Meta-Regression Estimates for CGE Models: A Case Study for Input Substitution Elasticities in Production Agriculture

Kathryn A. Boys[1] and Raymond J.G.M. Florax[1,2]

[1] Dept. of Agricultural Economics, Purdue University
403 W. State Street, West Lafayette, IN 47907–2056, USA
Phone: +1 (765) 494–0848, Fax: +1 (765) 494–9176
E-mail: kboys@purdue.edu, rflorax@purdue.edu

[2] Dept. of Spatial Economics, Vrije Universiteit
De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands

May 2007, Preliminary Version

Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Portland, OR, July 29 – August 1, 2007

Abstract: The selection of appropriate parameters for computable general equilibrium (CGE) models critically affects the results of applied economic modeling exercises. Valid and reliable parameter selection models are needed, and typically comprise direct estimation, expert opinion, or copycatting of results from seminal studies. The purpose of this study is to use meta-analysis to summarize and more accurately estimate elasticities of input substitution, specifically between labor and other inputs in agricultural production. We construct a comprehensive database of elasticity estimates through an extensive literature review, and perform a meta-regression analysis to identify structural sources of variation in elasticity estimates sampled from primary studies. The use of meta-analysis contributes to improved baseline analysis in CGE simulations because it allows for the computation of input parameters tailored to a specific CGE model setup. We correct for variations in research design, which are typically constant within studies, and account for bias associated with undue selection effects associated with editorial publication decision processes. Improved accuracy and knowledge of the distribution of imputed input parameters derived from a meta-analysis contributes to improved performance of CGE sensitivity analyses.

Keywords: meta-analysis, cross-price elasticity, input substitution, agricultural production, CGE parameters

JEL Classification: C13, C68, Q13

1. Introduction

Despite its general acceptance and widespread use, computable general equilibrium (CGE) models continue to suffer from criticism concerning fundamental aspects underlying the use and performance of general equilibrium principles. Much of this criticism stems from the weak econometric foundations upon which CGE models are typically based (Jorgenson 1984; Shoven and Whalley 1992; McKitrick 1998). The selection of appropriate parameters for CGE models impacts, and in some cases even drives, the results of applied economic modeling exercises (Arndt et al. 2002; McDaniel and Balistreri 2002). Despite the importance of judiciously chosen imputed values for input parameters, CGE modelers typically obtain behavioral parameters from external sources based upon data and models that may not be consistent with the CGE model for which they are used. Since the selected behavioral parameters provide the basis for calibrated outcomes and subsequent sensitivity analyses, the selection of appropriate baseline parameters is key to improving the validity of CGE model results.

Several alternative parameter selection methods are available. Direct estimation of input parameters, although obviously the preferred method because it is "site" specific and precise, is challenging and costly. Due to data limitations, and econometric challenges (misspecification bias, identification problems, and multicollinearity) as well as the considerable cost involved, researchers do not frequently pursue this approach. Instead, researchers typically draw estimated input parameters from secondary sources. These parameter estimates are usually derived using direct estimation or expert opinion, and require thoughtful consideration of both the source of the estimate and the purpose for which it will be applied. The calculation of specific input parameters, such as elasticities, is affected by conditions and assumptions specific to each estimation process (Blackorby and Russell 1989). Within the context of agricultural production, for example, estimates are dependent on the attitude, outlook, and production possibilities for producers (Masters et al. 1996). Time horizon, level of aggregation, size and relative openness of the market under consideration are among several other factors that should be considered when selecting input parameters. Multiplying these considerations by the large number of parameters that is typically needed and the large number of regions and extensive time periods potentially under consideration in any single model, it is easy to understand why the issues presented by the 'econometric critique' (McKitrick 1998), remain largely unaddressed.

Due to the challenge of selecting appropriate input parameters and to the lack of estimates available for some regions and applications, values for well-examined settings are often broadly applied. To evaluate and offset the impact that elasticity assumptions have on a simulation outcome, researchers frequently perform a sensitivity analysis in which the assumed elasticity is systematically varied around the imputed value. This process, while useful for indicating the sensitivity of results to elasticity assumptions, provides no guidance as to the appropriateness of the baseline assumption.

As an alternative to these approaches, one might chose to survey the existing literature and to combine published elasticity estimates in some manner. Among the most rigorous of such methods is meta-analysis. Meta-analysis can be used to improve the estimation of these crucial economic parameters by combining relevant estimates, investigating the sensitivity of estimates to variations in underlying assumptions, identifying and filtering out publication bias, and explaining variation in reported estimates through meta-regression analysis (Rose and Stanley, 2005). Further, through the use of meta-analysis, confidence intervals used in sensitivity analysis can be empirically derived and thus be a guide to improving the reliability of CGE-based applications.

This paper aims to analyze the sources of variation in empirically derived elasticity estimates and to determine reasonable estimates for input substitution elasticities in production agriculture. We performed a comprehensive review of the agricultural production literature, including both published and non-published sources, to attain the input needed for the meta-analysis. We used a random selection process to identify studies to be included in this analysis, and constructed a database of elasticity estimates. Subsequently, we utilized meta-regression analysis to summarize empirical elasticity estimates, and to explore variation in the outcomes across studies. In particular, elasticity variation due to model characteristics, data characteristics, and characteristics of the economy under investigation are examined (Koetse et al. 2006). The meta-analysis considers substitution elasticities regarding the substitutability between labor and other inputs in agricultural production. As it is developing country analyses that are most frequently forced to adopt elasticities from secondary sources, we also investigate the extent to which estimates vary significantly across regions.

We organize the remainder of this paper as follows. Section 2 provides a brief introduction to meta-analysis, and lays out the potential value of meta-analysis in terms of providing better inputs for CGE modeling. In Section 3, we discuss several sources of variation related to data, model characteristics, and sectoral differences that are potentially relevant in explaining structural variation among estimates reported in the literature. Section 4 discusses the sampling design employed in the current application and provides an exploratory account of the estimates sampled from the literature as well as the results of the meta-regression analysis. Section 5 concludes and provides suggestions for areas of future research.

2. Meta-analysis and CGE modeling

Econometric estimates from a more or less tailored primary study or an authoritative seminal contribution to the literature, literature reviews, international comparisons, expert opinion, or arbitrarily assigning values to free parameters all constitute standard approaches to solving the parameter imputation problem (Harrison et al., 1993; Abdelkhalek and Dufour, 2004). Among those, the use of econometric estimates is the most frequently employed. There are two sources of complications and concerns depending on whether the specific setting in terms of, for instance, region, industry and time period for which an estimate is desired, has been thoroughly studied or not.

Consider a well-studied setting for which a series of empirical estimates is available from different primary studies. Even if all estimates represent the same underlying fixed population value, we would statistically expect sampling variation to result in estimates of different magnitude, and even of opposite signs across the different primary studies. For instance, Koetse et al. (2006) show that cross-price elasticities for capital-energy substitution range from approximately –0.4 to +0.8, with 35 percent of the estimates being negative.[1] In addition, there may be mismatches in terms of the specification or the assumptions maintained in the primary study as compared to the CGE policy experiment (Hertel et al., 2006). Differences in the examined time-period are likely relevant, because many econometric studies use annual data, while CGE analyses typically assume significantly longer adjustment periods. Moreover, the ecological fallacy or micro-macro problem associated with applying results of microeconomic studies to the household representations and sector aggregations usually explored by CGE models, is unavoidable (Arndt et al. 2002). Finally, even if the literature would provide a clear indication of a "reasonable" value for the input parameter needed for CGE policy simulations, it would be difficult to come up with a confidence interval for that parameter. Typically confidence intervals vary widely (again, see Koetse et al. 2006, for an example), they are to a considerable dependent on the sample size of the primary study, and they may have played a role in the decision whether a specific study will be published or not.[2]

For less well examined settings, the challenge of obtaining free parameter values is even greater. Lack of empirical evidence encourages reliance upon expert or the modeler's sound judgment. Alternatively, practitioners apply parameter values for specific studied regions, industries and time periods to unexamined cases. In both instances, there is obviously great potential for, and likelihood of, significant difference between the employed and 'true' parameter values. In fact, the principle of using values for studied 'sites' and applying those to unstudied 'sites' is quite common in environmental economics, and is referred to as "value" or "benefit transfer". A growing number of studies shows that extreme caution is needed in applying transferred values, because the validity may be questioned (Brouwer 2000), and the performance and reliability is rather disappointing, even for values based on meta-analysis (Brouwer and Spaninks 1999; Engel 2002; Jiang et al. 2004; Brander and Florax 2006).

Recognizing the limitations of parameterizing applied general equilibrium models in this way, several alternative approaches have been proposed. Some authors have advocated an econometric approach in which parameters are estimated using the actual model data (Jorgenson 1984; McKitrick 1998). While intuitively appealing, the empirical application of this methodology is limited. Data demands, conceptual and computational challenges in estimation, and uncertainty concerning the validity of resulting estimates have limited the implementation of this approach (Arndt et al. 2002). Building upon this, and in an effort to address several of the limitations of this technique, Arndt et al. (2002) introduced a maximum entropy approach to parameter estimation. Other authors have adopted a multi-period validation/calibration approach in which, after running the model over a number of periods, influential free parameters are adjusted to permit the model to better replicate historical data (Kehoe et al. 1995). In the sequel we investigate the extent to which meta-analysis can be used to circumvent some of the abovementioned problems.

---

[1] This is not meant to imply that the authors maintain that these elasticities represent one underlying population value. They show that a *Q*-test rejects the null hypothesis of homogeneity of the estimates (see Koetse et al. 2006, for details).

[2] In comparing 46 distinct empirical economic literatures, Doucouliagos and Stanley (2007) find that publication selection distorts inferences and is generally widespread, except for areas where there is substantial competition and debate over rival theories.

2.1 Overview meta-analysis

Traditionally, we use qualitative literature reviews to summarize the information available in a specific literature, and to present an overview of issues relevant to a particular topic. Incidentally, the narrative is complemented by quantitative information, but this does usually not extend beyond simple cross-tabulations and graphs. In performing literature reviews, however, authors often make subjective choices about which studies are included, the relative attention (weight) paid to the results of those studies, and which factors are deemed to be responsible for study findings (Stanley and Jarrell 2005). Further, beyond simple comparison, the literature review approach does not permit for a quantitative assessment of study results, and it is imperative that a sample selection correction strategy is employed in order to avoid the withering influence of publication bias.

Although literature reviews are valuable in their own right, there are a number of disadvantages in solely relying on surveys of the literature. Most literature reviews are implicitly based on technique known as vote-counting, which essentially boils down to counting the number of significantly positive, significantly negative, and insignificant results (or in the case where unity is the reference case, elastic versus inelastic results). The results are simply tallied, and the category with the plurality of cases is usually taken to reveal the true characteristics of the underlying population. However, Hedges and Olkin (1985) point out that this procedure contains a fatal flaw, because paradoxically it tends to lead to making the wrong inference when the number of underlying studies increases.[3]

Qualitative approaches to the review of primary studies have, however, long been used in evaluating both inputs and outcomes of CGE simulations. As an example, in their review of Armington trade substitution elasticities, McDaniel and Balistreri (2002), summarized and identified qualitative trends in studies which econometrically estimated these elasticities for US imports. Several of the primary findings of this review conform to what one would expect for any series of elasticity estimates: long-run estimates are higher than short-run estimates, and more disaggregate analyses find higher elasticities. Although useful for offering comment concerning the direction and possibly a qualitative assessment of the magnitudes of impact of various estimation characteristics, potentially this type of approach suffers from the vote-counting flaw, the difficulty of identifying and remedying publication bias, and the general difficulty of assessing research results in a situation where a multitude of underlying factors (e.g., sector, specification, type data, time period) change simultaneously.

By comparison, meta-regression analysis offers a rigorous approach to both surveying and summarizing the literature. Described as the 'analysis of analyses' (Hunter and Schmidt 1990), meta-analysis is the statistical analysis of results collected from individual studies for the purpose of integrating the research findings (Glass 1976). With this approach, the process of primary study selection is made explicit, and statistical tests can be employed to test for the occurrence and severity of publication bias (Macaskill et al. 2001; Florax 2002; Stanley 2005; Roberts and Stanley 2005). Further, as meta-regression analysis involves an analytical method to examine results and their variance across studies, subjectivity is effectively excluded from

[3] The statistical cause for this rather counterintuitive result is that the Type-II errors of each of the underlying studies do not cancel out.

influencing review findings. In short, meta-regression analysis "offers a means of objectively explaining why, and quantifying how, estimates differ from a range of empirical studies" (Roberts 2005).

Several reviews exist which offer good introductions to meta-analysis in general and associated statistical methods (Hedges and Olkin 1985; Cooper and Hedges 1994), and to economic applications in particular (Stanley and Jarrell 1989; Stanley 2001), so we will only provide background information in brief. The objective of meta-analysis is to combine research results from previous studies, usually referred to as 'effect size' assuming that the underlying population effect size is fixed or random. Typically the fixed and random effects models in meta-analysis employ the inverse (estimated) variance of the effect sizes as weights in order to correct for the precision with which the effect sizes have been estimated. The series of estimated effect sizes and their associated standard errors are attained through a comprehensive review of the relevant literature, and they are included in a database of primary study results which also contains observable differences between studies such as data type, specification details, geographical location and time period to which the effect size pertains, and type of estimator used to estimate the effect size. Subsequently, instead of simply combining effect sizes into an overall effect size using a fixed or random effects model, one can also exploit the variation in effect sizes by allowing for differences in the underlying population effect sizes using a meta-regression approach.

Meta-regressions in economics have been implemented using a variety of different estimators ranging from ordinary least squares (eventually using the 'sandwhich' procedure to attain standard errors allowing for heteroskedasticity and clustering), to mixed effects models and hierarchical modeling approaches. These estimators have their own respective pros and cons (see also Abreu et al. 2005). OLS is obviously inefficient, because it discards the information on the estimated standard errors that can be taken from the primary studies, and disregards the autocorrelation that may result from sampling multiple estimates from the same primary study. Heteroskedasticity caused by unequal variances is taken into account in the fixed effects estimator, which is essentially weighted least squares using the inverse standard errors of the primary studies as weights. The fixed effect model is rather restrictive in the sense that it assumes the population effect size to be a fixed unknown constant that can be fully explained by observable differences between studies.[4] This is a rather heroic assumption if the underlying studies are heterogeneous and differences across studies are only partly observable. Instead of assuming a fixed population effect size, the mixed effect estimator rests on the assumption that the population effect size is drawn from a normal distribution centered on the "true" population effect size, with an unknown variance to be determined from the data. The heterogeneity in effect sizes is partly observable and can be specified as so-called moderator or conditioning variables in the meta-regression, and to the extent that it is not observable, it is accounted for in

[4] In meta-analysis the fixed effect estimator typically pertains to the situation where the variation in estimated effect sizes is fully attributable to a limited number of observable differences between studies. In that case the estimator is equivalent to the mean of the inverse-variance weighted estimated effect sizes. This is equivalent to using weighted least squares (WLS) with appropriately defined weights. Since a typical (economic) model would not assume that differences are perfectly explainable by the observable factors, the variance reported for WLS and the fixed effect estimator are not identical. The WLS-estimated standard errors need to be rescaled by the square root of the residual variance (see Abreu et al. 2005, for more details).

the additional random effect. This well-known estimator that is widely used in medical applications of meta-analysis (Sutton et al. 2000) is based on the following model:

$$\begin{aligned} T_i &= \theta_i + \varepsilon_i, \quad \text{where } \varepsilon_i \sim \mathrm{N}(0, \sigma_i^2) \\ \theta_i &= \alpha + x_i'\beta + \mu_i, \quad \text{where } \mu_i \sim \mathrm{N}(0, \tau^2), \end{aligned} \tag{1}$$

where T_i is the estimate of the underlying population effect size θ_i of study i, α is a common factor, and x_i contains a set of design and data characteristics. Deviations of the estimated effect size T_i from the true effect size θ_i are random, and the true effect size and the precision of the estimated effect size σ_i^2 vary across studies. The term σ_i^2 is known as the within-variance, and is taken from the primary studies. Any remaining heterogeneity between estimates is either explainable by observable differences modeled through moderator variables contained in x_i, or it is random and normally distributed with mean zero and variance τ^2, the so-called between-variance. The unknown variance can be estimated by an iterative (restricted) maximum likelihood process or, alternatively, using the empirical Bayes method, or a non-iterative moment-estimator (see Thompson and Sharp 1999, for details). We use the iterative restricted maximum likelihood estimator with weights $\hat{\varpi}_i = 1/(\hat{\sigma}_i^2 + \hat{\tau}^2)$ to obtain estimates for the regression coefficients and $\hat{\tau}^2$.

Meta-analysis is not without its limitations either. Some practical degree of subjectivity relates to the operationalization of the moderator variables and the specification and estimator choice for the meta-regression equation. From a fundamental perspective, the consideration of all available estimates regardless of their quality has been used as an objection to the technique. Some opponents have maintained that meta-analysis amounts to comparing apples and oranges, and others have advocated using the estimates from the best or biggest study in terms of sample size (Wachter 1988).

2.2 Meta-analysis contributions to CGE modeling

This general critique notwithstanding meta-analysis has now found a home in applied economics, and the technique proliferated from environmental economics, in which the early contributions were made, to economic fields such as industrial organization, and labor, transportation and international economics (see Florax et al. 2002; and Abreu et al. 2005, for various examples). In spite of its prevalent use, however, the tools of meta-analysis have not yet been explicitly applied in the context of CGE analyses.[5] There are several routes through which the tools of meta-regression analysis could potentially contribute to CGE modeling. The most obvious of these applications include meta-regression use in the selection of baseline parameter estimates, and in the provision of suitably small standard error results to improve CGE sensitivity analysis. Less directly, parameters derived through CGE model calibration and the standard errors of those parameters would also benefit due to potential improvements in the accuracy of 'free' parameters. Following a brief review of CGE model structure, these contributions are further explored.

[5] At present, literature searches on the topic offer, at best, examples of meta-analyses in which CGE simulation results were included together with econometric results.

The general form of a static CGE model may be represented as $F(Y, X, \beta, \delta) = 0$, where Y is a vector of i endogenous variables, X a vector of exogenous variables, β a vector of k free parameters, and δ a vector of p calibration parameters. While both β and δ are categories of parameters, they are derived in different ways by the CGE analysis process. The free parameters include behavioral parameters such as elasticities, and are (most often) obtained from external sources or estimated in analyses exogenous to the CGE solution process. In contrast, the calibrated parameters are usually share or scale parameters; values for these are determined within the model solution process and are dependent upon the functional form F, free parameter values specified in β, and the simulation base year data. Through calibration, given values of β, (unique) values of δ are determined, which permits the model to exactly reproduce base or reference year data. Meta-regression analysis could assist in providing estimates and associated standard errors for the free parameters β, and hence indirectly affect the magnitude and variance of the calibrated parameters δ.

Meta-analysis we believe, can contribute to CGE modeling in at least two different ways. First, by improving the accuracy of free parameters. Meta-analysis permits the incorporation of all available empirical information concerning an economic relationship of interest into a CGE models (Florax et al. 2002). As meta-analysis by nature increases the power of hypothesis testing in the process of combining research results, the combined effect size has a comfortably smaller variance. In addition, meta-regression analysis can be used to assess and model potential heterogeneity across effect size estimates by systematically accounting for characteristics of the data, the research design of the primary studies, and characteristics in terms of sectors, geographical coverage and the time-period to which the estimates pertain.

Secondly, the use of meta-analysis can contribute towards improved sensitivity testing. Much attention has been paid thus far to the potential contributions of meta-analysis to improving the estimation of free parameters. Equally important, though, is the potential contribution of meta-analysis to assessing the CGE model robustness. To evaluate and offset the impact that elasticity assumptions have on a simulation outcome, many authors frequently perform a sensitivity analysis in which the assumed elasticity is systematically varied around the imputed value. Somewhat surprisingly, however, although confidence in CGE model conclusions depend critically on the size of the confidence interval around parameter estimates, standard robustness analysis is usually local and often involves only increasing or decreasing the values of key parameters. This approach, however, does not consider potentially available information about the precision of the original estimates (Hertel et al. 2007). [6]

[6] A third way in which meta-regression could contribute to CGE modeling was already mentioned above, and pertains to the situation in which value transfer is used to obtain reliable estimates for regions or sectors for which there is limited available data (Florax et al. 2002). To date, outside of environmental applications, meta-analysis has not been widely used for this purpose (see Miller 2000, for an interesting application to value of life estimates for different countries).

In many instances, the distribution of the free parameter is unknown.[7] As a result, distributions are often drawn from literature sources and it is generally assumed that all parameters of a similar type share the same distribution. Further, even when normality is assumed and standard errors are available the factors driving the magnitude and variance of the free parameters are unknown. Thus, the likely changes in the values of these parameters in response to exogenous shocks cannot be anticipated. Through meta-analysis, standard errors of parameters can be determined and the relative magnitude of sources contributing to variation in size and variance can be identified. Using this information rather than assumed distributions of free parameters can be evaluated through the usual systematic sensitivity analysis methods.

3. Sources of elasticity estimate variation

Prior to providing a practical example of the meta-regression technique and the ways in which it can contribute to CGE modeling, we first consider potential sources causing variation across effect size estimates. Although the distinction between free and calibrated parameters is largely arbitrary (Abdelkhalek and Dufour 2004), we focus our discussion on elasticity estimates, which are usually treated as free parameters.

Analyses in which the heterogeneity of elasticity estimates is explored, typically consider a wide array of potential explanatory variables relevant to that particular literature. In identifying possible common sources of variance, this study draws from numerous recent applications of meta-analysis as well as the theoretical literature regarding the nature of production process estimation. Sources of variation are divided into three broad categories: model characteristics, data characteristics, and characteristics of the sector under consideration.

3.1 Model characteristics

Several features of the model used to derive elasticities are expected to impact the obtained estimates, among which the most important are the choice of the estimating function and functional form, the sample size and time horizon under consideration, and the exclusion of relevant variables. These potential sources of elasticity estimate variation are examined below.

Function, functional form, and estimation procedure. A first issues concerns the choice between the use of a cost, profit, or production function. While, theoretically these alternative approaches should yield consistent estimates, in practice this is not always the case. In considering the dual cost and profit functions, for example, Hameresh and Grant (1979) found that estimates of their stochastic forms are not necessarily dual to one another. Further, the choice of functional form also varies between studies and has important implications for the magnitude of elasticity estimates. By way of example, use of a constant elasticity of substitution function (CES) provides for relatively easy estimation, but it requires substitution elasticities between all pairs of

[7] The most common exception to this is in cases where a single, empirically derived estimate is used. Recently, Hertel et al. (2007) proposed a method by which elasticities of substitution among imports from different countries were calculated by using delivered good prices to trace out commodity demand curves. Using the econometrically estimated standard errors, the distribution of trade elasticity estimates was constructed; these values were then used to repeatedly solve the model to determine the confidence intervals for results of interest (i.e., welfare effects). This innovative approach is successful and, through its results, does highlight the importance incorporating empirically based confidence intervals into systematic sensitivity analyses. The extensive data requirements of this approach, however, may make the approach less appealing in view of widespread implementation in CGE modeling.

factors to be equal. As will be described below, this study will also consider the time period among possible explanatory variables. It is worth noting that, due to theoretical and computational advancements over time, the choice of functional form is in many cases likely to be correlated with the period of study. Further, as the selection of estimation procedure is frequently driven by the choice of estimation technique, the technique chosen is similarly likely to be correlated with both the period of study and the functional form.

Omitted variables. Differences in model specification and exclusion of relevant variables from some (but not all) primary studies will affect the estimates generated by both primary studies as well as the meta-analysis. To account for these differences in model specification, all variables included in primary elasticity estimation are recorded and treated as exogenous factors for the meta-regression. Other characteristics of the model specification, such as assumptions concerning returns to scale, and the relative neutrality of technological change, are considered in a similar manner.

Sample size. As with other types of estimates, the size of the original sample affects the precision of the estimated elasticities. Sample size of primary studies is included in the meta-analysis either through direct inclusion in the estimating equation, or through using the sample size as a tool to assign weights to observations in the regression analysis (studies with higher number of observations receive greater weight). Standard errors of the original elasticity estimates may alternatively be used in either of these ways.

For the present analysis we have collected information concerning both the number of observations and standard errors. Although standard errors are the preferred measure, in many instances these values are not provided in the primary studies. Koetse (2006) provides an outline for estimating the standard errors of different substitution elasticity measures using auxiliary information provided in the primary studies. However, even when employing these techniques, it is not always feasible to attain standard errors. Eventually, estimates for which standard errors are not available will be excluded from the analysis.

Time horizon. The Le Chatelier-Samuelson principle implies that, in absolute terms, unconditional elasticities are larger than conditional elasticities. In accordance with this principle long-run elasticities are expected to be greater than short-run elasticities. Further, and due to the implicit differences underlying these measures, this principal implies that short-, medium- and long-run elasticities should be examined separately. Where not explicitly defined by the primary study, differentiation among the 'horizon' of estimated elasticities is determined using general characteristics of each type of elasticity. Specifically, short-run elasticities are assumed to include non-neutral technological change and use time series data. It will be assumed that medium-run elasticities are those that use panel data, and long-run elasticities use cross-section data. Given these assumptions, it is anticipated that there will be a high correlation between the time horizon of elasticity estimates and various data type details described below.

3.2 Data characteristics

Two sources of heterogeneity may be attributable to characteristics of the data. Both the frequency of data collection (i.e., monthly, quarterly, annual) and characteristics of the data such as the level of aggregation, or the temporal and/or spatial range that is captured by the data may have an impact on the elasticity estimates.

Concerning the data periodicity, studies have found that there is substantial variation in estimated elasticities in terms of the type of data used in primary studies. For example, in their study of price and income elasticities of residential water demand, Dalhuisen et al. (2003) found that the use of annual data yielded significantly lower absolute values of the price elasticities as compared to daily data. Differences in the type of data can similarly impact the magnitude of the estimates. Dalhuisen et al. (2003) report that the use of cross section data is associated with significantly lower price elasticities (in absolute value) as compared to time series data, while panel data caused the absolute value of price elasticities to be significantly greater than for time series data. Although these examples considered price and/or income elasticities rather than the input substitution elasticities, it is anticipated that similar trends in reported elasticities will be observed in this analysis.

3.3 Sectoral characteristics

Characteristics and local economic conditions of the production sector under consideration will introduce some systematic variation into the elasticity estimates. This study will include variation due to these exogenous sources due to the geographic region, the time period under consideration, and the relative tradability of the sector(s) considered in the primary studies.

Region and time period. Substitution between inputs will depend upon both characteristics of the production process and the relative cost of inputs. As both technology and prices vary across space, it is anticipated that some of the heterogeneity across estimates will be correlated with the region to which the estimate pertains. Due to technological advancement, induced innovation, and other exogenous conditions, elasticities of input substitution change over time. These relative changed in the trade-off over time has long been recognized as an important estimation consideration, and has been the focus of numerous studies. It is expected that a majority of the research which may make use of the results of this study will focus upon relatively current data, and as such would only require elasticity estimates drawn from recent literature. However, in the case where researchers may wish to use historical data for baseline analysis or other purposes, elasticity estimates from all available time periods will be considered.

Tradability. The relative openness of an economy with respect to both the inputs and the outputs of a particular sector has important implications for the elasticities of substitution between goods. From the input side, both the tradability and the relative intensity of use of an input will affect that input's relative price, and as such also its relative substitutability. Similarly, on the output side, the opportunities for a sector to access and be affected by international markets will shape the demand for that sector, and as such it will also shape the demand for inputs by that sector.

4. Input substitution elasticities in agriculture

As an illustration of how meta-regression analysis can contribute to CGE modeling, we explore the case of capital-labor input substitution in agricultural production. The following discussion presents the sampling design for the meta-analysis as well as exploratory results and the results from the meta-regression analysis.

4.1 Sampling design and exploratory results

For topics as important and well studied as input substitutability in the agricultural sector, the number of potentially relevant primary studies is quite large. When conducting a meta-analysis on smaller literatures it is possible to include all relevant studies. In instances with large populations, however, this is not reasonable (or, arguably, needed), and a sampling process is used instead.

To obtain an estimate of the population of studies available, a comprehensive review of the agricultural production literature was conducted. As a starting point, this review tapped both databases of academic journals (Agricola, Econolit) and working papers (AgEcon Search).[8] As this study seeks to examine temporal, sectoral and spatial variation in elasticity estimates, a large number of varied search terms were used, such as 'agriculture input substitution', 'labor (and labour) elasticity', and 'capital input'. No restrictions concerning the year of publication or release were imposed; however, only manuscripts available in English or French were included. Literature surveys on this topic were also identified (Salhofer 2000; Uchida 2005; Keeney and Hertel 2006), and their reference lists were added to the list of relevant primary studies. Finally, an Internet search engine (Google Scholar) was used to identify studies which may not (yet) be published in academic journals, and which were not identified through previous searches. While many meta-analyses only include articles that are published in (leading) academic journals (e.g., Knell and Stix 2005), this last search is particularly important to ensuring inclusiveness of the meta-database, because much research concerning the agricultural sector of developing countries is completed by national government organizations and NGOs. We identified 496 unique studies through this search process.[9]

Once the population of potentially relevant studies was identified, a random selection process was used to identify studies to be included in this analysis. Once selected, a copy of the article was obtained and reviewed for its relevance to this study. Papers that were not directly relevant to the research problem (i.e., presented only theoretical discussion, focused on analytical techniques, or derived elasticity estimates other than those of interest to this analysis) were excluded.[10] Further, a number of studies, which contained elasticity estimates of interest, had to be eliminated, because they did not present sufficient information for inclusion in the meta-regression analysis. Through this process a total of 225 studies were reviewed, of which 35 were judged suitable for inclusion in the meta-regression analysis.

---

[8] Working papers were included to help offset potential publication bias, or what is often called the 'file-drawer problem'. The file drawer phenomenon refers to the fact that the odds of empirical studies with statistically insignificant or counterintuitive theoretical results to get published are smaller (Rosenthal 1979). However, assuming a normal distribution of study results, such aberrations are to be expected and should not be excluded from publication. It is therefore desirable to include working papers and other unpublished reports in the meta-sample.

[9] As might be imagined, the use of repeated and similar keyword searches resulted in the same studies being identified repeatedly. Obviously, duplication was avoided in constructing the database. The total population of 496 studies was drawn largely from the database searches (n = 468), whereas examining the references of literature reviews identified another 28 unique studies. For this analysis, the Internet search process did not yield any studies that were not previously identified, fit the language criteria, and could be obtained directly or through academic loans.

[10] These excluded papers, however, did prove valuable in providing valuable 'leads' to other studies, which were considered for inclusion in this analysis.

Dependent upon the research objectives, data availability, and characteristics of the production sector under consideration, authors of primary studies may choose to use one or more alternative elasticity measures. Input substitution elasticities most commonly fall within one of three categories: one-input one-price elasticities (e.g., cross-price elasticity, Allen-Uzawa elasticity), two-input one-price elasticities (i.e., Morishima elasticities), and two-input two-price elasticities (i.e., shadow price elasticities). Differences between these measures are well documented and will not be discussed here (see, e.g., Koetse et al. 2006).

In constructing the database, observations of each of these types of elasticities were included. For the present analysis however, with the desire to focus upon potential contributions of meta-regression analysis to CGE modeling, only the elasticity most commonly used in the GTAP CGE model is included. We therefore select the Allen elasticities of substitution between capital and labor. As this measure is symmetric, primary study observations of labor-capital substitution are also included.

Section 3 presented a discussion of the factors that may contribute to the heterogeneity that is observable in the elasticity estimates. Each of these was included in the current analysis and, together with details of the specific types of heterogeneity captured by each, they are summarized in Table 1. The table should be self-explanatory. Figure 1 shows that approximately 80 percent of the estimated elasticities are positive, with an average value of 0.81. The range is substantial, mainly due to a negative outlier, and ranges from –46 to +6. The 95 percent confidence intervals are generally quite small.

< Table 1 and Figure 1 about here >

For meta-regression analysis the standard errors of the primary estimates are required; surprisingly often, however, these are not provided in the studies. In order to increase the number of observations in the dataset, where sufficient information is provided in the primary study, standard errors for observations are calculated following the procedure outlined by Koetse (2006). Finally, we would like to comment on the treatment of multiple time periods used in some of the primary studies. Frequently, especially among older articles, authors chose to estimate elasticities over several overlapping time periods.[11] In such instances, to reduce collinearity among observations, only one of the available time periods was included. The choice of period was based upon the primary study authors' description of the adherence of each estimated model to the assumptions of production theory (i.e., symmetry, concavity), and the relative size of standard errors for each estimate. By these criteria, most often the longer of the available time series were selected. For the purpose of estimation, unless otherwise indicated, reported estimates were attributed to the year that marks the mid-point of the selected time series.

In addition to sources of variance attributable to the selection of the model, data, and sector, explanatory and dependant variables included in the primary study regressions also must be considered. The broad categories of capital and labor explored in this analysis reflect aggregated

[11] By way of example, Boyle (1981) estimated input substitution in Irish agriculture for the periods 1953–1970, and 1953–1977.

categories of several types of capital and labor which were included in the primary study estimations. The underlying studies reviewed for this analysis also frequently incorporated measures of land, government policies, and characteristics of the production environment (e.g. weather) into their estimations. Similarly, inputs used to produce specific agricultural outputs. Due to the numerous and extremely diverse collection of variables which were included among the primary study estimations, it is not possible to directly reflect each of these measures in the meta-regression. Instead, types of variables were aggregated and a dummy variable used to indicate the inclusion of one or more members of each aggregate in the primary analysis. Descriptions of the inputs and outputs aggregated into each of these categories are presented in Table 2.

< Table 2 about here >

The current analysis includes only observations which reflect capital-labor substitution and which are measured using Allen partial elasticities. Within this restricted sample, several of the variables presented in Table 1 are either poorly represented or are entirely absent. Table 3 presents a list and descriptive statistics for variables which were sufficiently represented as to be retained in the meta-regression. As may be noted, within each variable category, in many instances poorly represented variables were aggregated into an 'Other' variable.

< Table 3 about here >

4.2 Meta-regression results

The general form of the meta-regression model was previously presented in equation (1), and the fixed effects included in the specification reflect differences in model characteristics, data characteristics, and sector characteristics. Further, although it should theoretically be irrelevant, we include a dummy variable capturing the use of labor-capital rather than capital-labor elasticities. An overview of the variables included in the analysis is provided in Table 3, and the results of the mixed effects model are presented in Table 4.

< Tables 4 about here >

Interpretation of these results is the same as that for other forms of regression. In this analysis, the constant provides a measure of capital-labour substation under the baseline conditions of a translog cost function with an iterative estimator used to calculate a short-run elasticity. The value obtained for this constant (4.08) was found to be precise and it's magnitude reasonable when considered relative to other estimation results.

Results presented in Table 4 suggest that significant differences in estimated elasticity values are observed and attributable to several sources of variance. Of characteristics under control of study authors, the choice of function and estimator were found to have a significant impact on the derived elasticity. Several characteristics related to the experimental design were also found to be important. In particular, use of regionally or nationally aggregated data, and the moderating variables included in the primary analysis were statistically significant.

Among these results is one unexpected outcome. As was previously noted, a dummy variable was included in this model to indicate whether the observation was drawn from an capital-labor or labor-capital APE measure. As, these values should be theoretically symmetric, it was anticipated that this variable would not be significant. Surprisingly however, this measure was found to be both relatively large in magnitude and precise. Further consideration of this result is required.

5. Conclusions

The purpose of this study was to explore the means by which CGE modeling could benefit through the use of tools offered by meta-regression analysis. Through the use of an application which explored the substitutability of capital and labor used in agricultural production, it was demonstrated that elasticity estimates drawn from literature sources can vary significantly due to characteristics of their estimation. As such, these results underscore the importance of carefully considering the construction of free parameters which are included in CGE simulations.

Opportunities for Future Research: Several opportunities exist to improve and extend this research. This study used as an example application input-substitution elasticities in agriculture. This methodology can, however, of course be usefully applied to the estimation of several other behavioral parameters of interest to CGE modelers. Among the most appealing candidates for such an analysis are the Armington trade parameters which are commonly used in many for CGE models.

Several opportunities for further research also exist within the context of the current study. As an obvious starting point, the number of observations used in this analysis needs to be extended. In doing so, beyond simply increasing the degrees of freedom, attention will also need to be paid to expanding the variance of explanatory variables captured in the reviewed studies. Further graphical and statistical exploration of the data for heterogeneity (i.e. through the use of the Q-static, normalized Z-scores, and/or the Galbraith diagram) would also be useful. Finally, and perhaps most importantly, future work should consider publication bias. As the objective of this research is to demonstrated how meta-regression can provide improved estimates for regions and sectors which are not particularly well studied, this last recommendation is particularly important to obtaining unbiased estimates for these areas and industries.

References

Abreu, M., H.L.F. de Groot and R.J.G.M. Florax. 2005. A Meta-Analysis of β-Convergence: The Legendary 2%. *Journal of Economic Surveys.* 19(3): 389-420.

Allen, R.G. and J.R. Hicks. 1934. A Reconsideration of the Theory of Value, Pt. II. Economica 1: 196-219.

Alston, J. M. C. Marra, P.G. Pardey, and T.J. Wyatt. 2000. Research returns redux: A meta-analysis of the returns to agricultural R&D. *Australian Journal of Agricultural and Resource Economics*. 44(2): 185-215.

Arndt, C., S. Robinson, and F. Tarp. 2002. Parameter estimation for a computable general equilibrium model: a maximum entropy approach. Economic Modelling 19: 375-398.

Binswanger, H. 1989. The Policy Response of Agriculture. Proceedings of the World Bank Annual Conferece on Development Economics.

Blackorby C. and R.R. Russell. 1975. The Partial Elasticity of Substitution, Discussion Paper, no. 75-1. University of California, Department of Economics, San Diego.

Blackorby, C. and R.R. Russell. 1989. Will the Real Elasticity of Substitution Please Stand Up? A comparison of the Allen/Azawa and Morishima Elasticities. American Economic Review. 79: 882-888.

Brander, L. and R.J.G.M. Florax. 2006. The Valuation of Wetlands: Primary Valuation Versus Meta-Analysis Based Value Transfer, in: J.I. Carruthers and B. Mundy (eds.), *Environmental Valuation: Interregional and Intraregional Perspectives*, Aldershot: Ashgate, 231-252.

Brouwer, R. (2000) Environmental Value Transfer: State of the Art and Future Prospects. *Ecological Economics* **32**, 137-152.

Brouwer, R. and Spaninks, F.A. (1999) The Validity of Environmental Benefits Transfer: Further Empirical Testing. *Environmental and Resource Economics* **14**, 95-117.

Cooper, H. and L.V. Hedges (eds.), *The Handbook of Research Synthesis*, Sage Foundation, New York, 1994.

Dalhuisen, J., R.J.G.M. Florax, H.L.F.M de Groot and P. Nijkamp. 2003. Price and Income Elasticities of Residential Water Demand: A Meta-Analysis. *Land Economics*. 79(2):292-308.

DeVuyst, E. and P. Preckel. 1997. Sensitivity Analysis Revisited: A Quadrature-Based approach. *Journal of Policy Modeling*. 19(2):175-185.

Doucouliagos, H. and T.D. Stanley. 2007. Theory Competition and Selectivity. Working Paper, Burwood: School of Accounting, Economics and Finance.

Engel, S. 2002. Benefit Function Transfer Versus Meta-Analysis as Policy-Making Tools: A Comparison. In: R.J.G.M. Florax, P. Nijkamp and K.G. Willis (eds.), *Comparative Environmental Economic Assessment*. Cheltenham, Edward Elgar, 133-153.

Florax, R.J.G.M, H.L.F. de Groot, and R.A de Mooij. 2002. Meta-analysis: A tool for Upgrading Inputs of Macroeconomic Policy Models. Tinbergen Institute Discussion Paper. 2002-041/3.

Florax, R.J.G.M. 2002. Methodological Pitfalls in Meta-Analysis: Publication Bias, in: R.J.G.M. Florax, P. Nijkamp and K.G. Willis (eds.), *Comparative Environmental Economic Assessment*, Cheltenham: Edward Elgar, 177-207.

Glass, G.V. 1976. Primary, Secondary, and Meta-analysis of Research. *Educational Researcher* 5(10):3-8.

Hamermesh, Daniel S., and James Grant. 1979. Econometric Studies of Labor-Labor Substitution and Their Implications for Policy. *Journal of Human Resources* 14(4):518-542.

Harrison, G. W., Jones, R., Kimbell, L. J. and Wigle, R. 1993. How robust is applied general equilibrium analysis? *Journal of Policy Modeling* **15**, 99–115.

Hedges, L.V., and I. Olkin. 1985. *Statistical Methods for Meta-Analysis*. New York: Academic Press.

Hertel, T., D. Hummels, M. Ivanic, R. Keeney. 2007. How confident can we be of CGE- based assessments of Free Trade Agreements? Economic Modelling. 24: 611- 635.

Hogg, D.W. 2002. A meta-analysis of cosmic star-formation history. Pubs. Astron. Soc. Pac. 2.

Jiang, Y., Swallow, S.K., and McGonagle, M.P. (2004) An empirical assessment of convergent validity of benefit transfer in contingent choice: introductory applications with new criteria. Paper presented at the American Agricultural Economics Association Annual Meeting, Denver, Colorado, August 1–4, 2004.

Keeney, R. and T.W. Hertel. 2006. Analysis of Aggregate Yield Response for the Major Grains and Oilseed Crops in Canada, Mexico, and the United States. Report commissioned by the OECD Agricultural Directorate.

Knell, M. and H. Stix. 2005. The Income Elasticity of Money Demand: A Meta- Analysis of Emprical Results. *Journal of Econometric Surveys*. 19(3):513-533.

Koetse, M. 2006. Chapter 7: Capital-Energy Substitution and Shifts in Factor Demand. *IN:* M. Koeste. Ph.D. Thesis. Department of Spatial Econometrics, Vrije Universiteit Amsterdam.

Koetse, M. J., H. L. de Groot, R.J. Florax. 2006. Capital-energy Substitution Potential and Shift in Factor Demand: A Meta-Analysis. Working Paper.

Macaskill, P., Walter, S. D., Irwig L. (2001) A Comparison of Methods to Detect Publication Bias in Meta-Analysis, *Statistics in Medicine*, 20: 641–654.

Masters, W., B. Coulibaly, D. Sanogo, M. Sidibé, A. Williams. 1996. *The Economic impact of Agricultural Research: A Practical Guide*. Purdue University: West Lafayette, Indiana, USA.

Matarazzo, B. and P. Nijkamp. 1997. Meta-analysis for comparative environmental case studies: methodological issues. International Journal of Social Economics. 24(7/8/9): 799-811.

McFadden, D. 1963. Constant Elasticity of Substitution Production Functions. *Review of Economic Studies*. 30: 73-83.

Miller, T.R., 2000. Variations between countries in values of statistical life. *Journal of Transport Economics and Policy* **34**, 169-188.

Mulatu, A., R.J.G.M. Florax and C.A. Withagen. 2002. Environmental regulation and competitiveness: An exploratory meta-analysis. In: A. Läschel (ed.), *Empirical Modeling of the Economy and the Environment*. Berlin, Springer-Verlag, 2002.

Oum, T.H., W.G. Waters II, and J.-S. Yong. 1992. Concepts of price elasticities of transport demand and recent empirical estimates: an interpretive survey. Journal of Transport Economics and Policy. 26: 139-54.

Roberts, C.J. 2005. Issues in Meta-Regression Analysis: An Overview. *Journal of Economic Surveys.* 19(3): 295-298.

Rose, A. and T. Stanley. 2005. A Meta-Analysis of the Effect of Common Currencies on International Trade. *Journal of Economic Surveys.* 19(3): 347-365.

Rosenthal, R., The "File Drawer Problem" and Tolerance for Null Results, *Psychological Bulletin*, vol. 86, 1979, pp. 638-461.

Salhofer, K. 2000. Elasticities of Substitution and Factor Supply Elasticities in European Agriculture: A Review of Past Sudies. Universität für Bodenkultur Wien, Institut für Wirtschaft, Politik und Recht. Diskussionspapier Nr. 83-W-2000.

Stanley, T. and S. Jarrell. 2005. Meta-regression analysis: A Quantitative method of literature surveys. *Journal of Economics Surveys.* 19(3): 299-308.

Stanley, T.D. and Jarrell, S.B., 2005. Meta-regression analysis: A quantitative method of literature surveys. *Journal of Economic Surveys* 19(3):299-308.

Sutton A. J., K.R. Abrams, D.R. Jones, T.A. Sheldon, and F. Song. 2000. *Methods for Meta-Analysis in Medical Research*. New York: John Wiley and Sons.

Tellis, G. 1988. The price elasticity of selective demand: a meta-analysis of econometric models of sales. *Journal of Marketing Research*, 25: 331-41.

Thompson, S. G. and Sharp, S. J. (1999) Explaining Heterogeneity in Meta-Analysis: A Comparison of Methods, *Statistics in Medicine*, 18: 2693–2708. Uchida, S. 2005. Factor Shares Update.

Vollett, D. and J.-P. Bousset. 2002. Use of Meta-analysis for the comparison and transfer of economic base multipliers. Regional Studies. 36(5): 481-494.

Wachter, K.W. (1988) Disturbed by Meta-Analysis? *Science* **241**(4872), 1407–08.

Whalley, J., and R. Wigle. 1991. The International Incidence of Carbon Taxes. *In:* Global Warming Economic Policy Responses (R. Dornbusch and J. Poterba Eds.) Cambridge, M.A.: The MIT Press.

References studies included in meta-analysis

Andrikopoulos, A.A. and J.A. Brox. 1992. Cost Structure, Interface Substitution and Complementarity, and Efficiency in the Canadian Agricultural Sector. Canadian Journal of Agricultural Economics. 40: 253-269.

Ali, F., D. Bailey and A. Parikh. 1993. Price Distortions and Resource Use Efficiency in a Pakistani Province. *European Review of Agricultural Economics.* 20:35-47.

Antle, J.M and A.S. Aitah. 1983. Rice Technology, Farmer Rationality, and Agricultural Policy in Egypt. *American Journal of Agricultural Economics.* November: 667- 674.

Balistreri, E.J., C.A. McDaniel, and E.V. Wong. 2002. An Estimation of US Industry- Level Capital Labor Substitution Elasticities: Cobb-Douglas as a Reasonable Starting Point? Working Paper. Available online at: http://ideas.repec.org/p/wpa/wuwpco/0303001.html.

Binswanger, H.P. 1974. A Cost Function Approach to the Measurement of Elasticities of Factor Demand and Elasticities of Substitution. *American Journal of Agricultural Economics.* 56(2): 377-386.

Bonnieux, F. 1989. Estimating regional-level input demand for French agriculture using a translog production function. *European Review of Agricultural Economics.* 16:229-241.

Boyle, G. 1981. Input Substitution and Technical Change in Irish Agriculture - 1953- 1977. *The Economic and Social Review.* 12:3149-161.

Boyle, G. and D. O'Neill. 1990. The Generation of output supply elasticities and Irish demand elasticities for a Johansen type model of the Irish agricultural sector. *European Review of Agricultural Economics.* 17:387-405.

Chaudhary, M.A. and M.M. Khan. 2001. Technological Change and Input Substitution Possibilities in Pakistan's Agriculture. *Pakistan Journal of Applied Economics.* 17(1&2): 19-43.

Dalton, T.J., W.A. Masters, K.A. Foster. 1997. Production costs and input substitution in Zimbabwe's smallholder agriculture. *Agricultural Economics*. 17:201-209.

Debertin, D.L., A. Pagoulatos and A. Aoun. 1990. Impacts of technological change on factor substitution between energy and other impacts within U.S. agriculture, 1950-79. Energy Economics. January: 2-10.

Farman, A. and A. Parikh. 1992. Relationships Among Labour, Bullock, and Tractor Inputs in Pakistan Agriculture. *American Journal of Agricultural Economics*. May: 371-377.

Fousekis, P. and C. Pantzios. 1999. A Family of Differential Input Demand Systems with Application to Greek Agriculture. *Journal of Agricultural Economics.* 50:3549- 563.

Glass, J.C. and D.G. McKillop. 1989. A Multi-Product Multi-Input Cost Function Analysis of Northern Ireland Agriculture, 1955-85. *Journal of Agricultural Economics.* 40:57-70.

Grisley, W. and K.W. Gitu. 1984. The Production Structure of Pennsylvania Dairy Farms. *Northeastern Journal of Agricultural and Resource Economics.* 13(2): 245-253.

Grisley, W. and K.W. Gitu. 1985. A Translog Cost Analysis of Turkey Production in the Mid-Atlantic Region. *Southern Journal of Agricultural Economics*. July:151- 158.

Harrison, G.W., R. Jones, L.J.Kimbell, and R.Wigle. 1993. How Robust Is Applied General Equilibrium Analysis? *Journal of Policy Modeling.* 15(1): 99-115.

Hertel, T.W. 1989. Negotiating Reductions in Agricultural Support: Implications of Technology and Factor Mobility. *American Journal of Agricultural Economics.* August: 560-573.

Hoque, A. and A. Adelaja. 1984. Factor Demand and Returns to Scale in Milk Production: Effects of Price Substitution and Technology. *Northeastern Journal of Agricultural and Resource Economics.* October: 238-244.

Lopez, R.E. 1984. Estimating Substitution and Expansion Effects Using a Profit Function Framework. *American Journal of Agricultural Economics*. August: 358-367.

Khatri, Y. and C. Thirtle. 1996. Supply and Demand Functions for UK Agriculture: Biases of Technical Change and the Returns to Public R&D. *Journal of Agricultural Economics.* 47:3338-355.

Kinnunen, J. 2003. Capital-Labour Elasticity of Substitution in the Agriculture of Åland and Southern Finland. Available online at: http://ideas.repec.org/p/wpa/wuwpco/0303001.html.

Kurdoa, Y. 1987. The Production Structure and Demand for Labour in Postwar Japanese Agriculture, 1952-82. *American Journal of Agricultural Economics*. May: 328- 337.

Kurdoa, Y. 1988. Biased Technological Change and Factor Demand in Postwar Japanese Agriculture, 1958-84. *Agricultural Economics.* 2: 101-122.

McIntosh, C.S. and C.R. Shumway. 1991. Multiproduct Production Choices and Policy Response. *Western Journal of Agricultural Economics.* 16(2): 291-303.

McKillop, D.G. and J.C. Glass. 1991. The Structure of Production in Irish Agriculture: A Multiple-Input Multiple Output Analysis. *The Economic and Social Review*. 22:3213-228.

Mergos, G., and P. Yotopoulos. 1988. Demand for feed in the Greek Livestock Sector. *European Review of Agricultural Economics*. 15:38734.

Napasintuwong, O. and R.D. Emerson. 2005. Institutional and socioeconomic model of farm mechanization and foreign workers. Selected paper prepared at the American Agricultural Economics Association Meeting, Providence, Rhode Island, July 24-27, 2005.

O'Donnell, C.J. C.R. Shumway, and V.E. Ball. 1999. Input Demands and Inefficiency in U.S. Agriculture. *American Journal of Agricultural Economics.* 81: 865-880.

Parkikh, A. 1983. Some Aspects of Employment in Indian Agriculture. *World Development.* 13(6): 691-704.

Pierani, P. and P. Rizzi. 2003. Technology and efficiency in an panel of Italian dairy farms: an SGM restricted cost function approach. *Agricultural Economics.* 29: 195-209.

Poonyth, D., J. Van Zyl, N. Vink, and J.F. Kirsten. 2001. Modeling the South African Agricultural Production Structure and Flexibility of Input Substitution. Working Paper: 2001-10. Department of Agricultural Economics, Extension and Rural Development, University of Pretoria, South Africa.

Ryhänen, M. 1994. Input substitution and technological development on Finnish dairy farms for 1965-1991. *Agricultural Science in Finland.* 3:None519-601.

Rossi. 1984. The Estimation of Product Supply and Demand by the Differential Approach. *American Journal of Agricultural Economics.* 66:3368-375.

Sharma, S.C. 1991. Technological change and elasticities of substitution in Korean agriculture. *Journal of Development Economics*. 35: 147-172.

Sidhu, S. and C. Baanante. 1981. Estimating Farm-Level Input Demand and Wheat Supply in the Indian Punjab Using a Translog Profit Function. *American Journal of Agricultural Economics.* May: 237-246.

Thijssen, G. 1994. Supply response and dynamic factor demand of Dutch dairy farms. *European Review of Agricultural Economics.* 21: 241-258.

Thirsk, W. 1974. Factor Substitution in Colombian Agriculture. *American Journal of Agricultural Economics*. 56(1): 73-84.

Table 1: Description of explanatory variables in the meta-analysis.

Variable Category	Variable Name(s)	Variable Description
	Model Characteristics (MC)	
Function	Cost	Cost Function
	Profit	Profit Function
	Production	Production Function
	Input Demand	Input Demand Function
Functional Form	CES	(Nested) CES Function
	Quadratic	Quadratic Function
	Translog	Translog Function
	Differential	Differential Function
	Other*	Other functional forms. Includes Cobb-Douglas, Generalized Leontief functions.
Estimator	OLS	Ordinary Least Squares.
	ML	Maximum Likelihood.
	GLS	2SLS, IV
	Iterate*	Includes ITSUR, Iterative Zellner, 13LS
	Est. Other	Other estimation techniques, including random/fixed effects
Model Structure	AR1	Time series
	Dynamic	Dynamic
Omitted Variables	RTS	Estimated with Returns to Scale parameters.
	NNTC	Estimated with Non-neutral Technological Change parameters
	Data & Study Characteristics (DC)	
Time Period	First Year	First year included in analysis
	Number Years	Total number of years included in analysis
Time Horizon of Elasticity Estimate	Short/Medium Run*	
	Long Run	As indicated by authors
Type of Data	Data Frequency	Indicator of the frequency of data collection; daily, monthly, quarterly, annual, 3-year
Data Type Details	Cross-Sectional	
	Time Series	
	Panel Data	
	Household/Firm Data	
	Aggregate Data	
Scale of Production	Small Scale	As indicated by authors.
Study Published	Published	Study in a refereed publication
	Characteristics of Sector (CS)	
Country Income	High	Country name or geographic region
	Medium/Low*	
Geographic Region	Region	Indicator of the region: East Asia & Pacific, Europe & Central Asia, Latin America & Caribbean, Middle East & Northern Africa, South Asia, Sub-Saharan Africa.
Trade Structure	Closed	
	Open - Small	
	Open - Large	
	UC	Extent of openness Unclear/unknown. Dummy variable

* These variables were aggregated due to the relatively small number of observations with these characteristics in the complete dataset.

Table 2: Description of moderating variables and output sectors included in the meta-regression model.

Variable Category	Variable Name	Inputs aggregated into Variable
	Input Categories	
Types of Capital	Capital	Animal traction, Buildings, capital, energy, feed, chemicals, fuels/oil, irrigation, live animals or poultry, machinery, materials, seed, variable inputs, intermediate inputs, crop inputs, livestock inputs
Types of Labor	Labor	Labor, family labor, hired labor
Types of Land	Land	Land, grazing land
Types of Policy	Policy	Education, extension expenditures, patents, R&D expenditure, technology
Production Environment	Water	Water
	Weather	Weather
	Output Categories	
Types of Output	Crops	All crop varieties
	Livestock	All livestock, dairy, poultry
	Crops & Livestock	Mixed output, non-specified output

Table 3: Descriptive Statistics of Analyzed Dataset

Category	Variable Name	Number of Observations	Percent of Sample
	MODEL CHARACTERISTICS (MC)		
Function	Cost (BL)	61	58.1
	Production	38	36.2
	Other	6	5.7
Functional Form	Translog (BL)	96	91.4
	Other	9	8.6
Estimator	OLS	11	10.5
	Iterate (BL)	90	85.7
	Other	4	3.8
	DATA & STUDY CHARACTERISTICS (DC)		
Time Horizon of Estimate	Short/Medium Run (BL)	99	94.2
	Long Run	6	5.7
Data Frequency	Annual (BL)	101	96.2
	Other	4	3.8
Data Type Details	Time Series	16	15.2
	Household/Firm Data	55	52.4
	Aggregate Data	22	20.9
	Other	16	15.2
Scale of Production	Small Scale	18	17.1
Study Published	Published	101	96.2
Moderating Variables	Land	77	73.3
	Policy	19	18.1
Type Of Output	Crops Only	3	56.2
	Livestock Only	59	2.9
	Crops & Livestock (BL)	43	40.9
	CHARACTERISTICS OF SECTOR (CS)		
Country Income	High (BL)	40	39.1
	Medium/Low	65	61.9
	OTHER		
Input Order	Capital-Labor Substitution (BL)	45	42.8
	Labor-Capital Substitution	60	57.1

Notes:
BL = Baseline. These variables are not included in the meta-regression estimation as these categories contain mutually variables.

Table 4: Results of meta-regression with mixed effects for differences between studies[1]

VARIABLE	ESTIMATE (STD. ERROR)
Constant	4.080 (0.710)***
Function	
Production	-2.480 (0.575)***
Other	-0.248 (0.515)
Functional Form	
Other	0.376 (0.302)
Estimator	
OLS	-1.606 (0.470)
Other	-0.125 (0.662)***
Estimate Horizon	
Long Run	0.122 (0.190)
Data Type	
Time Series	-0.354 (0.283)
Household/Firm Data	0.110 (0.459)
Aggregate Data	-1.699 (0.562)***
Other	-0.668 (0.480)
Production Scale	
Small	-0.009 (0.390)
Study Published	-3.432 (0.745)***
Moderating Variables	
Land	1.017 (0.514)**
Policy	-0.893 (0.338)***
Type of Output	
Crops Only	1.731 (0.605)***
Livestock Only	-0.674 (0.530)
Country Income	
Medium/Low	-2.128 (0.605)***
Other	
Reverse Inputs	1.869 (0.008)***
n	105

Notes:
Significance is indicated by ***, ** and * for the 1, 5, and 10 percent level respectively.
[1] Weights are determined as the standard error of observations in the underlying studies used to provide the elasticity estimates.

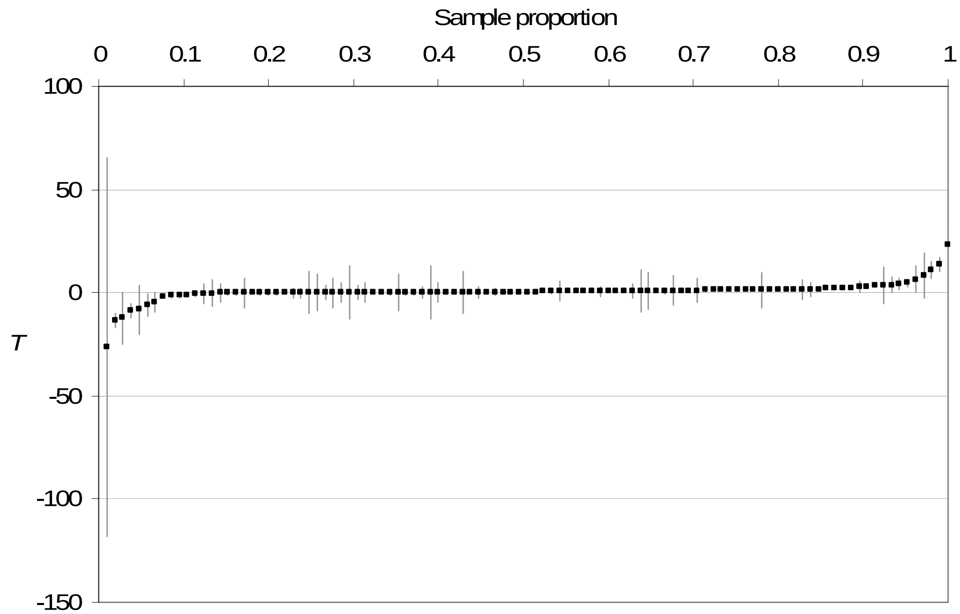

Figure 1: Effect sizes (T) including their 95% confidence interval ranked in increasing magnitude with deciles of the meta sample size on the horizontal axis.