Greenhouse Gas Mitigation Policies, Input Expenditure, and U.S. Farm Structure

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Abstract

Little is known about how various greenhouse gas mitigation policies will impact the market structure of U.S. agriculture. Existing and proposed policies can increase the cost of carbon-intensive farm inputs, directly or indirectly, similar to a carbon price or tax. Using farm-level data, we assess the ex-ante distributional impacts of a hypothetical carbon price on fuel-intensive inputs. Structural cost functions are first estimated for corn operations by farm typology in the Corn Belt, and the results are used to predict the effects of a carbon price on short-run total costs. A novel statistical test is then employed to determine if a carbon price would be regressive across farm typologies. Our findings suggest that a short-run exogenous carbon price would be regressive for smaller farms, while larger farms are able to better adapt to higher input costs. This regressivity becomes especially noticeable at threshold level above $10 per ton of carbon.

Keywords: Carbon policies and prices; Competitive agricultural input markets; Agricultural market structure; Distributional impacts to farm typologies

JEL codes: Q12, Q13, Q54

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1 Introduction

Despite stalled progress on global climate agreements, several countries and jurisdictions are using or considering carbon taxes, prices, or other policies that mitigate greenhouse gas emissions (Sumner et al., 2011; Criqui et al., 2019; Thisted and Thisted, 2020; Ewald et al., 2021). While the European Union has taken a direct cost-based approach with carbon taxes (Metcalf and Stock, 2023), China and the U.S. are pursuing approaches that rely on subsides (Bown and Clausing, 2023). National policies, such as the Low Carbon Fuel Standard (LCFS) – adopted in Canada and some U.S. states (California, Oregon) – could to lead to an increase in fuel prices (Lade and Lin, 2013).[1] In the absence of domestic cost-based mitigation policies, a jurisdiction may be subject to import tariffs, such as a carbon border adjustment mechanism Bistline et al. (2024). These policies jointly have the potential to impact agricultural market structures through changes to both input and output prices, as well as compliance costs. Our study focuses on the impact to agricultural input costs and the potential distributional impacts across farm typologies, which have received less attention in the literature.

The magnitude and distribution of costs associated with a carbon price on farms can inform policy, as cost structures can vary across scale of production, specialization and region (Gerdts, 2022). However, the majority of empirical studies use mathematical programming or general equilibrium models, which typically cannot explicitly account for farm-level heterogeneity. In this study we use nationally representative farm-level survey data to estimate structural cost functions, which allow us to establish a microeconomic foundation how farms respond to price changes and predict the impacts of a carbon tax on farm expenditure. From this we propose a method to quantify the distributional impacts of a carbon tax on U.S. corn farms[2] by farm typology. We also identify at what tax levels distributional implications are meaningful. We use data from the USDA Agricultural Resource Management Survey

[1] Other studies suggest a decrease in fuel prices is feasible under LCFS (Huang et al., 2013; Yeh et al., 2016), dependent on various factors and elasticities. It is beyond the scope of this study to determine which outcome is more likely; our point here is that an increase in farm input costs is feasible under a range of greenhouse gas mitigation policies.

[2] This is the largest category of crop farm classified by the USDA for which carbon prices are relevant. As will be discussed later, the approach could be expanded to other farm types.

(ARMS) from 2005-2013.[3]

One unifying feature among the cost-imposing carbon policies is that they increase farm cost through the same channel: carbon-intensive input prices. Our strategy is to exploit the variation in input prices across farms to estimate the farm's cost function and use it to predict the cost change for any of the particular policies. To obtain the policy-induced variation in input prices, we can use the institutional details of each proposed policy and engineering estimates of the carbon-equivalent content of farm inputs. To estimate the cost function, we leverage the farm-level USDA-ARMS data from 2005 to 2013 for corn farms in Corn Belt states. For a flexible parametric approach, we fit a translog cost function with the output level and the prices for fuel and fertilizer (the carbon intensive inputs) as independent variables. We augment the translog cost equation with log-linear cost-share equations for fuel and fertilizer and estimate the system of equations via OLS and SURE[4], with and without cross-equation constraints.

Using a carbon price policy as a benchmark, we report the farm's cost increases, associated with carbon-intensive inputs, for various levels of carbon prices in the 0-$150 per ton range. In addition, we explore the distributional impacts of the cost-inducing policies through a "regressivity measure" between different farm typologies and/or sizes.[5]

To explain, consider a condition in which there are only two farm typologies. Our measure maps an exogenous carbon price (or tax) level into the forecasted difference between the percentage cost increase between the separate farm types. To eliminate the baseline difference between the two separate farm types, we recenter our measure so that it is zero under no carbon price. The measure is positive when larger farms pay a lower relative percentage of their costs as a result of a pre-defined carbon price level. With our measure, we construct a statistical test of regressivity between the two separate farm types, conditional on an exogenously defined carbon price.

Our findings suggest intermediate and commercial farms display statistically significant

[3]The currently analysis covers 2005-2013 and is in process of being updated through 2022. We anticipate results from this longer time period to be available before December.

[4]Seemingly Unreleated Regression Equations.

[5]We refer to this as a regressivity measure, although the measure could reflect a progressive, typology-neutral or regressive cost structure.

regressivity. We find that the regressivity measure is monotonic in the carbon price level. We are able to invert the test for statistical significance of the regressivity measure to find confidence intervals for the regressivity measure at all carbon price levels. The exact threshold carbon price level varies with the pair (that is, the point at which the regressivity between two separate farm typology pairs becomes statistically significant), but all are within the range of $10-$50 per ton of carbon equivalent.

As farms will likely adapt to prices changes in the long term, an important caveat is that our estimates represent an upper bound on increases in farm production expenses. However, within wide range of "politically feasible" carbon price levels, at least up to $100 per ton, the implied changes in fuel and fertilizer prices are within historical levels. As such, we are able to use past production and management responses to predict how farms will adjust to higher fuel and fertilizer prices. Historically, production expenses of larger farms were less sensitive to fuel and fertilizer prices, which likely drives our prediction that larger farms by be better positioned to adapt to carbon prices.

1.1 Policy and Research Background

Based on varying policy priorities, the U.S. and China have emphasized subsidy-based approaches to reduce greenhouse gas emissions, instead of carbon prices (or taxes) as in the European Union. Due to these divergent policy choices – one policy raises prices, while the other lowers prices on goods – there are concerns about economic competitiveness and implications for upstream and downstream industries in the global supply chain (Bown and Clausing, 2023). In reaction to these changes, many nations are reexamining the World Trade Organization's rules-based trading systems that place requirements on subsidies, boarder measures, and export restrictions. To wit, a carbon border adjustment mechanism (CBAM) is designed to protect domestic firms that have to compete with firms producing goods in countries with weaker greenhouse gas regulations. Put differently, a CBAM is an import tariff on carbon-intensive goods that matches a country's domestic carbon price (Bistline et al., 2024).

As climate policy implementation is costly, the US will likely face growing international trade pressures and other challenges, such as addressing budget deficits and national debt. Bown and Clausing (2023) argue that greater global policy alignment on climate change will reduce frictions between jurisdictions. For example, if CBAMs are enforced, then trading partners could give credit to countries that have imposed their own carbon pricing regimes. Although CBAMs are targeted towards carbon-intensive industries, some are beginning to explore such mechanisms for the agricultural sector as well (Fournier Gabela et al., 2024). Despite the outcome, these trade and budgetary pressures collectively may force the U.S. to pivot toward cost-imposing climate policies, with a likely focus on the most carbon-intensive goods first (such as fossil fuels or steel) (Bistline et al., 2024).

Throughout the remainder of this study, we will use the terms carbon price and carbon tax, interchangeably. A carbon price is a broader term referring to any policy that assigns a monetary cost to carbon emissions (Vitello, 2021). Whereas, a carbon tax is a specific type of carbon price where a Pigouvian tax is levied on the amount of carbon emitted. The use of the term carbon price is to illustrate that there are numerous potential policy channels that could exogenously change agricultural input prices in the short run.

There is a large past literature on the effects of carbon taxes, although only a subset of studies analyze carbon taxes from a distributional perspective, with occasional reference to agriculture as a sector. For example, there are a number or studies that employ partial or general equilibrium models, or structural models, to look at distributional impacts of carbon taxes (e.g. Rausch et al. 2011, Dinan 2012, Gonzalez (2012), Carbone et al. 2013, Yusuf and Resosudarmo (2015), Rosas-Flores et al. 2017). The focus has generally been on consumers, non-agricultural households, or economy-wide effects within individual countries. In studies where agriculture has been addressed explicitly, it is often treated as an aggregate sector. For example, Lu et al. (2010) considers the agricultural sector in China in comparison to other parts of the Chinese economy, and Wesseh et al. (2017) compares carbon tax impacts impacts across multiple countries and 10 economic sectors, one of which is agriculture.

A much smaller subset of studies have focused on agriculture and carbon taxes directly.

Employing a variety of partial and general equilibrium modeling techniques, Konyar and Howitt 2000, Peters et al. 2001, and Schneider et al. 2005 analyze the impacts of carbon taxes on U.S. agriculture using regional data. These studies generally find modest impacts to agriculture at low levels of taxation, and emphasize (1) the adaptability of agriculture over the medium- to long-run and (2) that the effects will vary significantly by crops and regions. Using reduced-form estimation, Rivers and Schaufele (2015) estimate the actual impacts of carbon taxes in British Columbia on agricultural trade flows (log of gross agricultural exports and imports by commodity) using a panel of international agricultural trade data and provincial farm receipts in Canada from 1990 to 2011. The closest study to ours is likely Antle et al. (1999), who use a mid 1990s sample of 425 Montana dryland grain farms with more than 1,000 acres of cropland to estimate production and variable cost functions (in log-linear form) in order predict the impact of imposition of a carbon tax on a number of inputs. One of their main results is that for spring wheat, the primary crop produced by the farmers in their data, variable costs were predicted to increase by 3 to 13% and reduce net returns above variable costs by 6 to 18% (assuming a $100 to $200 per ton of carbon tax, respectively). While our main specification focuses on corn farms, our proposed approach allows us to study the impact of cost-imposing policies across farms with different crop types. Moreover, as detailed in the Appendix, our approach can be easily extended to multi-crop farms to investigate how a farm's crop mix may help mitigate the increase in carbon-intensive input prices.

2 Theoretical & Empirical Models

2.1 Production and Welfare Theory

Use of farm-level production data allows us to consider distributional impacts of a carbon price, which could lead to structural changes in the farm sector or otherwise influence the effectiveness of GHG mitigation.We develop a model to predict the impacts of a carbon price on the total farm cost, which allows us to measure how these impacts vary between farms.

There are a number of ways to theoretically ground measurement of distributional impacts. For example, in trade-focused contexts Rivers and Schaufele (2015) use the Hecksher-Olin trade model of "clean" versus "dirty" industries. If "dirty" industries are affected by a tax, for example, there will be movement from the "dirty" to the "clean" sectors. The latter stand to gain, while the former can face relative losses. Our focus is to analyze the distributional impacts within agriculture itself. To our knowledge, this approach to carbon tax impacts has received limited attention outside of consumer-focused research.

We begin with the standard profit maximization problem, where the firm chooses capital, k, and labor, l, the optimal choices of which completely characterize the solution to the firm's problem.

$$\max_{k,l} \pi = p \cdot f(k,l) - c(x,q) \tag{1}$$

We use a parsimonious set-up that requires minimum assumptions and is sufficient for measurement of quasirents (producer surplus). Following the exposition from Just et al. (2005), quasirents, R, are defined as total gross revenue minus total variable costs.

$$QR = \pi + TFC = TR - TVC = p \cdot y^* - c(w, y^*) \tag{2}$$

Here, y^* denotes optimal output, TFC denotes total fixed costs, and $c(w, y^*)$ denotes the value function for the short-term total variable cost function[6] with w and p representing input and output prices respectively.

Focusing on the last term on the right hand side of Equation (2), it is clear that QR will change in response to changes in either TR, TVC, or some combination of both. Given our focus on short-term impacts, we note that if p and y^* are held constant then estimation of $c(w, y^*)$ under various levels of carbon prices on inputs completely characterizes QR. As such, if $c(w, y^*)$ can be estimated for a variety of farm types, then the estimated functions

[6]For example, following Chambers (1988) the cost function can be denoted by:

$$c(w, y^*) = \min_{x \geq 0} \{w \cdot x : x \in V(y)\} \tag{3}$$

where w is a vector of strictly positive input prices, x is a vector of inputs, and $V(y)$ is the input requirement set necessary for producing output greater than or equal to, y.

provides at least two useful outcomes. First, we can estimate changes in total variables costs, which reflect changes in QR ceteris paribus. Second, we can estimate change in total variable cost by farm type, which further allows for measurement of the extent to which increasing input prices may disproportionately raise costs (and thus reduce QR) between farms groups. The former requires estimation of cost functions by farm type, for which we base on the existing USDA farm typology classification. For the latter, we introduce a notion of cost comparison across farms in the next section.

2.2 A Measure of Regressivity

Contrary to standard approaches that use quantiles of the income distribution to assess regressivity, we prefer comparison between the official USDA farm typologies. In addition to being widely used in research and reporting of official statistics, these typologies have a strong theoretical and empirical grounding (Hoppe and MacDonald, 2013; Hoppe et al., 2000). This research has shown that the occupation and other operator characteristics, as well as farm size, are important components of farm structure. We modify ERS's updated farm typology (Hoppe and MacDonald, 2013) to create four different typologies based on both size as measure by gross cash farm income (GCFI) and operator primary occupation. These GCFI and operator characteristics are described in Table 1 for four classes: residence, intermediate, commercial-midsize, and commercial-large. Most residence farms have negative farm income, while a small share of intermediate farms have positive farm income, which is an important distinction in interpreting our results.

We denote W as the set of regressors (i.e, wages, fuel and fertilizers prices), X as the exogenous carbon price level (referred to as a tax, hereafter), and C_i as farm's i total cost. We define the regressivity of carbon tax at tax level x, between typology i and j, to be:

$$\mathcal{R}(x) = \mathbb{E}(\log(C_i)|X = x, W = \bar{w}) - \mathbb{E}(\log(C_j)|X = x, W = \bar{w}). \tag{4}$$

$\mathcal{R}(x)$ captures the expected value of the difference in log total costs, C, between farm type i and farm type j at tax level of x \$/ton and average input costs $\bar{w}$. The re-centered $\tilde{\mathcal{R}}(x)$,

defined below, captures the same difference but with the added term of the difference in costs with zero taxes. This measure has two attractive properties. First it has some basic intuitive appeal since:

$$\mathcal{R}(x) = 0 \iff \mathbb{E}(\log(C_i)|X = x, W = \bar{w}) = \mathbb{E}(\log(C_j)|X = x, W = \bar{w}). \tag{5}$$

Second, with a suitable choice of functional form, for example any specification that is linear in parameters, the sample analog of Equation (4) can be rewritten in a simple way.

$$\mathbf{F}(x, \bar{w}) = \left[\begin{array}{cccc} f_1(\bar{w}, x) & f_2(\bar{w}, x) & ... & f_n(\bar{w}, x) \end{array} \right] \tag{6}$$

$$\begin{aligned} \widehat{\mathcal{R}^{ij}}(x) &= \mathbf{F}(x, \bar{w}) \cdot \hat{\beta}^i - \mathbf{F}(x, \bar{w}) \cdot \hat{\beta}^j \\ &= \mathbf{F}(x, \bar{w})^T (\hat{\beta}^i - \hat{\beta}^j) \end{aligned} \tag{7}$$

Here $\mathbf{F}(x, \bar{w})$ denotes a vector of basis functions, so that $\mathbf{F}(x, \bar{w})^T \hat{\beta}^i$ is an estimate of the conditional expectation of the short-term log cost function for farms of type i). From (7) we see that the measure of regressivity equals 0 whenever the conditional mean function for the subpopulation i is equal to the conditional mean function for subpopulation j, both evaluated at the vector of covariates levels $\bar{w}$.

One may be concerned that the measure of regressivity presented above may attribute to the tax what is due to baseline differences in the purchasing power and structure of farms of different typologies which is captured by $\mathcal{R}^{ij}(0)$. Therefore, we recenter the above measure by subtracting the baseline difference between the log of total costs of i and j.

$$\tilde{\mathcal{R}}^{ij}(x) = \mathcal{R}^{ij}(x) - \mathcal{R}^{ij}(0) \tag{8}$$

In other words, we account for existing differences by subtracting them out from the regressivity measure.[7] Since $\hat{\beta}$ are stochastic, the variance of $\tilde{\mathcal{R}}(x)$ can be derived and test

[7]This measure is anti-symmetric, which follows immediately from the linearity of the conditional expectation function.

statistics can be determined. $\mathbf{F}(\cdot)$ is a deterministic function of the tax level x and $\mathcal{R}$ is a linear function of the estimated parameters. Hence, under the standard assumptions, we can derive the variance-covariance matrix for the $\hat{\beta}$ coefficient estimates. The null hypothesis that there are any distributional impact across farm typologies of a carbon tax at level x is given by $H_0 : \tilde{\mathcal{R}}^{ij}(x) = 0$. If farms of typologies i and j are independent and Σ_i and Σ_j as the variance-covariance matrices for $\hat{\beta}_i$ and $\hat{\beta}_j$ respectively, the t-statistic for H_0 is given by:

$$T^{ij}(x) = \frac{\hat{\mathcal{R}}^{ij}(x) - \hat{\mathcal{R}}^{ij}(0)}{\sqrt{\frac{\mathbf{F}(x,\bar{w})^T \Sigma_i \mathbf{F}(x,\bar{w})}{N_i} + \frac{\mathbf{F}(x,\bar{w})^T \Sigma_j \mathbf{F}(x,\bar{w})}{N_j}}} \tag{9}$$

2.3 Empirical Model Derivation

To estimate representative cost functions we assume that the true underlying cost function is unknown, but that it is at least twice continuously differentiable. With these assumptions, we minimize the potential bias that can arise with choosing a specific functional form by adopting the transcendental logarithmic functional form (hereafter, "translog"). The advantages of the translog functional form are many and are well-documented in the literature.[8] The translog function is a second-order approximation of any twice continuously differentiable function, and it nests many other commonly used functional forms as special cases (see Chambers (1988) for a concise treatment of these issues). This form is linear in parameters, which fits with the needed properties of $\mathbf{F}(x, \hat{w}) \cdot \beta^i$. Given this assumption, a general representation of the cost function we estimate is presented below, where I is the set of inputs and their associated prices.

$$\begin{aligned} \ln(C_i) = \beta_0 + \beta_Y \ln(Y_i) + \frac{1}{2}\beta_{YY}(\ln(Y_i))^2 + \sum_{i \in I} \beta_Y \ln(Y_i) \ln(P_i) \\ + \frac{1}{2} \sum_{i \in I} \sum_{j \in I} \beta_{ij} \ln(P_i) \ln(P_j) + \sum_{i \in I} \beta_i \ln(P_i) + \varepsilon_i \end{aligned} \tag{10}$$

where ε_i represents all factors other that input prices and output levels that influence the farm cost for unit i. We will estimate cost-share equations along with the cost function. The

[8] We therefore refer the interested reader to related theoretical and applied literature on the subject.

first step to deriving these functions is to apply Shepard's lemma[9] to the cost function to derive the conditional input demand functions as follows

$$\frac{\partial C^*}{\partial P_i} = D_i^*(Y, P_i, ..., P_j, ...). \tag{11}$$

The general definition of a cost-share for an input, is the ratio of total costs of one input to total costs

$$S_i = D_i^*(Y, P_i, ..., P_j, ...)\frac{P_i}{C^*(y, D, P)} \tag{12}$$

Since we have adopted the translog functional form, $ln(C)$, we note that in applying the chain rule we have the following.

$$\frac{\partial ln(C^*)}{\partial P_i} = \frac{\partial ln(C^*)}{\partial C^*}\frac{\partial C^*}{\partial P_i} = \frac{D_i^*(\cdot)}{C^*} \tag{13}$$

Applying $\frac{\partial ln(C^*)}{\partial P_i}$ to (15) we derive (19),

$$\frac{\partial ln(C^*)}{\partial P_i} = \frac{1}{P_i}(\beta_i + \beta_{Yi} ln(Y) + \sum_{i \in I} \beta_{ij} ln(P_j)) \tag{14}$$

which, combined with (18), provides an expression for cost-share estimation.

$$S_i = D_i^*(Y, P_i, ..., P_j, ...)\frac{P_i}{C^*} = \beta_i + \beta_{Yi} ln(Y) + \sum_{i \in I} \beta_{ij} ln(P_j) \tag{15}$$

In its most general form, our analysis requires estimation of the following system of equations.

$$\begin{cases} \ln(C) = \beta_0 + \beta_Y \ \ln(Y) + \frac{1}{2}\ \beta_{YY}(\ln(Y))^2 + \sum_{i \in I} \beta_{Yi} \ \ln(Y) \ \ln(P_i) \\ \qquad + \frac{1}{2}\sum_{i \in I}\sum_{j \in I} \beta_{ij} \ \ln(P_i) \ \ln(P_j) + \sum_{i \in I} \beta_i \ \ln(P_i) \\ \\ S_i = \beta_i + \beta_{Yi} \ln(Y) + \sum_{i \in I} \beta_{ij} \ln(P_j) \end{cases} \tag{16}$$

[9]As (16) is a direct application of the Envelope Theorem and we omit the proof and refer to the reader to standard references on the subject

With our measure for regressivity and our cost system outlined as our proxy for quasirents, R, now defined we now proceed to describe important aspects of our data and empirical estimation.

3 Data and Empirical Strategy

3.1 Data sources

Our primary data source is the USDA Agricultural Resource Management Survey (ARMS). This nationally representative survey samples approximately 20,000 farms annually (1996-present) and collects data on farm-level finances and production. For input prices, we rely on state and regional data from the National Agricultural Statistical Services (NASS). While a more granular level of input price data would be ideal, this is the only consistently publicly available input price data, at the smallest geographical level reported. Availability of price data limits our analysis to 2005-2013.

We use corn farms from ARMS for our analysis, which are defined by the USDA as farms with over half of total value of production from corn. Corn and soybeans are typically grown in rotation on many of these farms. We further limit ourselves to farms in Cornbelt states.[10] Our focus on Corn Belt states is due to this being the predominant U.S. region for corn and soybean production. There are several reasons for this focus. Farms operating in this region would presumably be more likely to have similar production conditions and cost structures.

The production and input expenditure data for corn and soybeans are available in ARMS, which allows us to estimate a model that is consistent with theory. There are many more corn and soybean farms sampled annually in ARMS than other any crop specialization, which improves our ability to estimate cost functions by farm typology. For example, sample sizes for crops such as cotton are often less than 100 observations per year. Corn especially has a large share of expenses attributable to fuel and fertilizer. Corn and soybeans jointly made

[10]We use Cornbelt to refer to the Heartland ERS Farm Resource Region, which includes all countries in Illinois, Indiana, Iowa, and some counties from parts of Ohio, Kentucky, Missouri, Minnesota, South Dakota, and Nebraska.

up nearly 50 percent of cash receipts for U.S. crops in 2016.

Fuel costs, fertilizer costs and total variable costs are all collected in ARMS or calculated from survey responses. We use NASS diesel price data for U.S. farm production regions to represent fuel costs, as we assume diesel to be more heavily used to run farm machinery. To estimate fertilizer price, we use a weighted average of commonly used fertilizers. We choose three fertilizers that individually represent the most common chemical fertilizers applied to field crops. For the nitrogen, phosphorus and potassium fertilizers we select, respectively, anhydrous ammonia, diammonium phospahate (DAP) and muriate of potash. Prices for each of these fertilizers are reported annually by NASS by farm production region. To define a fertilizer price that accurately reflects the combination that farmers effectively use, we weight each of the fertilizer's price listed above by the US average share of each nutrient quantity. It should be noted that the nutrient usage is computed by year, even though we do not observe a high degree of variation across years. For example, the price of fertilizer in year i is given by the following combination of fertilizer prices:

$$P_F = \left(\frac{Q_N}{Q_N + Q_K + Q_P}\right) P_N + \left(\frac{Q_K}{Q_N + Q_K + Q_P}\right) P_K + \left(\frac{Q_P}{Q_N + Q_K + Q_P}\right) P_P \qquad (17)$$

where Q_l is the quantity of nutrient l and P_l is its price.

We include total expenditure of seeds and plants, as we believe that fertilizer expense may be related to actual number of seeds purchased. The total expense is adjusted by the national Seed Price Index reported by NASS, with 2011 as a base year. We include labor as a short term input for the cost function. We use NASS-reported regional hired labor wages to represent labor prices. This approach does not account for all people employed since farms typically use family labor along with hired labor; we assume that the family members working on the farm use the hired labor wages they observe as a benchmark for their labor reservation price.

We use total bushels of corn and soybeans produced as the output level. This simplification might introduce a downward bias in the level of output that farm produce, as

it disregards the possibility of multi-crop farms. Because we assume that farmers make decisions on input quantities as they relate to their main business, this modeling simplification may still be a realistic representation of most corn and soybean farms, which is the predominant crop production mix for Corn Belt farms.

3.2 Empirical strategy

Up to now, we have left the exact form of the model we wish to estimate general (see equation 16). Based on our variable choices we can see that the general form of equation 16 takes on the form below:

$$\begin{cases} \ln(C) = \beta_0 + \beta_Y \ \ln(Y) + \frac{1}{2}\ \beta_{YY}(\ln(Y))^2 + \sum_{i\in I} \beta_{Yi} \ \ln(Y) \ \ln(P_i) \\ \qquad\qquad + \frac{1}{2}\sum_{i\in I}\sum_{j\in I} \beta_{ij} \ \ln(P_i) \ \ln(P_j) + \sum_{i\in I} \beta_i \ \ln(P_i) + u_{1i} \\ S_F = \beta_F + \beta_{YF} \ \ln(Y) + \sum_{j\in I} \beta_{Fj} \ \ln(P_j) + u_{2i} \\ S_O = \beta_F + \beta_{YO} \ \ln(Y) + \sum_{j\in I} \beta_{Oj} \ \ln(P_j) + u_{3i} \end{cases} \tag{18}$$

where Y denotes output, P_i denotes input price i. The set I={ fuel, fertilizer, labor}.

We estimate the model using OLS and Seemingly unrelated Regression Equations. The latter is essentially a GLS estimator and it will increase efficiency. Because the set of regressors in the three equations differs across equations, the two procedure are not equivalent.[11] The structure of the cost functions and cost shares imposes some cross equation restrictions on the parameters estimated. Let the superscripts C, F, O indicate the coefficients of the cost equation, the fertilizer cost share and the fuel cost share, respectively. We further denote EQ for equipment, DPR for depreciation and SD for seed purchases. The full list of cross equation restrictions is in the Appendix.

In order to measure percentage cost increases we consider the predicted value of the log cost when all input prices are set at their average value. If we denote the log cost at tax level

[11] Seemingly Unrelated regression equations reduces to OLS in two cases: if the variance-covariance matrix is the identity or if the set of regressors is the same for every equation (Wooldridge, 2010).

x and input price level w as $\hat{C}(x, w)$ then the object of our estimation becomes $\hat{C}(x, \bar{w})$.[12] We collect all the β coefficients in a vector β and each variable (output as well as input prices) of the cost function in a vector $F(x, w)$. Note that the vector $F(x, w)$ depends on the tax level x and the input price w in a nonlinear fashion.[13] In particular, according to our assumption, the only input prices that vary with the tax level are fuel and fertilizer prices. Then, the percentage cost increase at average input prices is given by the formula:

$$\%\Delta(C)(x) = \hat{C}(x, \bar{w}) - \hat{C}(0, \bar{w}) \tag{19}$$

$$= (F(x, \bar{w})^T \beta - F(0, \bar{w}))^T \beta \tag{20}$$

$$= (F(x, \bar{w}) - F(0, \bar{w}))^T \beta \tag{21}$$

Observe that the left hand side can be interpreted as a percentage change in the cost increase because it can be written as the difference between two logarithms, that is equivalent to the logarithm of the ratio of cost post-tax versus cost pre-tax.

4 Results

We present two sets of results. First we report the estimated regression coefficient for each farm typology, then we evaluate at what level of taxation we would observe regressivity across farm typologies.

4.1 Cost Function Estimation Results

The regression results for the four farm typologies are reported in tables 2 to 5. The model is described by the system of equations (18), with the cross-equation restrictions in line with the production theory. We present both OLS and SURE results. The SURE estimator is efficient as reflected by lower standard errors in the regression estimates.

[12] Admittedly, a more sophisticated approach would not impose such functional forms on the data and would estimate the cost function non-parametrically. A measure of regressivity could then be defined as a linear functional of the cost function.

[13] This reminder is obvious: the translog cost function is only linear in parameters.

We use the SURE results to predict the average percentage increase in the total farm cost relative to a farm that faces no tax and average input prices. Figure 1 to 4 present the predicted cost increase together with 95% confidence intervals. We note that increases are modest across farm typologies but more pronounced for intermediate farms. This result is likely driven by the crop mix that includes soybeans. Soybeans are nitrogen fixators and reduce the reliance of the nitrogen fertilizer as a farm input. Thus corn farms that grow soybeans mitigate a lot of the percentage cost increase that would otherwise affect them through the increase of the price of nitrogen fertilizer.

4.2 Carbon Tax Regressivity

Figures 5 to 10 report the average predicted value for the farm regressivity measure for each level of taxation, together with 95% confidence intervals. Each graph reports the lowest level of tax that would result in rejecting the null hypothesis of no regressivity across the two farm typologies. In general the model predicts that, for reasonably low levels of taxation, there is statistically significant regressivity of the carbon tax for most pairs.

A seemingly surprising result is the comparisons that involve residence farms (figures 5 to 7). Residence farms display *no* statistically significant regressivity at any tax level; the relationship is more often progressive. This is likely due to residence farms not being profit maximizing; over 90 percent have negative farm income. These farms may be participating in farming for lifestyle purposes and may simply cut back on inputs when expenses increase, without fully accounting for yield or profit implications.

The relationship between intermediate, commercial midsize, and commercial large farms generally suggests regressivity. For example, in Figure 8, we find that a carbon tax of 25$/ton is likely to have a regressive incidence on intermediate farms over commercial midsize farms. The analogous figure for the regressivity between intermediate and commercial large farms is 13$/ton, while between commercial midsize and commercial large is 19$/ton in figures 9 and 10, respectively. These results suggest that, the regressivity of carbon tax may arise at relatively low levels. This is likely due to larger farms having more capacity to negotiate

lower input prices during high price periods or to accordingly restrict input use.

5 Conclusion

In this paper we have provided a framework to measure the potential implications of carbon prices across farm typologies. We predict that regressivity arises for relatively low levels of carbon pricing or taxation for intermediate and commercial farms. In other words, the impact of policies that effectively increase the cost of carbon will have a larger impact on input expenditure of intermediate than commercial farms. As such, our results suggests that policies that increase input costs, including carbon taxation or carbon pricing, may accelerate ongoing structural change in the US farm sector.

This study focuses on the market structure implications of one specific channel of impact of carbon mitigation policies – input costs. As such, the study complements partial and general equilibrium approaches, as well as highlighting the relevance of farm heterogeneity when estimating impacts of these policies. This study only considers the short-run response to input price changes; impacts may be muted if adaptation occurs over the long run.

This research could be expanded by considering additional commodities or time periods or climate change mitigation policies. Use of additional datasets from the US or other countries would also provide important insights. Causal approaches that take advantage of unanticipated random price shocks would also provide insights into the potential distribution impacts of a carbon policy. The methods developed in this study could be applied to other policies that increase input costs.

Policymakers that are interested in distributional impacts of carbon prices, or any climate-related policy that increases production costs, may want to consider the implications for farm structure. Climate policy objectives might not always align with other farm policy objectives. While most government spending for the US farm safety net (crop insurance and other programs) is related to current or historic production, there are also several policies and programs to support "underserved" producers or increase diversity, broadly defined, in production agriculture. Movement towards more stringent climate change mitigation policies

may exacerbate these existing tensions in US farm policy.

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6 Tables

Table 1: Modified Farm Typology Categories

	Operator's primary occupation	Farm Size by GCFI
Residence	Retired or nonfarm	Less than $350,000
Intermediate	Farming	Less than $350,000
Commercial-Midsize	Not a criterion	$350,000-$999,999
Commercial-Large	Not a criterion	Greater than $1,000,000

Table 2: **Regression Results-Residence Farms**

	OLS Restricted			SURE Restricted		
VARIABLES	LogTotalCost	FuelShare	FertShare	LogTotalCost	FuelShare	FertShare
LogCornOutput	0.296	-0.0120***	-0.0269***	0.202	-0.0124***	-0.0271***
	(0.366)	(0.00172)	(0.00176)	(0.363)	(0.00172)	(0.00181)
LogSoybeanOutput	0.0855	-0.000391	-0.00296***	0.0878	-0.000421	-0.00297***
	(0.108)	(0.000447)	(0.000382)	(0.107)	(0.000447)	(0.000383)
LogCornSoybeans	-0.0195***			-0.0201***		
	(0.00355)			(0.00352)		
LogCornSquared	0.0316***			0.0326***		
	(0.00514)			(0.00510)		
LogSoybeanSquared	0.00920***			0.00962***		
	(0.00261)			(0.00258)		
LogFuel	0.352***	-0.0133*	-0.0115**	0.350***	-0.0135*	-0.0116**
	(0.0890)	(0.00704)	(0.00473)	(0.0878)	(0.00698)	(0.00469)
LogFuelSquared	-0.00667*			-0.00676*		
	(0.00352)			(0.00349)		
LogWages	-22.80***	-0.0842***	-0.0237	-21.96***	-0.0841***	-0.0233
	(7.232)	(0.0310)	(0.0260)	(7.174)	(0.0310)	(0.0261)
LogWagesSquared	4.558***			4.331***		
	(1.456)			(1.445)		
LogFertilizer	0.492***	-0.0115**	-0.00822	0.492***	-0.0116**	-0.00831
	(0.0836)	(0.00473)	(0.00599)	(0.0819)	(0.00469)	(0.00593)
LogFertilizerSquared	-0.00411			-0.00416		
	(0.00299)			(0.00297)		
LogFuelLogCorn	-0.0120***			-0.0124***		
	(0.00172)			(0.00172)		
LogFuelLogSoybean	-0.000391			-0.000421		
	(0.000447)			(0.000447)		
LogFertilizerLogCorn	-0.0269***			-0.0271***		
	(0.00176)			(0.00181)		
LogFertilizerLogSoybean	-0.00296***			-0.00297***		
	(0.000382)			(0.000383)		
LogWagesLogCorn	-0.0385			-0.00706		
	(0.150)			(0.149)		
LogWagesLogSoybean	0.0253			0.0252		
	(0.0425)			(0.0422)		
LogFuelLogWages	-0.0842***			-0.0841***		
	(0.0310)			(0.0310)		
LogFuelLogFertilizer	-0.0115**			-0.0116**		
	(0.00473)			(0.00469)		
LogFertilizerLogWages	-0.0237			-0.0233		
	(0.0260)			(0.0261)		
LogSeedLogFertilizer	0.0372***			0.0374***		
	(0.00144)			(0.00153)		
LogEquipmentLogFuel	0.0169***			0.0177***		
	(0.00149)			(0.00148)		
year	0.0132***			0.0130***		
	(0.00469)			(0.00466)		
LogEquipment		0.0169***			0.0177***	
		(0.00149)			(0.00148)	
LogSeed			0.0372***			0.0374***
			(0.00144)			(0.00153)
Constant	4.375	0.321***	0.0717	4.304	0.317***	0.0714
	(13.98)	(0.0782)	(0.0667)	(13.87)	(0.0781)	(0.0666)
Observations	3,038	3,038	3,038	3,038	3,038	3,038
R-squared	0.794	0.038	-0.160	0.794	0.036	-0.162

The asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 3: **Regression Results-Intermediate Farms**

	OLS Restricted			SURE Restricted		
VARIABLES	LogTotalCost	FuelShare	FertShare	LogTotalCost	FuelShare	FertShare
LogCornOutput	0.134	-0.00754***	-0.0233***	0.221	-0.00818***	-0.0238***
	(0.285)	(0.00148)	(0.00137)	(0.279)	(0.00147)	(0.00142)
LogSoybeanOutput	-0.0974	-0.00146***	-0.00254***	-0.0834	-0.00148***	-0.00257***
	(0.0680)	(0.000336)	(0.000280)	(0.0667)	(0.000336)	(0.000280)
LogCornSoybeans	-0.00597***			-0.00636***		
	(0.00228)			(0.00224)		
LogCornSquared	0.0250***			0.0241***		
	(0.00441)			(0.00433)		
LogSoybeanSquared	0.00551***			0.00566***		
	(0.00149)			(0.00146)		
LogFuel	0.387***	-0.0148***	-0.0123***	0.376***	-0.0154***	-0.0126***
	(0.0644)	(0.00543)	(0.00368)	(0.0629)	(0.00538)	(0.00365)
LogFuelSquared	-0.00740***			-0.00772***		
	(0.00272)			(0.00269)		
LogWages	-14.62***	-0.0747***	-0.0411**	-14.37***	-0.0737***	-0.0405**
	(4.796)	(0.0222)	(0.0184)	(4.704)	(0.0222)	(0.0184)
LogWagesSquared	2.774***			2.785***		
	(0.978)			(0.959)		
LogFertilizer	0.368***	-0.0123***	-0.000188	0.366***	-0.0126***	6.15e-05
	(0.0599)	(0.00368)	(0.00464)	(0.0578)	(0.00365)	(0.00460)
LogFertilizerSquared	-9.41e-05			3.08e-05		
	(0.00232)			(0.00230)		
LogFuelLogCorn	-0.00754***			-0.00818***		
	(0.00148)			(0.00147)		
LogFuelLogSoybean	-0.00146***			-0.00148***		
	(0.000336)			(0.000336)		
LogFertilizerLogCorn	-0.0233***			-0.0238***		
	(0.00137)			(0.00142)		
LogFertilizerLogSoybean	-0.00254***			-0.00257***		
	(0.000280)			(0.000280)		
LogWagesLogCorn	0.0378			0.0101		
	(0.114)			(0.112)		
LogWagesLogSoybean	0.0520**			0.0473*		
	(0.0264)			(0.0259)		
LogFuelLogWages	-0.0747***			-0.0737***		
	(0.0222)			(0.0222)		
LogFuelLogFertilizer	-0.0123***			-0.0126***		
	(0.00368)			(0.00365)		
LogFertilizerLogWages	-0.0411**			-0.0405**		
	(0.0184)			(0.0184)		
LogSeedLogFertilizer	0.0364***			0.0371***		
	(0.00103)			(0.00112)		
LogEquipmentLogFuel	0.0144***			0.0156***		
	(0.00122)			(0.00120)		
year	0.0218***			0.0216***		
	(0.00313)			(0.00307)		
LogEquipment		0.0144***			0.0156***	
		(0.00122)			(0.00120)	
LogSeed			0.0364***			0.0371***
			(0.00103)			(0.00112)
Constant	-21.02**	0.315***	0.0350	-21.29**	0.308***	0.0315
	(9.405)	(0.0573)	(0.0491)	(9.227)	(0.0572)	(0.0490)
Observations	5,451	5,451	5,451	5,451	5,451	5,451
R-squared	0.763	0.022	-0.105	0.764	0.020	-0.110

The asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 4: **Regression Results-Commercial Midsize**

	OLS Restricted			SURE Restricted		
VARIABLES	LogTotalCost	FuelShare	FertShare	LogTotalCost	FuelShare	FertShare
LogCornOutput	-0.227	0.00208	-0.0127***	-0.178	0.00117	-0.0145***
	(0.419)	(0.00176)	(0.00194)	(0.405)	(0.00176)	(0.00197)
LogSoybeanOutput	-0.354***	-0.00279***	-0.00193***	-0.344***	-0.00281***	-0.00199***
	(0.0526)	(0.000284)	(0.000311)	(0.0508)	(0.000284)	(0.000311)
LogCornSoybeans	0.0172***			0.0155***		
	(0.00244)			(0.00236)		
LogCornSquared	0.0388***			0.0352***		
	(0.00925)			(0.00894)		
LogSoybeanSquared	0.00163*			0.00162*		
	(0.000885)			(0.000856)		
LogFuel	0.308***	-0.00283	-0.0127***	0.296***	-0.00375	-0.0133***
	(0.0512)	(0.00412)	(0.00326)	(0.0497)	(0.00409)	(0.00324)
LogFuelSquared	-0.00142			-0.00188		
	(0.00206)			(0.00204)		
LogWages	-19.30***	-0.0630***	-0.0505***	-17.04***	-0.0638***	-0.0489***
	(3.662)	(0.0162)	(0.0178)	(3.540)	(0.0162)	(0.0178)
LogWagesSquared	4.003***			3.502***		
	(0.681)			(0.659)		
LogFertilizer	0.126**	-0.0127***	-0.00137	0.117**	-0.0133***	-0.000907
	(0.0588)	(0.00326)	(0.00474)	(0.0565)	(0.00324)	(0.00471)
LogFertilizerSquared	-0.000687			-0.000454		
	(0.00237)			(0.00235)		
LogFuelLogCorn	0.00208			0.00117		
	(0.00176)			(0.00176)		
LogFuelLogSoybean	-0.00279***			-0.00281***		
	(0.000284)			(0.000284)		
LogFertilizerLogCorn	-0.0127***			-0.0145***		
	(0.00194)			(0.00197)		
LogFertilizerLogSoybean	-0.00193***			-0.00199***		
	(0.000311)			(0.000311)		
LogWagesLogCorn	-0.110			-0.0916		
	(0.144)			(0.140)		
LogWagesLogSoybean	0.0591***			0.0625***		
	(0.0183)			(0.0177)		
LogFuelLogWages	-0.0630***			-0.0638***		
	(0.0162)			(0.0162)		
LogFuelLogFertilizer	-0.0127***			-0.0133***		
	(0.00326)			(0.00324)		
LogFertilizerLogWages	-0.0505***			-0.0489***		
	(0.0178)			(0.0178)		
LogSeedLogFertilizer	0.0418***			0.0446***		
	(0.00102)			(0.00112)		
LogEquipmentLogFuel	0.00711***			0.00875***		
	(0.00112)			(0.00109)		
year	0.0267***			0.0257***		
	(0.00232)			(0.00224)		
LogEquipment		0.00711***			0.00875***	
		(0.00112)			(0.00109)	
LogSeed			0.0418***			0.0446***
			(0.00102)			(0.00112)
Constant	-19.49**	0.265***	-0.111**	-20.62***	0.261***	-0.127**
	(8.039)	(0.0465)	(0.0531)	(7.772)	(0.0464)	(0.0530)
Observations	6,483	6,483	6,483	6,483	6,483	6,483
R-squared	0.576	0.029	-0.091	0.581	0.027	-0.106

The asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 5: **Regression Results-Commercial Large**

	OLS Restricted			SURE Restricted		
VARIABLES	LogTotalCost	FuelShare	FertShare	LogTotalCost	FuelShare	FertShare
LogCornOutput	-1.452***	0.00407***	-0.0226***	-1.354***	0.00369**	-0.0252***
	(0.331)	(0.00154)	(0.00195)	(0.323)	(0.00154)	(0.00199)
LogSoybeanOutput	-0.355***	-0.00306***	-0.000375	-0.345***	-0.00307***	-0.000436
	(0.0457)	(0.000255)	(0.000312)	(0.0444)	(0.000255)	(0.000312)
LogCornSoybeans	0.0116***			0.00986***		
	(0.00194)			(0.00189)		
LogCornSquared	0.108***			0.108***		
	(0.00647)			(0.00629)		
LogSoybeanSquared	0.00334***			0.00320***		
	(0.000735)			(0.000715)		
LogFuel	0.410***	-0.000480	-0.0121***	0.404***	-0.000864	-0.0124***
	(0.0486)	(0.00401)	(0.00343)	(0.0471)	(0.00399)	(0.00341)
LogFuelSquared	-0.000240			-0.000432		
	(0.00201)			(0.00200)		
LogWages	-29.30***	-0.126***	-0.0666***	-26.96***	-0.126***	-0.0639***
	(3.387)	(0.0147)	(0.0182)	(3.296)	(0.0147)	(0.0182)
LogWagesSquared	6.485***			6.068***		
	(0.629)			(0.612)		
LogFertilizer	0.433***	-0.0121***	-0.0274***	0.426***	-0.0124***	-0.0274***
	(0.0614)	(0.00343)	(0.00543)	(0.0590)	(0.00341)	(0.00540)
LogFertilizerSquared	-0.0137***			-0.0137***		
	(0.00271)			(0.00270)		
LogFuelLogCorn	0.00407***			0.00369**		
	(0.00154)			(0.00154)		
LogFuelLogSoybean	-0.00306***			-0.00307***		
	(0.000255)			(0.000255)		
LogFertilizerLogCorn	-0.0226***			-0.0252***		
	(0.00195)			(0.00199)		
LogFertilizerLogSoybean	-0.000375			-0.000436		
	(0.000312)			(0.000312)		
LogWagesLogCorn	-0.271**			-0.299***		
	(0.115)			(0.112)		
LogWagesLogSoybean	0.0687***			0.0742***		
	(0.0168)			(0.0163)		
LogFuelLogWages	-0.126***			-0.126***		
	(0.0147)			(0.0147)		
LogFuelLogFertilizer	-0.0121***			-0.0124***		
	(0.00343)			(0.00341)		
LogFertilizerLogWages	-0.0666***			-0.0639***		
	(0.0182)			(0.0182)		
LogSeedLogFertilizer	0.0429***			0.0463***		
	(0.00113)			(0.00122)		
LogEquipmentLogFuel	0.00454***			0.00531***		
	(0.00112)			(0.00110)		
year	0.0259***			0.0247***		
	(0.00247)			(0.00241)		
LogEquipment		0.00454***			0.00531***	
		(0.00112)			(0.00110)	
LogSeed			0.0429***			0.0463***
			(0.00113)			(0.00122)
Constant	1.052	0.418***	0.191***	0.0310	0.415***	0.178***
	(7.913)	(0.0431)	(0.0552)	(7.702)	(0.0431)	(0.0551)
Observations	5,890	5,890	5,890	5,890	5,890	5,890
R-squared	0.709	0.059	-0.100	0.713	0.058	-0.117

The asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels.

7 Figures

Figure 1: Percentage cost increase for residence farms

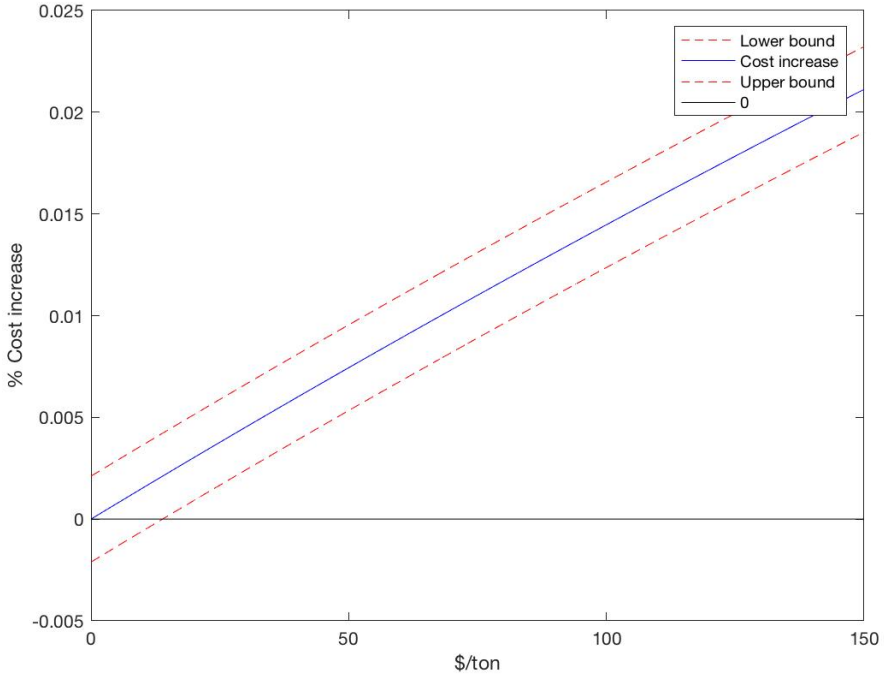


Figure 2: Percentage cost increase for intermediate farms

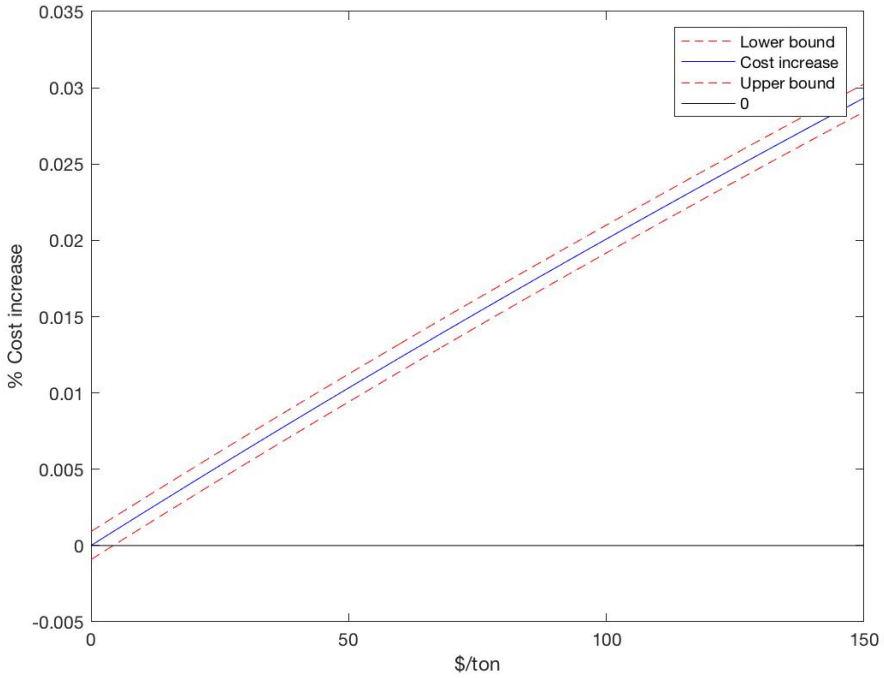


Figure 3: Percentage cost increase for commercial midsize farms

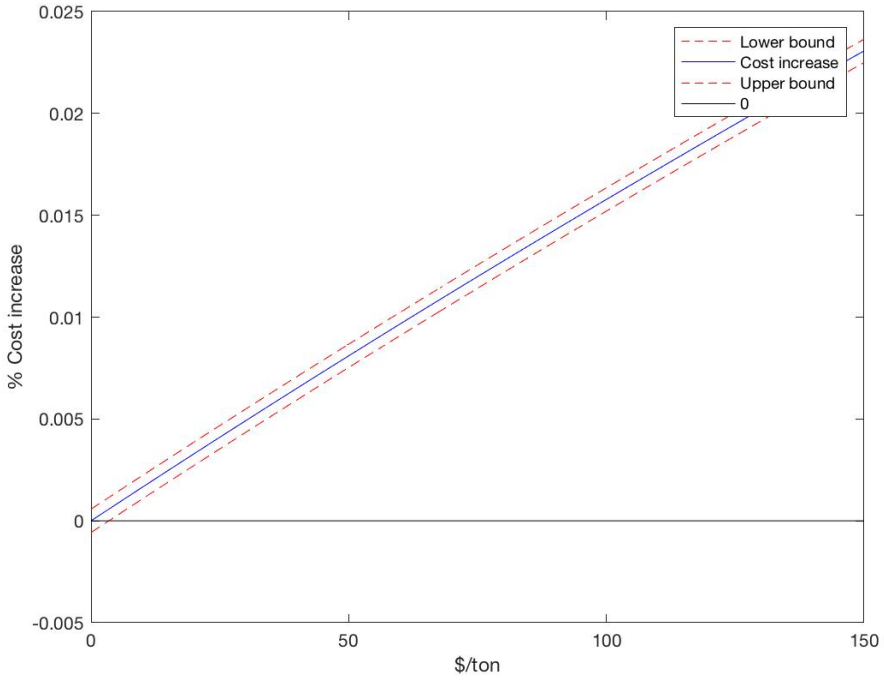


Figure 4: Percentage cost increase for commercial large farms

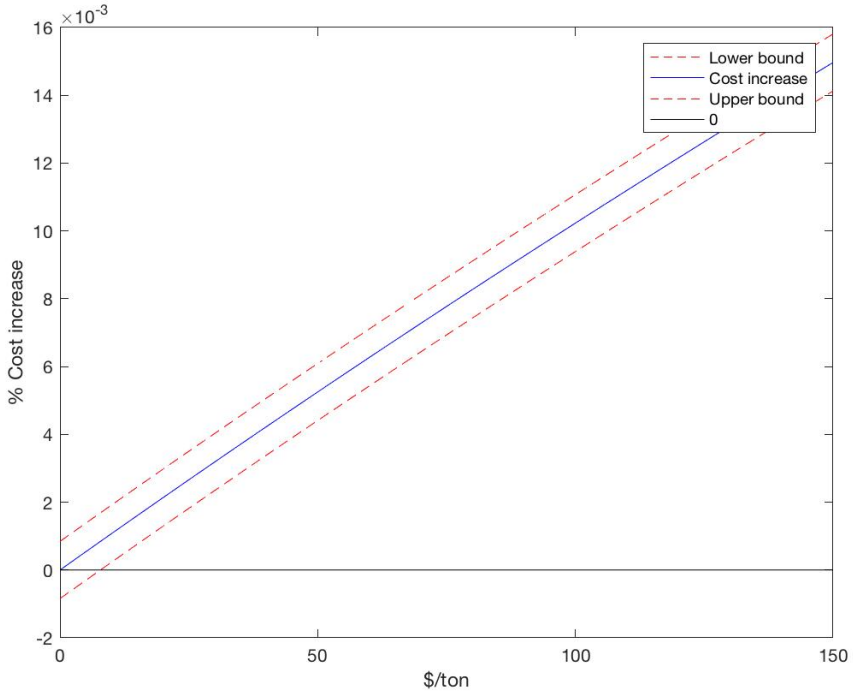


Figure 5: Regressivity between residence and intermediate farms

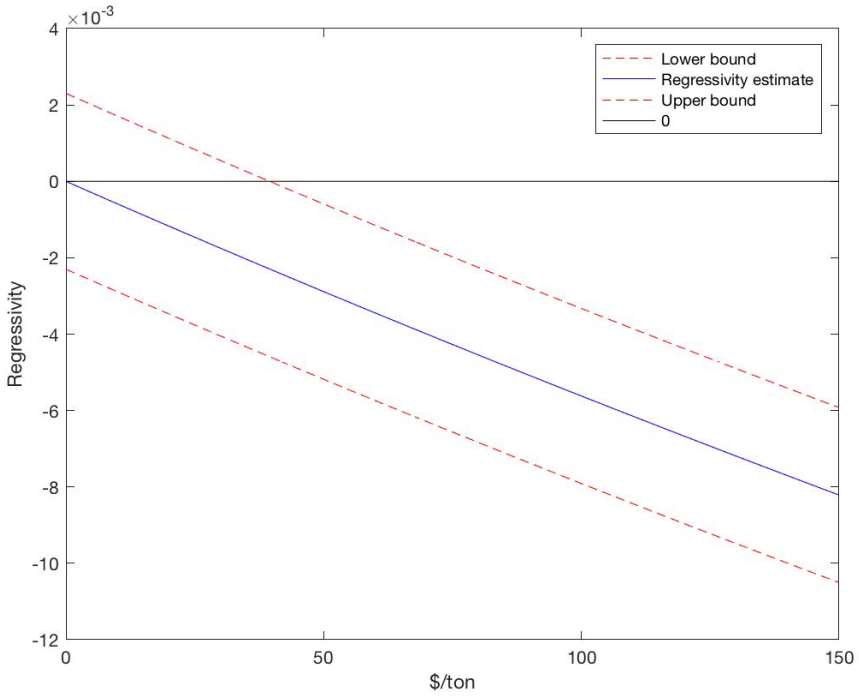


Figure 6: Regressivity between residence and commercial midsize farms

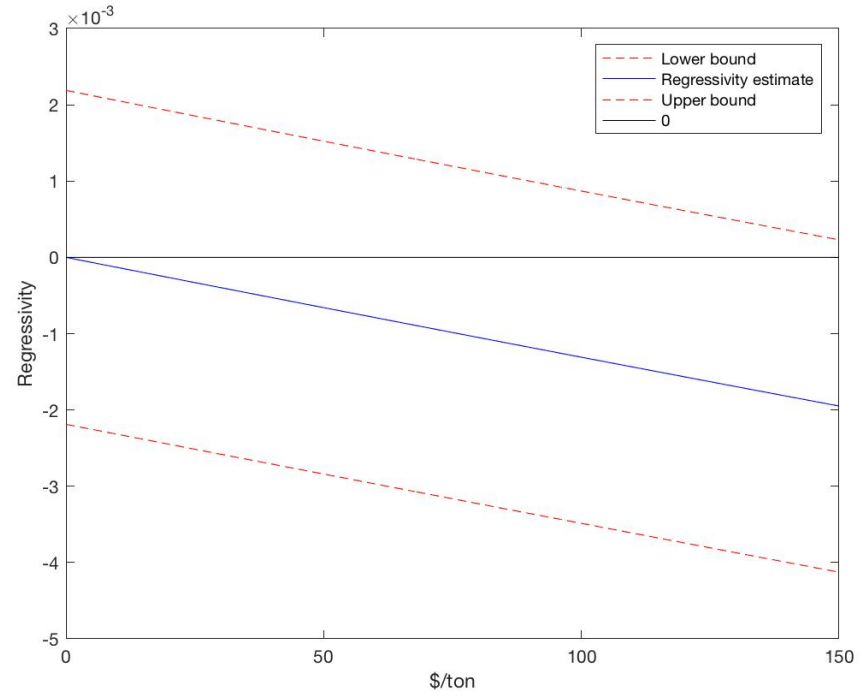


Figure 7: Regressivity between residence and commercial large farms

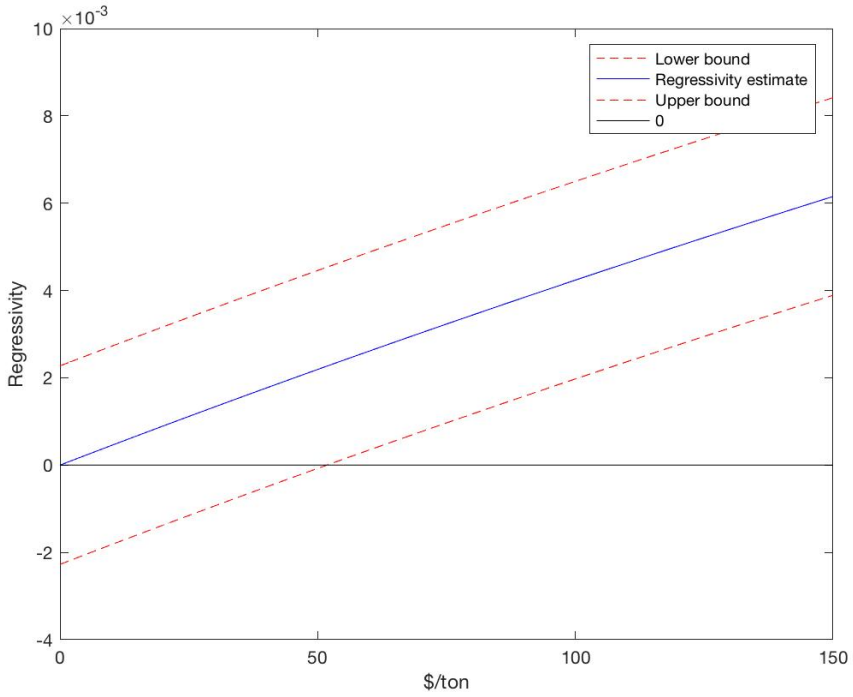


Figure 8: Regressivity between intermediate and commercial midsize farms

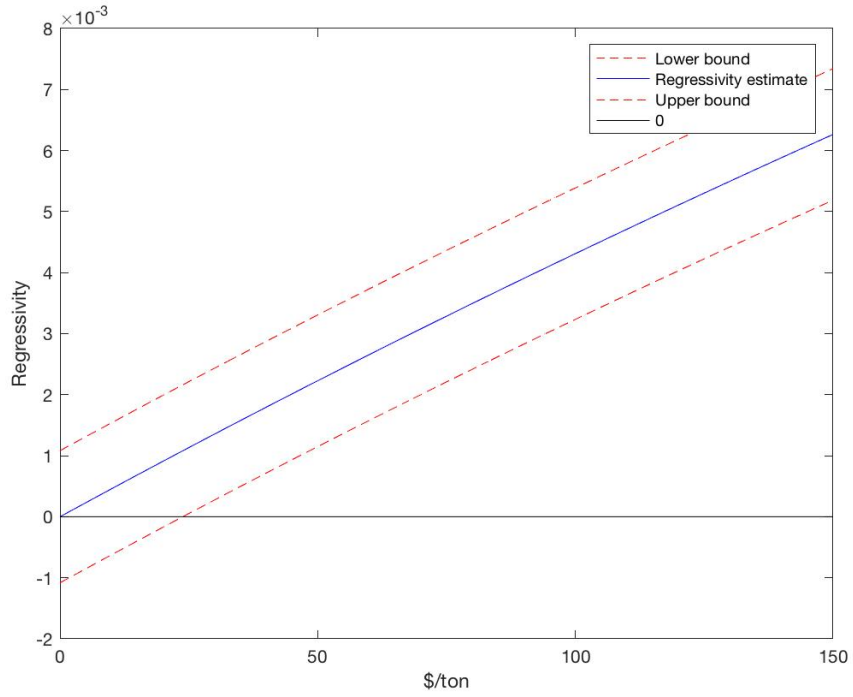


Figure 9: Regressivity between intermediate and commercial large farms

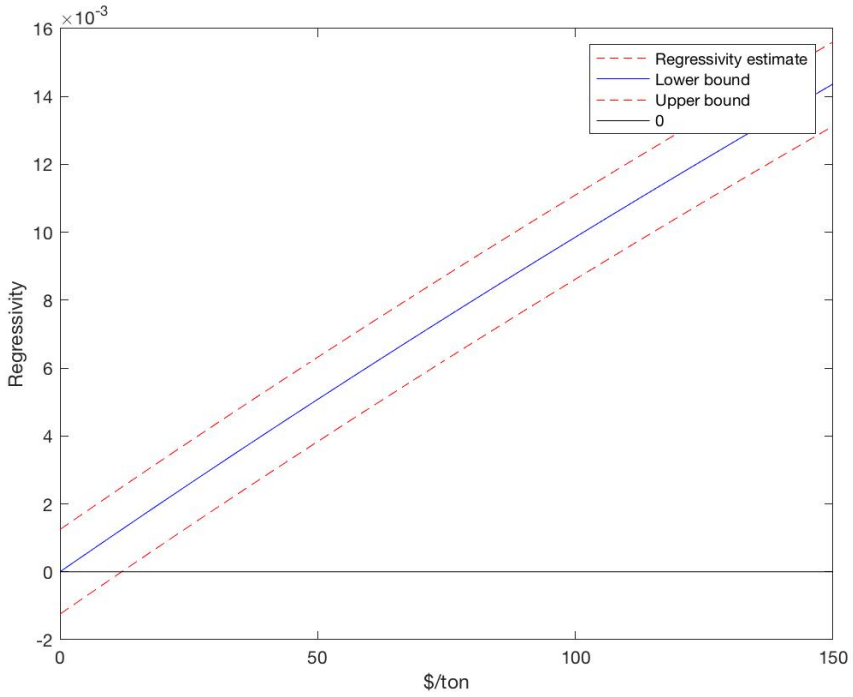
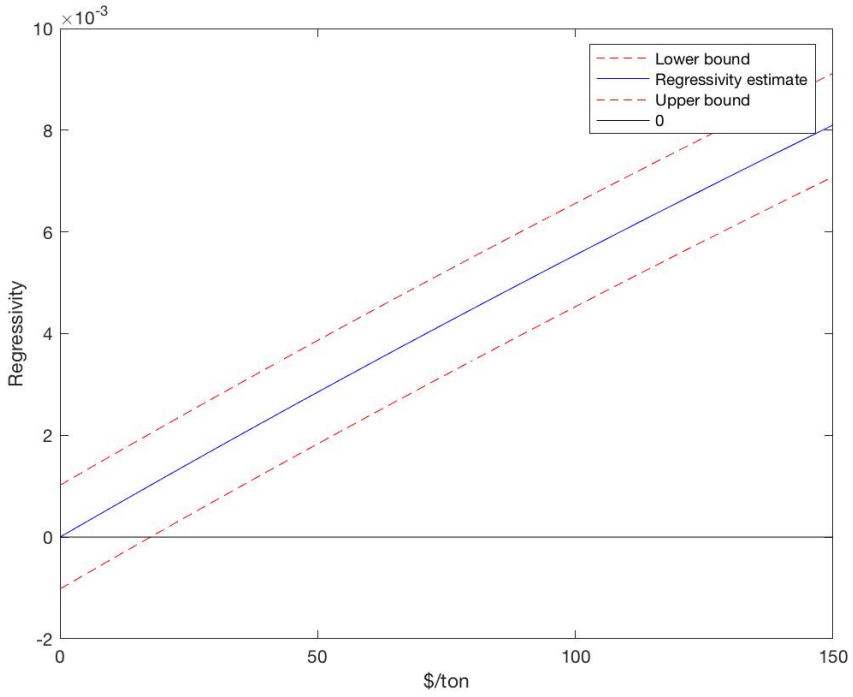


Figure 10: Regressivity between commercial midsize and commercial large farms



A List of cross equation restrictions

The cross-equation restrictions for the SURE system are given below:

$$\beta^C_{Y,O} = \beta^O_Y$$
$$\beta^C_{Y,F} = \beta^F_Y$$
$$\beta^C_{OO} = 2\beta^O_O$$
$$\beta^C_{FF} = 2\beta^F_F$$
$$\beta^C_{FO} = \beta^O_F = \beta^F_O$$
$$\beta^C_{OW} = \beta^O_W$$
$$\beta^C_{FW} = \beta^F_W$$
$$\beta^C_{O,DPR} = \beta^O_{DPR}$$
$$\beta^C_{O,EQ} = \beta^O_{EQ}$$
$$\beta^C_{F,SD} = \beta^F_{SD}$$

B A Multi-Output Translog Production Function

Farm's cost structure differs depending on the output mix produced. As a first pass, we have grouped farms into 4 typologies based on the main production: corn, cotton, soybeans, and wheat, and estimated a single output production function for each. Inevitably, this classification neglects the production synergies of multi-output farms. Most notably, many farms (insert figure) produce either soybeans and wheat or soybeans and corn. Because the cost of producing some of the most fuel or fertilizer-intensive crops is partially offset by the joint production of a nitrogen fixer crop like soybeans, it is important to account for this feature in the estimation of supply elasticises for input prices. Principally, we allow firms to respond to increases in input prices in a way that can differ depending on their output mix. In terms of estimation, the multi-output translog cost function features additional terms,

Y_j corresponding to the production levels of each output j in a set J. Just like the single output translog cost function, the estimating equation system uses the total cost and cost shares:

$$\begin{cases} \ln(C) = \beta_0 + \sum_{j \in J} \beta_{Yj} \cdot \ln(Y_j) + \frac{1}{2} \sum_{j \in J} \sum_{l \in J} \beta_{YjYl} \cdot \ln(Y_j) \ln(Y_l) + \sum_{i \in I} \beta_{Yji} \cdot \ln(Y_j) \ln(P_i) \\ \qquad + \frac{1}{2} \sum_{i \in I} \sum_{k \in I} \beta_{ij} \cdot \ln(P_i) \ln(P_j) + \sum_{i \in I} \beta_i \ln(P_i) + \epsilon_C \\ \\ S_i = \gamma_i + \sum_{j \in J} \gamma_{Yij} \ln(Y_j) + \sum_{i \in I} \gamma_{ij} \ln(P_j) + \epsilon_{S_i} \end{cases}$$

Similar cross-equation restrictions as in the single output case hold for the estimated coefficients. As before, stimation can be carried out via OLS or SURE.