Sustainable Biofuels, Marginal Agricultural Lands, and Farm Supply Response: Micro-Evidence for Southwest Wisconsin

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Abstract

Recent policy measures and research initiatives aim to make sustainable biofuel crops an important component of the nation's agricultural and energy sectors, yet few studies have examined farms' potential supply response using survey information. We use contingent valuation data from farmers in southwestern Wisconsin to develop *ex ante* supply estimates for corn stover and switchgrass, two leading prospects for sustainable biofuel crop technologies. Supply response is found to be highly inelastic and spatially fragmented, making widespread diffusion unlikely in the near-term. However, heterogeneity in farmers' reservation prices to adopt these technologies suggests that biofuel agglomerations or 'hot spots' could arise.

Key words: bioenergy, contingent valuation, corn stover, switchgrass, technology adoption

JEL Codes*:* Q12, Q16, Q42, Q47

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Introduction

The U.S. agricultural sector now represents the third most important source of domestic renewable energy, behind hydroelectric and wood-based sources (U.S. DOE 2011a). This achievement is largely due to the rapid increase in first-generation biofuels production over the past two decades, such as ethanol from corn grain and biodiesel from oilseed crops (Tyner 2008). However, these grain-based liquid biofuels have drawn heavy criticism due to their effect on world food prices (Zilberman et al. 2013), climate change and the environment (Khanna and Chen 2013; Landis et al. 2008; Costello et al. 2009), and taxpayer burden (Schmitz, Moss and Schmitz 2007). This has led more recent policy to focus on the development of second-generation or *sustainable* biofuels (Robertson et al 2008). These biofuels use non-food plant components, or biomass, as raw material and can take solid, liquid or gas forms—such as pellets for electricity generation or cellulosic ethanol as a transportation fuel. They are sustainable in that they avoid several of the environmental and social pitfalls associated with first-generation biofuels and because the crop technologies used for biomass production are conservation friendly (Tillman et al. 2009; Blanco-Canqui 2010; Meehan, Hurlbert and Gratton 2010).

Several recent policy measures and research initiatives aim to make sustainable biofuels important contributors to our nation's agricultural and energy sectors. For instance the U.S. Department of Agriculture's Biomass Crop Assistance Program (BCAP) created in the 2008 U.S. Farm Bill provides start-up subsidies to growers for the establishment and production of perennial biofuel crops. As of February 2013, BCAP had 4,500 contracts in place for over 6 million tons of biomass at a total cost of $245 million dollars (USDA 2013). The U.S.

Department of Energy is also involved in sustainable biofuels development, exemplified by its current ten-year, $700 million commitment to three regional Bioenergy Research Centers. In their first five years of existence (2008-2012) these centers generated over 1,100 scientific journal articles and over 400 documented biofuels-related innovations (U.S. DOE 2013).

Much of the extant literature on sustainable biofuels policy depends on forecasts about future biomass availability, which in turn rely on predictions about farm supply response to biofuel crop technologies. In one example, the U.S. DOE's "Billion-Ton" study estimates that 1 billion tons of biomass could be produced annually in the United States (U.S. DOE 2011b). To meet this goal, the authors predict that 40 to 60 million acres (about 10% of current U.S. cropland) would need to shift from its current use to a perennial biofuel crop. This is in addition to the several million acres of cropland that would contribute crop residues. Khanna et al. (2011) also find that a national supply of 1 billion tons of biomass is feasible but at a much higher cost than the U.S. DOE study. In another study in the U.S. Midwest, Gelfand et al. (2013) find that marginal lands (i.e., idle cropland, pasture, and other cultivable open space) in this region alone could provide up to one-fifth of the biomass needed to meet national renewable energy targets.

Most previous biomass supply studies do not directly account for the micro-level factors that affect farmers' ability and willingness to convert land to a sustainable biofuel crop. Predictions that do not identify and control for them when appropriate could differ markedly from actual outcomes that are likely to occur. As is well known, the adoption and diffusion of new crop technologies often depends on complex social and economic factors that go beyond simple profitability comparisons (Rogers 2003). For instance analysts have long recognized that age, education and awareness influence farmers' technology choices (Feder, Just and Zilberman 1985). These and other more dynamic factors such as sunk costs, uncertainty and learning often result in outcomes where a farmer's reservation price (i.e., the minimum price at which they are willing to adopt) exceeds the breakeven price (i.e., the minimum price at which the technology becomes profitable) (Dixit and Pindyck, 1994; Foster and Rosenweig, 2010). Finally, political attitudes and environmental preferences are also widely recognized to influence agricultural technology adoption (Barham 1996; Chouinard et al. 2011).

Yet, the adoption of sustainable biofuel crop technologies is expected to be influenced by similar factors. Several studies examine factors affecting farmers' willingness to adopt sustainable biofuel crops and intended acreage allocations using survey data and largely confirm findings from the earlier adoption literature (e.g., Altman and Sanders 2012; Qualls et al. 2012; Tyndall, Berg and Colletti 2011; Jensen et al. 2007). Other studies use modeling techniques to incorporate risk and uncertainty into farmers' adoption decisions. Bocquého and Jacquet (2010) analyze the competetiveness of perennial biofuel crops in Europe and show that liquidity constraints and price risks associated with their irregular harvesting schedules are likely to constrain adoption to levels below those predicted by a simple profitability comparsion. Similarly, Song, Zhao and Swinton (2011) compare switchgrass and corn-soybean rotations under sunk costs and uncertainty and find that switchgrass returns would need to more than double those for corn-soybean before it would become optimal to switch land uses.

This article examines farmers' potential supply response to sustainable biofuel crop technologies in southwestern Wisconsin, a region hypothesized to be a center for biofuels development based on abundant agricultural resources and a large stock of marginal land (e.g., Gelfand et al. 2013). Markets for agricultural biomass do not currently exist in the area, nor have they in the recent past. In addition, biomass cultivation typically requires different management and marketing approaches than those for food or feed crops and is thus outside the current range of experience for most farmers. As a result, information on past supply behavior is unavailable. To overcome this we exploit data from a unique contingent valuation (CV) module included in a recent 2011 mail survey. The module asked area farmers if they would be willing to participate in a hypothetical market program for corn stover and switchgrass as sustainable biofuel technologies and, if so, to report the land area that they would convert.

Our *ex ante* assessment first estimates the distribution of farmer reservation prices to adopt biofuel crop technologies using the CV survey data, and then uses these results to construct a behavioral supply response model. The model identifies characteristics that distinguish potential early adopters (i.e., the *extensive margin*) and their stated land conversion decisions (i.e., the *intensive margin*). Our empirically-grounded estimates show that farm supply response is likely to be highly inelastic and spatially fragmented, and provide a clear take home message. Widespread adoption of sustainable biofuel crops in southwestern Wisconsin is unlikely in the near-term, given the current commitment of most farmers to activities that support their own and surrounding integrated livestock operations. However, our findings also suggest that biofuel agglomerations or 'hotspots' could arise in locations with where farms are more specialized in crop production and where favorable attitudes towards the environment and biofuels prevail.

Background

The CV approach used here extends previous *ex ante* assessments of novel agricultural production technologies. Freeman (2003) defines CV as a survey-based study that elicits individuals' valuation of a specified commodity or environmental change using their responses to questions about hypothetical scenarios. It is distinct from other closely related stated-preference methods in that monetary values are directly incorporated into the survey question itself[1]. The popularity of CV stems from it ability to infer non-market values through carefully conducted surveys and because the theory behind it is well-established (Carson and Hanemann, 2005). So are a large set of empirical methodologies (Haab and McConnell, 2002).

The application of CV to *ex ante* technology evaluation is an emerging line of research in agricultural and applied economics. Among recent studies, most appear to use a dichotomous choice (DC) elicitation format. For instance, several utilize a single-bounded approach to explore farmers' valuation of tillage practices that provide environmental improvements (e.g., Chouinard et al. 2008; Dupraz et al. 2003). Other studies use multiple bounds to assess new or recently developed crop seed technologies. For example, Foltz, Useche and Barham (2013) examine the willingness to pay for genetic traits of emerging corn varieties among Wisconsin and Minnesota farmers using a double-bounded dichotomous choice (DB-DC) approach. This pure stated-preference approach proved advantageous in their case because the traits of interest (e.g. drought-tolerance) had not been commercialized at the time of data collection. Related double-bounded approach utilizing data on both stated and revealed preferences have also been used in cases where the technology under evaluation is in its nascent stages of diffusion. For instance Cooper (1997) explores farmers' willingness to accept payment to implement best management practices for water quality improvement, and studies by Hubbell, Marra and Carlson (2000) and Qaim and de Janvry (2003) assess farmers' willingness to pay for Bt cotton in the United States and Argentina, respectively.

Similar to Cooper (1997), we estimate the distribution of farmers' reservation price to adopt a new production technology. In doing so, we treat *output* price as a random variable and interpret its distribution as the minimum price that just induces the landowner to convert a parcel

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[1] Freeman (2003) classifies CV as one of three broad methodologies used in stated preference studies, the other two being *stated choice* methods and *contingent behavior* methods.

of land from its current use to the new technology. This focus on the land conversion outcome contrasts with the other previously mentioned studies that treat *input* price as a random variable (e.g., Foltz, Useche and Barham 2013; Qaim and de Janvry 2003; Hubbell, Marra and Carlson 2000). Our empirical *ex ante* supply response model is most similar to Hubbell, Marra and Carlson (2000) and Qaim and de Janvry (2003) in that we specify separate equations for the extensive adoption margin, intensive adoption margin, and aggregate supply. However, we elicit farmer reservation prices using a DB-DC framework like Foltz, Useche and Barham (2013). This approach is compatible with the *ex ante* nature of sustainable biofuel crop technologies and has been shown by Hanemann, Loomis and Kanninen (1991) to be statistically more efficient than the single-bounded approach.

Land Conversion to Biofuel Crop Technology

Consistent with the random utility theory of agricultural technology adoption, we model the farm as willing to convert land from its current use to a biofuel crop whenever the gain in expected utility is positive. The representation of utility is assumed to be sufficiently flexible so that the household may incorporate both static and dynamic economic factors (e.g., profit, risk, uncertainty, sunk costs, integration among crop-animal enterprises) and non-economic factors (e.g., environmental attitudes, social preferences) into their decision making process. Within this setting, it is useful to define the farm's threshold reservation price R as the minimum biomass price ($/dry ton) which makes them just willing to convert land uses. Defining P to be the market price for biomass, the farm's decision rule becomes to convert to a sustainable biofuel crop technology when $P < R$ and decline whenever $P \geq R$. As shown by Song, Zhao and Swinton (2011), this decision rule is expected to exceed the breakeven condition. That is, R must be sufficient to cover the opportunity cost of land *and* any additional costs implied by uncertainty, sunk costs, or loss of complementarity among integrated activities that results from conversion.

The CV approach employed here treats R as a random variable and estimates its distribution based on farmers' responses to two DC survey questions. These questions serve to identify the location of R relative to a set of known bid values[2]. In the case of biofuel crops, the bid takes the form of a biomass purchase price ($/dry ton). The first DC question provides respondents with an initial offer price, B^o, and asks whether they would convert some land to the biofuel crop technology. If they respond *yes*, the analyst interprets B^o as an initial upper bound on R $(\text{i.e.}, R < B^o)$. Similarly, if they respond *no* then B^o provides an initial lower bound $(R \geq B^o)$. The second DC question acts as a follow-up to the first, and varies depending on the initial response. Respondents who replied *yes* to B^0 are asked if they would remain committed to growing the biofuel crop at a lower offer price B^L. In contrast, respondents who said *no* are asked if a higher offer price B^H would be sufficient to induce conversion.

The two DC questions result in four possible response sequences. A *yes-yes* response refines the upper bound on the respondent's true value of R $(\text{i.e.}, R \leq B^L \leq B^0)$, whereas a *no-no* response improves the lower bound $(R \geq B^H \geq B^o)$. By comparison the *yes-no* and *no-yes* responses have both an upper and lower bound, and provide an interval over which the true value of R lies ($B^L \leq R \leq B^0$ for *yes-no* responses, and $B^0 \leq R \leq B^H$ for *no-yes* responses). With appropriate survey data in hand, the analyst can use Maximum Likelihood techniques to estimate parameters of the unknown probability density function for R (Haab and McConnell 2003; Hanemann, Loomis and Kannien 1991).

***Ex Ante* Supply Response Model**

The *ex ante* supply response model builds upon the estimated distribution of farmers' reservation

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[2] This approach is motivated by Hanemann, Loomis, and Kannien (1991) who use similar methodology to evaluate the willingness to pay for a non-market environmental good. Our study evaluates farmers' willingness to convert land uses.

price and consists of three parts: (i) the *extensive adoption margin*, (ii) the *intensive adoption margin*, and (iii) *aggregate supply*. The extensive margin equation *E* expresses the proportion of farms that adopt a sustainable biofuel crop technology and is given by,

$$E = F(R) = \int_0^R f(t)dt \tag{1}$$

where *R* is as previously defined, *F* is the cumulative distribution function for *R*, and $f(\cdot)$ is the probability density function for *R* that is based on the parameters estimated via the DB-DC likelihood function. Similar to Qaim and de Janvry (2003), we specify this likelihood function to model the mean of *R* using the linear form,

$$R = X\beta + e \tag{2}$$

where *X* is a vector of explanatory variables, β is a vector of coefficients to be estimated, and *e* is an error term assumed to be normally distributed. The intensive margin equation *I* estimates the share of cultivable land area that an adopting farmer converts to the biofuel crop technology,

$$I = X\gamma + \delta P + \phi M + u \tag{3}$$

where *X* is as previously defined, P is the biomass price offered to the individual respondents, *M* is the inverse Mills ratio to correct for non-random selection bias, the parameters γ, δ, and ϕ are coefficients to be estimated, and *u* is the normally distributed error term.

Selection bias arises here due to the variation in biomass purchase price offers across different versions of the survey. The dependent variable is only observed for those farms who responded *yes* during the hypothetical bidding process. A farm that received the low price version and responded *no* may have responded *yes* if they would have received the high priced version, and so on. We correct for this using the Heckman two-step procedure as shown by Qaim and de Janvry (2003), where the Mills ratio is first calculated from the Maximum Likelihood estimation and then included as an explanatory variable in equation (3). Total aggregate supply in acres (Q) is estimated for different price levels as the product,

(4) $$Q(P) = E(P) \times I(P) \times A$$

where $E(P)$ is the predicted proportion of farms that adopt a biofuel crop at each price level, $I(P)$ is the predicted share of cultivable acres that adopting farmers convert, and A is total cultivable acres. Before presenting the CV module used, we first describe the study area.

Potential for Biofuel Crop Production in Southwestern Wisconsin

Southwestern Wisconsin encompasses some of the most abundant and bio-physically diverse cultivable land in the state. Much of the region lies in the un-glaciated Driftless Area, which helps to explain the juxtaposition of rich agricultural soils with distinctive landscape features such as rolling hills, winding ridges, steeply sloped ravines, and sandstone bluffs. Integrated crop-animal farms dominate the landscape, both in terms of number of farms and land area managed. Dairy and beef cattle represent the most common types of livestock raised, but goats, sheep, pigs and llama are also present. Principal cropping activities include corn, soybeans, small grains, alfalfa, and other hay production, a large portion of which is used to support the livestock activities. Cultural production practices vary widely, with many growers implementing long-term cropping rotations and reduced or no tillage rather than conventional tillage.

Much of the region's land base is considered *marginal* for agricultural production purposes, either due to substandard soil conditions or close proximity to waterways and other environmentally-sensitive landscape features. A recent University of Wisconsin study found that the Driftless Area contains just over 1.25 million acres of environmentally-sensitive cropland including approximately 584,000 acres of active farmland with a moderate erosion hazard, 422,000 acres of active farmland with a significant erosion hazard, and 256,000 acres of land enrolled in the USDA's Conservation Reserve Program (CRP) [3]. The region also has an additional 0.25 million acres of cultivable but unfarmed open space. In total, this represents about 25% of the 6 million total environmentally-sensitive crop and non-crop acres found in Wisconsin, which makes it an important potential center for biofuel crop cultivation.

The widespread adoption and diffusion of biofuel crop technologies will ultimately depend on farmers' capacity and incentive to convert land uses. This 'supply response' facet to the biofuels puzzle remains uncertain and is likely to be influenced by several key factors particular to the region. For example, many farms may be unable to convert land to a new use in the short run even if it were profitable to do so. This is particularly relevant for southwestern Wisconsin where dairy and other integrated crop-livestock farms have large investments in specialized buildings and equipment. These integrated farms also commit most of their crop output to the livestock operation and are likely to have less land in their portfolio that is not related in some fashion into the total enterprise. As a result, enterprise type is hypothesized to be among the more important factors affecting the regions' farm supply response potential.

Similarly, farmers may be influenced by their perceptions (e.g., attitudes and beliefs) about biofuel crop technologies or their potential impacts. In the case of sustainable biofuels, farmers may view these technologies and related developments favorably. For instance some may view bioenergy as a step toward meeting the broader social challenges of energy independence, rural economic growth or climate change mitigation. Farmer preferences for local environmental quality may increase farmer acceptance or rejection of biofuels depending on their perceived effects. Biofuels production that improves soil quality, water quality, or wildlife habitat may be viewed favorably. By contrast, biofuels production that mines the soil or reduces

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[3] Ventura, S. and C. Garcia. *Potential Bioenergy Crop Data Layer*. Unpublished data set. Land Information and Computer Graphics Center, University of Wisconsin, Madison, WI.

water or wildlife quality may not. Finally, other factors mentioned previously (e.g., age, education, experience) affect farmer's technology decisions and need to be taken into account.

Contingent Valuation Module

The CV module contained an introduction, enrollment and compensation information, and brief description of the corn stover and switchgrass biofuel crop technologies (i.e., yield range, recommended management practices, expected environmental outcomes, and a photograph). Enough information was provided to allow respondents to form individualized expectations about the profitability and environmental tradeoffs associated with each technology, to use when weighing each option against their current portfolio of land uses. The crops chosen are well adapted to the study area, widely expected to be among the first technologies commercialized, and already have sustainable production and harvesting guidelines in place at the state level (Ventura et al., 2011). Each of these technologies also represent a larger class of biofuel crop technologies; namely, crop residues for corn stover and perennial grasses for switchgrass.

The elicitation format followed a DB-DC approach, with separate questions for each crop technology. The first dichotomous choice (DC) question was identical for all respondents and asked, "At $[offer price]/dry ton, would you enroll any acres in this program?" The second DC question varied depending on the response to the first. If they said *yes*, the offer price in the second question decreased. By comparison, if they responded *no* the offer price increased. The second question asked, "If the price increased (decreased) to $[offer price]/dry ton and all other contract provisions remain the same, would you now (still) enroll in the corn stover program?"

The study used three sets of offer prices[4]. Low version prices ($30 to $65/dry ton) were determined by reviewing existing literature on production costs (e.g., extension crop budgets, academic studies) and setting the bottommost price just below the average cost of production.

[4] A complete listing of biomass offer prices used is given in Table S1 of the appendix.

High version prices ($90 to $125/dry ton) were based on input from knowledgeable professionals in the field, with topmost prices set slightly above what a bioenergy facility would be able to pay at 2011 prices and still breakeven relative to sourcing from other fuels (e.g., coal or petroleum).

Upon enrolling, respondents indicated how many acres they would convert to the biofuel crop technology and on what type of land this conversion would occur. This information helped to ensure that individual responses were consistent with existing land constraints, as a guard against incentive compatibility problems that can arise with the DB-DC format (Haab and McConnell, 2003). To provide a reference for the opportunity cost of land, respondents were asked to make their allocation decisions based on a corn grain price of $5.20 per bushel. This is well below recent prices, so the supply response estimates from the data below are likely higher than they would be with price conditions where corn is at $6–8 per bushel.

Survey Data and Variables

Data are from a 2011 mail survey of 1,435 farms in southwestern Wisconsin. The selection process targeted farms in Iowa, La Crosse, Richland and Sauk counties operating in townships with abundant marginal and environmentally-sensitive cultivable land. The gross response rate was 50.1%, but included farmers that had retired or transferred the operation since development of the list in 2007 by the Wisconsin Agricultural Statistics Service. This analysis uses data from the 249 complete questionnaires returned by active farmers for an effective response rate of 24.4% after removing ineligible returns. In total, the included farms manage 58,163 acres, or 5.1% of all land in farms in the four-county focus area (USDA 2008).

Table 1 summarizes explanatory variables included in the *ex ante* supply response model in equations (2) and (3), respectively. Farm type variables distinguish among integrated operations: *dairy farms* raise dairy cows or breeding stock in combination with crop production and/or other livestock, *livestock farms* raise non-dairy livestock in combination with crop production, *crop farms* grow grain or forage crops and do not raise livestock. These indicators also control for other factors that are highly correlated with enterprise type such as farm size and participation in rental markets. For instance, dairy farms are the largest enterprises, on average, both in terms of total area and farmland operated[5]. By comparison, crop farms rent out more farmland and have higher rates of enrollment in the Conservation Reserve Program (CRP).

The remaining explanatory variables—age, education, awareness, attitudes and preferences—represent those often recognized as influential in the technology adoption literature. The energy attitudes index captures respondent's beliefs about the impact of alternative energy development on society. It is constructed from a survey question that asked respondent whether they *agree, disagree* or *don't know* to a series of three energy-related statements[6]. Similarly, the environmental tastes index is constructed based on respondents' answers to three questions about tradeoffs they are willing to make for various environmental improvements[7]. The set of explanatory variables used here is purposefully kept parsimonious, to maintain a narrow focus on the differences among farm enterprise types and to facilitate aggregation of the *ex ante* supply estimates.

Results and Discussion

We present the results in four sections. The first reports the estimated distributions of farmers' reservation prices, the second summarizes the empirical regression results, the third depicts the extensive and intensive adoption margins, and the fourth provides aggregate supply estimates.

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[5] Summary statistics of general farm characteristics by enterprise type are provided in Table S2 of the appendix.

[6] This index takes on a value from zero to three, depending on the number of statements that the respondent agreed with. The statements were: "*Meeting our renewable energy goals is key to rural economic growth*," "*Meeting our renewable energy goals is key to slowing climate change*," and "*Meeting our renewable fuel standards is key to reducing our dependence on foreign energy sources*."

[7] This index is similar in construction. It also takes on a value from one to three depending on respondents agreement with the statements: "*I would accept increased uncertainty in net return if local wildlife populations increase*," "*I would accept increased uncertainty in net returns if soil quality on my farm increased*," and "*I would accept increased uncertainty in net returns if water quality improves in nearby lakes or streams*."

Farmer Reservation Prices

Figure 1 presents the estimated distributions of farmer reservation prices for corn stover and switchgrass as sustainable biofuel crop technologies. The maximum likelihood estimation routine was carried out independently for each technology, and assumed that R follows a lognormal distribution. This appears reasonable because R is naturally bounded at zero and the lognormal allows for varying amounts of density in its upper tail. It is also attractive from an analytical perspective because the mean and variance are sufficient to recover the full probability density functions, as illustrated in the figure. The probability that a randomly selected farmer would convert some land to a biofuel crop technology at price P is given by the proportional area that lies beneath their respective curve and to the left of the given price.

Overall, these distributions confirm that farmer reservation prices for the adoption of sustainable biofuel technologies are consistent with previously discussed hypotheses. First, they illustrate the considerable heterogeneity that exists within and across the different farm enterprise types. Second, based on the median values reported in the figure, reservation prices for most farms lie well above the simple breakeven prices often referenced in the literature, such as the \$60/ton for corn stover and \$80/ton for switchgrass in Brechbill, Tyner and Ileleji (2011). Most notably, dairy and other non-dairy livestock farms are less likely than crop farmers to adopt either biofuel crop technology over the given range of offer prices. This likely reflects the relatively higher opportunity cost of land on integrated operations and the large and often sunk investments that they have in specialized buildings, equipment, and management knowledge—two factors which are expected to act as constraints on land use change in the near-term. However, this observation is also nuanced in that dairy farms are more likely to adopt corn stover than other non-dairy livestock farms whereas this ordering is reversed for switchgrass.

Characterization of Early Adopters

The econometric results presented in Table 2 permit an analysis of the characteristics that distinguish likely early adopters. The first two columns report coefficient estimates for the reservation price equation in (2), and help explain the heterogeneity in Figure 1 by showing how the mean reservation price depends on the selected covariates. The lognormal assumption means that the interpretation of the estimated coefficients follows that for a log-linear regression specification. That is, coefficients give the expected proportional change in reservation price for a one-unit increase in the explanatory factor.

In terms of magnitude, farm type and prior awareness are important explanatory factors. For corn stover, non-dairy livestock farms have the highest reservation price relative to the other enterprise types, holding other factors constant. By contrast, dairy farms have highest reservation price for switchgrass although this difference is not statistically significant. As might be expected from the literature, awareness or prior knowledge of the crop's potential as a biofuel decreases farmer reservation prices. This is particularly true for switchgrass, the less familiar of the two, where the difference is statistically significant. Farmers' reservation price is found to increase with age for both corn stover and switchgrass, with a one-year increase resulting in 1.7 and 1.3% increases, respectively. By contrast, education is found to lower farmers' reservation price by 5.0% per year attained for switchgrass but not for corn stover. Attitudes as represented by the environmental and bioenergy indices also lower farmers' reservation price estimates. This is an interesting result, as this heterogeneity suggests that spatial agglomerations or 'hotspots' of biofuels production and the reduced logistical costs that come with it may arise in places where landowners have similar attitudes. Indeed, there is even recent evidence of this spatial correlation in farmer adoption of other 'clean' technologies for this very same region (Lewis et al. 2011).

Results for the intensive adoption equation in (3) are reported in the final two columns of

Table 2, and show how the intended share of land to be converted depends on the explanatory factors. The critical regression estimates for predicting biomass supply response are the *ln(P)* measures in the middle of the table. They can be used to recover three price response estimates, one each for crop farms, dairy farms, and other non-dairy livestock farms. Note that only crop farms show a positive and significant degree of price responsiveness, with a supply elasticity estimate of about 0.26 for corn stover and 0.19 for switchgrass. The other two enterprise types have highly price inelastic responses. For dairy farms, the two coefficient estimates combine to make their supply elasticities effectively zero, while for livestock farms they are less than 0.1 and not jointly statistically different than zero. Given that dairy and other livestock farms manage the vast majority of agricultural land in this region, these estimates suggest that the overall price responsiveness of farms to changes in biomass price is likely to be quite low, and probably less than 0.1. This result is illustrated further in Figure 3 below.

The rest of the intensive margin regression estimates offer predictable and mostly statistically significant signs. Age has a negative effect on land allocated to bioenergy crops, suggesting that younger farmers who are willing to adopt sustainable biofuel crops would do so more intensively. Other coefficient estimates—such as farmer awareness about the biofuel crops, higher education levels, and positive attitudes about the environmental effects or the potential social benefits of bioenergy crops—all positively influence the amount of land that a farm would dedicate to biomass production given that they accepted the price offer. Of particular note, the estimates on the environmental tastes index for switchgrass are around double those for corn stover. That farmers may value sustainable biofuel crops differently based on their perceptions about social and environmental traits is important, and could help guide future agricultural policy as it relates to biomass supply, land conservation or some combination therein.

Extensive and Intensive Adoption Margins

Graphical illustrations of the adoption margins are shown in Figures 2 and 3, respectively. Figure 2 presents the extensive margin as a function of the biomass offer price for each biofuel crop technology by enterprise type. The upward sloping lines indicate the proportion of farms willing to convert at least some land to the sustainable biofuel crop technology for a given offer price. The main observation here, across all enterprise types, is the relatively small proportion of farmers willing to adopt bioenergy crops even at high prices. Switchgrass is the most striking example, where at $100 per dry ton, less than 20% of dairy farms are estimated to adopt. This result may not be surprising given that switchgrass disrupts the complementarity between the crop and livestock enterprises. Even for corn stover, which does not necessarily compete with current cropping choices, only about 40% of dairy farmers and crop farmers are estimated to be participants in the biomass market. The somewhat more price-responsive adoption curves for crop farmers in Figure 2 can be explained by the fact that they do not use crop output as an input into an integrated livestock operation.

In Figure 3, the upward sloping lines indicate the share of cultivable acres that an adopting farmer is expected to convert. The results here are even more striking than those for the extensive margin, and again are consistent across enterprise types and biofuel crop technologies. The proportion of land that is converted to biofuel crop technologies on dairy farms and other non-dairy livestock farms is extremely unresponsive to higher biomass offer prices. However, crop farms are more price-responsive. The important explanatory factors here are likely to be similar to those discussed above for extensive margin. Nearly all farm acres on crop-livestock farms are currently devoted to the integrated operation, and thus have a higher shadow value attached to them than would be the case on crop farms where the land is not directly linked with other on-farm livestock activities. Thus, even at relatively high biomass prices, the regression results suggest that only small amounts of land conversion will take place on those farms that are even willing to adopt a biofuel crop technology in the first place. As a result, whatever production does occur is expected to be spatially fragmented across the agricultural landscape.

Aggregate supply

The econometric results from Table 2 can be combined to generate aggregate supply curves using Equation (4) from above, which multiplies the extensive and intensive margin predictions at each price by the total cultivable land area. Specifically, we create aggregate supply estimates for each farm type (e.g., dairy) by combining the coefficient estimates with mean regressor values and varying the price level. In Figure 4, we present the resulting supply curves by type and then add them up to generate the overall aggregate biomass supply curve. In Figure 5, we take the aggregate supply curve for all of the farms in the sample (weighted by type) and divide it by total cultivable area to provide an estimate of the share of land dedicated to biomass crops.

In both cases, the low willingness to adopt and lack of response in cultivated area combine to predict aggregate supply curves that are highly price inelastic. The farm type curves in Figure 4 all appear quite similar with very small amounts of land provided, even at prices well above what the sector could probably sustain. Low overall supply from the crop farms in Figure 4 reflects the fact that they are less common in the agricultural landscape relative to the integrated operations, and that they generally operate at smaller scales. Thus, even though Figures 1 and 2 show them to be more price-responsive, the contribution of these farms to the aggregate supply is muted by their relatively small role. Conversely, the impact of dairy and other livestock farms on aggregate supply outcomes is large because these farmers manage most of the land in the study area, but report only moderate interest in participating in these markets.

The main take-home message from this research is well summarized by the low and almost horizontal aggregate supply curve estimate in Figure 5. It illustrates the very small proportion of cultivable land that farmers in southwestern Wisconsin would dedicate to biomass crops across a wide range of prices. For example, at prices of $100 per dry ton, which are generally considered to be almost 50% above what the bioenergy sector could sustain as a competitive price with other energy inputs, farmers are currently only predicted to dedicate 3% of the land to corn stover and 4% to switchgrass. It is difficult to imagine how a viable sector could arise for such a bulky and widely dispersed energy input at such low levels of acceptance and price responsiveness within and across farms in the landscape. The supply logistics of collecting and aggregating a few acres of biomass here and then a few more several miles down the road would prove infeasible due to the high costs relative to the volume of material collected. In sum, this inelastic and fragmented farm supply response make the widespread diffusion of sustainable biofuel crop technologies unlikely in the near term.

While these estimates are admittedly *ex ante* and only capture the initial market stages of these biofuel technologies for a small sample of producers, they accord with similar findings in other recent studies. For instance, Tyndall, Berg and Colletti (2011) foresee non-economic, socio-environmental factors as the largest barrier to widespread diffusion of corn stover technologies among farmers in Iowa. In another example, Swinton et al. (2011) show how recent high crop prices led to only minimal expansion in cultivated cropland, and use this observation to argue that large-scale expansion of biofuel crop production on marginal lands is unlikely to occur in the short run for reasons comparable to those discussed here.

Summary and Conclusions

This article utilizes contingent valuation (CV) data gathered from farmers in southwestern Wisconsin to assess the near-term supply response for corn stover and switchgrass, two prospective sustainable biofuel crop technologies. *Ex ante* estimates are generated using linked equations that predict the proportion of farmers willing to produce these crops and the share of land that they are willing to dedicate across a range of biomass prices. Farms are distinguished by main enterprise type to capture a diverse set of factors (such as sunk investments, economies of scope, and farmer knowledge) that influence the opportunity cost of land. This approach also provides for an analysis of factors that influence farm supply response including demographic indicators, environmental preferences, and attitudes about the benefits of energy alternatives. Overall, this *ex ante* approach identifies characteristics that distinguish likely early innovators and provides the basis for predicting aggregate response estimates for sustainable biofuel crops.

The econometric results reveal a highly inelastic short-run supply, with very low levels of biomass provision on individual farms and across the agricultural landscape. These farmer supply response estimates do not bode well for the development of a biofuels sector, because the small and fragmented pockets of biomass production that are predicted to arise portend very high collection and aggregation costs. The one possible bright spot is the potential for agglomerations of biomass cultivation arising from heterogeneity in reservation prices across farm types and attitudes toward the environment and energy alternatives. Based on the regression estimates, these 'hot spots' would likely comprise groups of crop farmers that are positively inclined toward 'doing the right thing' with respect to the environment and bioenergy. Further empirical analysis is underway to identify possible hot spots, and whether they are significant and frequent enough to support locales where biofuel crops might be produced and collected at significantly higher levels of aggregation than is suggested by the empirical results presented here. Ultimately, our work and others referenced above indicate a clear need for increased attention to the behavioral aspects of technology adoption in future studies of sustainable biofuel crop supply.

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Table 1. Explanatory variables included in the *ex ante* supply response model (n = 249)

Variable	Description	Mean	Std dev.
Dairy farm	Farm raises dairy cattle or breeding stock with crops or other livestock (1=yes, 0=no)	0.229	0.421
Other livestock farm	Farm raises non-dairy livestock or breeding stock with crops (1=yes, 0=no)	0.574	0.495
Crop farm	Farm grows crops and does not raise any type of livestock (1=yes, 0=no)	0.197	0.398
Age	Age of primary farm operator (years)	56.6	11.6
Education	Education of primary farm operator (years)	13.7	2.7
Awareness (corn stover)	Primary operator knew of corn stover as a biofuel crop prior to survey (1=yes, 0=no)	0.74	0.44
Awareness (switchgrass)	Primary operator knew of switchgrass as a biofuel crop prior to survey (1=yes, 0=no)	0.79	0.41
Bioenergy attitude index	Index of bioenergy attitudes (integer from [0 – 3])	1.92	1.09
Environmental taste index	Index of environmental preferences (integer from [0 – 3])	1.31	1.23

Source: Authors' mail survey (2011).

Table 2. Empirical estimation results for the *ex ante* supply response model (n = 249)

	Reservation price equation [ln($/dry ton)]		Intensive margin equation [proportion of land converted]	
	Corn stover	Switchgrass	Corn stover	Switchgrass
Coefficient estimates				
Dairy farm	–0.089	0.382	0.810	–0.033
	(0.31)	(1.37)	(2.14)**	(0.08)
Other livestock farm	0.626	0.158	0.387	0.148
	(2.32)**	(1.02)	(1.29)	(0.42)
Age	0.017	0.013	–0.008	–0.024
	(2.45)**	(2.48)**	(2.10)**	(2.51)**
Education	–0.024	–0.050	0.013	0.091
	(0.79)	(2.19)**	(2.16)**	(2.68)***
Awareness	–0.305	(0.61)	0.154	1.080
	(1.52)	(3.25)***	(2.07)**	(2.42)**
log(P)			0.258	0.192
			(2.47)**	(2.68)***
log(P) × dairy			–0.228	–0.171
			(2.09)**	(1.91)*
log(P) × other livestock			–0.199	–0.110
			(1.86)*	(1.14)
Bioenergy attitude index	–0.257	–0.147	0.117	0.270
	(2.68)***	(2.52)**	(2.09)**	(2.57)***
Environmental taste index	–0.233	–0.111	0.107	0.214
	(2.88)***	(2.16)**	(2.00)**	(2.74)***
Inverse Mills ratio			–0.064	–0.141
			(1.97)*	(2.45)**
Constant	5.335	5.692	–2.051	–6.190
	(7.78)***	(12.01)***	(2.44)**	(2.74)***
Variance estimates				
Dairy farm	0.400	0.014		
	(1.72)*	(0.06)		
Other livestock farm	0.551	0.093		
	(2.45)**	(0.63)		
Constant	0.497	0.599		
	(4.16)***	(4.92)***		
Log likelihood	–172.3	–216.5		
R-squared			0.17	0.21

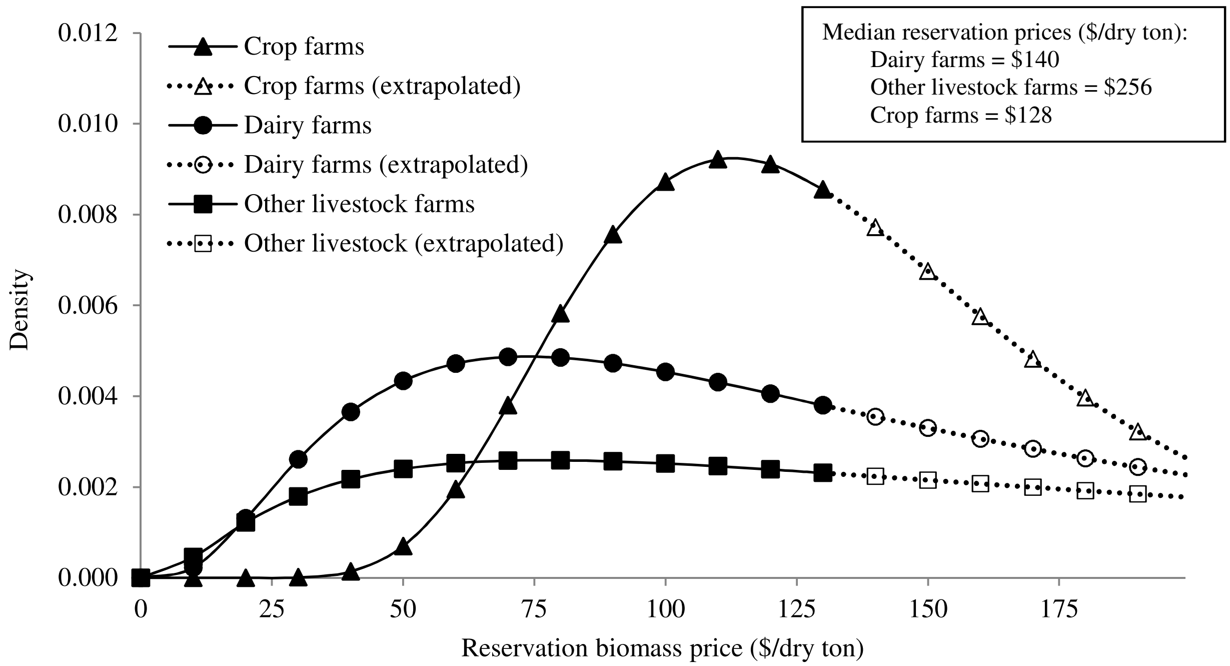
* = significant at a 10% level; ** = significant at a 5% level; *** significant at a 1% level.

Absolute value of robust *t*-statistics in parentheses.

The reference farm type excluded from the analysis is *crop farm*.

Source: Authors' mail survey (2011).

(a) Corn stover



(b) Switchgrass

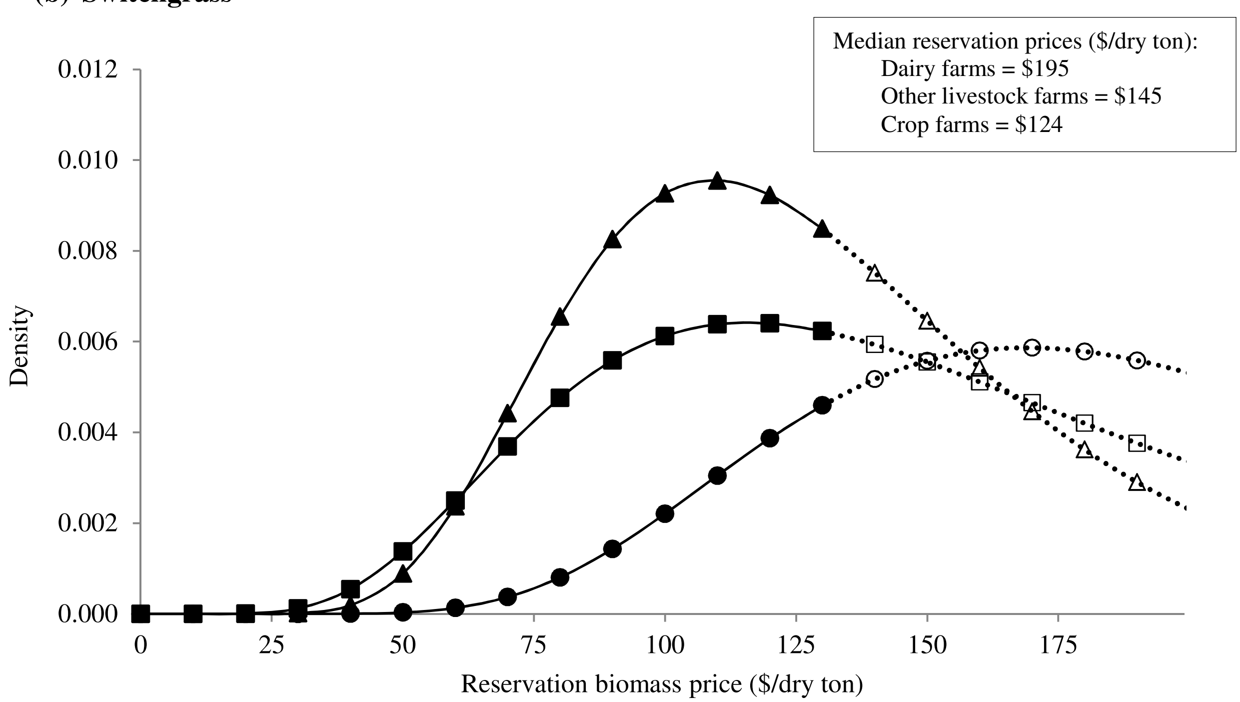
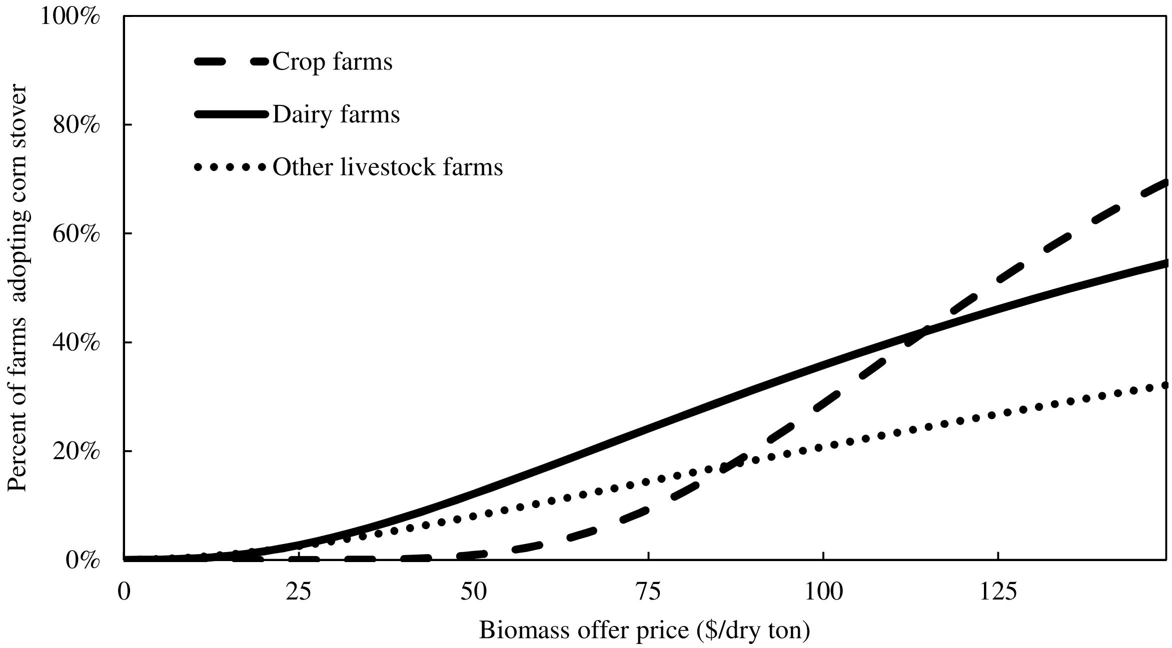


Figure 1. Distribution of farmer reservation prices for the adoption of (a) corn stover and (b) switchgrass as sustainable biofuel crop technologies in southwestern Wisconsin. The lines drawn represent the probability density function of *R* by each farm type.

a) Corn stover



b) Switchgrass

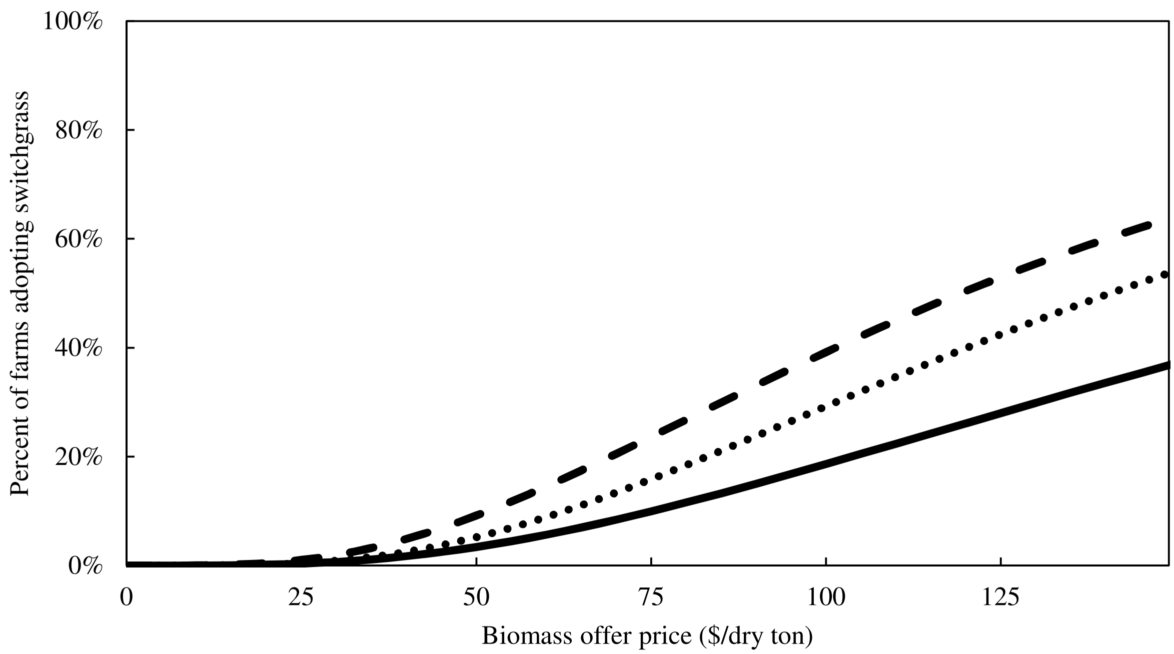
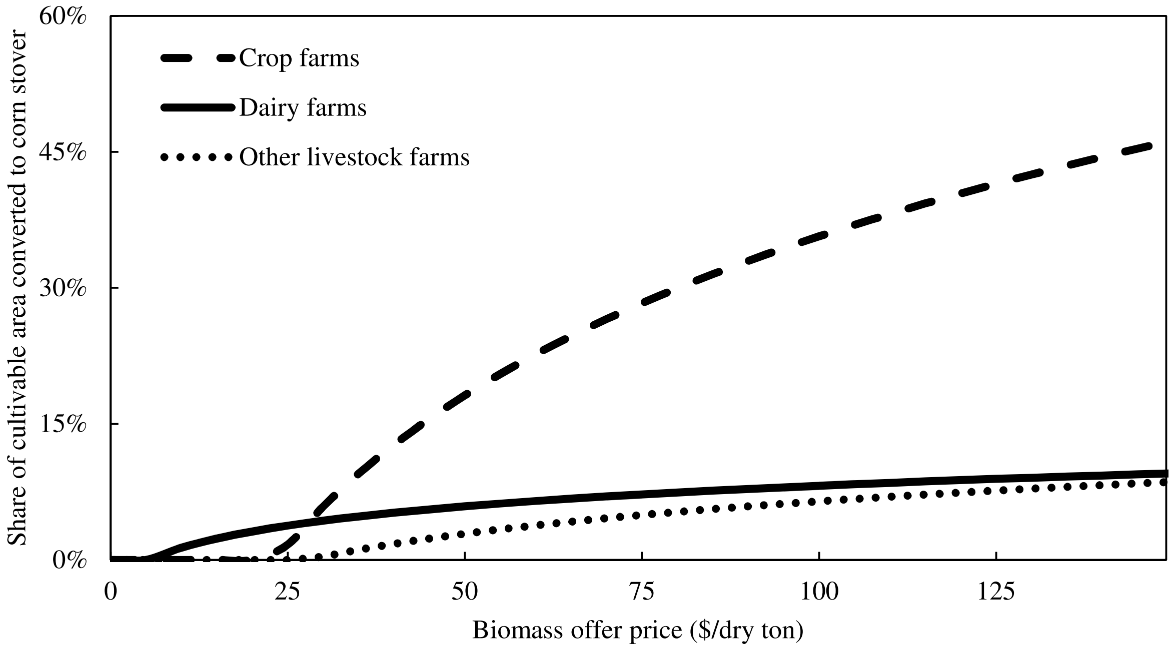


Figure 2. Extensive adoption margins for (a) corn stover and (b) switchgrass as sustainable biofuel crop technologies in southwestern Wisconsin.

a) Corn stover



b) Switchgrass

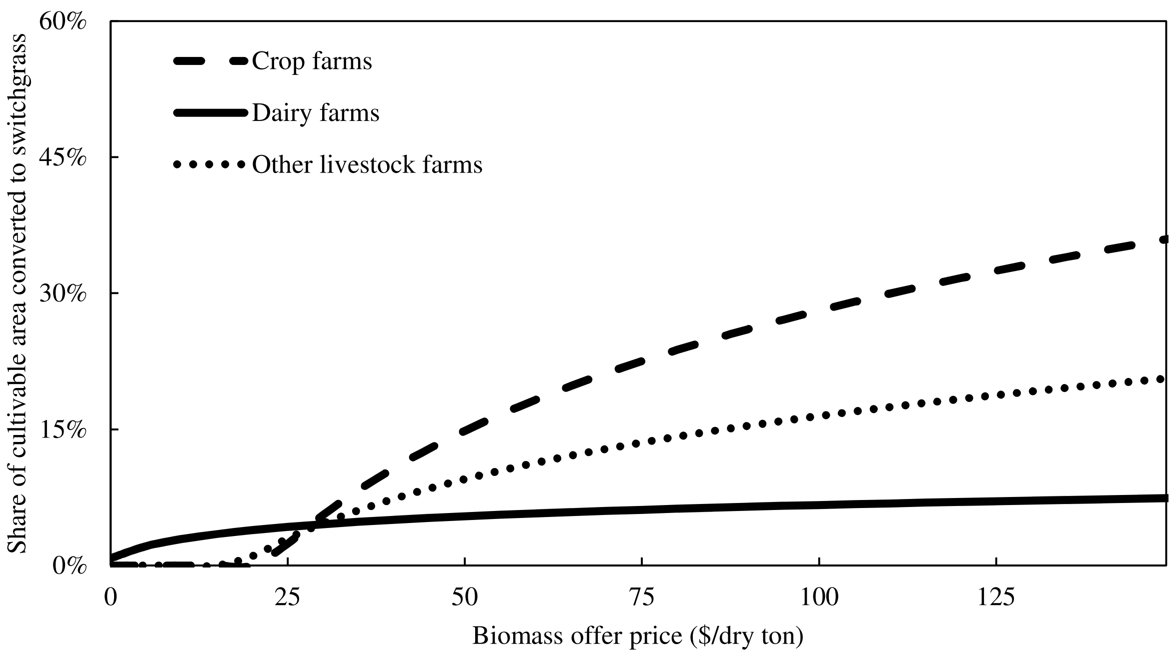
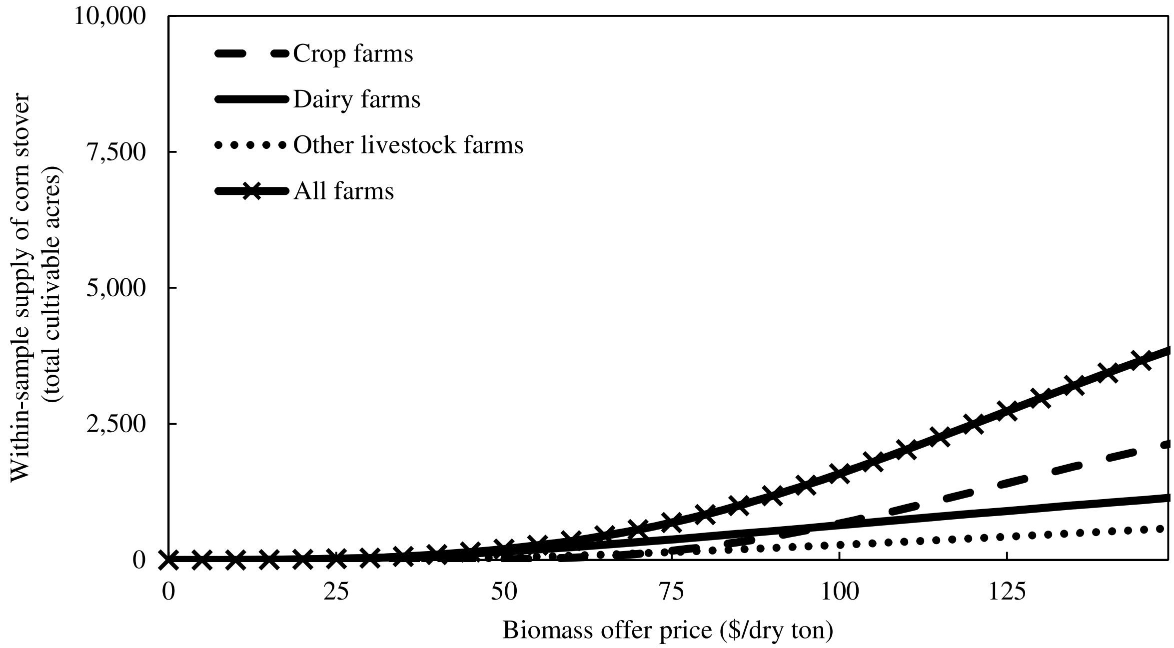


Figure 3. Intensive adoption margins for (a) corn stover and (b) switchgrass as sustainable biofuel crop technologies in southwestern Wisconsin.

a) **Corn stover**



b) **Switchgrass**

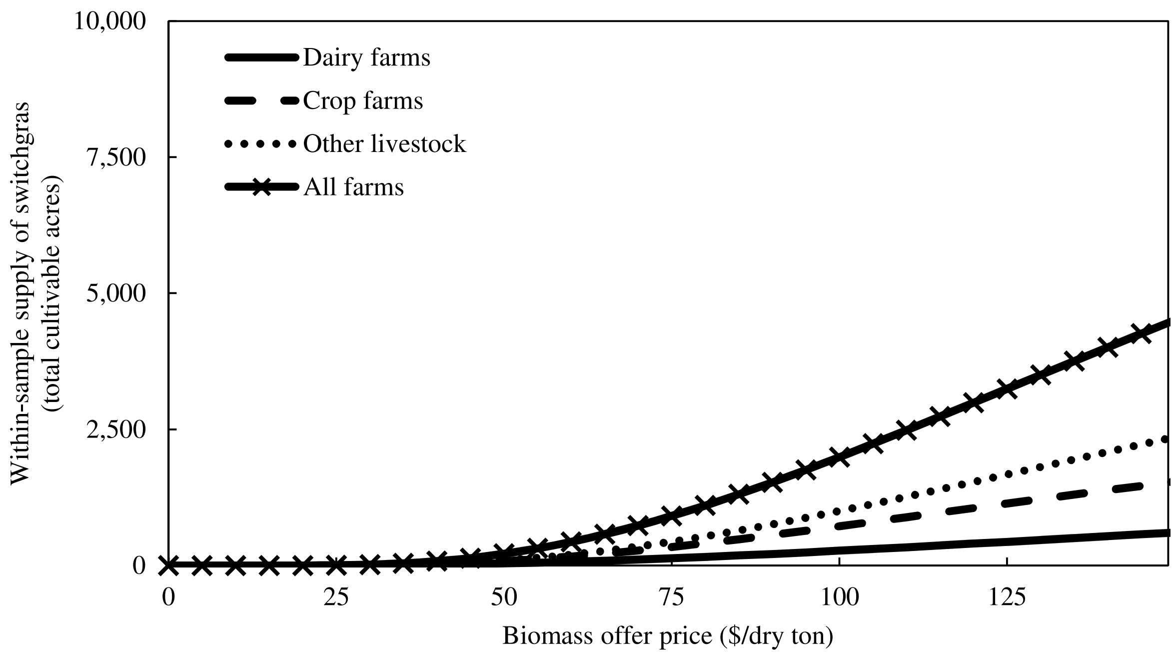
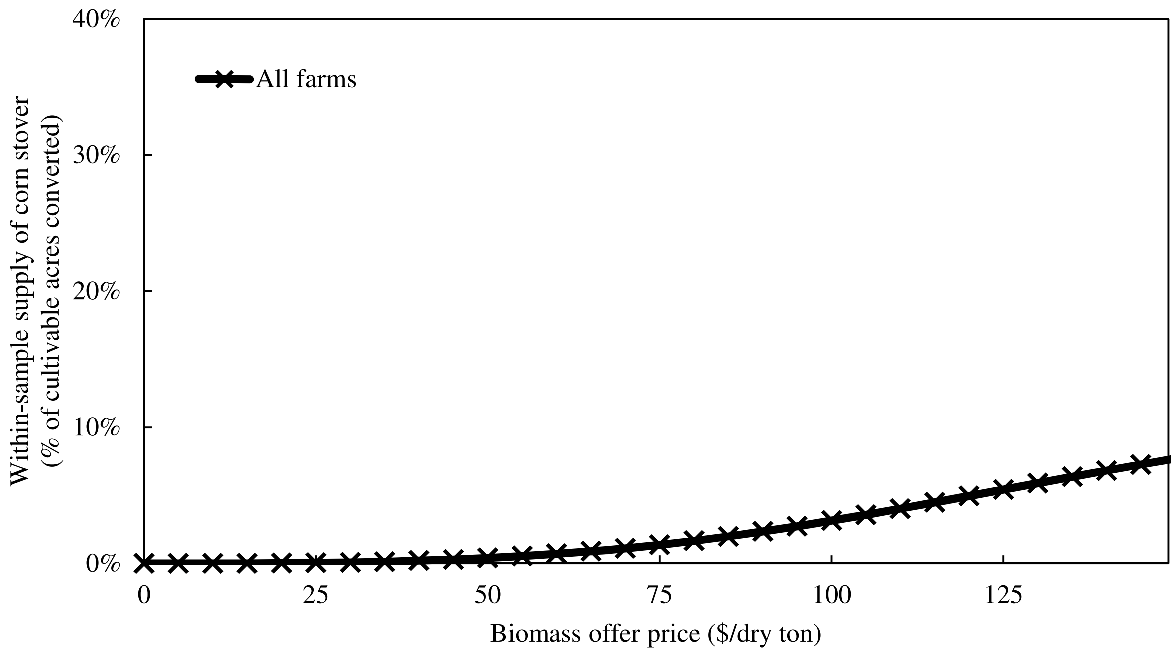


Figure 4. Within-sample supply estimates in acres for (a) corn stover and (b) switchgrass as sustainable biofuel crop technologies in southwestern Wisconsin.

a) Corn stover



b) Switchgrass

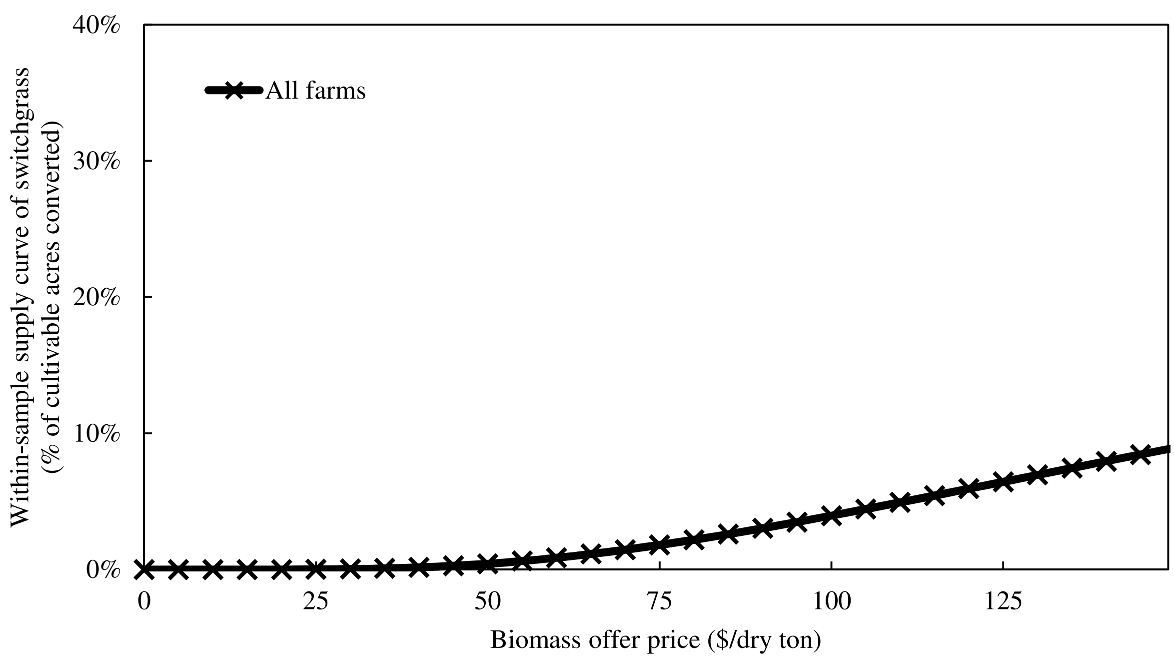


Figure 5. Within-sample supply estimates as a share of cultivable area for (a) corn stover and (b) switchgrass as sustainable biofuel crop technologies in southwestern Wisconsin.

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Appendix

Table A1. Biomass purchase offer prices

Biofuel crop (offer)	Questionnaire version		
	Low	Middle	High
	----------------------------	$/dry ton	----------------------------
Corn stover			
Initial offer (B^0)	30	60	90
Low follow-up offer (B^L)	20	50	80
High follow-up offer (B^H)	45	75	105
Switchgrass			
Initial offer (B^0)	45	75	105
Low follow-up offer (B^L)	30	60	90
High follow-up offer (B^H)	65	95	125

Source: Authors' mail survey (2011).

Table A2. Farm characteristics by enterprise type

Farm characteristic	Enterprise type		
	Crops only	Dairy livestock	Non-dairy livestock
Observations	49	57	143
Farm size (acres)	182	359	183
Cropland area (acres)	84	194	83
Pasture area (acres)	16	61	41
Woodland area (acres)	45	55	36
Unfarmed openspace (acres)	10	4	4
Other (acres)	14	41	10
Cropland characteristics:			
Area operated (acres)	113	294	99
Rents in cropland (proportion of farms)	0.24	0.65	0.22
Avg. area rented in (acres)	209	165	144
Rents out cropland (proportion of farms)	0.22	0.04	0.16
Avg. area rented out (acres)	46	207	50
Enrolled in CRP (proportion of farms)	0.29	0.09	0.22
Avg. area in CRP (acres)	13	3	8
Pasture characteristics:			
Area operated (acres)	15	91	47
Rents in pasture (proportion of farms)	0.00	0.33	0.11
Avg. area rented in (acres)	0	96	70
Rents out pasture (proportion of farms)	0.02	0.04	0.01
Avg. area rented out (acres)	30	143	40
Crop production (proportion of farms):			
Grows grain or forage crops	1.00	0.98	0.92
Grows corn	0.86	0.98	0.65
Grows forage	0.65	0.95	0.87
Grows soybeans	0.59	0.35	0.37
Grows small grains	0.22	0.53	0.24
Livestock (proportion of farms):			
Raise livestock	0.00	1.00	1.00
Raise dairy cattle	0.00	1.00	0.00
Avg. herd size (head)	0	161	0
Raise beef cattle	0.00	0.35	0.85
Avg. herd size (head)	0	44	36
Raise other livestock[c]	0.00	0.12	0.36

Source: Authors' mail survey (2011).