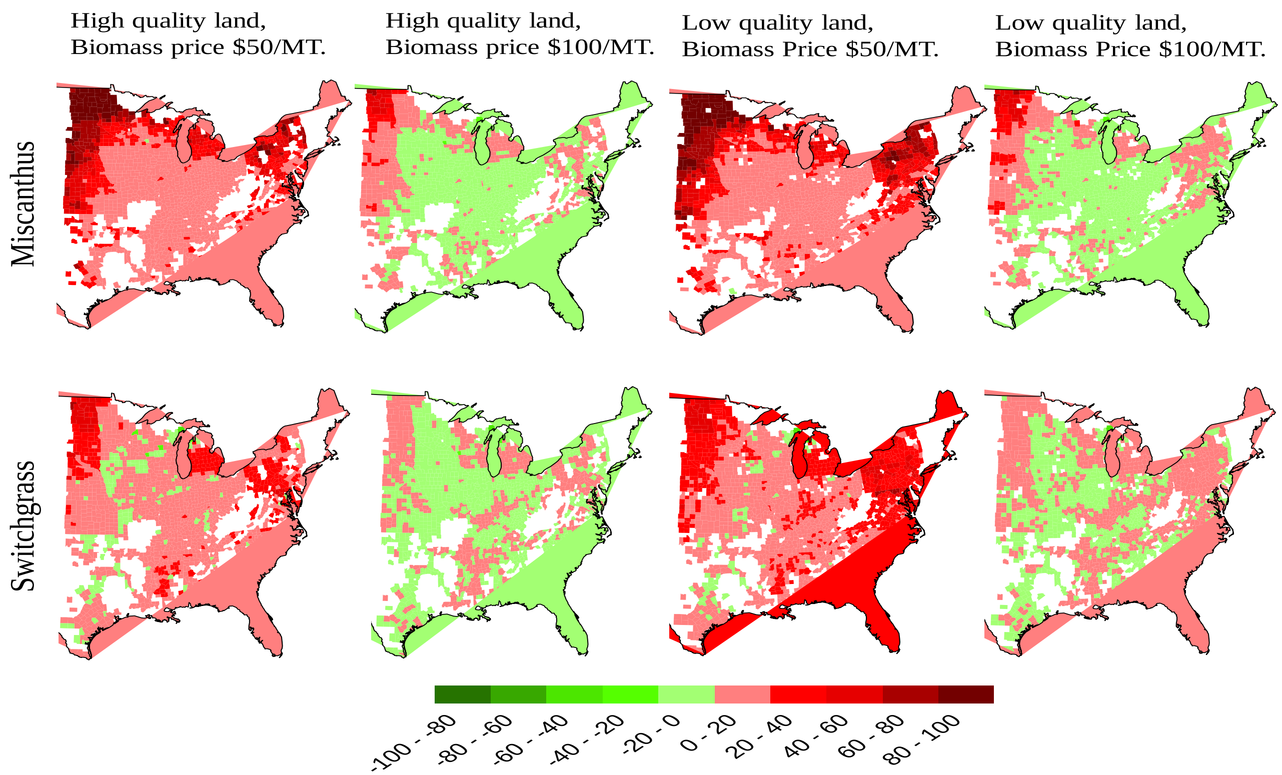


Figure SI-2. Difference in Probability of Having Negative 30-year NPV of Profits between Bio-energy Crop and the Conventional Crops (%)

Note: Each map depicts the county-level probability of having negative 30-year NPV of profits of miscanthus (or switchgrass) minus that of the conventional crops. Red colors (or positive numbers) indicate that probability of negative 30-year NPV of Miscanthus or Switchgrass is larger than that of the conventional crops; green colors (or negative numbers) indicate the opposite.

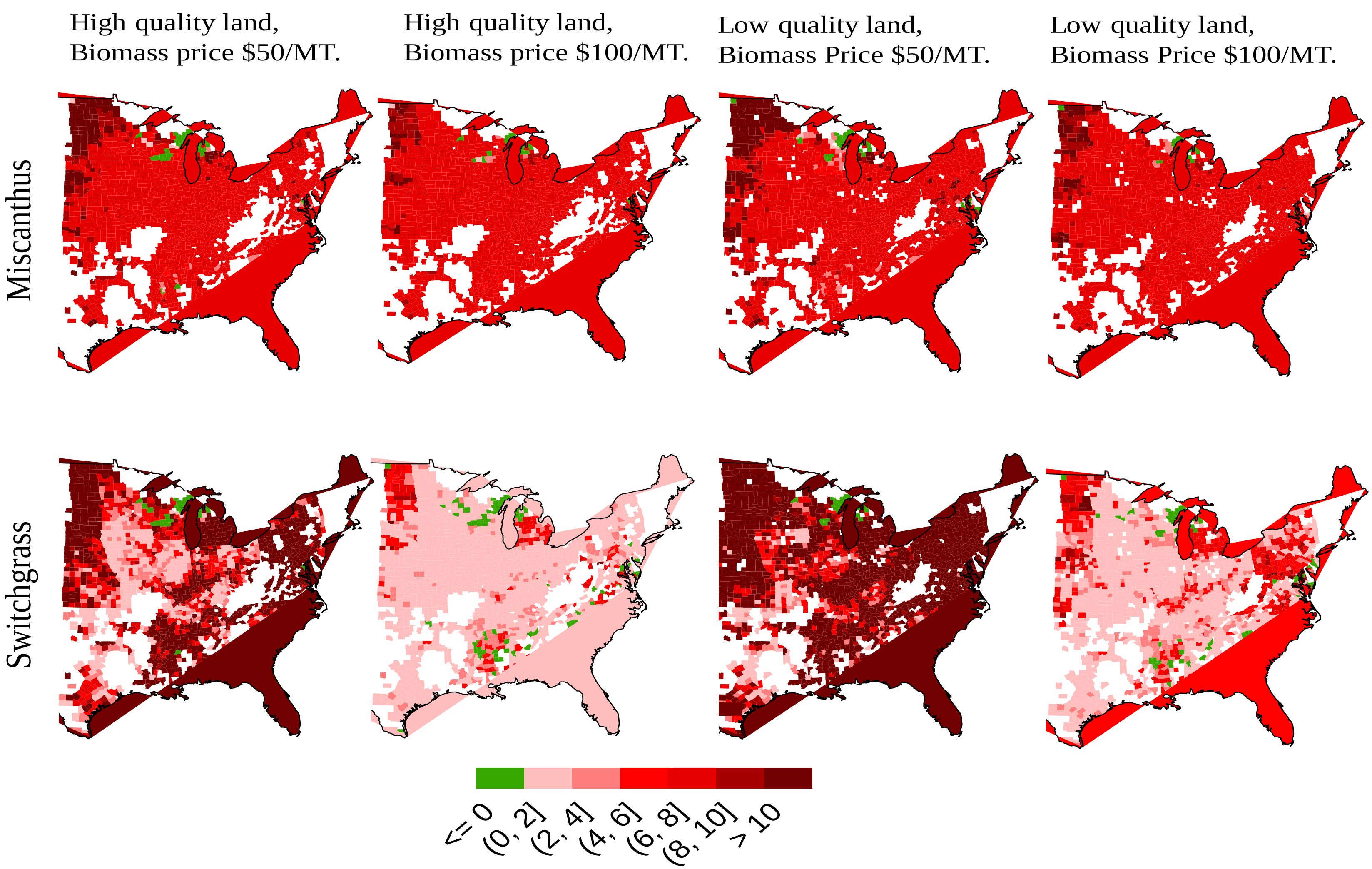


Figure SI-3. Difference in Probability of having loss (between years) between Bioenergy Crop and the conventional crops. (%)

Red color (or positive number) indicates that loss probability of Miscanthus/Switchgrass is larger than that of row crops;
Green color (or negative number) indicates the opposite

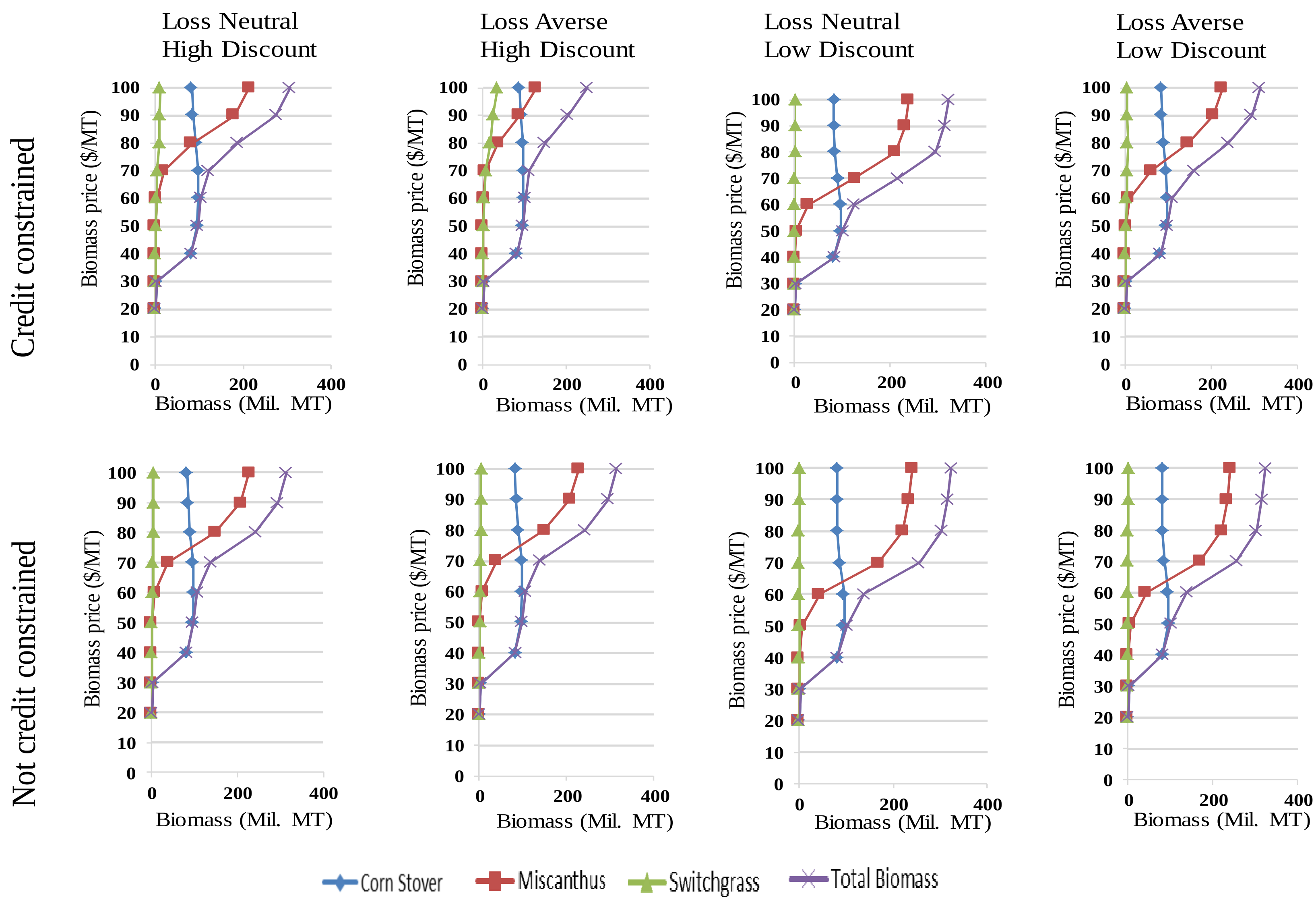


Figure SI-4. Biomass Supply Curves on High Quality Land

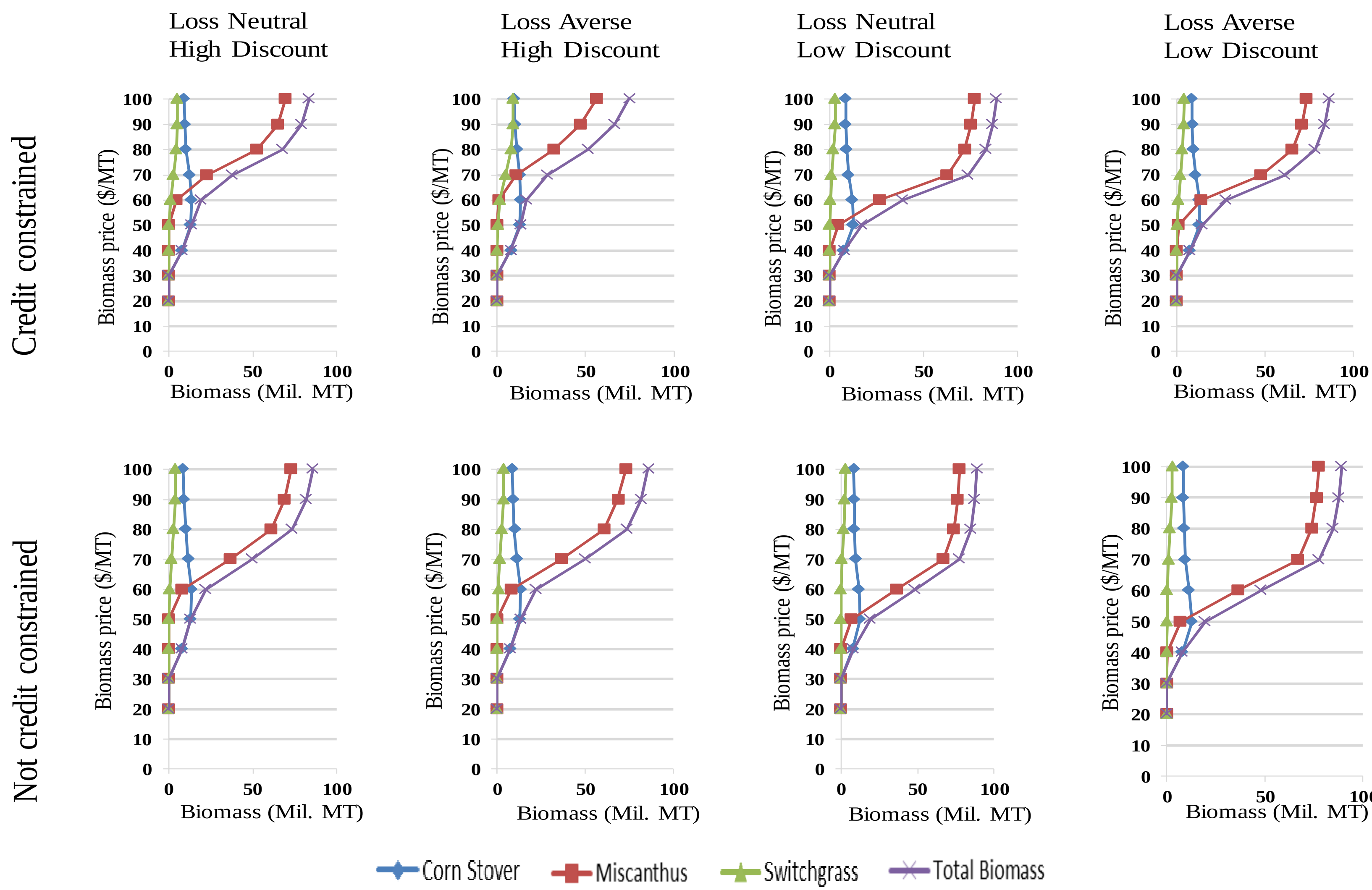


Figure SI-5. Biomass Supply Curves on Low Quality Land

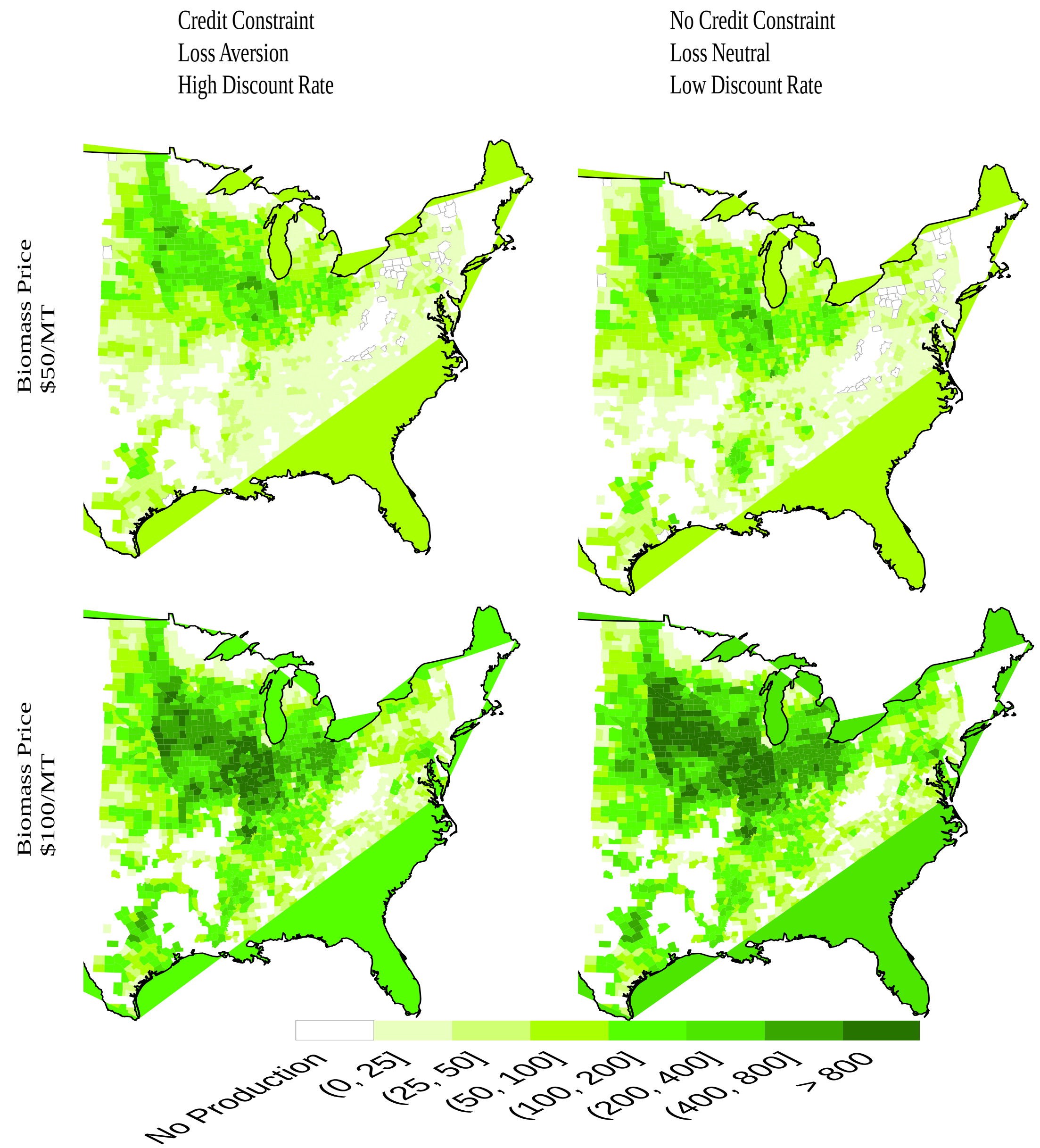


Figure SI-6. Average County-Level Total Biomass Production (1,000 MT per year)

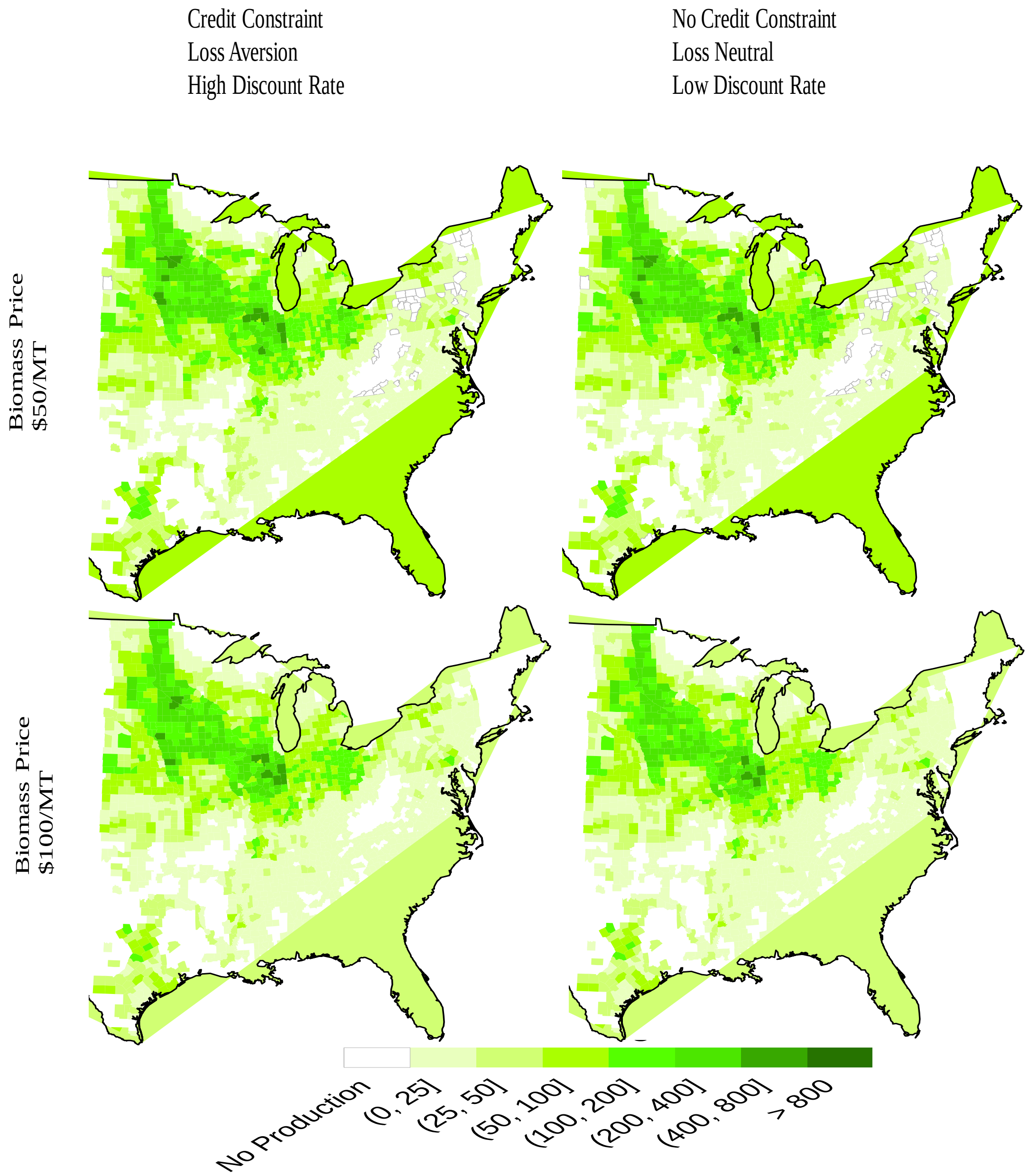


Figure SI-7. Average County-Level Corn-Stover Production (1,000 MT per year)

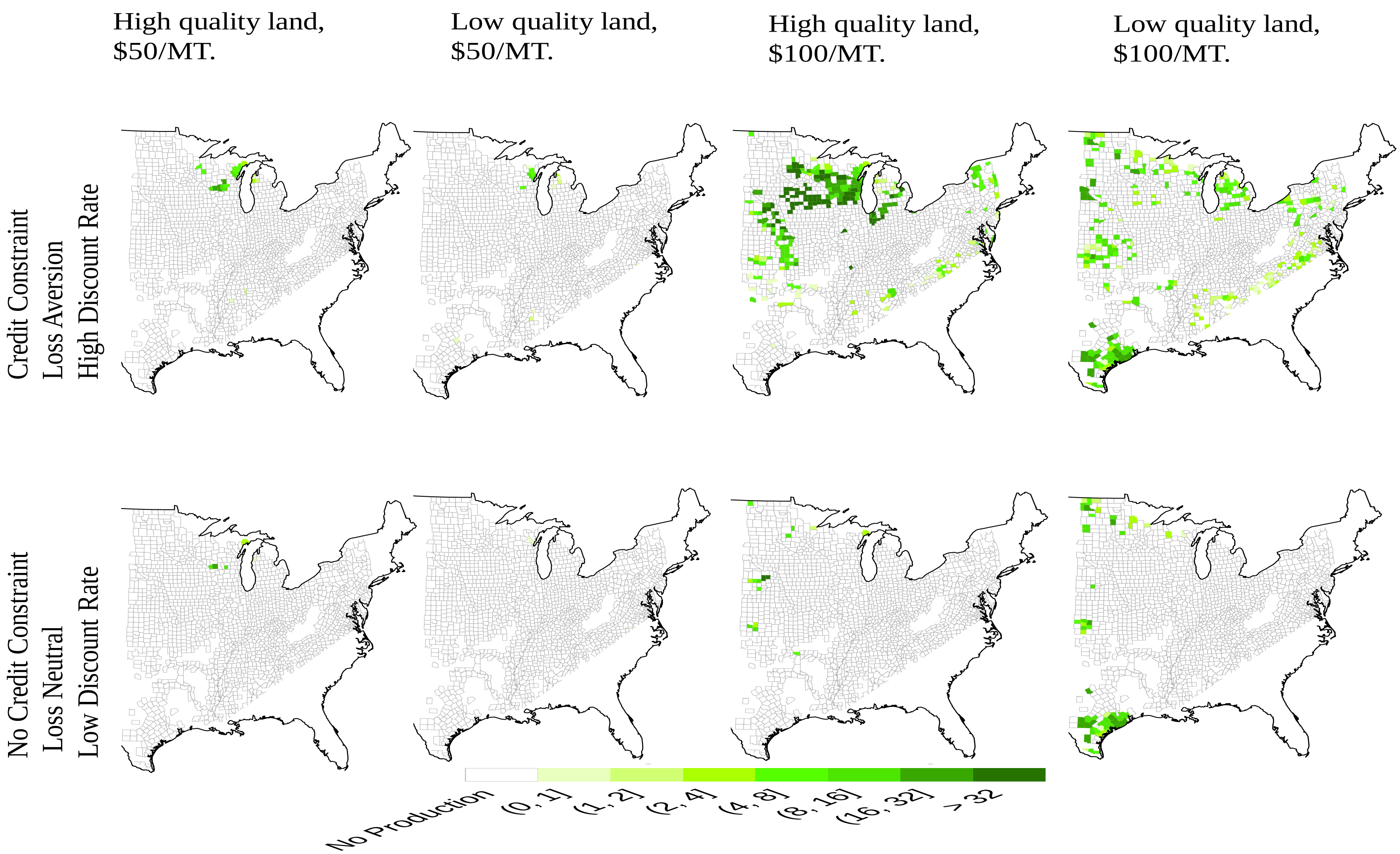
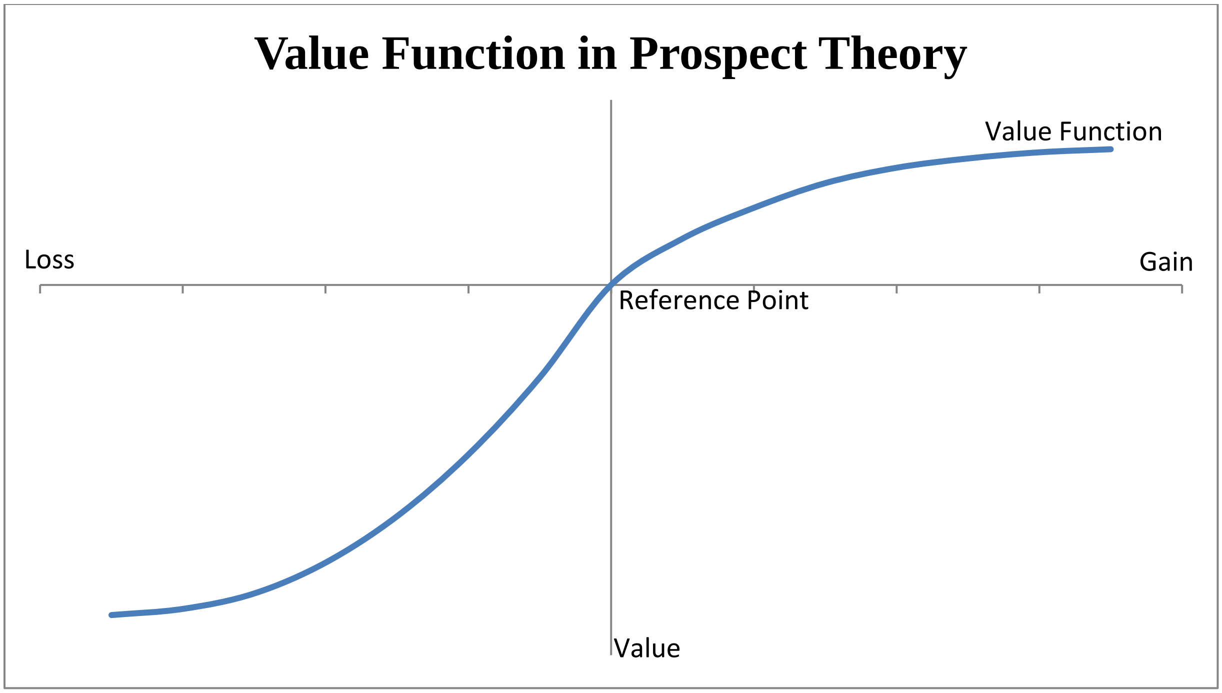


Figure SI-8. Land Use for Switchgrass on high quality land and low quality land for two different biomass prices under different scenarios (1,000 Acres)



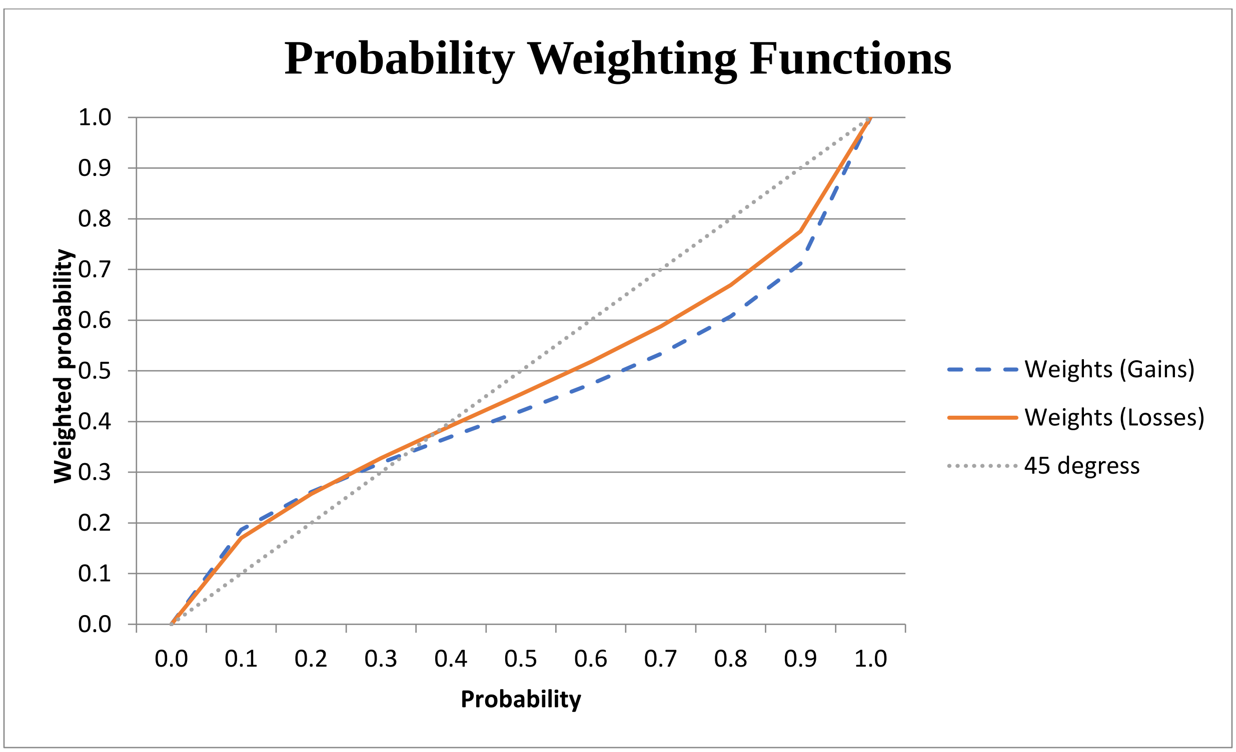
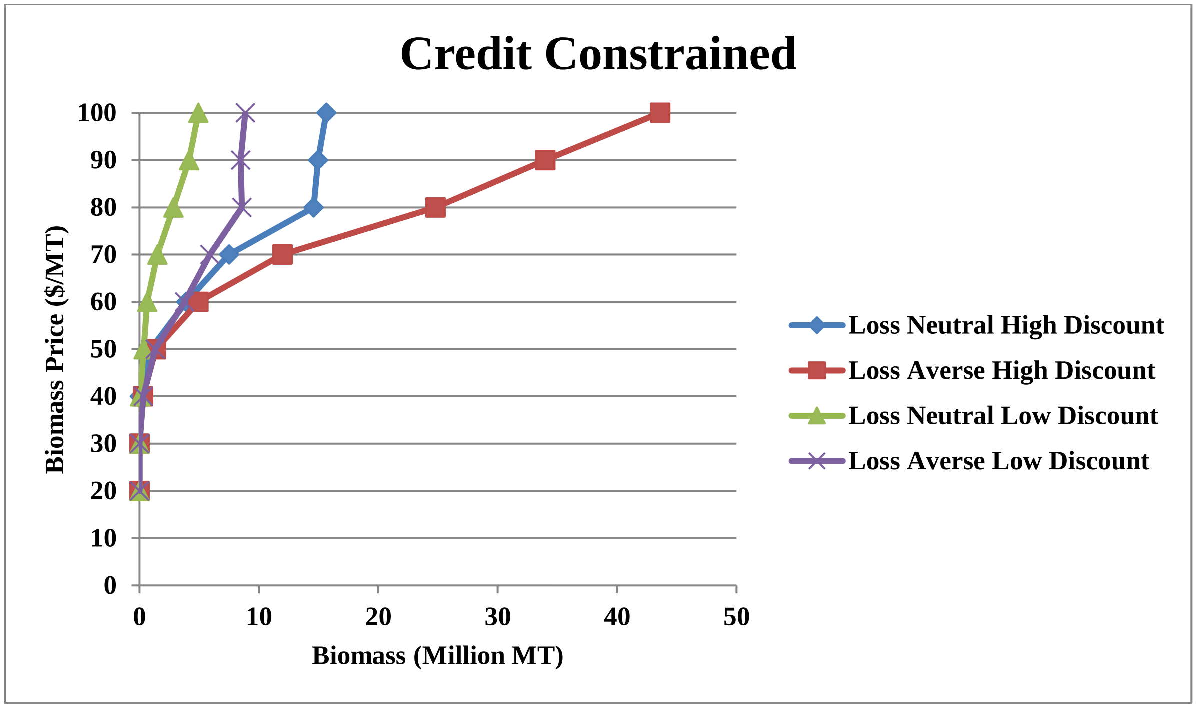


Figure SI-9. Graph showing Value Function in Prospect Theory (upper graph), and Probability Weighting Functions in Prospect Theory (lower graph).



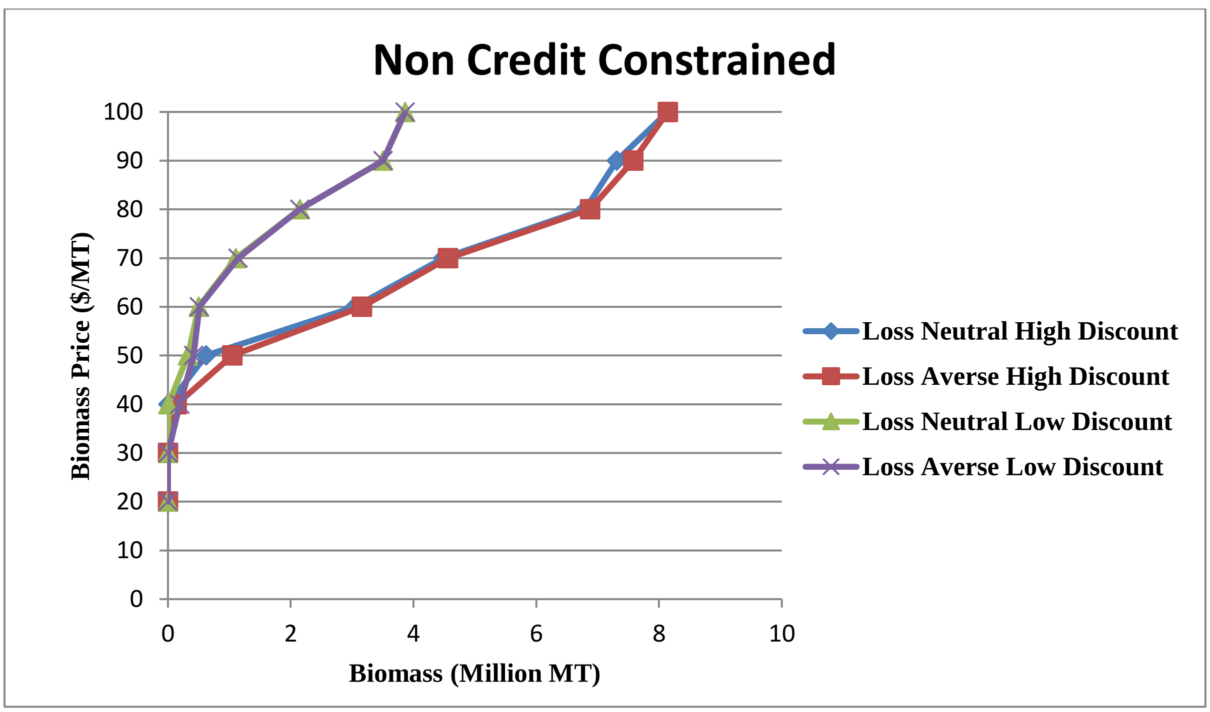


Figure SI-10: Biomass production (Million MT) from Switchgrass for a range of biomass prices.