The Impact of the Renewable Energy Standard on the Land Use and Crop Yields in the US Great Plains

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1. Introduction

One of the central concerns of policymakers is the economic effects of environmental policies. These interventions may be a burden on economic activities to the extent that they can constrain the set of production technologies and outputs. The design of some environmental regulations can hinge on whether production standards in one market affect interrelated sectors at the extensive or intensive margins.[1] Several countries in the developed settings have adopted biofuel blending targets or mandates to tackle greenhouse gas (GHG) emissions and reinforce the energy security of supply (Xiaoguang and Madhu, 2013; Clancy and Moschini 2017). The use of biomass to produce fuels and energy has rapidly grown, perhaps mainly because of such policies. Because of these mandates, biomass producers and farmers could have faced significant variations in their land opportunity costs, production possibilities, profitability, and environments where they operate.[2]

The Renewable Fuel Standard (RFS) was introduced in the 2005 Energy Policy Act (EPA) and then significantly expanded in the Energy Independence and Security Act (EISA) of 2007. This policy determines mandates for specified quantities of biofuels. This policy

[1] The term extensive margin here refers to the number of land units used to produce a determined amount of crop output. This term can be interchangeable with agricultural land. Intensive margin refers to the amount of crop output per land unit. A rise in land productivity means an increase in yield or the intensive margin. An increase in the use of land for agricultural production raises the extensive margin. The extensive margin would represent the total amount of agricultural land area that farmers have available each year. Then, a farmer would increase land use on the extensive margin by planting on new agricultural land. The intensive margin would represent cropland as a proportion of total land. Therefore, a farmer would increase the intensive margin by increasing yields or output within a fixed area.

[2] Carter *et al*. (2017) estimated that about 37% of the U.S. corn crop went to the ethanol industry to blend with gasoline in 2015, while in 2005, it was up from 14%. The federal government mandated this rapid growth in corn use by requiring a minimum annual quantity of renewable biofuel or ethanol content in motor fuel. Since then, the land is more planted with corn than with any other crop in the U.S.

mandates specific quantities of biofuels.[3] The legislation passed in 2007 by the Congress of the United States increased by about 1.3 billion bushels the net amount of corn required to be processed annually into ethanol for motor fuel use. This expanded RFS, also known as the RFS2 mandates, nearly doubled the previous ethanol mandate and turned corn ethanol into 10% of finished motor gasoline in the United States in 2017, up from 3% in 2005. To the best of our knowledge, the economic literature has not yet explored the simultaneous impact of RFS2 on the extensive and intensive margins within the crops used to produce biofuels. This study estimates the effects of the 2007 RFS biofuel mandates on the supply of corn biomass and alternative crops evaluated at the intensive and extensive margins. For this, we use data on agricultural biomass produced in counties along the 41st north latitude parallel in the U.S. for 1960–2018.

Biomass currently accounts for about one-quarter of the total primary non-fossil energy produced in the U.S. (EIA, 2014; U.S. DOE, 2016), and its use has been increasing since 2002 (U.S. EIA, 2005). The U.S. federal government and some state and local governments have aggressively pursued policies that encourage biomass used for energy production. Almost all the ethanol produced in the U.S. comes from corn biomass (U.S. EIA, 2012). Biofuels (biodiesel and ethanol) production from different crops has offered the main alternative to fossil fuels regarding GHG reduction from a political viewpoint. These biofuel regulations aim to support farm incomes, reduce dependency on fossil fuels, and mitigate global warming effects (Carter *et al.*, 2017). However, biofuels compete with products conventionally used for human and animal consumption, which has raised concerns on food security mainly because of the increase in food and feed prices (Steer and Hanson, 2015).

[3] According to Anderson and Elzinga (2014), the original RFS had little effect on the amount of corn used for ethanol because it set the mandate at the levels required to meet air quality regulations for reformulated gasoline under the 1990 Clean Air Act.

Regarding the last objective, biofuel production may underperform if it involves significant land-use changes leading to additional GHG emissions (Gohin, 2014).

The regulated expansion of biofuels could trigger structural changes in the US agriculture sector, mainly by increasing both croplands used for producing biofuels and the prices of these crops. The percentage of corn used in the ethanol industry grew to 40% around 2013 in the US, where corn is the feedstock used for 98% of the US ethanol production (Turker and Hudson, 2017). The increase in food prices has been attributed mainly to the rise in ethanol production. However, economics literature offers not enough empirical evidence that the federal ethanol mandates are related to this phenomenon. Runge and Senauer (2007) found that the expansion of ethanol production is closely associated with increasing corn demand, prices, and producer profit. As far as we know, there are no studies simultaneously quantifying the effects of such ethanol supply expansion on biomass supply and land productivity. This study estimates the impact of ethanol supply expansion on the corn biomass supply and the productivity of land planted with corn in the US. The mandates creating the increase in ethanol production are assumed to be exogenous in the model.

The remainder of this paper is structured as follows. Section 1.1 provides a background of biofuel policies and the RFS in recent decades in the U.S. and discusses the relationship between ethanol market changes and crop-related prices and supply. Section 2 presents the economic and econometric models of production used in this paper. Section 3 describes and illustrates the data used in the analysis. Section 4 presents the estimation results. Section 5 concludes.

1.1. *Mandates in the Ethanol Market*

The first crucial ethanol policy in the US was the Energy Tax Act of 1978. This policy provided subsidies and tax exemptions for blending ethanol with gasoline. Another relevant policy was the EPA of 1992 enacted to improve the overall energy efficiency and clean energy use in the US. However, the policy that plays the most significant role in the US biofuel industry recently is the EPA of 2005 because mandates on minimum quantities of biofuels consumption\production initiated with such legislation. Although the Act focused on biofuel energy production in the US between 2005 and 2007, the EISA of 2007 expanded mandated targets progressively since 2007 from 9 million gallons to 36 million gallons of use by 2022. Corn starch ethanol is the main component among the biofuels required by the RFS, followed ultimately by cellulosic biofuel and biomass-based diesel RFS (EIA, 2017).

The present analysis of biomass supply response to the RFS can provide insights to the discussion on energy crops competing with food crops for land. Responding to the potential increase in the price of corn relative to other crops due to the RFS, for instance, can lead producers of this crop to expand such crop area (at the cost of other crops) or increase productivity. Carter *et al*. (2017) estimate the effects of the RFS2 on the corn market and find that the mandates raised corn prices by about 30%. Smith (2018) finds that the RFS that became law in 2007 increased both soybean and wheat prices by about 20%. An estimation of the RFS2 impact on corn biomass supply could provide crucial insights into the farmers' willingness to expand both the crop supply and crop area in response to potential increased profitability attributed to the RFS-ethanol mandates.[4] Evaluating how much the biofuel

[4] There was a rapid ascent of commodity prices between late 2005 and 2008 that led to renewed debate about what drives the supply for basic food commodities. According to Roberts and Schlenker (2013), corn prices nearly quadrupled from about $2 per bushel to almost $8 per bushel followed by a brief dropped in 2009–2010 due to the recession, but corn again broke $8 since 2011. These authors estimate supply elasticities of storable commodities (corn, rice, soybeans, and wheat) to evaluate the impact of the 2009 RFS on commodity prices,

mandate contributed to higher crop prices would require estimates of the underlying crop supply and demand elasticities (Roberts and Schlenker, 2013). However, examining the effects on crop supply effects could benefit from the assumption of price-taking crop producers as the perfect competition archetype. The RFS-induced crop price increases (rise in the demand for crops to produce biofuels) can constitute a crucial element for identifying the crop supply price elasticity. The crop producers' response to such price variations could translate into yield changes (i.e., effects at the intensive margin) or changes in the area planted (i.e., impacts at the extensive margin). The identification strategy thus relies on exogenous price changes affecting the crop demand to produce the corresponding biofuels.

Previous literature has investigated agricultural crop supply elasticities and crop acreage responses together consistent with a dual theoretical framework (see, for example, Morzuch *et al.*, 1980, Ball, 1988, Chambers and Just, 1989, Coyle 1993a,b; and Arnade and Kelch, 2007). According to Coyle (1993a), because output and acreage decisions are not separable in crop production, it may be very unrealistic to assume that crop output decisions and inputs allocations are modeled independently in agriculture. In his seminal papers, Coyle (1993a,b) derived systems of equations for modeling crop acreage responses by incorporating allocation decisions for fixed inputs such as land into a two-stage aggregation model of multioutput production decisions. At least there are four advantages of Coyle's approach over alternative theoretical frameworks. The separability conditions are consistent with a two-stage aggregation approach, more plausible, and less restrictive than standard models, such as those following Nerlove (1979) or based on a single output supply or acreage response equation. The dual approach permits the inclusion of contemporaneous co-variance of disturbances

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quantities, and food consumers' surplus. They found that prices increase 20% percent if one-third of commodities used to produce ethanol (shift in demand stemming from the U.S.' ethanol policy) are recycled as feedstock. However, the U.S. corn farm price received has been between \$3.1 and \$4.2 during 2013-2019 (USDA, 2020).

across equations. The hypothesis of competitive profit maximization implies symmetry/reciprocity restrictions on coefficients across equations. Finally, the production decision scheme is an actual representation of a two-stage decision-making process for producers that is both more empirically reliable and more feasible to recover the underlying technology.

2. Methodology

2.1. Theoretical Framework

This study follows a dual model based on Chambers and Just (1989), Coyle (1993a,b), and Arnade and Kelch (2007) as an attempt to assess the effects of RFS on corn biomass supply and acreage demand for a specific agricultural region of the US. Our empirical approach analyzes the technology for producing biomass within a set of counties across the central Us Great Plains. A clue assumption is that production decisions are consistent with the profit-maximization behavior of farmers operating under perfect competition in both outputs and inputs markets.[5] Given the vector of output and input prices and exogenous factors, farmers choose an optimal vector of outputs and inputs. Among these exogenous factors are the price shocks created by the RFS and the environmental condition and institutional aspects or physical characteristics of a county (e.g., the topography, climate, water field, soil organic matter, and time).

[5] Given certain regularity conditions and the assumption of profit maximization, we can use duality theory to characterize multiple inputs, multiple output production systems by a profit function model (Lau, 1978; McFadden, 1978).

2.1.1. Two-stage Profit Maximization Approach with Land Fixed and Allocatable

The decision-making unit (DMU) produces a vector of m annual crop outputs $\boldsymbol{Y} = (Y_1, \dots, Y_m)$ using a vector of n allocatable variable inputs $\boldsymbol{X} = (X_1, \dots, X_n)$ and a fixed total amount of agricultural land (L_a) allocated among the individual crops. Given non-allocatable fixed inputs, exogenous factors (such as environmental and institutional variables), and time as a proxy for exogenous technical change included in the vector $\boldsymbol{Z} = (Z^1, \dots, Z^K)$, the producer follows a two-stage decision-making process. In the first stage, the DMU maximizes profits from each output given the land allocated to each crop. In the second stage, the available agricultural land is distributed optimally across crops. The profit function for each crop is presumed to be represented by

$$\pi^i(P_i, \boldsymbol{W}, l_i, \boldsymbol{Z}) = \max_{(\boldsymbol{X}, Y_i) \in T(\boldsymbol{Z})} \{P_i Y_i - \boldsymbol{W}\boldsymbol{X} : Y_i = F^i(\boldsymbol{X}; l_i, \boldsymbol{Z})\} \tag{1}$$

where P_i is the price of the crop i; Y_i is the produced quantity of crop i; $\boldsymbol{W} = (W_1, \dots, W_n)$ is the vector of the variable inputs' prices; l_i is the amount of land allocated to the production of crop i, and $T(\boldsymbol{Z})$ is the set of choice variables allowed by the technology given $\boldsymbol{Z}$. The producer's dual profit function is assumed to be continuous and twice differentiable with respect to all its arguments; linearly homogenous and convex in prices; and non-decreasing in output prices P_i, while non-increasing in variable inputs prices $\boldsymbol{W}$. The second stage implies that DMUs allocate available agricultural land to the optimally managed crops. The producers thus solve:

$$\pi(\boldsymbol{P}, \boldsymbol{W}, L_a, \boldsymbol{Z}) = \max_{l_1, \dots, l_m, \lambda} \left\{ \sum_{i=1}^{m} \pi^i(P_i, \boldsymbol{W}, l_i, \boldsymbol{Z}) + \lambda(L_a - \sum_{i=1}^{m} l_i) \right\} \tag{2}$$

where $\boldsymbol{P} = (P_1, \dots, P_m)$ represents a vector of the m crop prices; λ is the shadow price of agricultural land and the other variables are defined as above. Output supply and variable input demand equations conditional on L_a and $\boldsymbol{Z}$ are obtained by Hotelling's lemma, and acreage demands are implicit in the first-order conditions (FOC) from equation (2). The (negative of the) partial derivative of the profit function [equations $(1) - (2)$] with respect to the variable input price vector $\boldsymbol{W}$ yields the vector of optimal variable input demands:

$$-\frac{\partial \pi}{\partial \boldsymbol{W}} = -\sum_{i=1}^{m} \frac{\partial \pi^i}{\partial \boldsymbol{W}} = \sum_{i=1}^{m} \boldsymbol{X}_i^* = \boldsymbol{X}^*(\boldsymbol{P}, \boldsymbol{W}, L_a, \boldsymbol{Z}) \tag{3}$$

where $\boldsymbol{X}_i^* = (X_{1i}^*, \dots, X_{ni}^*)$ represents the vector of optimal allocatable variable inputs used in the production of crop i and $\boldsymbol{X}^* = (X_1^*, \dots, X_n^*)$ is a vector of the total levels of the n variable inputs employed over the m crops. Similarly, by differentiating equation (2) with respect to the output price of crop i we obtain the output supply function of that crop:

$$\frac{\partial \pi^i}{\partial P_i} = Y_i^*(\boldsymbol{P}, \boldsymbol{W}, l_i, \boldsymbol{Z}) \qquad \forall\, i = 1, \dots, m \tag{4}$$

where Y_i^* represents the optimal output quantity of crop i. We can also obtain the optimal allocation of the quasi-fixed factors such as land from the restricted profit function. If we differentiate the restricted profit function in equation (2) with respect to the quasi-fixed factor (l_i) we can obtain the shadow price equation for land used in the production of the output of crop i:

$$\frac{\partial \pi}{\partial l_i} = \lambda_i(\boldsymbol{P}, \boldsymbol{W}, L_a, \boldsymbol{Z}) - \lambda = 0 \qquad \forall\, i = 1, \dots, m \tag{5}$$

where λ_i is the shadow price of the additional unit of land allocated to the production of crop i. From the Lagrangian multiplier of the constraint in equation (2) we can infer that the shadow prices of land across alternative crop equations are equal at the optimum[6]:

$$\frac{\partial \pi^1(P_1, \boldsymbol{W}, l_1, \boldsymbol{Z})}{\partial l_1} = \frac{\partial \pi^2(P_2, \boldsymbol{W}, l_2, \boldsymbol{Z})}{\partial l_2} = \cdots = \frac{\partial \pi^m(P_m, \boldsymbol{W}, l_m, \boldsymbol{Z})}{\partial l_m} \tag{6}$$

We can further infer that the shadow price of land allocated to each crop (i.e. λ_i) equates to the overall shadow value of the marginal land unit:

$$\frac{\partial \pi}{\partial L_a} = \lambda = \lambda_i(P_i, \boldsymbol{W}, l_i, \boldsymbol{Z}) = \frac{\partial \pi^i}{\partial l_i} \qquad \forall\, i = 1, \dots, m \tag{7}$$

Because the term l_i represents the area allocated to the ith crop and is represented in each shadow price equation in (7), jointly solving the shadow price equations and the constraint: $\sum_{i=1}^{m} l_i = L_a$ for the allocation terms (l_i) obtains a function for the area devoted to crop i. This can be done for every crop by considering that equation (7) together with equation (6) would imply that: $\frac{\partial \pi^j}{\partial l_j} = \frac{\partial \pi^i}{\partial l_i} = \lambda$, with $i, j = 1, \dots, m$. This general model formulation implies that the inverse of each cropland shadow price equation in (7) has its equivalent acreage demand (l_i) which in turn is a function of all product prices, all variable inputs, and the total amount of cropland:

$$l_i = l_i(\boldsymbol{P}, \boldsymbol{W}, L_a, \boldsymbol{Z}) \qquad i, j = 1, \dots, m \tag{8}$$

The main feature of interest from each of these crop area functions is that they include output prices as arguments whose derivatives can be used to calculate the area response to a price change (Coyle 1993a,b; Arnade and Kelch, 2007).

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[6] It has been showed by previous studies that land allocation vector can be recovered explicitly from the multioutput profit function (see, for instance, Chambers and Just, 1988; Paris, 1989; and More and Negri, 1992).

2.2. *Empirical Implementation*

To implement the model empirically it is necessary to first specify a form for the profit functions. In the present study the normalized quadratic, a member of the class of flexible functional forms, was adopted. We normalize the input and output prices with the price of one of the outputs, let us say the output price of crop m, and impose symmetry. The crop-specific profit function for the normalized quadratic is:

$$\frac{\pi^i}{P_m} = \alpha_i + \beta_i\left(\frac{P_i}{P_m}\right) + \boldsymbol{\gamma}_i\left(\frac{\boldsymbol{W}}{P_m}\right) + \delta_i l_i + \boldsymbol{\zeta}_i\boldsymbol{Z} + \frac{1}{2}\varphi_i\left(\frac{P_i}{P_m}\right)^2 + \boldsymbol{\eta}_i\left(\frac{P_i}{P_m}\right)\left(\frac{\boldsymbol{W}}{P_m}\right) + \theta_i\left(\frac{P_i}{P_m}\right)l_i$$
$$+\boldsymbol{\kappa}_i\left(\frac{P_i}{P_m}\right)\boldsymbol{Z} + \frac{1}{2}\boldsymbol{\omega}_i\left(\frac{\boldsymbol{W}'\boldsymbol{W}}{P_m}\right) + \boldsymbol{\mu}_i\left(\frac{\boldsymbol{W}}{P_m}\right)l_i + \boldsymbol{\xi}_i\frac{\boldsymbol{W}'}{P_m}\boldsymbol{Z} + \frac{1}{2}\rho_i l_i^2 + \boldsymbol{\sigma}_i l_i\boldsymbol{Z} + \frac{1}{2}\boldsymbol{\phi}_i\boldsymbol{Z}'\boldsymbol{Z}$$
$$\forall\, i = 1, \dots, m \qquad (9)$$

and by using Hotelling's Lemma the optimal ith crop output supply function and optimal variable input demand equations are respectively expressed as:

$$\frac{\partial\left(\frac{\pi^i}{P_m}\right)}{\partial\left(\frac{P_i}{P_m}\right)} = Y_i^* = \beta_i + \varphi_i\left(\frac{P_i}{P_m}\right) + \boldsymbol{\eta}_i\left(\frac{\boldsymbol{W}}{P_m}\right) + \theta_i l_i + \boldsymbol{\kappa}_i\boldsymbol{Z} \qquad \forall\, i = 1, \dots, m \qquad (10)$$

$$-\frac{\partial\left(\frac{\pi^i}{P_m}\right)}{\partial\left(\frac{W_j}{P_m}\right)} = X_{ij}^* = -[\gamma_{ij} + \eta_{ij}\left(\frac{P_i}{P_m}\right) + \omega_{ij}\left(\frac{W_j\cdot\boldsymbol{W}}{P_m}\right) + \mu_{ij}l_i + \boldsymbol{\xi}_{ij}\boldsymbol{Z}]$$
$$\forall\, i = 1, \dots, m; \quad \forall\, j = 1, \dots, n \qquad (11)$$

where Y_i^* represents, more specifically, the profit-maximizing supply of the ith crop output of a county at some point in time, and X_{ij}^* denotes the profit-maximizing demand for the jth variable input use in the production of crop i. Summing up to m both sides of the equation (11) yields:

$$-\sum_{i=1}^{m}\frac{\partial\left(\frac{\pi^{i}}{P_m}\right)}{\partial\left(\frac{W_j}{P_m}\right)} = X_j^* = -\sum_{i=1}^{m}\left[\gamma_{ij} + \eta_{ij}\left(\frac{P_i}{P_m}\right) + \boldsymbol{\omega}_{ij}\left(\frac{W_j \cdot \boldsymbol{W}}{P_m}\right) + \mu_{ij} l_i + \boldsymbol{\xi}_{ij}\boldsymbol{Z}\right]$$

$$\forall\, j = 1, \dots, n \qquad (12)$$

where X_j^* denotes the profit-maximizing demand for the jth variable input of a county each year. We also differentiate equation (9) with respect to the acreage term (l_i) to obtain the shadow price of land used in the production of crop i:

$$\frac{\partial\left(\frac{\pi^{i}}{P_m}\right)}{\partial l_i} = \lambda_i^* = \delta_i + \theta_i\left(\frac{P_i}{P_m}\right) + \boldsymbol{\mu}_i\left(\frac{\boldsymbol{W}}{P_m}\right) + \rho_i l_i + \boldsymbol{\sigma}_i\boldsymbol{Z} \qquad \forall\, i = 1, \dots, m \qquad (13)$$

where λ_i^* denotes the shadow price of the parcel of land optimally allocated to produce the ith crop. To obtain the ith acreage response equation, we manipulate the system of m equations derived from (13) using the properties given by equations (6) and (7) and including the land constraint $l_m = L - \sum_{i=1}^{m-1} l_i$. Replacing this constraint into the expression (13) for the mth crop and then subtracting the resulting equation from each of the other equations in the system of equations in (13) to reduce the system to $m-1$ equations, we obtain:

$$0 = \delta_i - \delta_m + \theta_i\left(\frac{P_i}{P_m}\right) - \theta_m + (\boldsymbol{\mu}_i - \boldsymbol{\mu}_m)\left(\frac{\boldsymbol{W}}{P_m}\right)$$

$$+ \rho_i l_i - \rho_m(L - \sum_{i=1}^{m-1} l_i) + (\boldsymbol{\sigma}_i - \boldsymbol{\sigma}_m)\boldsymbol{Z} \qquad (14)$$

Solving this expression for l_i gives an estimable equation for the optimal allocation of land as a function of crop output prices, variable input prices, total available land (L_a), and other exogenous factors:

$$l_i = \upsilon_{i0} + \upsilon_{i1}\left(\frac{P_i}{P_m}\right) + \boldsymbol{\upsilon}_{i2}\left(\frac{\boldsymbol{W}}{P_m}\right) + \upsilon_{i3}L + \boldsymbol{\upsilon}_{i4}\boldsymbol{Z} \quad (15)$$

where $\upsilon_{i0} \cong \frac{1}{\rho_i}(\delta_i - \delta_m - \theta_m + \rho_m)$; $\upsilon_{i1} = \frac{\theta_i}{\rho_i}$; $\boldsymbol{\upsilon}_{i2} \cong \frac{1}{\rho_i}(\boldsymbol{\mu}_i - \boldsymbol{\mu}_m)$; $\upsilon_{i3} = \frac{\rho_m}{\rho_i}$; and $\boldsymbol{\upsilon}_{i4} = \frac{1}{\rho_i}(\boldsymbol{\sigma}_i - \boldsymbol{\sigma}_m)$ are all reduced form parameters to be estimated. We consider that the production of the agricultural outputs particularly corn, soybeans, and other crops, arise from an equilibrium allocation of (finite) cropland across the three alternatives.

To evaluate the effect of the policy at the extensive and intensive margins and consistent with recent work addressing agricultural supply response to price changes induced by the biofuel expansion (e.g., Carter *et al.*, 2017; Moschini *et al.*, 2017: Hendricks *et al.*, 2014, Berry 2011), we postulate both a land allocation response and a yield response. For this, we can rearrange the equations (10) and (12) using the constraint $\sum_{i=1}^{m} l_i = L$ or $l_i = L - \sum_{r}^{m-1} l_r\ \forall\, i \neq r$ in such a way that we have the estimable equations:

$$Y_i^* = \varphi_{i0} + \varphi_{i1}\left(\frac{P_i}{P_m}\right) + \boldsymbol{\varphi}_{i2}\left(\frac{\boldsymbol{W}}{P_m}\right) + \varphi_{i3}L + \boldsymbol{\varphi}_{i4}\boldsymbol{Z} \quad (16)$$

$$X_j^* = \omega_{0j} + \omega_{1j}\left(\frac{P_i}{P_m}\right) + \boldsymbol{\omega}_{2j}\left(\frac{W_j \cdot \boldsymbol{W}}{P_m}\right) + \omega_{3j}L + \boldsymbol{\omega}_{4j}\boldsymbol{Z} \quad (17)$$

where $\varphi_{i0} = \beta_i - \theta_i \sum_{r}^{m-1} l_r$; $\varphi_{i1} = \varphi_i$; $\boldsymbol{\varphi}_{i2} = \boldsymbol{\eta}_i$; φ_{i3}; $\boldsymbol{\varphi}_{i4} = \boldsymbol{\kappa}_i$; $\omega_{0j} = \sum_{i=1}^{m-1} \gamma_{ij} - \mu_{ij}\sum_{r}^{m-1} l_r$; and $\boldsymbol{\omega}_{hj} = \sum_{i}^{m-1} x_{ij}$ for h=1,2,4 and x standing for η, $\boldsymbol{\omega}$, and $\boldsymbol{\xi}$ are all parameters to be estimated. Furthermore, from the acreage response equations (15) and the supply function for biomass from corn in (16), we can infer the extensive and intensive margins using $\boldsymbol{p} = \frac{\boldsymbol{P}}{P_m}$, $\boldsymbol{w} = \frac{\boldsymbol{W}}{P_m}$ and considering that:

$$y_i(\boldsymbol{p}, \boldsymbol{w}, L, \boldsymbol{Z}) = \frac{Y_i^*(\boldsymbol{p}, \boldsymbol{w}, L, \boldsymbol{Z})}{l_i(\boldsymbol{p}, \boldsymbol{w}, L, \boldsymbol{Z})}$$

where y_i represents the crop yield per acre resulting from dividing Y_i^* by the optimally allocated cropland planted (l_i). The total change in Y_i^* can be thus given by $dY_i^* = \frac{\partial Y_i^*}{\partial l_i} dl_i \cdot y + \frac{\partial Y_i^*}{\partial y_i} dy_i \cdot l_i$, where the first term is the change in planted land as the extensive margin and the second term is the change in yield as the intensive margin. Following Babcock (2015), in elasticities form, this would be equivalent to $\tau_y = \tau_{Y_i^*} - \tau_{l_i}$, where $\tau_{Y_i^*}$, τ_{l_i}, and τ_y are price elasticities of crop i total supply, area, and yield, respectively. More specifically, we can estimate from the equation (16) the supply crop i price elasticity as $\tau_{Y_i^*} = \varphi_{i1} \cdot [(P_i/P_m)/Y_i^*]$, and from equation (15) the area price elasticity of crop i as $\tau_{l_i} = \upsilon_{i1} \cdot [(P_i/P_m)/l_i]$.

2.3. Estimation

This paper studies the impact of RFS mandates on the intensive and extensive margins of biomass produced in 101 counties in Colorado, Nebraska, Iowa, and Wyoming within the period from 1969 to 2018. For this, we estimate a system of equations (i.e., output supplies, derived demand for variable factors of production and crop acreage demands) obtained from $(15) - (17)$:

$$\boldsymbol{Y} = \boldsymbol{\varphi}_0 + \boldsymbol{\varphi}_1 \boldsymbol{p} + \boldsymbol{A_Y} \boldsymbol{w} + \boldsymbol{\varphi}_2 L + \boldsymbol{B_Y} \boldsymbol{Z} + \boldsymbol{\varepsilon_Y} \tag{18}$$

$$\boldsymbol{X} = \boldsymbol{\omega}_0 + \boldsymbol{\omega}_1 \boldsymbol{p} + \boldsymbol{A_j} \boldsymbol{w} + \boldsymbol{\omega}_2 L + \boldsymbol{B_j} \boldsymbol{Z} + \boldsymbol{\varepsilon_X} \tag{19}$$

$$\boldsymbol{l} = \boldsymbol{\upsilon}_0 + \boldsymbol{\upsilon}_1 \boldsymbol{p} + \boldsymbol{A_l} \boldsymbol{w} + \boldsymbol{\upsilon}_2 L + \boldsymbol{B_l} \boldsymbol{Z_k} + \boldsymbol{\varepsilon_l} \tag{20}$$

where $\boldsymbol{Y}$ is a vector of crop biomass quantities (tons harvested plus stalks and leaves) of corn, soybeans and other crops; $\boldsymbol{X}$ is a vector of variables inputs including fertilizer and chemicals (measured in implicit quantity indexes), labor, and capital; $\boldsymbol{l}$ is a vector of the acreage planted with corn, soybeans, and other crops; L is the total planted area in the county; $\boldsymbol{p}$ is a vector of corn and soybeans prices relative to an index of the biomass price from all other crops; $\boldsymbol{w}$ is a vector including the prices of fertilizer, chemicals, labor (wages), and capital relative to the price index of biomass from all other crops; $\boldsymbol{Z} = (irrigation, r, \boldsymbol{DD}, time)$ with $irrigation$ as the fraction of planted land in the county that is irrigated, r as annual precipitation in centimeters, $\boldsymbol{DD}$ as a vector of temperature degree-day interval variables (the total length of time, in days, that the crops were exposed to temperatures in a specific range during the growing season), and $time$ = 1,…,49 as a proxy for exogenous technical change; $\boldsymbol{\upsilon}$'s, $\boldsymbol{\varphi}$'s, $\boldsymbol{\omega}$'s, $\boldsymbol{A}'s$, and $\boldsymbol{B}'s$ are set of parameters to be estimated; and the $\boldsymbol{\varepsilon}$'s denote sets of stochastic error terms in the system of equations. We assume that these error terms ($\boldsymbol{\varepsilon}$'s) are correlated across the system of equations above. This is also because we are attempting to estimate output supplies curves and factor demand equations that are all in the form of quantities as functions of prices. However, shocks to output demand affecting output prices, for instance, make prices not to be strictly taken as exogenous. To identify the price elasticities in the system of equations it would be ideal to consider both the correlation of the error terms across equations and at least a sort of output demand shock to be used as a source of exogenous variation in the output price.

The main assumption here is the existence of significant effects of a policy in the ethanol market on the crop (or input) markets related to such biofuel production. As stated before, corn is the main crop used in producing ethanol in the U.S. such that the mandates on ethanol production would significantly and exogenously affect the prices (mainly through the demand) of the staple crops used to produce such biofuel, i.e., essentially corn.

Although the demand curve, including demand for corn to produce ethanol, would part of our system of simultaneous equations $(18) - (20)$ that jointly determine output quantity and price, we do not model output demand equation explicitly but instead we use the RFS mandated in the ethanol (gasoline) market as a potential source of exogenous variation in the price of corn. For the empirical implementation of the model and the sake of identification of the extensive and intensive margins in corn production due to the policy, we thus specify an additional equation for corn price as a function of a proxy to the effects of the RFS mandates since 2007. This proxy is used as an instrument for the corn price equation Thus, it is not included in the system $(18) - (20)$ as a separate determinant but it is considered crucial to identifying ultimately the effects of corn price variation due to the 2007 RFS on the output supplies, input demands, and crop-acreage demand equations.

We approximate the policy by the variable ζ. To specify this variable, we first consider a dummy variable ($\tau = 1$ if the year $\geq 2007; = 0$ otherwise) indicating years of exposure to RFS mandates expansion starting 2007. We also use a variable denoted RFS which is intended to be a direct measure of the 2007 RFS effect on the corn markets. More specifically, RFS is equal to the state-level fuel ethanol production in barrels potentially capturing shocks in the demand for biomass from corn. To create a county-level variation and to further specified ζ in such a way that it may capture the intensity of the policy effect or exposure, the terms τ and RFS are also interacted with (or multiply by) the inverse of the distance of each county's centroid to the closet biorefinery producing ethanol (let denote this variable as $distance^{-1}$). Therefore, the instrument for corn price is given by:

$$\zeta = \tau \times distance^{-1} \times RFS$$

where ζ is assumed to be a proxy for the 2007 RFS mandates shock to corn demand and more concretely to corn prices. This variable is used as an instrument for corn prices. It indicates the years when the counties were exposed (τ) to some extent or intensity ($distance^{-1}$) to potential corn demand shocks increasing corn prices induced by the mandated quantities reflected in the ethanol production (RFS).

3. Data

We obtain data for 101 counties that lie along the 41st parallel north in part of the Midwestern U.S over 1969-2017. Figure 1 shows the area of analysis that stretches from the Rocky Mountains to the Mississippi River across Nebraska (47 counties), Iowa (47 counties), Colorado (4 counties) Wyoming (3 counties). The region is not just a major cereal production area in the U.S. but may also have worldwide implications for similar agroecosystems. This area includes both a vast gradient of weather and soil as well as underground water characteristics that are highly representative of agriculture production in other temperate regions of the world (Trindade, 2011).

The construction of the variables used is based on information from the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA), the United States Historical Climatology Network (USHCN), and the U.S. EIA State Energy Data System (SEDS). The information about state-level ethanol production was retrieved from the Primary Energy Consumption Estimates by Source, 1960-2017 of the U.S. EIA. To compute the distance of each county to the closest ethanol biorefinery, we also use data on the georeferenced locations of these biorefineries in the U.S retrieved for the year 2010 from the Renewable Fuels Association (RFA).[7]

Data on annual crop outputs and total acreages planted per crop in the county are from the surveys conducted by the NASS-USDA. The vector of crop outputs $\boldsymbol{Y}$ indicates total biomass production in metric tons[8] of dry matter. To simplify the econometric model, we aggregate crops into three groups: corn, soybeans, and all other crops produced in the county including wheat, barley, sorghum, rye, oats, hay, and sugar beets. Thus, vector $\boldsymbol{Y}$ consists of the aggregate of all aboveground biomass produced by corn, soybeans, and all other crops in the county. The total amount of biomass produced from $corn$, $soybeans$ and all other crops ($others$) for county c in year t is calculated as:

$$Y_{corn,c,t} = \frac{Q_{corn,c,t}}{HI_{corn}} \times (DM_{corn})$$

$$Y_{soybeans,c,t} = \frac{Q_{soybeans,c,t}}{HI_{soybeans}} \times (DM_{soybeans})$$

$$Y_{others,c,t} = \sum_{c} \frac{Q_{o,c,t}}{HI_o} \times (DM_o)$$

where o indexes all other crops produced in the county each year. The county-wide harvest for crop $i = corn, soybeans, o$ expressed in metric tons is denoted by Q_i. The term

[7] The RFA provides the location of U.S. fuel ethanol plants by county. These production facilities are classified as installed ethanol biorefineries, operational ethanol biorefineries and biorefineries under construction/expansion. We use the location of the installed and operating ethanol biorefineries on September 1, 2010 retrieved from http://www.ethanolrfa.org/bio-refinery-locations/ to construct the weighting variable $distance^{-1}$. In 2010, the U.S. ethanol industry was made up of 200 nameplate refineries with a total capacity of 13.544 million gallons per year (MGY): 192 of which were operating with an annual capacity of 12.9 MGY, while 12 plants were under construction or expansion. See Urbanchuk (2010) for a detailed description of ethanol plants location in 2010. In general, the ethanol biorefineries concentrated in the Midwest corn-belt states, mainly in Iowa and Nebraska. See the current location in https://ethanolrfa.org/biorefinery-locations/ at a county level, and https://ethanolrfa.org/where-is-ethanol-made/ at a state level.

[8] For instance, coefficients to convert to metric tons (i.e., tonnes) from bushels were 0.0254 for corn, sorghum, and rye and 0.0272 for wheat and soybeans.

HI denoting harvest index is the fraction of the above-ground biomass of crop $i = corn, soybeans, o$ that is harvested (Hay, 1995; Unkovich *et al.*., 2010)[9]. The term DM indicates the dry matter proportion of the harvest for crop $i = corn, o$.[10] We also compute relative (state-level) prices of corn and soybeans by dividing each of these crop prices by a biomass weighted average value of all other crops excluding corn and soybeans. This value is calculated by dividing the value of total production (price×quantity) of each crop by the total biomass produced. This value was then calculated as:

$$\hat{p}_{others,c,t} = \sum_{o} \frac{(P_{o,c,t}) \cdot (Q_{o,c,t})}{HI_o} \times (DM_o)$$

where $P_{o,c,t}$ is the reported price for crop o (other than corn and soybeans) in county c at year t and $\hat{p}_{o,c,t}$ represents the "average price" of all other crops except corn and soybeans.

The variable inputs considered are fertilizer, chemicals, labor, and capital. The inputs fertilizer and chemicals are measured in implicit quantity indexes. These indexes were estimated using county-level expenditures on these inputs reported approximately every five years by the Census of Agriculture published by the USDA–NASS. For each census year, we divided the reported input expenditure by a national level input price index obtained from USDA–Economic Research Service for fertilizers and USDA–NASS for chemicals (base 1990-1992=100). Inter-census interpolation of these county-level quantity indexes was applied by using annual state fertilizer indexes. All these values were finally divided by the index in Adams County, Nebraska, for the year 1969. The variable labor was constructed following a similar approach to that of fertilizer and chemicals. Data on the number of total

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[9] The harvest indexes used were 0.5 for corn and sorghum for grain; 1 for corn and sorghum for silage and hay; 0.4 for soybeans, rye, and barley; and 0.35-0.85 for other minor crops.

[10] The dry matter fraction for a crop is equivalent to one minus the respective moisture index of that crop. Following Loomis and Connors (1992), the moisture indexes used were 0.145 for corn and sorghum for grain, barley, and rye; 0.55 for corn and sorghum for silage; 0.135 for wheat; 0.13 for soybeans and beans; and 0.10-0.78 for all other minor crops.

hired farm workers and total expense with hired farm labor (US$1,000 payroll) was obtained from the USDA Census of Agriculture Historical Archive for the census years from 1964 to 1992 and USDA–NASS for the census years from 1997 to 2017. We use that total county-level number of hired farmworkers as a proxy for labor and create the nominal wages for each census year/county as the result of dividing the total payroll by the number of these hired workers. To fill the gaps of information between the census years, linear interpolation was used for both series. All wages obtained were also deflated using the corresponding value for Adams County, Nebraska in the year 1969.

A series on the annual stock of capital was created using data on the county-level inventory on tractors, trucks, and agricultural equipment on farm place also retrieved from the NASS-USDA censuses. The time series for the price of capital was constructed using US expenditures on each of these items from ERS/USDA and based on the Producer Price Index for Farm Machinery and Equipment Manufacturing (Index Dec 1982=100, Annual, Not Seasonally Adjusted), available from the Federal Reserve Economic Data (FRED), and the depreciation rates used are from the Bureau of Economic Analysis (BEA). To calculate the "quantity of capital" for each county, the share of each type of equipment (tractors, trucks, and machinery) to the national level was calculated for each county based on the values of each census year. Linear interpolations were used between census years. These shares were multiplied by the national annual stock of capital calculated using corresponding rates of depreciation, service life (in years), and declining-balance rates. All the resulting annual values were aggregated such that county-level annual stock of capital was obtained.

The independent variables consist of the prices of variable inputs and outputs (all normalized or divided by the $\hat{p}_{o,c,t}$), quasi-fixed irrigation input and other exogenous factors such as environmental/institutional variables as well as time as a proxy for exogenous technical change. The irrigation variable is measured as the ratio of irrigated cropland to total planted cropland by county and year. Environmental (weather) variables included are yearly precipitation and annual temperature intervals. Using weather stations' data collected from the High Plains Regional Climate Center, we estimated degree-days (DD)[11] and precipitation as a distance-weighted average (at the five weather stations closest to the county center) of daily minimum and maximum temperature, and daily precipitation in centimeters, respectively (see Trindade, 2011, for more details). The annual precipitation variable was bounded to the "growing season"[12] by summing up values obtained as previously from March through August each year. Similarly, the vector of annual DD was calculated as the sum of the daily temperature averages from March through August and obtained as the amount of time during the "growing season" that the crops were exposed to specific intervals of temperature (see Schlenker and Roberts, 2009; Trindade, 2011; García *et al.*, 2019, for a detailed explanation of this process). More specifically, the number of hours each day in each interval was then added for March through August and then divided by 24 to compute the DD variables. We further use a set of three aggregated DD variables, i.e., the number of days in a year with temperatures between 0 and 29ºC ($DD0029$); 30 and 35ºC ($DD3035$); and higher than 35ºC ($DD35plus$). Table 3.1 presents summary statistics of all previously described variables.

[11] An adaptation of the agronomic measure "growing degree days" is used to measure the effect of temperature. According to the agronomic literature a "growing degree day" can be defined as the amount of time (in days) when the temperature is above certain threshold; hence one degree-day is accumulated when the temperature is one degree above a given threshold for a period of 24 hours (Ritchie *et al.*., 1991; Trindade, 2011).
[12] In this study, we define the "growing season" as March to August as in Schlenker and Roberts (2009), Trindade (2011), Miao *et al.*. (2015), and García *et al.*. (2019) because planting and harvesting of corn, for example, in most growing states starts in March (NASS 2010).

4. Empirical Results

The purpose of this study is to determine quantitatively the effects of Renewable Fuel Standards on the corn supply and acreage in a county-level panel data framework of an area in the Great Plains for the period from 1969 to 2017. One way to estimate the entire system of equations given by $(18) - (20)$ would be through a Seemly Unrelated Regression Estimation (SURE) or Zellner-efficient regression. The estimates would be likely rather efficient by estimating all equations together because the SURE takes account of the very likely potential correlation between the error terms in the vectors $\boldsymbol{\varepsilon_Y}$, $\boldsymbol{\varepsilon_X}$, and $\boldsymbol{\varepsilon_l}$. Also, we want to further impose cross-equation "symmetry" restrictions, particularly the corresponding cross-price effects in the equations. This implies that, for instance, the cross-price effect (slope) of demand for fertilizer with respect to the price of chemicals equals the slope of demand for chemicals with respect to the price of fertilizer.

A three-stage least squares (3SLS) estimation is used because we want to endogenize the right-hand side variable corn price to the demand shocks caused by the RFS mandates for identifying corn supply and corn acreages demand equation. This identification strategy is conducted to retrieve the respective effects of such policy on the extensive and intensive margins of corn biomass production. While instrumenting corn prices, efficiency gains by accounting for correlation of errors $\boldsymbol{\varepsilon}$'s as well as the possibility of imposing cross-equation coefficient restrictions are still a feature allowed by the 3SLS estimation.

Table 3.2 and Table 3.3 present the 3SLS estimation of the system of equations in $(18) - (20)$. The crop output supply equations in (18) and the variable input demand equations in (19) are presented in Table 3.2. These equations were restricted to satisfy symmetry between the cross-price parameters in the crop supplies, variable input demands, and crop acreage demands. The table contains a total of ninety-one parameters, sixty-two of which are significant at the 1% level, five at the 5% level, and five at the 10% level. Columns (1)-(3) present the estimates for the three crop output supply equations considered here, whereas columns (4)-(7) correspond to those of the variable inputs derived demand equations. The estimated coefficient for the own-price coefficient of corn is positive and statistically significant at the 1% level, while the coefficient for soybeans is not significant though it is positive as expected. These coefficients imply that the average biomass supply of corn (soybeans) would have increased by about 1,865 (93) thousand metric tons per year in response to the observed corn price increases. The cross-price coefficients indicate that corn and soybeans are complements in production, but corn (soybeans) and all other crops can be considered as substitutes (complements) in production. Regarding the effect of an increase in the total available cropland, it seems to affect corn quantity supplied more than all other crops. On the other hand, the coefficients estimated for the variable time across the columns (1)-(3) suggest that the trend of the output supplies reflects a biased technological change mainly towards corn and apparently against all other crops together excluding soybeans.

The input demands in columns (4) to (7) of Table 3.2 show that all the computed own-price effects are statistically significant, and they have a negative sign as expected. Moreover, the cross-price coefficients between fertilizer and chemicals indicate that these inputs are complementary in production, while labor and capital inputs appear as substitutes for fertilizer. We can also observe that the cross-price elasticities for capital and labor suggest that these factors of production can be considered substitutes. All inputs are affected positively by an increase in the total amount of land allocated to crop production, especially capital. If the price of corn (or soybeans) increases, the demands for fertilizer, chemicals, and capital also increase, while the demand for labor decreases (though this last effect is not statistically significant). The coefficient in the variable time indicates that the presence of a technical change in crop production is biased towards fertilizer and chemical usage and against capital and labor. More generally, an increase in the ratio of irrigated land increases corn supply and the demand for fertilizer, chemicals, and labor, but it reduces the supplies of soybeans and the set of other crops, and the demand for capital.

3SLS estimates of crop acreage demand equations (20) for corn, soybeans, and other crops are presented in Table 3.3. The table contains a total of thirty-nine parameters, thirty-one of which are significant at the 1% level, and only one at the 5% level. All own-price effects (corn and soybeans) have a positive sign and are statistically significant at the 1% level. An increase of corn (soybeans) price relative to other crops would increase the demand for land allocated to corn (soybeans) by about 329 (37) thousand acres per year. The crop output cross-price effects have positive signs between corn and soybeans acreage demands, but negative between corn and other crops acreage demand. The output cross-price effects are in turn positive between soybeans and other crop areas. These estimated coefficients implied that the crop area demand curves are upward sloping to their crop output prices and that corn and soybeans are complements (also other crops with soybeans) in cultivation, while corn and other crops are substitutes. The coefficients of total crop acreage are significant at the 1% level for all three categories of crops and relatively larger for other crops. The coefficient for time trend is positive for corn and soybeans while it is negative for other crops. This implies that changes in technologies have led to a relatively more significant increase in land allocated to corn and soybeans, whereas land allocated to other crops has fallen across years.

Table 3.4 reports own-price and cross-price elasticities calculated from the parameter estimates in tables 2 and 3, evaluated at the mean value of the corresponding variables. We have three sets of elasticities: output supply and input demand elasticities, and crop area elasticities. All own price elasticities have the correct sign, i.e., both corn and soybeans supply elasticities are positive, and all variables input demand elasticities are negative. The elasticities crop acreage demand elasticities are also positive with respect to own output price. Overall, the coefficients reflect the patterns of those in Tables 2 and 3. The estimated elasticities could be considered somewhat small (or in turn mostly inelastic) but indicate crop supply responses to prices that are not unreasonable given the RFS mandates. The own-price elasticity of corn supply indicates that if the corn price were to double due to the RFS mandates, corn output would rise by about 86%. Own price elasticities on inputs and for crop area are generally inelastic. A doubling of corn prices due to the RFS mandates would raise the area devoted to corn production by approximately 59%.[13] With these price elasticities, particularly, for corn supply ($\tau_{Y^*_{corn}}$) and area ($\tau_{l_{corn}}$), the corn yield elasticity is obtained as $\tau_{y_{corn}} = \tau_{Y^*_{corn}} - \tau_{l_{corn}} \approx 0.86 - 0.59$. The estimated yield elasticity is thus around 0.27.

We find positive and statistically significant estimates of the corn price effect of RFS mandates on corn biomass supply and acreage demand. Our findings show that the corn biomass supply response to the RFS-induced increase in corn price (relative to other crops) occurs partly due to changes at the intensive margin that increase yield (output per acre) and partly due to the extensive margin that increases the demand for cropland to produce corn. Moreover, the results indicate that both the corn supply and area planted are price inelastic, which means that the relative corn price increases by more than its quantity supplied and cropland. The average biomass supply of corn would have increased by more than 1.8 million metric tons per year in response to the observed corn price increases caused by the RFS requirements. The annual response of the acreage demand for corn to the corn price increases since the 2007's RFS mandates is approximately 32 thousand acreages. Finally, we can assert that of the total increase in corn biomass supply caused by the mandates-induced corn price

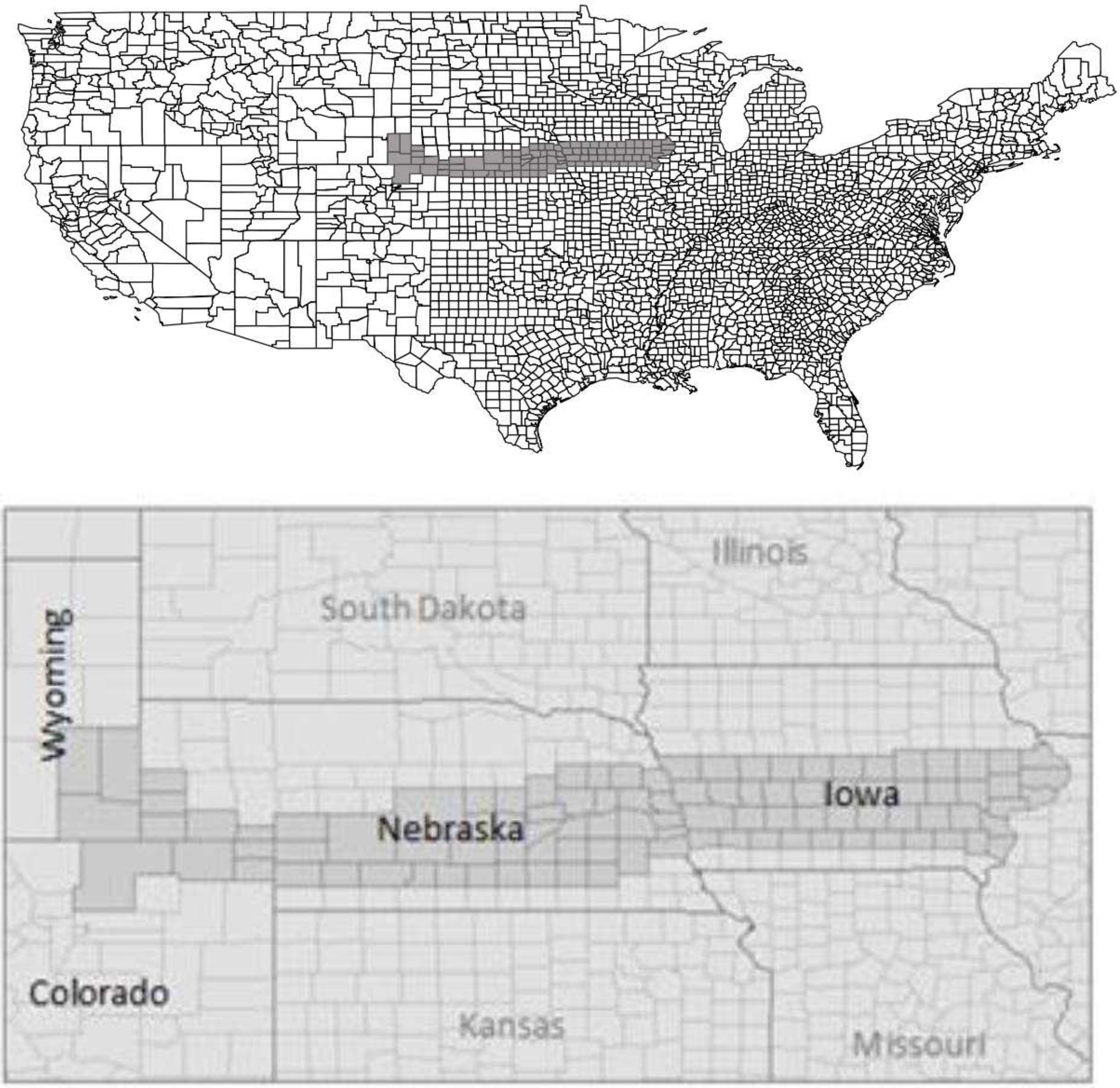
[13] Note, however, that the relatively less elastic response of own price elasticities for crop acreages may be so since large area is already devoted to corn (and soybeans) production. A doubling of corn prices would still significantly reduce the areas devoted to other crops in the region by more than 100%.

increase, 31.4% is due to yield increase (intensive margin) and 68.6% is due to acreage expansion (extensive margin).

5. Conclusions

We investigated the effect of crop and variable inputs prices and environmental and policy variables on corn, soybeans, and other crop yields and acreage in the US Midwest using a panel dataset for the 1969–2017 period. It has been of particular interest to assess to what extent the corn price effects induced by the policy also affected corn biomass supply and crop acreage demands. These effects translate into elasticities at the intensive and extensive margins of agricultural land use of crops produced at the county level. A profit function model is specified to represent agricultural decision-making units in the region. We use a two-stage profit maximization approach with land assumed fixed but allocatable for crop production. Crop acreage demands are estimated jointly with output supply and variable input demand equations using a normalized quadratic functional form and county-level panel data from the region over 49 years. Simultaneous equations panel model is adopted to analyze land use and crop yield responses using the 2007's Renewable Fuel Standard. Through this policy, the US federal government mandates specific quantities of total biofuels. These mandates are assumed to create exogenous market shocks to the supply of biomass from corn in several counties along the US Great Plains. Our results show that the corn biomass supply and the demand for land to produce corn have grown because of the price increases induced by such mandates. The RFS raised corn prices such that corn biomass supply also increased by about 1.8 million metric tons per year. This change occurs because the counties in the region allocated more land to corn production and partly because they produced more corn per land unit. Of the increase in corn biomass supply caused by the mandates, 31.4% is due to policy-induced yield increase, and 68.6% is because of policy-induced acreage expansion. Response to the RFS thus occurs primarily at the extensive margin. These findings have important implications for future policies on promoting renewable energies combined with economic policies. The results of this analysis might have a crucial external value because the climatic and hydrologic ranges observed in the analyzed area may be representative of other important temperate regions of the world. The main contribution of this paper is to provide some insights in the current discussion on the implications of the US RFS for the agricultural commodity markets, productivity analysis of agricultural production, the conversion of natural land to crop production, and to a certain extent, the environmental consequences of this type of policies.

Figure 3. 1– Selected Counties along the 41st Parallel



Source: Elaborated based on Trindade *et al.* (2011).

Table 3. 1 – Summary Statistics, 101 41st Parallel Counties, 1969-2017

Variables	Units	Mean	Min	Max	Std. Dev.
Corn Biomass (*Q*-Corn)	Metric tons	652,207.1	0.00	2,293,663	410,756.17
Soybeans Biomass (*Q*-Soy)	Metric tons	146,977.3	0.00	670,914	130,053.89
Other Crops Biomass (*Q*-Ocrops)	Metric tons	116,485.9	0.00	1,309,579	145,127.64
Corn Planted Area (*A*-Corn)	Acres	112,142.4	0.00	279,700	56,089.62
Soybean Planted Area (*A*-Soy)	Acres	56,933.4	0.00	232,000	45,249.15
Other Crops Planted Area (*Q*-Ocrops)	Acres	99,126.8	0.00	1,356,010	161,140.21
Total Cropland (Land)	Acres	268,202.7	1,250	1,008,710	95,148.89
Fertilizer	Index	3.17	0.08	10.83	1.61
Chemicals	Index	9.61	0.12	39.32	6.57
Labor	Workers	1,084	0.20	11,662	1,019.28
Capital	Machines	34,578.1	8,251	147,584	8,446.43
Price of Corn (*P*-Corn)	1969 dollars per metric ton	1.13	0.40	2.43	0.28
Price of Soybeans (*P*-Soy)	1969 dollars per metric ton	2.48	0.00	5.76	0.92
Price of Other Crops (*P*-Ocrops)	numeraire	–	–	–	–
Price of Fertilizer (*P*-Fertilizer)	Index	0.03	0.01	0.08	0.01
Price of Chemicals (*P*-Chemicals)	Index	0.02	0.01	0.06	0.01
Wages	1969 dollars per worker	47,005.3	107.34	47,8045	44,650.44
Price of Capital (*P*-Capital)	Index	0.05	0.01	0.13	0.02
Irrigation	Fraction	0.20	0.00	0.91	0.27
$DD(0\ to\ 30)$	24 hours	165.37	132.23	178.83	5.84
$DD(31\ to\ 34)$	25 hours	4.03	0.14	12.78	2.32
$DD(35+)$	26 hours	0.16	0.00	3.55	0.29
Precipitation	Centimeters	52.09	9.48	125.21	16.62

Table 3. 2– 3SLS estimation of the output supplies and derived input demands from the system of equations in (18) and (19)

	Dependent Variable:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Q-Corn	Q-Soy	Q-Ocrops	Q-Fertilizer	Q-Chemicals	Labor	Q-Capital
P-Corn	1,864.7	551.2	-1,581.01	645.3	3,714.4	-0.053	3.767
	[130.5]***	[103.9]***	[191.02]***	[97.1]***	[208.7]***	[0.0862]	[1.83]**
P-Soy	551.2	93.159	1,975.9	458.413	1,964.7	-0.1114	7.215
	[103.9]***	[302.4]	[484.1]***	[149.9]***	[168.3]***	[0.032]***	[3.62]**
P-Fertilizer	645.3	458.4	1,168.4	-1,052.6	-141.785	0.1265	42.249
	[97.12]***	[149.9]***	[317.5]***	[234.0]***	[207.1]	[0.043]***	[4.43]***
P-Chemicals	3,714.4	1,964.7	-1,064.2	-141.785	-8,966.6	-0.0361	2.355
	[208.7]***	[168.3]***	[606.23]*	[207.17]	[646.7]***	[0.1452]	[10.13]
Wages	-0.053	-0.111	0.0062	0.1265	-0.0361	-0.0004	0.0023
	[0.086]	[0.032]***	[0.039]	[0.043]***	[0.145]	[0.0002]*	[5E-4]***
P-Capital	3.767	7.215	-18,265.9	42.249	2.354	0.0023	-3394.7
	[1.836]**	[3.625]**	[27441.3]	[4.439]***	[10.13]	[5E-5]***	[459.5]***
Land	0.0024	0.0006	0.0006	0.0012	0.0037	0.0035	0.051
	[3E-5]***	[1E-5]***	[1E-5]***	[4.7E-5]***	[0.0001]***	[1E-4]***	[0.015]***
Irrigation	721.2	-56.798	-27.3011	189.565	282.163	0.826	-0.638
	[15.95]***	[5.655]***	[6.892]***	[9.404]***	[31.003]***	[0.067]***	[0.118]***
$DD(0\ to\ 30)$	2.101	0.797	-0.0085	0.9522	2.711	-0.0003	0.0019
	[0.586]***	[0.212]***	[0.2608]	[0.287]***	[0.958]***	[0.0012]	[0.0035]
$DD(31\ to\ 35)$	-12.696	6.927	-4.2131	-1.274	-14.691	-0.0049	0.0357
	[2.133]***	[0.778]***	[0.9596]***	[1.0755]	[3.553]***	[0.0047]	[0.013]***
$DD(35+)$	-4.1607	-46.048	18.139	19.378	115.912	0.045	-0.171
	[16.61]	[6.164]***	[7.4938]**	[8.4134]**	[27.91]***	[0.0341]	[0.1015]*
Precipitation	1.491	0.911	-0.746	0.222	1.277	-0.0008	0.0026
	[0.244]***	[0.091]***	[0.1149]***	[0.1227]*	[0.4046]***	[0.0005]	[0.0015]*
Time	9.262	4.307	-2.426	2.598	27.818	-0.026	-0.033
	[0.288]***	[0.140]***	[0.2440]***	[0.2044]***	[0.4829]***	[6E-4]***	[0.003]***

Table 3. 3 – 3SLS estimation of the crop area equations from the system in (20)

	Dependent Variable:		
	(1)	(2)	(3)
	A-Corn	A-Soy	A-Ocrops
P-Corn	32.8726	3.6637	-140.086
	[2.9606]***	[2.5779]	[7.4749]***
P-Soy	3.6637	24.3718	63.6517
	[2.5779]	[5.8928]***	[11.2011]***
P-Fertilizer	-79.2338	-45.018	311.7633
	[7.9217]***	[6.7351]***	[21.1538]***
P-Chemicals	118.4308	6.3852	-298.416
	[17.7431]***	[14.5532]	[49.7565]***
Wages	-0.0011	-0.0042	0.0114
	[0.0013]	[0.0011]***	[0.0033]***
P-Capital	-2,742.83	3,815.36	-113.863
	[792.0644]***	[633.5617]***	[2225.2103]
Land	0.00004	0.00002	0.0008
	[0.0000004]***	[0.0000003]***	[0.000001]***
Irrigation	9.3451	-2.0106	-16.4603
	[0.2622]***	[0.2039]***	[0.6969]***
$DD(0\ to\ 30)$	-0.004	-0.0198	0.0568
	[0.0086]	[0.0069]***	[0.0222]**
$DD(31\ to\ 35)$	-0.1826	0.1532	0.2504
	[0.0318]***	[0.0255]***	[0.0821]***
$DD(35+)$	1.2161	-1.0438	0.006
	[0.2473]***	[0.2003]***	[0.6363]
Precipitation	0.0188	0.0219	-0.046
	[0.0036]***	[0.0029]***	[0.0093]***
Time	0.0876	0.1275	-0.4497
	[0.0070]***	[0.0057]***	[0.0186]***

Notes: Both output prices (*P*-Corn and *P*-Soy) and variable input prices (*P*-Fertilizer, *P*-Chemicals, Wages, and *P*-Capital) are real values relative to *P*¬Ocrops in 1969.

Table 3. 4– Output Supply and Variable Input Demand Elasticities, and Cropland Response Elasticities

	P-Corn	*P*-Soy	*P*-Fertilizer	*P*-Chemicals	Wages	*P*-Capital	Land
Q-Corn	0.856	0.040	0.071	0.332	-0.0082	6.3E-06	2.050
	[0.060]***	[0.008]***	[0.011]***	[0.019]***	[0.013]	[3.1E-06]**	[0.029]***
Q-Soy	0.869	0.035	0.151	0.561	-0.040	0.0003	1.704
	[0.164]***	[0.113]	[0.049]***	[0.048]***	[0.012]***	[0.0002]**	[0.037]***
Q-Ocrops	-1.536	0.431	0.302	-0.204	0.017	-0.633	1.065
	[0.186]***	[0.106]***	[0.082]***	[0.116]*	[0.105]	[0.951]	[0.026]***
Fertilizer	0.338	0.050	-0.153	-0.015	0.026	9.3E-05	1.072
	[0.051]***	[0.016]***	[0.034]***	[0.022]	[0.009]***	[9.7E-06]***	[0.015]***
Chemicals	0.869	0.092	-0.008	-0.418	-0.003	2.1E-06	1.552
	[0.049]***	[0.008]***	[0.012]	[0.030]***	[0.011]	[8.9E-06]	[0.023]***
Labor	-0.021	-0.010	0.020	-0.003	-0.114	4.5E-06	-0.667
	[0.035]	[0.003]***	[0.007]***	[0.012]	[0.066]*	[1.0E-06]***	[0.116]***
Capital	0.130	0.055	0.438	0.018	0.035	-0.539	0.045
	[0.063]**	[0.028]**	[0.046]***	[0.077]	[0.008]***	[0.073]***	[0.014]***
A-Corn	0.589	0.013	-0.386	0.436	-0.008	-0.202	1.327
	[0.053]***	[0.009]	[0.039]***	[0.065]***	[0.009]	[0.058]***	[0.017]***
A-Soy	0.101	0.158	-0.263	0.032	-0.028	0.326	1.007
	[0.071]	[0.038]***	[0.039]***	[0.073]	[0.007]***	[0.054]***	[0.020]***
A-Other Crops	-1.900	0.195	1.130	-0.840	0.045	-0.006	1.689
	[0.101]***	[0.034]***	[0.077]***	[0.140]***	[0.013]***	[0.112]	[0.027]***

Source: Own computations.
Notes: Elasticities are computed at the sample mean values of the variables from Table 3.1 and using coefficient estimates taken from Tables 2 and 3; numbers in brackets are standard errors computed with the delta method provided by Papke and Wooldridge (2005). Output prices (*P*-Corn and *P*-Soy) and variable input prices (*P*-Fertilizer, *P*-Chemicals, Wages, and *P*-Capital) are real values relative to *P*-Ocrops in 1969.

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