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# Modeling biomass procurement tradeoffs within a cellulosic biofuel cost model

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ABSTRACT

We develop a long-run cellulosic biofuel cost model that minimizes feedstock procurement and processing costs per gallon. The distinguishing feature of the model is that it accounts for the procurement tradeoff between the intensive margin (biomass producers' participation rate) and extensive margin (biomass capture region). To investigate the extent to which this procurement tradeoff affects processors' cost-minimizing decisions, we apply the model to switchgrass ethanol production in U.S. crop reporting districts. Results suggest that location characteristics will determine the extent to which processors can reduce their total procurement costs by offering a higher biomass price to increase participation near the plant and reduce transportation costs.


## 1. Introduction

Unstable energy prices and energy security, as well as environmental impacts of fossil fuels, have increased global interest in alternative and renewable energy sources. One potential energy source is cellulosic biofuel. By using feedstock such as grasses and crop residues, cellulosic biofuel is a renewable substitute for traditional transportation fuels. Several countries have implemented policies to encourage cellulosic biofuel development (An et al., 2011), but the economics of cellulosic biofuel production have limited industry expansion. U.S. cellulosic biofuel production has been well below initial policy targets.[1]

It is generally agreed that significant cellulosic biofuel expansion will require more certainty in future cellulosic biofuel demand or improved efficiencies and lower costs in both feedstock procurement and biofuel processing (Miranowski et al., 2010; Sharma et al., 2013). As the industry is moving from pilot- to commercial-scale operations and policymakers are considering future biofuel policy, it is an opportune time to look more closely at commercial-scale cellulosic biofuel processor decisions as well as potential tradeoffs within these decisions.

A major challenge for cellulosic biofuel producers is identifying the optimum plant size given expected local supply of feedstock; processors must weigh processing cost economies of a larger plant with cost diseconomies of feedstock procurement. A plant built to a specific capacity based on expected local feedstock supply may find importing feedstock from outside the local market prohibitively expensive if local shortfalls occur.[2]

We present a long-run cost model that identifies the optimal combination of plant size and feedstock procurement to minimize biofuel

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[1] The U.S. Revised Renewable Fuels Standard (RFS2) outlined in the 2007 Energy Independence and Security Act (EISA) includes a cellulosic biofuel volume requirement that increases from 100 million gallons in 2010 to 16 billion gallons in 2022 (U.S. EPA 2012). Actual U.S. cellulosic biofuel production has not expanded as rapidly as the mandated quantities.

[2] This differs from traditional commodity crops such as corn, soybeans, small grains, etc. Established infrastructure for production, storage, and transportation allows commoditized crops to be traded on regional, national, and global markets. While commodity-based biofuel plants may get a majority of their feedstock from the local region, additional feedstock can be imported from another region without incurring prohibitively higher short-run feedstock costs. Infrastructure of this type has not yet developed for biomass (Babcock et al., 2011; Miranowski et al., 2010).

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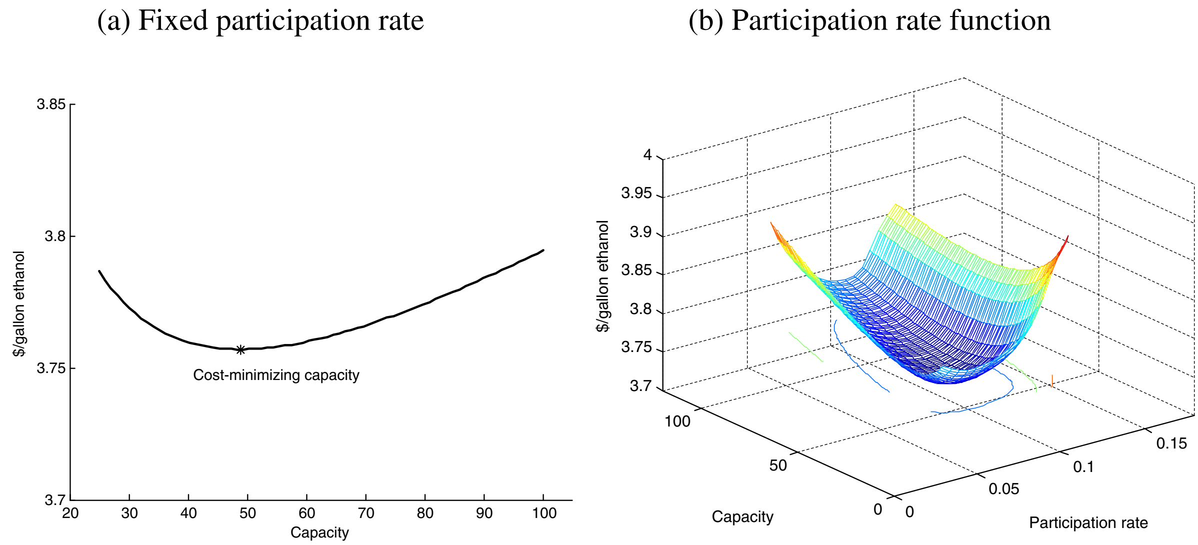


**Fig. 1.** Biofuel cost function for a select location.

costs per gallon for a given location. The common approach in the literature is to assume there is a fixed amount of local land allocated to biomass production. Any increase in feedstock demand is met by purchasing biomass from more distant areas in the local market (e.g., Brechbill and Tyner, 2008; Gan and Smith, 2011; Haque and Epplin, 2012; Khanna et al., 2011; Leboreiro and Hilaly, 2011; Parker et al., 2011; Popp and Hogan, 2007; Rosburg and Miranowski, 2011; U.S. DOE, 2011). The model proposed here relaxes this assumption by making the biomass price offered by the processor a choice variable. Increases in local biomass supply may be achieved by increasing the price paid for delivered feedstock, thus increasing biomass production (participation) nearer the plant as well as beyond. We explore how participation rate and capture distance affect the processor's cost-minimizing decision and the potential local feedstock supply.[3]

This article presents a descriptive overview of the model, with a detailed description of the model available in the online supplementary appendix. The model is operationalized using switchgrass as a feedstock for ethanol production and assumptions regarding biofuel processing costs, switchgrass production costs, feedstock transportation costs, and the opportunity cost of potential biomass cropland. Non-linear optimization is used to find expected cost-minimizing combinations of biomass price and plant size for each location. Then we identify location characteristics that jointly determine plant size and biofuel production.

## 2. Cellulosic biofuel cost model

We model a biofuel processor which considers building a commercial-scale biofuel plant at a given location. The processor's objective is to minimize the long-run total cost per gallon.[4] This objective is achieved by choosing the optimal plant size subject to the cost of procuring feedstock delivered to the plant.

The processor's cost function has two components: biomass conversion costs and biomass procurement costs. Biomass conversion costs include operating and capital costs; operating costs are assumed independent of plant size while capital costs are assumed to exhibit economies of plant size (Brown, 2003). Biomass procurement costs include the cost to acquire, store, and deliver feedstock to the plant.

In this model, the local supply of biomass depends on the price offered, and the processor pays each biomass supplier the same price per ton of delivered feedstock. Biomass producers have different land opportunity costs and may respond differently to market prices. As biomass price increases, producers within the capture radius of the plant may choose to supply biomass in greater quantities. We refer to this as the local participation rate function and it is non-decreasing in the biomass price. Modeling the participation rate as a function of price is a departure from models that assume a fixed local participation rate, where the processor takes the local field-side biomass price as given and increases in biomass demand (i.e., increase in plant size) are met by increasing the radius of the local biomass supply area.[5] Recent farmer surveys provide evidence that farmers in many regions are willing to allocate more land to biomass production as the biomass price increases. Further, farmers may differ in the minimum price at which they are willing to supply biomass even under relatively uniform production conditions (Altman et al., 2015; Bergtold et al., 2014; Menard et al., 2011; Qualls et al., 2011). Modeling participation as a function of biomass price allows processors to increase feedstock supply closer to the plant by increasing the offer price.

With a variable participation rate, the optimal biomass price (or intersection of biomass derived demand and local biomass supply) will occur where the marginal benefits from increasing plant size are equal to the marginal costs of acquiring additional feedstock for each location. Fig. 1 illustrates how this model compares with biofuel cost models that fix the participation rate.

In models where the participation rate is fixed, there is a single cost-minimizing plant size choice, as in Fig. 1(a). The model proposed here identifies the least-cost combination of plant size and participation rate (i.e., minimum point on the cost surface). Allowing participation rates to vary reveals the set of isocost lines that form the cost surface depicted in Fig. 1(b). The extent to which biofuel cost and plant size are over- or underestimated using the approach in Fig. 1(a) will depend

3 To our knowledge, the cost model we present is the first to account for this procurement tradeoff. A working paper version of this model was initially presented online in Rosburg et al. (2012) and Rosburg (2012). While Leboreiro and Hilaly (2011) acknowledge the existence of this tradeoff, their analysis uses a fixed participation rate. More recently, Sesmero and Gramig (2013) and Sesmero et al. (2014) consider the intensive and extensive margin tradeoff for stover procurement in Indiana, and Yu et al. (2014) include an intensive and extensive tradeoff for a switchgrass supply system in Tennessee.

4 Optimal biofuel plant size is determined by minimizing long-run average cost rather than maximizing long-run profits. Given current conditions, cellulosic biofuel is not likely to achieve long-run breakeven, implying a plant size of zero without significant fiscal incentives, higher fuel prices, or enforced mandates (Rosburg and Miranowski, 2011).

5 Recent examples include: Gan and Smith (2011), Haque and Epplin (2012), Leboreiro and Hilaly (2011), and Parker et al. (2011).