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A Meta-Regression

Boying Liu
C. Richard Shumway

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Substitution Elasticities between GHG Polluting and Nonpolluting Inputs in Agricultural Production: A Meta-Regression

Boying Liu[1]

C. Richard Shumway[1]

Abstract

This paper reports meta-regressions of substitution elasticities between greenhouse-gas (GHG) polluting and nonpolluting inputs in agricultural production. We treat energy, fertilizer, and manure collectively as the "polluting input" and labor, land, and capital as nonpolluting inputs. We estimate meta-regressions for samples of Morishima substitution elasticities for labor, land, and capital vs. the polluting input. Much of the heterogeneity of Morishima elasticities can be explained by type of primal or dual function, functional form, type and observational level of data, input categories, the number of outputs, type of output, time period, and country categories. Each estimated long-run elasticity for the reference case, which is most relevant for assessing GHG emissions through life-cycle analysis, is greater than 1.0 and significantly different from zero. Most predicted elasticities remain significantly different from zero at the data means in the long run. These findings imply that life-cycle analysis based on fixed proportions production functions could provide grossly inaccurate measures of GHG of biofuel.

Keywords: greenhouse gas polluting inputs, input substitution, life-cycle analysis, meta-regression, Morishima elasticity, production function.

JEL Codes: Q16, Q20.

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[1] Boying Liu is a Ph.D. Graduate Research Assistant and C. Richard Shumway is a Regents Professor in the School of Economic Sciences, Washington State University.

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1. Introduction

Biofuel has become a major substitute for fossil fuel energy sources. It has important benefits such as decreasing dependence on foreign oil imports, providing additional markets for agricultural products, and creating job opportunities in rural areas. However, despite its appeal as a renewable energy source, there is ongoing debate whether biofuel alleviates environmental concerns. Some studies conclude that biofuel can mitigate greenhouse gas (GHG) emissions (*e.g.*, Farrell *et al.*, 2006), whereas others find that biofuel may result in nearly as much or even more GHG emissions as petroleum-based fuels (*e.g.*, Solomon, 2010; Fargione *et al.*, 2008; Searchinger *et al.*, 2008).

Measurement of GHG emissions from biofuel is typically examined through life-cycle analysis (LCA). LCA assesses the emissions associated with the entire life of biofuel, from its feedstock production to its end use. An accurate LCA is important for environmental policy decisions. For instance, the U.S. Energy Independence and Security Act (EISA 2007) requires the U.S. Environmental Protection Agency to create and enforce a threshold of life-cycle GHG reduction through use of renewable energy. Previous studies on LCA generally assume fixed-proportions production functions and consequently do not account for any input ratio response to changing market and policy conditions. However, a change in the relative price of an input that generates GHG emissions could induce substitution away from that input and alter emissions and environmental policy consequences (Rajagopal and Zilberman, 2008).

This paper provides empirical evidence on substitutability between GHG-polluting inputs and nonpolluting inputs in agricultural production, which is the main feedstock source for biofuel in the U.S.[2] We estimate a meta-regression for samples of elasticities of substitution for polluting and non-polluting inputs. Our findings have important implications because significant substitutability between polluting and non-polluting inputs may greatly alter life-cycle GHG emissions from renewable energy.

A large number of empirical studies have estimated elasticities of input substitution in agricultural production, but their estimates vary considerably. The research tool, meta-analysis, provides a way to summarize and analyze the scattered empirical outcomes on a certain topic (Glass, 1976). In economics, meta-regression is the most commonly applied method of meta-analysis (*e.g.*, Bateman and Jones, 2003; Bellavance *et al.*, 2009; Bureau *et al.*, 2010). The observations used for the dependent variable are estimates obtained from prior empirical studies. The independent variables are factors expected to be relevant for explaining the heterogeneity of empirical outcomes (Stanley and Jarrell, 1989). Meta-regression can provide a combined estimate as well as identify sources of variation in prior estimates (Nelson and Kennedy, 2009). In this paper we use meta-regression to investigate substitution elasticities between polluting and non-polluting inputs in agricultural production relevant to biofuel feedstock production.[3]

Three previous meta-regression articles have addressed substitution elasticities. Boys and Florax (2007) conducted a meta-regression to examine the Allen elasticity of substitution between labor and capital in the agricultural sector. Koetse *et al.* (2008)

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[2] Biofuel feedstock can be provided by agricultural crops and cellulosic biomass. In the U.S. very little cellulosic biomass is currently used because of the inadequacy of technology to convert cellulose to fuel, so agricultural crops are the primary source of feedstock. Therefore, in this paper we confine our attention to input substitutability in agricultural feedstock production.

[3] We only consider GHG emission in this paper. Hence, "polluting input" means "GHG-polluting input".

focused on the Morishima elasticity of substitution between capital and energy for all industries. Stern (2012) investigated shadow substitution elasticities between oil, coal, gas, and electricity in the whole economy. We differ from the existing literature in three aspects: We examine Morishima elasticities of substitution between GHG-polluting inputs (energy, fertilizer, and manure) and non-polluting inputs (labor, land, and capital) in agricultural production. We include a larger number of primary articles (65) on agricultural production for our meta-regression than do Boys and Florax (2007) which includes 35 papers. And, our estimates of substitution elasticities provide a basis for integrating input substitution into LCA of biofuels for purposes of GHG assessment.

The paper is organized as follows. We address issues associated with the choice and measurement of input substitution elasticities in section 2. We describe the selection process and the characteristics of primary studies in section 3. Section 4 identifies potential sources of heterogeneity in empirical outcomes and explains the choice of independent variables. We next discuss the econometric issues and models in section 5. The results of meta-regression are reported in section 6. Section 7 concludes.

2. Choice of Dependent Variables

2.1 Elasticity of substitution definition

The elasticity of input substitution, originally introduced by Hicks (1932) for analysis of production with two inputs, measures the relative change in input ratios with respect to a relative change in the marginal rate of technical substitution with output held constant:

$$\sigma_{12} = \frac{d \ln(x_1 / x_2)}{d \ln MRTS_{12}} \tag{1}$$

Where σ is the elasticity of input substitution, x_i represents input i, $i = 1, 2$, and $MRTS_{12}$ is the marginal rate of technical substitution between the two inputs.

Three alternative generalizations are identified in the literature when production involves three or more inputs – Allen, Morishima and Shadow elasticities of substitution. The Allen elasticity of substitution (AES) is a one-price-one-factor elasticity of input i to the price of input j with all other prices and output held fixed. It measures the share-weighted relative change in conditional input demand with respect to a change in the price of another input:

$$\sigma_{ij}^{A} = \eta_{ij} / S_j \tag{2}$$

where σ_{ij}^{A} is the AES between inputs i and j; η_{ij} is the conditional cross-price elasticity of input i with respect to the price of input j; S_j is the cost share of input j. The AES is the most commonly reported substitution elasticity and is symmetric, i.e., $\sigma_{ij}^{A} = \sigma_{ji}^{A}$. However, it is also the least useful because it adds no additional information beyond the conditional input demand cross-price elasticity and the input's cost share (Blackorby and Russell, 1989).

The Morishima elasticity of substitution (MES) is a one-price-two-factor elasticity of the input ratio to the price of input j with all other prices and output held fixed. It can be written as

$$\sigma_{ij}^{M} = \eta_{ij} - \eta_{jj} \tag{3}$$

where σ_{ij}^{M} is the MES between inputs i and j. It can also be calculated from the AES:

$$\sigma_{ij}^{M} = S_j (\sigma_{ij}^{A} \text{-} \sigma_{jj}^{A}) \tag{4}$$

Unlike the AES, the MES is asymmetric, so $\sigma_{ij}^{M} \neq \sigma_{ji}^{M}$.

The shadow elasticity of substitution (SES) is a two-price-two-factor elasticity of the input ratio to the price ratio, so it allows the prices of input i and j to change while holding output and all other prices constant. Like the AES, the SES is symmetric. Although it is the broadest generalization of the two-input elasticity of substitution, it is rarely reported in empirical studies.[4]

Two cost shares are essential for each method of computing the SES from reported conditional price elasticities, AES, or MES. However, they are seldom reported in empirical studies. It is sometimes impossible to compute all cost shares from reported data and parameter estimates, especially for papers estimating functions other than the cost function.[5] Consequently, we necessarily dismiss the SES as a candidate for our dependent variable because of inadequate data.

Although the MES is seldom reported in our primary articles, it is a conceptually superior definition to the AES because it focuses on changes in the input ratio, and it is typically possible to compute it directly from reported conditional price elasticities or AES. Except for the two studies that report MES, i.e., Debertin *et al.* (1990) and Napasintuwong *et al*. (2005), we convert whatever elasticities are reported in each study into MES. We use equation (3) to determine MES for studies that report conditional input price elasticities. For studies that use the translog cost function and only report AES, it is often feasible to first compute an input cost share and then use equation (4) to determine

[4] In our selected studies, only Debertin *et al.*(1990) report the SES.

[5] Stern (2012) investigated shadow substitution elasticities between different types of fuel, but he only included papers in his meta-regression sample that estimated a translog cost function.

MES. For studies that report neither conditional input price elasticities nor AES, additional computation is required, the specific nature of which depends both on functional form and type of function (*e.g.*, cost, profit, production) estimated.

2.2 Computation of MES based on different functional forms and types of function

2.2.1 Translog cost function

The largest number of empirical studies estimate a translog cost function. For such, the cost share equations can be expressed as (Bingswanger, 1974):

$$S_j = v_j + \sum_i \gamma_{ij} \ln w_i + \gamma_{jy} \ln Q \tag{5}$$

where w is input price, Q is the output level, and v_j, γ_{ij} and γ_{jy} are parameters to be estimated. The conditional own- and cross-price input demand elasticities can be expressed, respectively, as:[6]

$$\eta_{jj} = \gamma_{jj} / S_j + S_j - 1 \tag{6}$$

$$\eta_{ij} = \gamma_{ij} / S_i + S_j \tag{7}$$

The AES can be specified directly from these parameters and shares as:

$$\sigma_{jj}^A = (\gamma_{jj} + S_j^2 - S_j) / S_j^2 = \eta_{jj} / S_j \tag{8}$$

$$\sigma_{ij}^A = \gamma_{ij} / S_i S_j + 1 = \eta_{ij} / S_j \tag{9}$$

Parameter estimates are routinely presented in the primary studies but cost shares often are not. The cost shares can be obtained if a study reports the conditional own-price input demand elasticities or the own AES. By rearranging equation (6) or (8), we achieve

[6] The expressions for the own- and cross-price conditional input demand elasticities and the AES are the same for multiple-output as for single-output models.

$$S_j^2 - (1+\eta_{jj})S_j + \gamma_{jj} = 0 \text{ or} \tag{10}$$

$$(1-\sigma_{jj}^A)S_j^{\,2} - S_j + \gamma_{jj} = 0 \tag{11}$$

Then we solve for the cost shares subject to the constraints that $S_j \in (0,1)$ and $\sum_{j=1}^{n} S_j = 1$.[7]

The conditional input demand elasticities or the AES can then be calculated via equations (6)-(7) or (8)-(9), respectively, and the MES via equation (3) or (4).

2.2.2 Generalized Leontief cost function

A typical Generalized Leontief cost function can be specified as (Lopez 1982):

$$C(w,Q) = Q\sum_i \sum_j b_{ij} w_i^{1/2} w_j^{1/2} + Q^2 \sum_i \alpha_i w_i \tag{12}$$

where b_{ij} and α_i are parameters to be estimated. The conditional input demand functions are defined as

$$x_i = \sum_j b_{ij}\left(\frac{w_j}{w_i}\right)^{1/2} Q + \alpha_i Q^2 \tag{13}$$

The conditional own- and cross-price input demand elasticities for this cost function can be computed from the parameters as follows:

$$\eta_{ii} = -\frac{Q}{2x_i}\sum_{j\neq i} b_{ji}\left(\frac{w_j}{w_i}\right)^{1/2} \tag{14}$$

$$\eta_{ij} = \frac{Q}{2x_i} b_{ij}\left(\frac{w_j}{w_i}\right)^{1/2} \tag{15}$$

[7] If an article also presents AES, cost shares can be further validated by rearranging equation (9):

$S_i S_j = \gamma_{ij} / (\sigma_{ij}^A - 1)$.

Alternatively, as long as a study reports the parameter estimates and the own-price elasticities of conditional input demand, the cross-price elasticities can be solved by $\eta_{ij} = -\frac{\eta_{ii}}{\sum_{j \neq i} b_{ij}} b_{ij}$. Then the MES can be obtained via equation (3).

2.2.3 Profit function – transformation from uncompensated to compensated elasticities

Uncompensated elasticities are often reported (or easily derivable) in studies that estimate a profit function in which both outputs and inputs are treated as variable. To compute the MES, we need to first convert the uncompensated elasticities into compensated elasticities. In addition, the model based on the profit function is often associated with multiple outputs. The compensated elasticities of input demand can be obtained as (Lopez, 1984):

$$\left\{\eta_{ij}\right\} = \left\{\eta_{ij}^{u}\right\} - \left\{\eta_{im}^{u}\right\}\left\{\eta_{mn}^{u}\right\}^{-1}\left\{\eta_{mi}^{u}\right\} \quad (16)$$

where the subscript *m (n)* denotes output *m (n)*, $\left\{\eta_{ij}^{u}\right\}$ is a matrix of uncompensated input demand elasticities with respect to input prices, $\left\{\eta_{mn}^{u}\right\}$ is a matrix of uncompensated output supply elasticities with respect to output prices, $\left\{\eta_{im}^{u}\right\}$ is a matrix of uncompensated input demand elasticities with respect to output prices, and $\left\{\eta_{mi}^{u}\right\}$ is a matrix of uncompensated output supply elasticities with respect to input prices.

Then we can use equation (3) to determine the MES. A study reporting an estimated profit function is included in our meta-sample if all the above uncompensated elasticities are given or can be calculated from information reported in the study.

2.3 Input classification

In agricultural production, GHG emissions occur mainly from the use of three inputs: energy, nitrogen fertilizer, and manure. [8] In this paper, we treat energy, fertilizer, and manure use as the “polluting input”. [9] The polluting input accounts for nearly all the GHG emissions created through the production of agricultural biofuel feedstock. We include labor (l), land (d), and capital (k) as non-polluting inputs.[10] For one pair of inputs, the MES is asymmetric and its value depends on which input price changes. For purpose of facilitating price regulation (*e.g.*, a carbon tax) on the polluting input, we are interested in changes in the ratio of a non-polluting input and the polluting input as the price of the polluting input varies. As a result, three MES, denoted as σ_{op}^{M}, are computed and investigated separately in this study, where subscript o and p, respectively, represent non-polluting inputs (l, d, and k) and the polluting input.

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[8] There are four types of GHG: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases. The first three types of GHG pollution occur with agricultural production. Specifically, CO_2 is generated by the use of electricity, fossil fuel, or oil; CH_4 is generated from animal manure; N_2O is emitted when nitrogen is added to the soil through the use of synthetic fertilizer and through the breakdown of nitrogen in animal manure and urine (EPA, 2014).

[9] All fertilizer is included because the empirical studies rarely treat nitrogen fertilizer as a separate input. Nitrogen is nearly always aggregated with other fertilizers such as phosphorous and potassium. Nitrogen is the major nutrient in fertilizer and accounted for 48 percent of total fertilizer cost during the years 1960 to 2011 (USDA, 2014b).

[10] Land can increase GHG through land clearing. In this paper, our primary focus is on U.S. agricultural production, so extensive margin impacts that could be particularly important in developing countries are ignored. Hence, land is treated as a non-polluting input.

The assignment of specific inputs in the empirical models to our input categories is reported in Table 1. Two input category classification issues warrant particular explanation. First, part of the polluting input is frequently aggregated with other inputs. Specifically, energy is reported as a separate input in only 23 percent of the selected studies. It is usually aggregated into materials, intermediate inputs, or other inputs. Additionally, 15 percent of the articles aggregate fertilizer into a chemicals input category. In general, chemicals is an aggregate of fertilizer and pesticides. The expenditure share of fertilizer in the USDA chemicals category averaged 66 fpercent during the period 1960 - 2011 (USDA, 2014a). In terms of manure, 97 percent of the studies aggregate applied manure into the fertilizer category or another input category rather than reporting it as a separate input. Second, nonpolluting input categories in the primary studies are sometimes structured differently from our classification. Labor and capital are sometimes disaggregated into several subcategories. For example, labor is often separated into family labor and hired labor. If family labor is treated as a fixed or quasi-fixed input, we only use the MES between hired labor and the polluting input as the observation in the labor elasticity sample. If both family labor and hired labor are variable inputs, we include the elasticities with respect to family labor and hired labor as two separate observations. Also, land is sometimes aggregated into land and structures, real estate, or even capital. We introduce dummy variables in our meta-regression to control for these input classification issues.

3. Meta-Regression Sample

We developed our sample of studies by first searching combinations of keywords anywhere in an article using Google Scholar. The keywords used were “agriculture” or “agricultural” or “corn” or “soybean”, “production”, “elasticity” or “elasticities”, “substitution” or “substitutability”, and “input demand” or “factor demand”. As a complement, we referred to a literature review by Salhofer (2000) and two previous meta-analysis papers: Boys and Florax (2007) and Koetse *et al.* (2008). For each selected article, we also checked papers in the reference lists. Finally, we used Econlit and Agricola databases to supplement our search.

Our literature search generated 126 studies. Several sampling restrictions were imposed on the retained articles. Since we need to allow for different substitution elasticities between pairs of inputs, studies estimating only a constant elasticity of substitution functional form were excluded from our sample. An article was dismissed if it did not report the MES and did not provide enough information for calculating it. We also dismissed studies in which the variable inputs were not adequate for our purpose. For example, we ruled out Williams and Shumway (2000) because its variable inputs only included fertilizer, pesticides, and nonchemical materials. Some studies for which the MES could be computed only by using cost shares were dismissed because two or more computed cost shares were out of the range $(0,1)$.[11] The reported results in such studies were suspect. Finally, a paper was excluded if the sample size for its estimation was not provided. After the sampling restrictions were imposed, we were left with 65 primary studies.

The MES can be negative; however, this indicates lack of necessary curvature of the production function for cost minimization. For instance, a negative estimate of σ_{op}^{M}

[11] If only one computed cost share in a study was out of the range $(0,1)$, we used $S_j = 1 - \sum_{i \neq j} S_i$ to approximate it.

implies substitution from a non-polluting input to the polluting input when the price of the polluting input increases. Alternatively, it can result from a positive own-price conditional demand elasticity, which also is not consistent with cost minimization. Following Koetse *et al.*(2008), we dismissed negative MES empirical outcomes. This resulted in a sample of 225 estimates from 64 studies for σ_{lp}^{M} , a sample of 120 estimates from 34 studies for σ_{dp}^{M} , and a sample of 262 estimates from 58 studies for σ_{kp}^{M} .[12]

4. Independent Variables

4.1 Sources of MES variation

All but one of the independent variables included in the meta-regression are dummy variables. They are mostly variables that describe characteristics of the primary studies, such as features of the model and data. We follow three criteria for creating dummy variables. First, we consider common explanatory variables that were used in the three previous meta-regression papers on substitution elasticities: Boys and Florax (2007), Koetse *et al.* (2008), and Stern (2012).Their variables emphasized function type, functional form, technology, model structure, data characteristics, estimation methods, and measurement of output. Second, we introduce additional dummy variables relevant to elasticities of substitution in biofuel feedstock production. For example, we include variables to deal with classification problems between polluting and non-polluting inputs, data period relative to initiation of biofuel production, and country categories. Finally, we eliminate dummy variables that are both insignificant in the meta-regression and cause

[12] For studies with one or more inputs treated as fixed, only the MES between variable inputs are computed. A dummy variable to indicate it is a short-run elasticity is created as one of the independent variables in the meta-regression.

severe multicollinearity. Table 2 describes the dummy variables and reports the distribution of values for each.

Function type. Different estimates of substitution elasticities are potentially due to the different function types used in the primary studies (Boys and Florax, 2007; Capalbo, 1988; Burgess, 1975). For example, duality theory documents that substitution elasticities can be equivalently derived mathematically from estimates of production, cost, or profit functions. In practice, the elasticities derived from these three function types are often very different, even when the same data are used. This is because the stochastic assumptions in the estimation equations are not equivalent. In our meta-regression, we create two dummy variables for the function types. A cost function is the primary function from which elasticities of substitution are computed and has a value of zero in both dummy variables.

Functional form. Much evidence from empirical studies shows that estimated elasticities vary across flexible functional forms (*e.g.*, Baffes and Vasavada, 1989; Shumway and Lim, 1993). We introduce a dummy variable for functional forms to distinguish between the translog and alternative functional forms.

Technology. Estimates of elasticities are dependent on assumptions about technological change and returns to scale maintained in the estimation (Koetse *et al*., 2008). Two dummy variables are generated to distinguish between models that allow for non-neutral technological change and non-constant returns to scale, and those that constrain estimates on either of these dimensions.

Model structure. Dynamic models which take account of sluggish input adjustment typically provide different empirical estimates of substitution elasticities than static models (*e.g.*, Leblanc and Hrubovcak, 1986; Lambert and Gong, 2010). A dummy variable distinguishes between them.

Data characteristics. Koetse *et al*. (2008) and Stern (2012) found that substitution estimates vary significantly with different types of data series. Two dummy variables are introduced in our meta-regression for data series to distinguish between time series data and either cross-sectional or panel data. The observational unit of data may also impact substitution estimates (Boys and Florax, 2007; Stern 2012) and results in our generating two dummy variables to distinguish between national and either farm-level or regional data.

Estimation method. The meta-regression results of Boys and Florax (2007) found that estimation method had a substantial effect on the substitution estimates. Iterative estimation methods, which are most commonly used in the primary studies, produce empirical results consistent with maximum likelihood estimation. A dummy variable distinguishes between these estimation methods and other techniques.

Measurement of output. Empirical substitution estimates from multiple-output models are often different from those estimated with single-output models, even when other conditions are the same (*e.g*., Hertel and McKinzie, 1986; Capalbo, 1988). The same is true for studies that examine aggregate agriculture as a single output and those that examine an individual commodity or commodity group (Boys and Florax, 2007). We introduce two dummy variables for the output type to distinguish between single-output models of aggregate agriculture and other output specifications.[13]

[13] Ideally we would specify a dummy variable to have a value of zero if the output is corn or soybean supply and one otherwise. Unfortunately, none of the selected articles examines only corn and/or soybeans.

Input classification. We introduce three dummy variables regarding the polluting inputs. A dummy variable equals zero if energy is a separate input and one if not. Similar dummy variables are also created for fertilizer and manure, respectively. Four dummy variables are introduced in the classification of nonpolluting inputs. Two are used to indicate aggregate labor and capital, respectively. The other two indicate whether land is a separate variable or aggregated with buildings and structures or with all capital.

Time period. Agricultural products began to be used as a source of biofuel feedstock in the early 1980's. A temporal dummy variable is created to distinguish models that include data after biofuel feedstock production began and those that only use earlier data. We also include a dummy variable for the time horizon of the estimate. It distinguishes elasticities calculated from models with all inputs treated as variable, defined as a long-run elasticity for our analysis, from those calculated from models with one or more constrained inputs.

Country classification. Input substitution elasticity estimates may differ across countries due to different levels of technology development, different relative input costs, and different agricultural product mixes. In order to obtain an elasticity estimate that is representative for the U.S., we generate two dummy variables to distinguish the U.S. from developing countries and from other developed countries.

4.2 Publication bias

Publication bias may be caused by refereed publication preferences for selecting statistically significant results and censoring values that are inconsistent with theoretical expectations.[14] It can pose a problem for any summary of literature, including meta-

[14] Heckman two-step method is not applicable for publication bias because it requires a sample containing both published and unpublished effects to estimate the inverse Mills ratio. However, for meta-analysis, we

analysis, if it tends to disguise the real empirical effects (Sutton *et* al., 2002; Stanley, 2008). It has been found to exist in areas of empirical economics (*e.g.*, Ashenfelter *et al.*, 1999; Doucouliagos, 2005). In terms of elasticities of input substitution, Stern (2012) points out that the publication bias for elasticities is likely the result of censoring positive own-price demand elasticities, which would cause the average of reported MES estimates to be more positive than it actually is. Therefore, a control for publication bias is essential for an accurate meta-analysis. Following his argument, we correct for publication bias by including the inverse of the square roots of sample size as an independent continuous variable in the meta-regression.

5. Econometric Method

5.1 Econometric issues

Econometric problems in the meta-regression typically include heteroskedasticity, dependence of observations, and multicollinearity (Florax, 2002; Nelson and Kennedy, 2009; Dalhuisen *et al*., 2003; Florax *et al*., 2005).

5.1.1 Heteroskedasticity

The Breusch-Pagan test shows that heteroskedasticity cannot be rejected, even at a 1 percent significance level for each case.[15] Heteroskedasticity can be dealt with in several ways. Koetse *et al.* (2010) document that a weighted least squares approach is preferred to either OLS or a mixed effects model for meta-regression. It is also more robust in the presence of potentially omitted variables. Two weights commonly used in meta-regression are the square roots of sample size and the inverse of standard errors of

do not observe unpublished and unreported estimates. Hence, meta-regression usually includes the inverse of the square roots of sample size in prior studies or standard deviation of prior estimates as one regressor to correct the publication bias.

[15] The χ^2 for σ_{lp}^M, σ_{dp}^M and σ_{kp}^M are 52.46, 68.64 and 43.08, respectively.

the estimates. We follow Stern (2012) and Florax *et al.* (2005) by using the square roots of sample size as the weights. There are two reasons for this selection: (a) like Stern's SES dependent variable, the MES is also a nonlinear combination of parameter estimates,[16] and (b) the standard errors of many MES estimates are not provided or cannot be computed accurately by information available in the primary studies so use of standard errors is not an option.

5.1.2 Dependence of observations

Many primary studies report multiple elasticity estimates, typically for different years or time periods, which implies that the observations are probably correlated. The three meta-analyses of elasticities of substitution (Boys and Florax, 2007; Koetse *et al.*, 2008; and Stern, 2012) all employ models that are silent on potential dependence of observations. Failure to account for correlation across observations from the same study may cause underestimation of standard errors. The correlation across observations in the same study can be accounted for by using a panel data model estimator. The fixed effects panel data model is not suitable for our study because some of our primary studies only report a single elasticity estimate. In this case, the fixed effects model does not improve accuracy of the estimation and also results in severe multicollinearity.[17] The Lagrange Multiplier test is conducted for each MES sample to determine whether a random effects panel data estimator should be used. The null hypothesis is that a weighted least squared model without random effects is appropriate. We reject the null hypothesis only for the

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[16] Stanley and Rosenberger (2009) argue that the square root of sample size is the more appropriate weight in the weighted least squares approach than the inverse of the standard error when the dependent variable of the meta-analysis is a nonlinear combination of parameter estimates in primary studies.

[17] Jeppesen *et al.* (2002) discuss why the random effects model is preferred to the fixed effects model.

MES sample of capital.[18] Therefore, a weighted least squares estimator is used for the MES of both labor and land with respect to the polluting input and a random effects panel data estimator is used for the capital-polluting input MES.

5.1.3 Multicollinearity

For a meta-analysis comprised of a relatively small number of observations and a large number of dummy variables, multicollinearity among independent variables can be a problem even without using a fixed effects estimator (Dalhuisen *et al*. 2003; Florax *et al*. 2005). We compute variance inflation factors (VIF) for each of the MES samples to determine whether multicollinearity seriously inflates our estimate of the variance. If the variance inflation factors (VIF) are less than 5 for all independent variables in an MES model, we keep all variables in the meta-regression. If some are greater than 5, we drop the insignificant independent variable with the highest VIF if the number of significant variables and the goodness of fit (adjusted R-square) increase. We continue this process until there are no insignificant variables with a VIF greater than 5 or until deleting another variable fails to increase both the number of significant variables and the goodness of fit. This results in our excluding dummies for cross sectional data and panel data in the estimation of the MES of land and capital vs. the polluting input. We do not exclude any dummies in the estimation of the MES of labor vs. the polluting input.

5.2 Econometric model

5.2.1 Weighted least squares model

The meta-regression model with correction for publication bias can be specified as (Stanley *et al.*, 2008; Stanley, 2008):[19]

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[18] The χ^2 for σ_{lp}^M, σ_{dp}^M and σ_{kp}^M are 0.29, 2.09 and 9.56, respectively.

$$\hat{\sigma}^{M}_{op,s} = \alpha_{op} + \sum_{r=1}^{R} \beta_{op,r} X_{op,sr} + \beta\left(\frac{1}{\sqrt{n_s}}\right) + \varepsilon_s \tag{17}$$

where $o = l, d$, $\hat{\sigma}^{M}_{op,s}$ is the MES estimate between input o (labor or land) and the polluting input from the s^{th} study, $X_{op,sr}$ is the r^{th} dummy variables for the s^{th} study, n_s is the sample size of the s^{th} study, ε_s is the error term of the s^{th} study with zero mean and variance τ_s^2 .

Using the square roots of sample size as the heteroskedasticity weights, the weighted least squares model is:

$$\tilde{\sigma}^{M}_{op,s} = \beta + \alpha_{op}\sqrt{n_s} + \sum_{r=1}^{R} \sqrt{n_s}\beta_{op,r} X_{op,sr} + u_s \tag{18}$$

where $\tilde{\sigma}^{M}_{op,s} = \sqrt{n_s}\hat{\sigma}^{M}_{op,s}$ is the weighted MES estimate, and $u_s = \sqrt{n_s}\varepsilon_s$ is the new error term of the s^{th} study with zero mean and variance v_s^2 .

5.2.2 Random effects panel data model

The random effects panel data model with publication bias can be specified as (Jeppesen *et al.*, 2002; Greene 7th edition, p.411):

$$\hat{\sigma}^{M}_{kp,st} = \alpha_{kp,s} + \sum_{r=1}^{R} \beta_{kp,r} X_{kp,str} + \beta\left(\frac{1}{\sqrt{n_s}}\right) + \varepsilon_{st} \tag{19}$$

where $\hat{\sigma}^{M}_{kp,st}$ is the t^{th} MES estimate between capital and the polluting input from the s^{th} study, $\alpha_{kp,s}$ is the random heterogeneity specific to the s^{th} study and is constant across

[19] Stanley et al. (2008) estimates a similar model using the standard error instead of sample size to account for publication bias.

observations from the s^{th} study, $E(\alpha_{kp,s}) = 0$, $E(\alpha^2_{kp,s}) = \tau^2_\alpha$, $E(\alpha_{kp,s}\alpha_{kp,m}) = 0$ for $s \neq m$.

Due to the heteroskedasticity of the MES sample, we first weight the capital-polluting input dataset by the square root of sample size (Florax *et al.*, 2005). Then the random effects model becomes

$$\tilde{\sigma}^M_{kp,st} = \beta + \alpha_{kp,s}\sqrt{n_s} + \sum_{r=1}^{R}\sqrt{n_s}\beta_{kp,r}X_{kp,str} + u_{st} \tag{20}$$

where $\tilde{\sigma}^M_{kp,s} = \sqrt{n_s}\hat{\sigma}^M_{kp,s}$ is the weighted MES estimate, and $u_{st} = \sqrt{n_s}\varepsilon_{st}$ is the new error term with zero mean and variance τ^2. Since the number of MES estimates that can be calculated between capital and the polluting input is not the same for all primary studies, the data of $\hat{\sigma}^M_{kp,st}$ constitutes an unbalanced panel data set.

6 Meta-regression results

Empirical estimates of the meta-regression equations for labor, land, and capital MES relative to the polluting input are reported in Table 3. The adjusted R^2 values range from 0.49 for labor to 0.87 for land, both of which are higher than the mean adjusted R^2 of 0.44 from 140 meta-analyses reported by Nelson and Kennedy (2009). For the panel data estimation of the capital-polluting input MES, the between R^2 value is 0.93 and the overall value is 0.68. These goodness of fit measures show that our meta-regression models do a reasonable job of explaining the variation present in each sample. In our assessment of variables that affect MES estimates, we will use a significance level of 10%.

6.1 MES variation

Coefficients of the publication bias correction variable for the MES of labor and land vs. the polluting input are -7.909 and -7.405, respectively. They are significantly different from zero, which implies that prior studies with larger sample sizes produce significantly higher empirical estimates of these MES. The coefficient of publication bias correction for the MES of capital vs. the polluting input is also negative but not statistically significant.

Both dummy variables for function type are negative and statistically significant for the labor elasticity. They imply that the labor-polluting input MES estimates obtained from estimated profit, production, or differential input demand functions are significantly lower than from estimated cost functions. Estimated profit functions give a significantly lower estimate of the capital-polluting input MES than other estimated functions, and production and differential input demand functions give a significantly higher estimate of the land-polluting input MES than estimated cost or profit functions. This provides clear evidence of support for the claim that alternative types of functions yield different empirical outcomes.

Neither alternative functional forms, the imposition of neutral technological change, nor dynamic model structures has a significant effect on any of the MES estimates. Boys and Florax (2007) similarly found that the choice of functional form does not significantly alter the AES between labor and capital. Koetse *et al.*(2008) also found that the MES between capital and energy is not significantly affected by the inclusion of a non-neutral technical change parameter.

Although found to be insignificant in previous meta-analyses, the imposition of constant returns to scale causes significant positive effects on labor and negative effects on land vs. the polluting input MES estimates. If agricultural production actually exhibits non-constant returns to scale, an empirical study with the imposed misspecification of constant returns to scale gives biased estimates of the MES of labor and land vs. the polluting input.

Data characteristics significantly influence each MES estimate. Our results suggest that the use of cross sectional or panel data rather than time series data significantly reduces the estimates of labor-polluting input MES. This is counter to Koetse *et al.*(2008) and Stern (2012) who found that using cross sectional or panel data provides higher substitution elasticities. Using state or regional level data significantly raises the estimated MES of labor and capital vs. the polluting input and lowers the MES estimate of land vs. the polluting input. Using farm level data leads to a significantly higher MES estimate of labor and lower estimate of land vs. the polluting input.

Only the MES estimate between land and polluting inputs is significantly affected by the estimation method. It is reduced by choosing estimation methods other than maximum likelihood or iterative methods. This is similar to what Boys and Florax (2007) found for the AES between labor and capital.

A model with multiple outputs leads to significantly higher estimates for the MES of land and capital with respect to the polluting input relative to a single output model. Analyzing a subsector of agriculture rather than aggregate agriculture, however, produces a significantly lower estimate for the land-polluting input MES.

Not including polluting inputs separately in the model significantly affects one or more MES estimates. For example, not treating energy as a separate input significantly lowers the labor and land vs. polluting input MES. Not treating fertilizer or manure as separate inputs significantly alters the land-polluting input MES.

Disaggregating labor significantly lowers the labor-polluting input MES, and aggregating land with capital significantly lowers both the land and capital vs. polluting input MES. Aggregating land with buildings and structures or disaggregating capital has no significant effect on the respective MES.

Using all pre-1981 data has a significant negative effect on the MES estimate for labor-polluting input and a significant positive effect on the MES estimate for land-polluting input. These coefficients imply that the period during which an agriculture-based biofuel industry has developed has made it easier for labor but harder for land to substitute for the polluting input.

Short-run substitution elasticities estimates for land and capital vs. the polluting input are significantly lower than long-run elasticities. That would be consistent with land and capital inputs adjusting more slowly than labor to long-run equilibrium levels.

The estimated MES between land and the polluting input is significantly higher in developing than in developed countries. The substitutability between land and capital vs. the polluting input is also significantly higher in non-U.S. developed countries than in the U.S. and developing countries.

6.2 MES estimates and LCA

Based on our choice of meta-regression explanatory variables, the reference case (i.e., when all dummies are equal to zero) represents a long-run MES between non-polluting inputs for a study that includes aggregate labor, land, and capital as non-polluting input categories and the polluting input of energy, fertilizer, and manure. It is based on a static translog cost function that permits non-neutral technological change and non-constant returns to scale, treats U.S. aggregate agriculture as a single output, includes post-1981 time series data, and uses a maximum likelihood estimator. It is regarded as the most pertinent case for LCA models. The intercepts of the meta-regression represent the estimated MES of the reference case. They are all greater than 1.0 and significantly different from zero, indicating that substantial substitution potential exists between the polluting and non-polluting inputs in the reference case. Our results also suggest that labor is the best substitute for the polluting input, followed by land and capital. Therefore, if an LCA model is set up based on our reference case, the assumption of fixed-proportion production of biofuel feedstock would lead to a potentially seriously inaccurate measure of GHG emissions.

Three additional sets of MES estimates are presented in Table 4. The mean MES is the elasticity evaluated at the means of all explanatory variables. The short-run mean MES is the elasticity evaluated at the means of all variables except for the dummy variable for short-run elasticity, which is set to one. The long-run mean MES is the elasticity evaluated at the means of all variables except short run elasticity, which is set equal to zero. These alternatives are admittedly less relevant to LCA modeling because there are no observations with mean (or nearly mean) values of most dummy variables.

All MES estimates are lower than for the reference case, and those between capital and the polluting input are insignificantly different from zero. Nevertheless, the MES for labor and land vs. the polluting input is significant both at the data means and for the long run with other variables at their mean values. Also, the MES for labor-polluting input is significant for the short run with other variables at their mean values. Consequently, even if the agricultural feedstock production sector in an LCA model is based on cases that differ from our reference case in some aspects, it would still be necessary to take account of substitutability between some non-polluting inputs and polluting inputs.

These four sets of MES estimates provide a strong implication that LCA models need to allow for input substitution in the production of agricultural feedstocks for biofuel. When an energy-price regulation is imposed or market price ratios change, the change in the quantity of the polluting input used in feedstock production does not follow a fixed-proportions path. LCA models that do not account for input substitutability cannot accurately assess GHG emissions when facing a price change in the polluting input and thus could lead to an inappropriate environmental policy conclusion.

7. Conclusions

This paper examines whether the empirical evidence on input substitution in agricultural biofuel feedstock production is sufficiently strong to warrant integration into life-cycle analyses. We estimate Morishima elasticities of substitution of non-polluting inputs with respect to the GHG polluting inputs in agricultural production relevant to biofuel feedstock by using meta-regression procedures. Energy, fertilizer, and manure are collectively treated as the “polluting input” while labor, land, and capital are considered as free of GHG pollution. For the meta-regression, we examined 65 empirical studies that include 225 elasticity estimates for labor, 120 for land, and 262 for capital vs. the polluting input. We estimate separate meta-regression models for each of these three samples. The first two elasticities are estimated by weighted least squares regression and the third by a random effects panel-data estimator.

The results show that much of the heterogeneity of Morishima elasticities of substitution for nonpolluting inputs vs. the polluting input in the primary studies can be explained by type of primal or dual function, functional form, type and observational level of data, input categories, the number of outputs, type of output, time period, and country categories. The reference case in our meta-regression is regarded as the most relevant case for assessing GHG emissions through life-cycle analysis. It represents a long-run MES between the non-polluting inputs of labor, land, and capital and the polluting input of energy, fertilizer, and manure. It is based on a static translog cost function that permits non-neutral technological change and non-constant returns to scale, treats U.S. aggregate agriculture as a single output, includes post-1981 time series data, and uses a maximum likelihood estimator. It is regarded as the most pertinent case for LCA models of U.S. biofuel feedstocks. Each estimated substitution elasticity for the reference case is greater than one and significantly different from zero. Additionally, mean predicted elasticities imply that long-run input substitutability of labor and land vs. the polluting input might also exist in a wide variety of cases.

These findings imply that when a price regulation (*e.g.*, carbon tax) is imposed on the polluting input, the proportions of non-polluting inputs and the polluting input vary and could have an important effect on GHG emissions. Therefore, life-cycle analyses based on fixed proportion production functions for biofuel feedstocks could lead to an inaccurate measure of GHG emissions from biofuel and thus provide an inappropriate reference for policy makers.

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Table 1: Classification of input categories

Input category	Inputs in primary studies that are included in the category
Labor	Family labor, hired labor, human labor, operator labor, self-employed labor, contract labor
Land	Land, real estate
Capital	Capital, machinery inputs, animal power, inventories, water, irrigation, tractors, physical capital, durable equipment, buildings and farm produced durables, working capital, plowing services, minor implements, major implements
Energy, fertilizer and manure	Energy, mechanical energy, chemical energy, fuel and oil, fertilizer and lime, manure, chemicals, agrichemicals, biological inputs

Table 2: Descriptions of explanatory variables

Dummy variable value = 0	Dummy variable value = 1	Percent of observations with values of one in each sample σ_{lp}^{M}	σ_{dp}^{M}	σ_{kp}^{M}
Dummy variables				
Function type				
Cost or other functions	Profit function	18.2%	5.8%	26.0%
Cost or profit functions	Functions other than cost and profit functions	4.4%	6.7%	4.2%
Functional form				
Translog functional form	Other functional form	10.2%	6.7%	10.7%
Technology				
Allows non-neutral technological change	Imposes neutral technological change	27.1%	34.2%	33.2%
Allows non-constant returns to scale	Imposes constant returns to scale	24.4%	86.7%	23.3%
Model structure				
Static model	Dynamic model	7.6%	3.3%	6.1%
Data Characteristics				
Time series or panel data	Cross sectional data	22.7%	19.2%	26.3%
Time series or cross sectional data	Panel data	2.3%	2.5%	2.3%
National or farm level	Regional/state level data	14.2%	11.7%	18.7%
National or regional/state level	Farm level data	16.9%	12.5%	20.6%
Estimation method				
MLE	Other types of estimators	27.6%	41.2%	36.3%
Measurement of output				
Single output	Multiple outputs	20.4%	18.3%	35.1%
Aggregate agriculture	A subsector of agriculture	5.8%	8.3%	5.0%
Input classification				
Energy is a separate input	Energy is not a separate input	84.9%	81.7%	82.4%
Fertilizer is a separate input	Fertilizer is not a separate input	50.2%	39.2%	36.3%
Manure is a separate input	Manure is not a separate input	93.8%	96.7%	98.5%
Aggregate labor	Disaggregate labor	33.3%	-	
Land	Buildings and/or structures	-	5.8%	-

Aggregate capital	Disaggregate capital	-	-	69.5%
Land is separated from capital	Land is included in capital	-	20.8%	14.9%
		Time period		
Includes post-1981 observations	All pre-1981 observations	59.1%	71.7%	54.2%
Long run elasticity	Short run elasticity	41.3%	9.2%	37.8%
		Country classification		
The U.S. or non-U.S. developed countries	Developing countries	38.7%	59.2%	34.4%
The U.S. or developing countries	Non-U.S. developed countries	14.2%	5.8%	14.9%
		Correction for publication bias		
Inverse of square roots of sample size	Mean	0.157	0.158	0.152
	Maximum	0.250	0.250	0.250
	Minimum	0.021	0.021	0.021

Table 3: Meta-regression results, Morishima elasticities of substitution with respect to polluting input

	Labor, σ_{lp}^{M}	**Land,** σ_{dp}^{M}	**Capital,** σ_{kp}^{M}
Intercept	**2.977*** **	**1.772*** **	**1.414** **
	(0.626)	(0.524)	(0.678)
Publication bias correction	-7.909***	-7.405***	-1.938
	(2.337)	(1.642)	(2.028)
	Function type		
Profit function	-0.685***	0.155	-0.436**
	(0.200)	(0.266)	(0.253)
Functions other than cost and profit functions	-1.277***	1.543***	0.044
	(0.246)	(0.266)	(0.367)
	Functional form		
Other functional form	0.348	-0.101	0.426
	(0.245)	(0.299)	(0.287)
	Technology		
Neutral technological change	-0.232	-0.030	-0.294
	(0.201)	(0.133)	(0.196)
Constant returns to scale	1.091***	-0.715***	0.292
	(0.219)	(0.265)	(0.272)
	Model structure		
Dynamic model	-0.390	0.360	-0.019
	(0.268)	(0.310)	(0.319)
	Data characteristics		
Cross sectional data	-1.057***	omitted	omitted
	(0.336)		
Panel data	-0.916**	omitted	omitted
	(0.421)		
Regional/state level data	1.052***	-0.727***	0.739**
	(0.272)	(0.275)	(0.333)
Farm level data	0.682**	-1.060**	-0.044
	(0.309)	(0.611)	(0.344)
	Estimation method		
Other types of estimators	-0.054	-1.207***	0.137
	(0.172)	(0.192)	(0.217)
	Output measurement		
Multiple outputs	0.195	1.741***	0.459**

	(0.175)	(0.165)	(0.191)
A subsector of agriculture	-0.001	-0.393***	0.120
	(0.207)	(0.534)	(0.234)
Input classification			
Energy is not a separate input	-0.283***	-0.299*	-0.183
	(0.166)	(0.157)	(0.201)
Fertilizer is not a separate input	-0.194	-0.733***	-0.119
	(0.163)	(0.208)	(0.288)
Manure is a not separate input	-0.489	0.918*	-0.407
	(0.296)	(0.513)	(0.452)
Disaggregate labor	-0.492***	-	-
	(0.173)		
Real estate/land and structure	-	-0.114	-
		(0.271)	
Disaggregate capital	-	-	0.150
			(0.290)
Land is included in capital	-	-1.369***	-0.853***
		(0.157)	(0.242)
Time period			
All pre-1981 data	-0.239*	0.601***	-0.193
	(0.144)	(0.186)	(0.218)
Short run elasticity	-0.059	-0.439*	-0.518***
	(0.161)	(0.246)	(0.189)
Country classification			
Developing country	0.187	1.240***	0.112
	(0.202)	(0.454)	(0.282)
Non-U.S. developed country	0.071	0.704***	0.540**
	(0.159)	(0.145)	(0.210)
F value	10.84***	37.22***	-
Chi-square value	-	-	395.39***
R-square	0.542	0.889	-
Adjusted R-square	0.492	0.865	-
Within R-square	-	-	0.004
Between R-square	-	-	0.926
Overall R-square	-	-	0.678
Sample size	225	120	262

Notes: "-" indicates the variable is not used as an explanatory variable in the initial regression, and "omitted" means the variable is eliminated due to multicollinearity; ***, **, * = statistically significant at 1 percent, 5 percent and 10 percent level, respectively; standard errors are in parentheses.

Table 4: Predicted mean MES

	Labor, σ_{lp}^{M}	**Land,** σ_{dp}^{M}	**Capital,** σ_{kp}^{M}
Predicted mean MES	0.718* (0.488)	0.598* (0.404)	0.631 (0.583)
Predicted mean short-run MES	0.684* (0.497)	0.199 (0.462)	0.309 (0.586)
Predicted mean long-run MES	0.742* (0.493)	0.638* (0.405)	0.463 (0.593)

Notes: * = statistically significant at 10 percent for 1-sided test; standard errors are in parentheses.

Appendix: References for Meta-analysis

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