

CAN WE CLOSE THE GAP BETWEEN THE EMPIRICAL MODEL AND ECONOMIC THEORY?

AN APPLICATION TO THE U.S. DEMAND FOR FACTORS OF PRODUCTION

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Abstract

This paper proposes a procedure to test for behavioral assumptions which relies on the principle that behavioral assumptions manifest themselves in form of “shape conditions.” For example a cost-minimizing firm exhibits a dual cost function concave and increasing in input prices. We first estimate a flexible function without imposing shape conditions. Secondly, we re-estimate subject to shape conditions. The comparison of the restricted to the unrestricted estimate provides the test statistic. We show that recently proposed new shape-restricting estimators support duality theory in the “Berndt and Wood” dataset, a setting where multiple studies have found violations of economic theory.

Keywords: Demand System, Cost Function, Shape Restrictions, Flexible Functional Forms, Hypothesis Test, Elasticity of Substitution, Energy

JEL Code: C51 - Model Construction and Estimation; D21 - Firm Behavior; C11 - Bayesian Analysis; Q43 - Energy and the Macroeconomy; C52 - Model Evaluation and Testing

While a difficult literature, we believe that research on models permitting flexible imposition of true regularity should expand.

-- William A. Barnett & Meenakshi Pasupathy, 2003 --

1. INTRODUCTION

A lot of work in economics can be characterized as follows: researchers start by making a set of behavioural assumptions and developing a theoretical model. After deriving the functions of interest, we estimate the resulting system of equation(s), and finally, use the empirical model for policy analysis. The data provide the link between ‘economic theory’ and the ‘empirical model’. Two questions motivate this paper: is the data in line with the assumed behaviour implied by the economic theory, and how can we test for this relationship?

One critical implication of economic theory is that behavioural assumptions manifest themselves in the form of uniquely defined ‘shape conditions’. For example, if it is assumed that a firm exhibits behaviour of a cost minimizer, a standard assumption in many economic models derived from duality theory, then the dual cost function is concave and monotonically increasing in input prices and convex and increasing in output.¹ Rejecting shape conditions is equivalent to rejecting the underlying assumptions of economic theory.

The potential gap between a well-established economic theory, on one side, and the empirical model on the other, is of great concern as reflected in the large literature on regularity preserving estimation procedures produced in the past 30 years, see Gallant and Golub (1984), Diewert and Wales (1987) and Barnett and Binner (2004) for literature reviews on this topic. Nonetheless, in empirical applications theoretical assumptions are often violated and policy recommendations derived from such models are dubious at best; see the discussions in Salvanes and Tjøtta, 1998; Griffiths, O'Donnell and Tan-Cruz, 2000; Barnett, 2002; Blundell, 2004.²

¹ Also, by the Shephard Lemma, a dual cost function implies that the input demand system is downward sloping such that the law of demand holds and the marginal cost functions are increasing in both prices and output. Similar relationships between behavior and shape conditions hold in many other contexts: if individuals are utility maximizers, then the indirect utility function is quasi-convex in prices. If firms are profit maximizing, then the supply function is upward sloping and the profit function is convex in both output and input prices.

² Monotonicity and convexity conditions are the most frequently violated. Curvature alone might be successfully implemented with quadratic functional forms but these may fail to produce correct monotonicity. For common parametric and semi-non-parametric procedures, these violations are the consequence of the fact that standard estimation methods can

This paper presents a framework for estimation and inference to test the fundamental behavioral assumptions, such as profit maximization or utility maximization, characterized by optimizing some objective function subject to constraints. To make our test procedure work, we first estimate a flexible parametric functional form unrestrictedly. If it satisfies all the required shape restrictions, then the estimated empirical model does not reject the economic theory. If, however, the estimated model violates the shape restrictions, a second procedure follows: we re-estimate the function, subject to the constraint that all shape conditions are satisfied. Finally, the comparison of the restricted estimate to the unrestricted estimate provides us with the test statistic. The intuition of the proposed test is simple: if we statistically reject the implied shape properties, we then reject the economic theory as well. Hence, the objective is to test the gap between the empirical model and the economic theory.

In the literature on parametric functional forms, we seldom observe cases where the underlying theory is formally tested, and the tests that have been conducted are rather partial or ad hoc. For example, some papers report the percentage of data points at which they violate the shape conditions. This informal test statistic, however, is problematic. In fact, it turns out that a function violating the shape conditions at all data points can be very “close” to the economic theory. However, the other case is possible as well: a function violating a shape restriction at one singular data point can still imply an empirical model that is completely out of sync with economic theory. We argue that our procedure therefore outperforms such ad-hoc tests.

For illustration we apply our method to the “Berndt and Wood” dataset—that has been extensively used to test the performance of new estimators in the econometric literature—estimating a flexible input demand system of four production factors to the U.S., see among others Berndt and Wood 1975, Berndt and Khaled 1979, Galant and Golub 1984, Diewert and Wales 1987, Barnett, Geweke and Wolfe 1991, Friesen 1992, Terrell 1996.³ Here we take a fresh look at the data. Whereas previous applications only impose a subset of shape conditions, this is the first paper enforcing *all* shape conditions on the data. We also discuss

impose the shape restrictions partially only—as proven by Lau, 1986 for a general class of parametric models.

³ In fact, it may even be one of the most frequently estimated input demand systems in the entire econometrics literature.

which estimators have the flexibility to impose all of the required shape conditions. Importantly, our empirical results demonstrate that the estimator choice can lead to significantly different policy implications. In particular, we find that estimates based on standard estimators could have erroneously rejected the duality hypothesis, whereas the preferred estimator provides strong support that the Berndt and Wood data is in fact consistent with economic theory.

To demonstrate the implications, one of the central parameters in the Berndt and Wood data is the elasticity of substitution between energy to capital. We show that different estimation and testing procedures can dramatically change the results in terms of whether energy and capital are substitutes or complements, a fundamental question that has received much attention in economics, i.e. see Dasgupta & Heal (1979) or Apostolakis (1999).

The writing of this paper emphasizes the empirical issues relevant to the application. In reviewing the literature on shape imposing estimators, we find few arguments on *why* these methods require application. Section 2 provides background on the theory of shape conditions and regularity-imposing techniques, Section 3 illustrates these approaches empirically, and in Section 4 we provide conclusions.

2. BACKGROUND

2.1 Shape Conditions

Although many will agree that a sound empirical model must be consistent with the underlying economic theory, some may doubt the validity of employing regularity-imposing estimators. If we do not allow the data to speak for itself—but rather force it into relationships dictated by theory—does this not imply that the assumed economic theory is wrong, the model inaccurately specified, or that the data quality is not appropriate for the estimation? Before offering an answer, we first review some of the concepts involved. In this paper we estimate a factor demand system which is derived by Shephard's Lemma from the dual cost function $c^*(p,y,t) = \min\{p \cdot x \mid f(x,t) \geq y\}$. Inputs are denoted by $x \in \mathfrak{R}_+^N$ and are transformed into output $y \in \mathfrak{R}_+$ by a smooth production function $f(x,t)$, which depends upon technological change $t \in \mathfrak{R}_+$.

Duality theory implies that $c^*(z)$, where $z = [p,y,t] \in \mathfrak{R}_+^{2+N}$, is

- HD1 : homogenous of degree one in input prices $p \in \mathfrak{R}_+^N$
- M_p : monotone increasing in p
- C_p : concave in p
- C_y : convex in y , and
- M_y : monotone increasing in y .

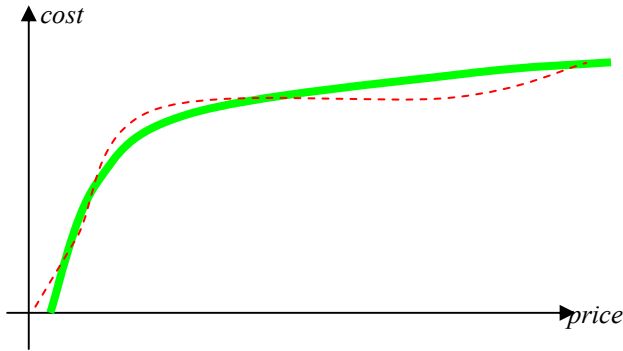
If a function satisfies properties HD1, $M_{p,y}$ and $C_{p,y}$, we then say that the function is ‘regular’ or synonymously, ‘well-behaved.’ To impose these regularity conditions, for many years the literature concentrated on the estimation of factor demand systems from globally regular generating functions, such as the Cobb-Douglas and the Constant Elasticity of Substitution. These *first order flexible functional forms* satisfy the restrictions of homogeneity, monotonicity, and curvature by well-known parametric restrictions; at the same time, these forms restrict the potential values for the second order effects prior to the estimation. This implies that the elasticities of substitutions, which are often key parameters to reveal for policy analysis, cannot be estimated, but are fixed. Moreover, this does not allow formal testing of the underlying economic theory because these functions are themselves strictly a subset within the class of functions generated by the theory.

In applied work, the researchers’ aim is the consistency of the empirical model with the underlying economic theory. Even if there existed a function that satisfied all shape conditions there would be no way to test that the data were actually generated by economic theory because such a function is within the set of functions spanned by economic theory. Consequently, the literature in the 1970s moved toward local approximation functions to the true data generating function itself, by series expansions. The result was the class of *second order flexible functional forms*, such as the popular Translog, Generalized McFadden, and the Generalized Leontief, providing the capability to attain arbitrary elasticities of substitution. Nevertheless, this increased flexibility came with a cost: sacrificing the guarantee of regularity.⁴ In fact, a series of studies (for a review, see Barnett, Geweke and Wolfe (1991)) demonstrated that these forms often have very small regions

⁴ For linear-in-the-parameters functional forms, Lau (1986) proved that flexibility is incompatible with global regularity with the imposition of both concavity and monotonicity. For example, a globally consistent second order Translog reduces the feasible parameter values of its squared terms to be zero, thus restricting the functional form to its first order series expansion, the Cobb-Douglas, which has constant cross elasticities of value one.

of theoretical regularity.

Fig. 1 : True versus approximation function



Even if the true data generating cost function c^* is deterministic and regular (bold), the estimated approximation function \hat{c} (dashed) can be irregular. The movement from c^* to \hat{c} is not a simple parallel movement. Instead, (because realized (weighted) residuals sum up to zero) \hat{c} oscillates around c^* . This phenomenon has been demonstrated with numerical examples using the Translog, the Generalized Leontief, and the AIM (Wolff *et al.* 2010).

As previously noted by Moschini (1999), from a positive point of view, violations of the regularity conditions may call into question the applicability of the dual demand theory to a particular data set. This raises the issue of whether one should really force the function to satisfy economic theory, or if one should rather let the data speak for itself and search for other (non-neoclassical) explanations. We argue that regularity-preserving techniques are indispensable for at least three reasons⁵:

(a) Any finite order flexible functional form c represents an approximation to the true function c^* . If c^* is regular and *stochastic*, then \hat{c} , estimated with some non-regularity preserving estimator, can fit outliers produced by c^* and thus violate regularity (even though the deterministic part of c^* is regular!).

(b) The upshot is, even if c^* was regular and *deterministic*, \hat{c} can oscillate around the true relationship. Because of its approximating nature, \hat{c} has a different tracking behavior over its domain, so it does not lie completely above c^* , but slightly next to it, as shown in fig. 1. This is perhaps the most important reason for the use of regularity-retaining techniques. Otherwise one risks erroneously concluding that some data is ill behaved, whereas, in fact, the true data generation process is regular.

(c) A regularity preserving point estimate is required for correctly specifying hypothesis tests. More on this

⁵ While the literature on shape restrictions has emphasised that imposition of regularity is important, we are unaware of any systematic treatment of the arguments (a) to (c) in previous papers. Despite this, repeatedly it had been argued that the empirical evidence demonstrated that economic theory matters: A 'regular model' may often forecast better out of sample - although their 'in sample' fit statistics are inferior compared to an irregular model. This is an interesting point but not a general result. For a discussion on this, see Edwards and Terrell (2004).

issue is outlined in the empirical section.

2.2 The Domain

The focus of this section is on methods to impose the inequality constraints to obtain $M_{p,y}$ and $C_{p,y}$. Such methods can be categorized into three groups: (a) global, (b) local and (c) regional imposition of regularity. Let us define ψ as a subset of the domain of the right hand side variable space \mathfrak{R}^{N+2}_+ (here spanned by z). Whereas global refers to the unbounded positive orthant \mathfrak{R}^{N+2}_+ , local refers to one singular point or multiple singular points, and regional refers to a connected subset of \mathfrak{R}^{N+2} . Note that conceptually the local, global and regional approaches only differ in the way ψ is defined. If $M_{p,y}$ and $C_{p,y}$ holds $\forall z \in \psi$, we say that regularity is imposed (i) *globally* if $\psi = \mathfrak{R}_+^{2+N}$, (ii) *locally* if ψ consists of one or more singular disconnected points, and (iii) *regionally* if ψ is some connected subset of \mathfrak{R}_+^{2+N} .

Global and local approaches are by far the most common methods currently employed by economists, because of their relative ease of computation. Instead the regional approach is more demanding both computationally and because the researcher needs to explicitly specify the connected set ψ of the domain. The connected subset, first proposed by Gallant and Golub (1984) represents the *empirically relevant region*, and is defined by the model analyst. In particular it is assumed that it is known prior to the estimation at which ranges of the data the model shall generate forecasts. We argue that once it is ensured that the empirically relevant set ψ is regular, it is not particularly important if the function is irregular immediately outside the boundary of ψ because inferences will not be drawn from those regions. Whereas the functions shape properties like $M_{p,y}$ and $C_{p,y}$ on ψ are purely determined by economic theory, the coordinates of ψ (within the right hand side variable space \mathfrak{R}_+^{2+N}) have to be defined by the analyst having in mind the purpose of the model, hence knowing about the data points at which ranges one aims to make inferences. The *regional approach* offers important advantages over the *local* approach because it imposes theoretical consistency not only locally, at a given singular evaluation point, but also over the entire empirically relevant region of the domain associated with the function being estimated. The method also provides benefits relative to the *global* approach, through higher flexibility derived from being less constraining, generally leading to a better model fit to the sample data

compared to the *global* imposition of regularity. In the empirical Section 3 we test for these claims, comparing local, regional and global approaches.

2.3 Shape imposing estimators

The estimators are best explained through our empirical application of Section 3 with $N = 4$ inputs and $T = 25$ observations. The two curvature conditions $C_{y,p}$ and the two monotonicity conditions $M_{y,p}$ must hold on a connected subset $\Psi \subset \mathfrak{R}_+^{2+N}$ of the price \times output \times time space. $C_{y,p}$ and $M_{y,p}$ can be characterized by $H = 4$ vector-valued-functions $i_h(\mathbf{z};\boldsymbol{\beta})$, $h = 1, \dots, H$, whereby the restrictions hold whenever, for a given $\boldsymbol{\beta}$, \mathbf{i} is nonnegative for all z in the relevant region Ψ ,

$$\mathbf{i}(\mathbf{z};\boldsymbol{\beta}) \equiv [i_1, i_2, \dots, i_H] \geq \mathbf{0} \quad \forall p, y, t \in \Psi.$$

Hence for monotonicity and curvature we define the following four sets of constraints:

$$i_1 = \nabla_p c \geq 0, \quad i_2 = \nabla_y c \geq 0, \quad i_3 = -\text{eig}[\nabla_{pp}c] \geq 0, \quad \text{and} \quad i_4 = \text{eig}[\nabla_{yy}c] \geq 0.$$

An estimator of local regularity maximizes some statistical criterion function subject to $\mathbf{i}(\mathbf{z};\boldsymbol{\beta}) \equiv [i_1, i_2, \dots, i_H] \geq \mathbf{0}$ at one or a finite (small) number of multiple points of the regressor space. Using only one point Ryan and Wales (1998) yield functional forms with a high degree of flexibility. However the risk exists that regularity is violated near the selected point. The problem of large areas where regularity could be violated motivates searching for different specifications of the locally regular region. Finding the optimal set of local constraints for a given dataset can be time consuming and lead to complications for statistical testing/verification. To circumvent this Gallant and Golub (1984) impose regularity at every data point in the regressor sample space using an inequality constrained optimization technique, which offers added flexibility and better model fit compared to the global approach. However, two problems persist: (i) the technique is computationally difficult for large sample sizes or complex constraints and (ii) it is still possible that regularity is violated at points outside the sample space.

Imposing global regularity requires that shape conditions hold at all values of the regressor space. This is typically done by now well-known parametric restrictions described for example in Diewert and Wales 1987. The guarantee that the whole domain is consistent with economic theory comes at the cost of sacrificing

flexibility and model fit. For example, imposing global regularity on the Generalized Leontief cost function eliminates the possibility of complementary inputs. Traditionally, monotonicity has been ignored in globally regular estimators, leading to potentially misleading results as shown by Barnett (2002) and Barnett and Pasupathy (2003). Monotonicity restrictions have traditionally been omitted because estimators imposing both monotonicity and concavity globally lose second order flexibility, and therefore offer no significant advantage to functions with only first order flexibility such as CES and Cobb-Douglass, which has been proved by Lau (1986).

The regional regularity approach was first proposed by Gallant and Golub (1984). Here a statistical criterion function is maximized subject to an infinite number of constraints $\mathbf{i}(\mathbf{z}; \boldsymbol{\beta}) \equiv [i_1, i_2, \dots, i_H] \geq \mathbf{0} \quad \forall p, y, t \in \Psi$ which have to hold at any point within Ψ . Imposing regional regularity generally leads to a better statistical fit of the data to the model, compared to the global regularity approach. However, Gallant and Golub (1984) did not demonstrate the tractability of their double inequality constrained optimization technique for this regional approach and it seems that empirical implementation can be formidable with optimization tools currently available. It was more than a decade until Terrell (1996) advanced ideas relating to the empirical application of regional regularity. Instead of explicitly using a constrained optimization algorithm as in Gallant and Golub (1984), Terrell (1996) decomposed the problem into a series of steps: Firstly, a convex set Ψ of some region of interest in the domain of the function is approximated by a dense grid consisting of thousands of singular regressor values. Secondly, using a Bayesian framework, an unconstrained posterior distribution of the parameter vector $\boldsymbol{\beta}$, conditional on the endogenous variable \mathbf{y} , $p_u(\boldsymbol{\beta}|\mathbf{y})$, is derived that does not incorporate the regularity conditions. Thirdly, a Gibbs sampler is used to draw parameter vector outcomes from $p_u(\boldsymbol{\beta}|\mathbf{y})$, and an Accept-Reject algorithm is applied to assess regularity for each outcome at all grid points. Finally, point estimates are derived and inferences are drawn based on the set of regular parameter vectors and its truncated posterior distribution. Further details of the method are provided in the appendix. This procedure has two problems: (a) Due to the approximation of the relevant regressor space by the grid, the possibility cannot be eliminated that the function is irregular for some non-grid points. In this sense this technique does not compel

regularity on a connected set but imposes local regularity at multiple singular points. (b) The Gibbs simulator requires sampling from the entire support Θ of the unconstrained posterior $p_u(\beta|y)$. This can be time consuming if, as is often the case in practice, the regular region is only a small subset of Θ (Terrell 1996). An alternative estimator that imposes regional regularity, developed by Wolff, Heckelei, and Mittelhammer (2010), decreases computing time by reducing the amount of regularity checks. Their Metropolis-Hastings Accept-Reject Algorithm (MHARA) simulator creates a mode estimator that promises to increase the model fit compared to previous techniques. Secondly, compared to previous approaches (that defined ψ to be a connected and convex set), Wolff *et al.* (2010) further propose a method to impose regularity on non-convex sets adding flexibility to the estimation that may further enhance the model fit.

3. EMPIRICAL ILLUSTRATION

Background to the Application of Estimating Input Demand Systems

A motivating application exemplifies the use of the demand system: Climate change concerns drive many countries to debate over imposing a tax on energy use intending to reduce CO₂ emissions. To quantitatively assess the costs and benefits of such a policy an analyst requires two information: the own price elasticity of demand, and secondly the cross-price elasticities that describe the effects on important markets that are linked to energy. Firms facing such a tax could substitute away from energy towards other inputs such as capital and labor—which may be less polluting but more costly. To this end, estimated demand systems have provided key ingredients to answer many important questions in production analysis (Chambers 1988, Griffiths, O’Donell and Tan Cruz 2000, Kumbhakar and Tsionas 2005), policy studies and welfare analysis (Evans and Heckman 1984, 1986, Koebel, Falk and Laisney 2003), as well as in the debate on the sources of economic growth (Mankiw, Romer and Weil 1992, Hsieh 2000, Antras 2004).

Our empirical illustration contains 3 subsections: In Section 3.1, we re-estimate the demand system for four production inputs to the U.S. manufacturing sector using the Berndt and Wood (1975) data set for capital (K), labor (L), energy (E), and materials (M). This data set has been reported to violate the regularity conditions implied by economic theory. For that reason the KLEM data have been applied to a considerable

number of studies imposing regularity techniques, providing a substantial foundation on which to investigate and to compare the performance of these alternative estimators.

One can ask if the theoretical notions described in Section 2 have any practical importance. For instance, does the local approach produce estimates that are significantly different from the global or regional approaches? To exemplify, Section 3.2 looks at the elasticity of substitution between capital and energy, a parameter that has attracted a great deal of attention in the last decades (see e.g. Apostolakis 1990). Finally, the last section, 3.3, goes one step beyond and asks whether duality theory is appropriate for modelling the U.S. input demand system, and provides a systematic technique for testing shape conditions. Simply forcing the empirical model to be consistent with economic theory (by employing shape imposing estimators) could produce misleading results. Instead formal hypothesis tests should be carried out.

The Berndt and Wood data have been described in more detail in many places in the literature (e.g. Berndt and Wood (1975), Berndt and Khaled (1979), Gallant and Golub (1984)). Table 1 provides summary statistics of the annual data from 1947 to 1971. In particular the min/max values of the right hand side price variables will be considered below for the construction of the various ψ sets.

Table 1: Summary statistics of the Berndt and Wood data set from 1947 to 1971

	input quantities				input prices				output
	K	L	E	M	p_K	p_L	p_E	p_M	y
mean	20.45	106.07	16.78	237.56	1.18	1.77	1.35	1.30	313.80
std	7.77	43.59	5.54	85.14	0.19	0.46	0.12	0.14	87.67
min	8.58	45.10	7.76	112.35	0.74	1.00	1.00	1.00	182.83
max	34.11	190.26	29.48	407.71	1.50	2.76	1.65	1.55	466.83

NOTE: Variables are produced using index numbers and deflators. For details on the data construction see Berndt and Wood (1975) and Berndt and Khaled (1979).

3.1 Comparing Shape Imposing Techniques – An Illustration using the Berndt and Wood Data

The main purpose of the following eight sets of estimations is to assess potential advantages and disadvantages of the regional, local and the global approaches both in terms of model fit and the propensity for regularity violations. Performance statistics of various estimators as applied to the second order flexible Generalized Leontief cost function

$$c(\mathbf{z}; \boldsymbol{\beta}) = \sum_{i=1}^N \sum_{j=1}^N b_{ij} p_i^{0.5} p_j^{0.5} + \sum_{i=1}^N b_i p_i + \sum_{i=1}^N b_{it} p_i t y + t \sum_{i=1}^N a_i p_i + y^2 \sum_{i=1}^N \beta_i p_i + y t^2 \sum_{i=1}^N \gamma_i p_i$$

with $b_{ij} = b_{ji}$, are displayed in Table 3. In order to be able to directly compare our results with previous studies, we use the exact same specification of the demand system as in Diewert and Wales (1987), and in Terrell, (1996).⁶ Hence the N estimated equations are

$$\mathbf{x}/\mathbf{y} = \nabla_p c(\mathbf{z}; \boldsymbol{\beta})/\mathbf{y} + \mathbf{u}. \quad (1)$$

It is assumed that the $T \times 1$ error vectors \mathbf{u}_n , $n = 1, \dots, 4$ are contemporaneously correlated, such that the estimating equations can be written in form of the Gaussian seemingly unrelated regression (SUR) system. Finally $t = 1, 2, \dots, T$. For details on the specification see Diewert and Wales, 1987 and Terrell, 1996.

Economic theory restricts the Generalized Leontief cost function to be M_p , M_y , C_p and C_y . In general, economists are well aware of these fundamental relations, imposing *all* four of these conditions when estimating first order flexible functional forms. In contrast, the standard practice is that only a small subset of these conditions is enforced when using the Generalized Leontief or any other second order flexible forms. In particular, the three conditions $M_{p,y}$ and C_y conditions have rarely been considered. A remarkable exception of a paper explicitly imposing both C_p and M_p (but not M_y and C_y) is Terrell (1996), whose results will be shown below.

The fact that the literature (Berndt and Wood 1975, Berndt and Khaled 1979, Galant and Golub 1984, Diewert and Wales 1987, Berndt, Geweke and Wolfe 1991, Friesen 1992, Terrell 1996) contemplated subsets of the regularity conditions cannot be justified from a perspective of economic theory. Why should a violation of monotonicity be less harmful than a concavity violation? This development might only be explained by the lack of estimators that have the ability to maintain *overall regularity*. Such a gap between economic theory and the empirical model is problematic for the interpretability of the results and is especially worrisome if one

⁶ For a motivation of this particular specification see Diewert and Wales (1987) and Terrell (1996). In particular, all right hand side variables are assumed to be exogenous. This seems to be a standard approach in this literature: Except for the Berndt et al. articles in the seventies, none of the above papers estimating the KLEM input demand system uses instruments. For a justification of this, see the discussions by Diewert (2004), Barnett and Binner (2004), and Antras (2004). Another possible extension is to estimate the system in the context of an error correction model (Friesen, 1992).

wishes to derive any policy conclusions for the U.S. manufacturing sector, which accounts for about 20% of the GDP. To our knowledge for this input demand system this paper represents the first study systematically taking into account *overall* regularity when using flexible functional forms.

Table 2: Regularity imposing sets

Approach		Row	Definition of ψ	Comment
Unconstrained		(1)	$\psi = \emptyset$:	$M_{p,y}$ and $C_{p,y}$ is not imposed. ‘Unconstrained’ refers to the ‘inequality constraints’ only: we do impose symmetry and HD1 by parametric equality restrictions.
Local		(2)	$\psi = z_1$	We use z_1 , the first observation in the sample (1947) because this represents our results comparably to the tables in Berndt and Wood (1979), Diewert and Wales (1984), Barnett et al., (1991) and Terrell (1996). ⁷
Global		(3)	$\psi = \mathfrak{R}_+^{2+N}$	Nonnegative orthant of all right hand side variables of z .
Regional	Cube ⁸ approach	(4)	$\Psi^{cp}_1 = \{\mathbf{p}: \mathbf{p} \in \times_{k=1}^3 [1.0, 1.5]\}$	This was chosen by Terrell (1996). It does not cover the entire empirical relevant data space. Some observed prices lie outside the [1.0, 1.5] interval, see min/max values in table 1. ¹
		(5)	$\Psi^{cp}_2 = \{\mathbf{p}: \mathbf{p} \in \times_{k=1}^3 [0.5, 3.0]\}$	This set was chosen by Terrell (1996). It ensures that Ψ^{cp}_2 covers all observed prices and beyond.*
		(6)	$\Psi^{cz}_i = \{\mathbf{z} \in \Psi^{cp}_i \times [y_{\min}, y_{\max}] \times [t_{\min}, t_{\max}]\}$	$\Psi^{cz}_i, i \in \{1, 2\}$: These sets expand Ψ^{cp}_i over the remaining dimensions t and y .
	String approach	(7)	$\psi^{\text{string}} = \bigcup_{i=1}^{26} \psi_i$	ψ^{string} covers $26 = T+1$ points in \mathfrak{R}_+^{2+N} by connecting straight lines ψ_i between the right hand side variables mean, \mathbf{z}^M , and each of the T observations. We approximate each line ψ_i by ψ_{ig} by taking 10 equidistant grid points between \mathbf{p}^M and the i^{th} observation z_i , leading to $1+(F-1)T = 226$ grid points.

NOTE: 1. Set is Lebesgue measure zero because it does not expand into the dimension y and t .

⁷ In case of the Berndt and Wood dataset, imposing the regularity conditions at other points in the sample space (z_2 to z_{25}) does not essentially change the empirical results. This conclusions, however, is not a general result but is entirely data-driven.

⁸ In this paper all grid sets ψ^{\square}_{ig} are constructed with $F = 10$, as in Terrell, 1996. For details see the appendix.

Definitions for Ψ are first provided in Table 2. Column wise Table 3 displays the various approaches imposing restrictions on these differently designed sets Ψ . In addition in Table 3, the symbols in parentheses indicate which shape conditions are imposed. For example, $\Psi^{CP}_i(M_p, C_p)$ implies that the estimator imposes concavity and monotonicity with respect to p , which corresponds to row (4) (for $i = 1$) and row (5) (for $i = 2$) of Table 2, which are Lebesgue measure zero because they do not expand into the dimension of y and t . Instead, if all four regularity conditions are imposed, we simplify notation to ('all') which corresponds to row (6) of Table 2. In Table 3, for each approach we display the results as applied to both point estimates, the mean of the regularity posterior distribution, and the mode. Ex post, as in Terrell, after each estimation the regularity conditions are evaluated at the smaller set Ψ^{\square}_1 and larger set Ψ^{\square}_2 as indicated in the respective rows. In particular, the smaller hypercube $\Psi^{CP}_1 = \{\mathbf{p}: \mathbf{p} \in \times_{k=1}^3 [1.0, 1.5]\}$ is defined such as it covers most but not all of the observations in the dataset, while the larger set $\Psi^{CP}_2 = \{\mathbf{p}: \mathbf{p} \in \times_{k=1}^3 [0.5, 3.0]\}$ covers all data entirely plus areas of the regressor space that are intended for subsequent policy forecasts (i.e. to introduce a tax on one of on multiple input price). Violations are expressed as the percentage of grid points where violations occur, whereby the grids are constructed as outlined in the Appendix.

Table 3: Generalized Leontief Input Demand System, estimated with 8 different approaches

Model Performance Statistics: Regularity Violations/ Fit Statistics		Estimation Approach															
		Unrestricted	Global			Local		Regional									
		1	2a		2b	3		4		5		6		7		8	
Restricted domain with shape conditions imposed in parenthesis		\emptyset ('none')	$\mathfrak{R}_+^{2+N}(C_p)$		\mathfrak{R}_+^{2+N} ('all')	Z_1 ('all')		$\Psi^{\square p}_1(M_p, C_p)$		$\Psi^{\square p}_2(M_p, C_p)$		$\Psi^{\square z}_1$ ('all')		$\Psi^{\square z}_1$ ('all')		Ψ^{string} ('all')	
evaluated at	% of shape violations at grid points	mode	mean	mode	mode(b^{gr})	mean	mode	mean	mode	mean	mode	mean	mode	mean	mode	mean	mode
Ψ^{\square}_1	C_p violations	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	M_p violations	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	C_y violations	4.0	25.1	33.4	0.0	0.0	0.0	0.0	0.0	0.0	53.0	0.0	0.0	0.0	0.0	0.0	0.0
	M_y violations	0.0	2.0	11.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Ψ^{\square}_2	C_p violations	100.0	0.0	0.0	0.0	27.1	27.1	16.1	27.0	0.0	0.0	15.2	27.0	0.0	0.0	27.4	27.4
	M_p violations	3.1	45.8	0.0	0.0	5.0	5.0	5.2	5.3	0.0	0.0	3.6	5.3	0.0	0.0	4.9	5.8
	C_y violations	31.2	33.4	25.1	0.0	32.9	32.9	34.4	33.3	29.7	50.5	1.6	33.3	0.0	0.0	0.0	32.8
	M_y violations	1.3	11.3	2.0	0.0	1.8	1.8	1.7	1.9	1.8	0.9	2.4	1.9	0.0	0.0	4.8	2.4
Generalized Variance of the Fit ¹		1.44	0.52	0.52	0.27	1.26	1.26	1.18	1.26	0.74	0.76	1.14	1.26	0.17	0.27	1.20	1.26

NOTE: 1. The model fit is calculated by *Generalized Variance of the Fit*. See e.g Barnettt (1976). Here it is defined as $100 \cdot |\Sigma|^{-1}$. The statistic is proportional to the ordinate value of the unconstrained posterior $p(\mathbf{b}|y, \mathcal{O})$ evaluated at the respective point estimate. Due to the choice of priors here it is proportional to the likelihood value of the unconstrained Maximum Normal Likelihood regression.

3.1.1 Unconstrained estimation

In the first column of Table 3 we estimate the demand system by iterated SUR unrestrictedly. Firstly, compared to any other columns, the unrestricted estimate, \mathbf{b}^u , provides the best model fit statistics but $c(z; \mathbf{b}^u)$ violates the regularity conditions *everywhere*, both in Ψ^1 and Ψ^2 leading to, among other things, a failure of the fundamental law of demand.⁹ Contemplating these poor regression results, a researcher could pursue a multitude of directions, until something more consistent is obtained, i.e. trying other functional forms or applying the data to another economic theory which might be less demanding in terms of the regularity conditions. However, if goalposts are changed in an ad hoc manner, such procedures can be rife with statistical testing and verification problems. Hence other estimation approaches leading to a well-behaved economic model are required to test this hypothesis.

3.1.2. Global Approach

The global approach to impose concavity is probably one of the most common techniques, when estimating flexible input demand systems. In the case of the Generalized Leontief, this unfortunately allows the cost function to model substitutes only (Diewert and Wales 1987). Because in the KLEM data at least energy and capital seem to have a stark complementary relationship, maintaining global concavity reduces the model fit. Moreover, the global imposition of concavity is not sufficient for *overall* regularity. In fact, all remaining conditions are violated as can be seen in column 2a. Now, applying the global approach not only to C_p but to all regularity conditions (estimated by (1) with $b_{ij}^u=0, i \neq j$) a-priori fixes the elasticity of substitution estimates to 0. Here, as displayed in column 2b, such a procedure performs very poorly in terms of model fit because this globally regular estimate \mathbf{b}^{gr} emerges from the ‘small’ parameter subset $\Theta^R | \mathfrak{R}_+^{2+N} \subset \Theta^R | \Psi$. In conclusion our empirical results indicate that the global approaches are extremely restrictive, a finding that agrees with the results in Diewert and Wales, 1987, Terrell, 1996 and the simulation study in Wolff et al. 2010.

⁹ For comparison, this estimation exactly repeats the unrestricted estimation of Diewert and Wales (1987: table II) and Terrell’s (table 3: 1996).

3.1.3 Local approach

The third column displays results from local imposition of overall regularity. As expected, here model fit is inferior when compared to the unrestricted approach, but is superior to the global approach. Unfortunately, the local approach does not guarantee that regularity is satisfied in all of the relevant empirical areas leading to very high percentages of violations at Ψ^{\square}_2 . One has to be careful, however, with the interpretation of these statistics on “percentage of violations at grid points”: On one side, violating shape conditions at 100% of the data points does not necessarily imply that the estimated model is “very far” from a good model. And on the reverse, a single violation of one grid point could lead to extremely poor results. The latter point is illustrated in Fig. 2. Also note that Ψ^{\square}_1 does not cover all the relevant data points (compare the min/max values in Table 1 and the definition of Ψ^{\square}_1 in Table 2).

Since neither the unconstrained, local nor the global approach can produce a well-behaved flexible demand system of interest, we now turn to the regional approach.

Fig 2: Illustration of an irregular cost function violating the shape restriction at one grid point

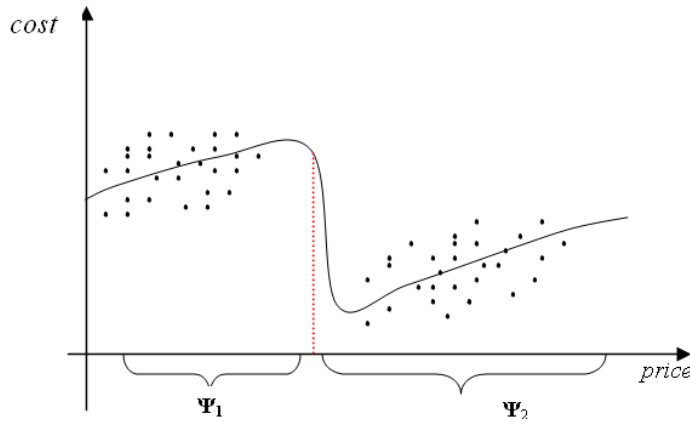


Illustration of a cost function partially regular within Ψ_1 and within Ψ_2 . The overall model is irregular on the domain $\Psi = \Psi_1 \cup \Psi_2$ although only one grid point is violated (here indicated on the domain by the dotted ray). Overall regularity is violated because cost must not decrease with rising input prices. Even in less dramatic circumstances – such as having softly oscillating functions – evaluating demand statistics at any violated grid point can lead to nonsensical results. At the non-concave areas in Fig. 1, for example, the estimated own price elasticity has the wrong sign.

3.1.4 Regional Regularity

We first replicate Terrell’s (1996) estimation, i.e. using the Gibbs accept-reject simulator and the same Ψ -sets. Terrell applied this method to impose M_p and C_p . This successfully leads to regularity preserving results if interested in the function’s domain Ψ^{\square}_1 . In contrast, on the domain Ψ^{\square}_2 , the constraints with respect to y are violated (see column 4 and 5 in Table 3).

We now turn towards the estimation method proposed in Wolff et al. (2010). This method effectively imposes all regularity conditions on any set Ψ of interest. Hence, as shown in the columns 6 and 7 regularity holds in Ψ^{\square}_1 and Ψ^{\square}_2 . We display the results for both, the mean and the mode of the posterior. In case of column 6, the mode increases the model fit (as measured by the likelihood value) by over 10% (from 1.14×10^{-2} to 1.26×10^{-2}). The percentage increase is even more dramatic in the case of imposing the regularity conditions on the larger set Ψ^{\square}_2 , in column 7, achieving an increase in model fit by 43.6% from 0.17 to 0.27.

So far, we only have described the approaches based on a convex cube Ψ^{\square} . A motivation for the KLEM data set to investigate in non-convex sets for Ψ is probably best described by Gallant and Golub, 1984: *'The exogenous variable $[p_t$ and $y_t]$ for $t = 1947, \dots, 1971$ lie in a five dimensional space and can be projected into a three dimensional space with a negligible loss of information...The projected point cloud has an irregular shape. It is a sort of a fat rope lying mostly on the ground in the shape of a tilde (\sim) with the two end-points and the middle elevated.'* This description indicates that constructing Ψ^{\square} as a convex cube including all the data points may lead to an unnecessary voluminous set containing relatively little data information. A simple construction rule of a nonconvex set containing all the KLEM data points is described in Table 2 and labelled as the 'string approach'. Comparing the regular parameter support of the string approach versus the cube approach implies that the former is a parameter superset of the latter, $\Theta^R | \Psi^{\text{string}} \supset \Theta^R | \Psi^{\square}_1$, potentially benefiting the flexibility of the functional form. Finally, note that comparing the mean of the string approach to the mode leads to an improvement of the model fit of about 5.3%.

The string approach may have potential important advantages because: (a) it represents the method which is to the largest possible extend 'data driven', (b) it leads to a well-behaved demand model and (c) with 226 regularity checks, it is computationally *much* faster than the regional regularity preserving cube method, that checks one million times.¹⁰

Summarizing Table 3, unconstrained and local regularity estimates increase the model fit in all

¹⁰ With the Q^* -grid construction approach we need about 30% of the original Q -grid computing time. In comparison the string approach estimation is faster requiring less than 0.05% of the original computing time.

specifications at the cost of violating regularity within ψ . This produces estimation results that are problematic in terms of economic interpretation and further policy analysis. Imposing regional regularity solves this problem and significantly increases the model fit when compared to the global approach. Moreover, apart from its appealing regularity preserving property, it is relevant for model fit to use the mode instead of the mean. Finally, the technique proposed by Wolff et al. (2010) reduces computing time significantly, making the regional regularity approach more tractable for empirical analysis. Instead of the full evaluation grid consisting of over one million points, only a maximum of 343900 points have to be evaluated for the cube approaches. Furthermore, for the string approach only 226 points have to be assessed. This significantly decreases the computational burden when compared to previous approaches.

We have identified tools to generate well-behaved input demand models. Initially, this may appear to be of interest to econometricians only. However, this also leads to noticeable changes in own and cross price elasticities estimates, parameters that are of interest to a wide range of applied economists. These changes are investigated in the following subsection.

3.2 Elasticities

Further insights into the effects of imposing shape restrictions can be gained by examining estimated marginal posterior distributions for input demand elasticities $\partial x_i / \partial p_j \cdot x_i / p_j$. Table 4 reports the means, modes and standard deviations of these by MHARA simulated density functions. For the purpose of analyzing the potential effects of an environmental tax on energy use, here we are interested in the capital-energy elasticity. The long-run growth potential of the manufacturing sector depends crucially on the magnitude of this parameter (see Dasgupta and Heal (1979), Chapter 6). In particular the question of whether capital and energy are complements or substitutes has received a great deal of attention (see e.g. Apostolakis 1990).¹¹

¹¹ If they are substitutes, then an increase in energy taxes would lead, *ceteris paribus*, to an increase in the capital stock, potentially benefiting the sector in the long run. In this case, energy conservation policies promoting new energy-saving physical capital would be predicted to have the desired effect. However, if they are complements, then rising energy prices would adversely effect capital formation and, hence, such policies would be counterproductive. Even without an explicit energy tax, a complementary relationship is generally more concerning to economists, in particular in the present times of high energy prices.

Table 4: Price elasticities matrices at 1947, evaluated at the mode and the mean estimate

Unrestricted SUR

mode estimates				
	K	L	E	M
K	-0.0974	0.4461	-0.1315	-0.2172
L	0.0921	-0.1774	0.0922	-0.0069
E	-0.1579	0.5362	-0.6167	0.2384
M	-0.0168	-0.0026	0.0154	0.0040
mean estimates				
K	-0.0978	0.4384	-0.1320	-0.2086
L	0.0905	-0.1909	0.0926	0.0078
E	-0.1585	0.5384	-0.6136	0.2337
M	-0.0162	0.0029	0.0151	-0.0018
std				
K	0.0625	0.1576	0.0422	0.1998
L	0.0325	0.2355	0.0402	0.2393
E	0.0507	0.2338	0.1284	0.2067
M	0.0155	0.0898	0.0133	0.0994

Local Approach

mode estimates				
	K	L	E	M
K	-0.1488	0.2897	-0.1412	0.0004
L	0.0598	-0.4092	0.0888	0.2606
E	-0.1696	0.5163	-0.6659	0.3192
M	0.0000	0.0978	0.0206	-0.1184
mean estimates				
K	-0.1485	0.2896	-0.1412	0.0002
L	0.0598	-0.4110	0.0888	0.2624
E	-0.1696	0.5160	-0.6655	0.3191
M	0.0000	0.0985	0.0206	-0.1191
std				
K	0.0492	0.1228	0.0415	0.1422
L	0.0253	0.1751	0.0392	0.1689
E	0.0498	0.2280	0.1203	0.2006
M	0.0110	0.0634	0.0129	0.0665

Global concavity

mode estimates				
	K	L	E	M
K	-0.1369	0.0685	0.0145	0.0539
L	0.0141	-0.3349	0.0569	0.2638
E	0.0174	0.3307	-0.5425	0.1943
M	0.0042	0.0990	0.0125	-0.1157
mean estimates				
K	-0.1364	0.0682	0.0145	0.0537
L	0.0141	-0.3334	0.0570	0.2624
E	0.0174	0.3311	-0.5431	0.1945
M	0.0042	0.0984	0.0126	-0.1151
std				
K	0.0502	0.0437	0.0141	0.0417
L	0.0090	0.1712	0.0289	0.1676
E	0.0169	0.1681	0.1307	0.1208
M	0.0032	0.0629	0.0078	0.0638

Regional approach on cube1

mode estimates				
	K	L	E	M
K	-0.1488	0.2897	-0.1412	0.0004
L	0.0598	-0.4092	0.0888	0.2606
E	-0.1696	0.5163	-0.6659	0.3192
M	0.0000	0.0978	0.0206	-0.1184
mean estimates				
K	-0.1672	0.2300	-0.1312	0.0683
L	0.0475	-0.3898	0.0831	0.2592
E	-0.1575	0.4830	-0.6566	0.3310
M	0.0053	0.0973	0.0214	-0.1239
std				
K	0.0468	0.1046	0.0389	0.1239
L	0.0216	0.1721	0.0339	0.1720
E	0.0467	0.1971	0.1109	0.1864
M	0.0096	0.0645	0.0120	0.0691

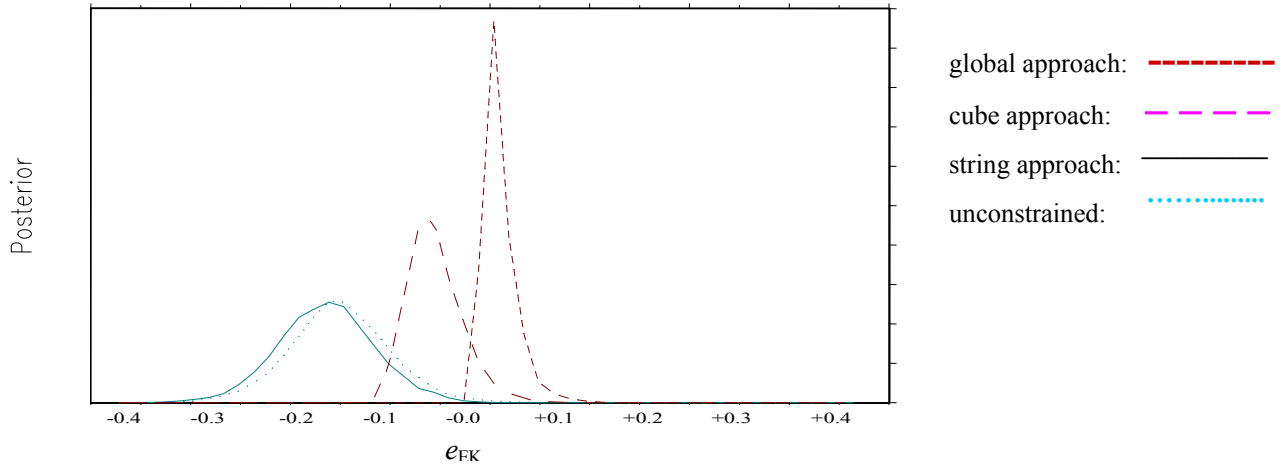
Regional approach on cube2

mode estimates				
	K	L	E	M
K	-0.1605	0.1938	-0.0585	0.0251
L	0.0400	-0.3584	0.0915	0.2268
E	-0.0703	0.5321	-0.6585	0.1966
M	0.0019	0.0851	0.0127	-0.0997
mean estimates				
K	-0.1613	0.1237	-0.0398	0.0774
L	0.0255	-0.3661	0.0691	0.2715
E	-0.0477	0.4015	-0.5641	0.2103
M	0.0060	0.1019	0.0136	-0.1214
std				
K	0.0483	0.0729	0.0228	0.0781
L	0.0151	0.1599	0.0330	0.1575
E	0.0274	0.1921	0.1100	0.1610
M	0.0061	0.0591	0.0104	0.0616

String approach

mode estimates				
	K	L	E	M
K	-0.1488	0.2897	-0.1412	0.0004
L	0.0598	-0.4092	0.0888	0.2606
E	-0.1696	0.5163	-0.6659	0.3192
M	0.0000	0.0978	0.0206	-0.1184
mean estimates				
K	-0.1474	0.2900	-0.1429	0.0004
L	0.0599	-0.4215	0.0886	0.2730
E	-0.1716	0.5153	-0.6714	0.3277
M	0.0000	0.1024	0.0211	-0.1236
std				
K	0.0475	0.1246	0.0406	0.1443
L	0.0257	0.1748	0.0397	0.1725
E	0.0487	0.2308	0.1204	0.1992
M	0.0112	0.0647	0.0129	0.0698

Fig. 3: Posterior distributions of the elasticity of substitution between energy and capital



In Fig. 3 we present the results of the cross price elasticity of energy with respect to capital e_{EK} under four different levels of constraints. The global concavity approach produces the far most right distribution having a mode value at $e_{EK} = 0.0145$ (see Table 4) suggesting that capital and energy are weak substitutes. Instead, the entirely data driven ‘unconstrained’ approach would suggest that capital and energy are complements with $e_{EK} = -0.1315$. Since the unconstrained estimate however violates duality theory, one has to be very careful with such a conclusion. The regularity preserving string approach produces the distribution only slightly to the left of the unconstrained approach with the mode at $e_{EK} = -0.1412$. Alternatively, the cube approach produces a distribution, which is likely to be biased towards zero.

Table 5: Estimated changes in capital stock in millions of U.S. dollars in manufacturing sector due to 10% increase in energy price

	year	Global concavity approach			String approach		
		(lower 5% bound)	point estimate	(upper 95% bound)	(lower 5% bound)	point estimate	(upper 95% bound)
elasticity e_{EK}		(0.00102)	0.01450	(0.04007)	(-0.20928)	-0.14120	(-0.07555)
change in capital stock	1947	(1.0)	13.5	(37.3)	(-194.8)	-131.5	(-70.3)
	2001	(45.6)	646.0	(1785.2)	(-9323.9)	-6290.7	(-3365.7)

NOTE: In the first row calculations are based on the year 1947. This represents our results comparably to the tables and figures provided in previous studies (such as Berndt and Wood (1979), Diewert and Wales (1984), Barnett et al. (1991) and Terrell (1996)). Numbers in parenthesis provide the 90% coverage probability intervals of respective changes and elasticities. Intervals are computed by using 100,000 MHARA simulator outcomes.

Table 5 illustrates the enormous consequences of using different estimators. Results using the

cross price elasticity estimate of the standard global concavity approach imply that a 10% increase in energy price leads in the U.S. manufacturing sector to a 14 million U.S. dollars *increase* in capital formation. Instead using the preferred MHARA string approach predicts a significant *decrease* of the capital stock by about 132 million dollars. The second row uses more recent 2001 data provided by the Bureau of Labor Statistics. Due to the use of the different estimators, the same calculations lead to an absolute change in capital stock of about 7 billion U.S. dollars ($= 6.3 + 0.6$). Given that in the year 2001 the total value of the capital stock in the manufacturing sector amounts to 446 billion dollars, the change of 7 billion solely due to the use of different estimators is alarming.

Two more observations are notable. Firstly, comparing the spreads of the distributions a robust pattern arises. The larger ψ , the smaller is the sample variance of the posterior distribution. Although one might be attracted by an estimator with a small variance, choosing the estimator on this basis would be very misleading. As can be seen from Table 3, the variance of the estimator is rather inversely related to the model fit statistics. For a simple proof, that expanding the regularity imposing set, *ceteris paribus*, decreases the supremum of any statistical criterion functions measuring the model fit, see Wolff et al. (2010), lemma 1.

Secondly, from Fig. 3, an apparent pattern suggests that the starker the restrictions, the greater is the difference in the relative positions between the unrestricted approach and the restricted approaches. One therefore could conclude that, the unrestricted approach might be a good ‘approximation’, since it seems to be close to the string approach. Although for many parameters this correlation seems to be holding, there exist some important exceptions destroying this analogy. For example, the own price elasticity of material of the unconstrained approach is positive (see Table 4), implying a rather perverse positive sloping demand function.

3.3 Does the KLEM data set support duality theory?

3.3.1 Testing Duality Theory using regionally regular estimators

For the KLEM data set, Section 3.1 demonstrated that regularity-imposing estimators are required to make the empirical model consistent with the assumed underlying economic theory. Forcing the data into such theoretical relationships should raise serious concerns, however, whether the empirical evidence supports the

economic theory, or if the theory should be rejected. In order to investigate this issue, a simple hypothesis test can be carried out. We test the unrestricted estimate \mathbf{b}^u (Table 3, column 1) against the hypothesis of ‘economic theory’¹². The null of ‘economic theory’ hypothesis is represented by the regionally regular estimate \mathbf{b}^r of the string approach (since \mathbf{b}^r , (column 8) satisfies all shape restrictions, the model $c(z, \mathbf{b}^r)$ is consistent with duality theory). F, Wald and Likelihood Ratio tests (with Bartlett correction) are carried out comparing \mathbf{b}^u with \mathbf{b}^r . The duality theory hypothesis is not rejected by any test at the 5% significance levels. Similarly, one may propose the test in the Bayesian framework¹³. Using the uninformative Bayes factor of 1 the posterior odd ratio in favor of the well-behaved model is 0.874 (Zellner, 1971).¹⁴ This leads to the conclusion that the KLEM data in deed might have been generated by an underlying cost function that is consistent with economic theory.

An alternative is to report the percentage of data points where regularity violations occur. This percentage, however, should not be interpreted as a test statistic. For example, despite the fact that the hypothesis tests cannot reject the regular model, our unconstrained estimate violates regularity at 100% of the data points.

3.3.2 Testing problems using standard estimators

Our empirical example demonstrates how the availability of regularity preserving techniques results in more exhaustive hypothesis testing. Assume for a moment that no regional regular estimator were available. If interested in Ψ^{\square}_2 , in the absence of regionally regular estimators the analyst must hence

¹² Here ‘economic theory’ is defined as the cost function maintaining the shape conditions of $M_{p,y}$ and $C_{p,y}$.

¹³ The Classical point estimate is exactly identical to the above defined Bayesian point estimate $\beta^{(\text{mode})}$ if, as we have done above, an uninformative prior distribution on $\Theta^R|\Psi$ is employed. The Bayesian interpretation has computational advantages because the finite sample confidence intervals and standard errors of functions of β can be directly computed with the MCMC draws. Instead deriving the Classical distributions could be tremendously challenging and in general requires more time intensive numerical procedures (like bootstrapping). The computational burden is mainly due to the many inequality constraints $\mathbf{i} \geq \mathbf{0}$ which have to hold for all $z \in \Psi$. Also since $\beta^{(\text{mode})}$ could lie on the boundary of $\Theta^R|\Psi$ further complications arise (see Geweke 1986, Andrews 1999, 2001).

¹⁴ An alternative is to report the percentage of data points where regularity violations occur. This percentage, however, should not be interpreted as a test statistic. For example, despite the fact that the hypothesis tests cannot reject the regular model, our unconstrained estimate violates regularity at 100% of the data points.

resort to using the globally regular parameter \mathbf{b}^{gr} (column 2b) to represent the null of duality theory. Testing \mathbf{b}^{u} against \mathbf{b}^{gr} however leads to over-rejection. This is due to the fact that \mathbf{b}^{gr} is a member of the much smaller subset $\Theta^{\text{R}}|\mathcal{R}_+^{2+N} \subset \Theta^{\text{R}}|\Psi$. To show this fact for the KLEM data, we repeated the above procedure (from Section 3.3.1) by testing \mathbf{b}^{u} against \mathbf{b}^{gr} . In stark contrast to the above findings, here the F, Wald and Likelihood ratio test results erroneously would lead to the conclusion that the duality theory hypothesis ought to be rejected. With only 0.189 in favor of the well-behaved model, the Bayesian posterior odd gives the same result.

In conclusion, using modern shape-imposing techniques provides evidence that the KLEM data do indeed seem to support the duality theory hypothesis. Instead, using standard econometric methods creates an unfortunate divide between the empirical model and the underlying economic theory. The regularity preserving MHARA estimator closes this gap.

4. CONCLUSION

Behavioral assumptions are often the central building blocks of many economic theories, such as the assumption of profit or utility maximization. One critical implication of these assumptions is that they manifest themselves in the form of uniquely defined ‘shape conditions’. Well-known examples are curvature and monotonicity restrictions that apply to indirect utility, expenditure, production, profit, and cost functions. Unfortunately, when using flexible functional forms, estimated functions frequently violate these regularity conditions. Clearly, such a gap between economic theory and the empirical model is problematic for the interpretability of the results, and especially worrisome if one wishes to derive forecasts or policy recommendations. In view of both, the need to produce theoretically consistent models and the empirical difficulties in implementation, Diewert and Wales (1987) observed: *One of the most vexing problems applied economists have encountered is that theoretical curvature conditions that are implied by economic theory are frequently not satisfied by the estimated cost, profit or indirect utility function.*

This paper investigates how careful estimator selection can help eliminate the wedge between the empirical model and economic theory. We illustrate the policy implications by investigating elasticities for the US demand system of the manufacturing sector. With this method we successfully produce an

empirical demand system that is entirely consistent with the underlying economic theory for a dataset that traditionally rejected economic theory. As a demonstration of its empirical relevance, we produce various sets of elasticity estimates and their respective distributions and interpret differences in the light of the new methodological advances. We find that the choice of estimators can have severe implications on the outcomes from economic policies, as displayed by the impact of an energy tax on the capital stock.

Finally we motivate a testing procedure that checks the plausibility of the assumed economic theory. Crucially, our testing technique formalizes the process of testing the validity of economic theory in empirical applications by imposing *all* shape conditions simultaneously, as opposed to previous techniques that test individual shape conditions. Enforcing all necessary shape conditions provides a test that decisively indicates whether the underlying theory is appropriate in a given setting. Applying a series of alternative shape imposing estimators reveals that the choice of estimator can have dramatic implications when determining whether to reject the underlying economic theory. We show that standard econometric applications could erroneously reject the hypothesis that the observed U.S. input data emerge from a true data generation process consistent with duality theory. Instead, using a regional regular estimator statistically supports the assumption that the KLEM data can be modelled within a system for which all regularity conditions hold.

The benefits of the technique described in this paper can be extended to other areas of economics. For example the method could be applied to the estimation of producer supply or consumer demand systems, which have multiple underlying shape conditions implied by economic theory. Equivalently, many functional relations in game theoretic, industrial organization and auction models exhibit curvature, quasi-convexity or monotonicity restrictions. It would also be interesting to compare these estimation results with the developing new techniques in nonparametric estimation that attempt to impose shape restrictions (see Matzkin 1994, Tripathi 2000, Aït-Sahalia and Duarte 2003, and Racine and Parmeter 2008). This is to be explored in future research. We hope that the methods demonstrated in this paper promote tractability and facilitate the analysis of empirical models for which consistency with an underlying economic theory is required.

APPENDIX

Estimation via numerical integration

The distribution of interest is the regularity censored likelihood or posterior $p(\boldsymbol{\beta}|\mathbf{y},\boldsymbol{\psi})$, which depends on $\boldsymbol{\psi}$.¹⁵ To generate outcomes from $p(\boldsymbol{\beta}|\mathbf{y},\boldsymbol{\psi})$ either a Gibbs sampler can be used, or based on Griffiths, O'Donnell and Tan-Cruz (2000) the Metropolis-Hastings Accept Reject Algorithm (MHARA) can be used to generate J (pseudo-) random outcomes, $\mathbf{b}^{(j)}$, $j = 1, \dots, J$ from $p(\boldsymbol{\beta}|\mathbf{y},\boldsymbol{\psi})$ on the regular support $\Theta^R|\boldsymbol{\psi} = \{\boldsymbol{\beta}: \mathbf{i}(\mathbf{p};\boldsymbol{\beta}) \geq \mathbf{0} \ \forall \mathbf{z} \in \boldsymbol{\psi}\}$. To account for the regularity condition $\mathbb{1}\{\boldsymbol{\beta} \in \Theta^R|\boldsymbol{\psi}\}$, the simulator should ensure that any drawn parameter vector $\mathbf{b}^{(j)}$ implies regularity of $\mathbf{c}(\mathbf{z};\mathbf{b}^{(j)})$ for every point \mathbf{z} in the predefined set $\boldsymbol{\psi}$, i.e. $\mathbf{b}^{(j)} \in \Theta^R|\boldsymbol{\psi} \ \forall j$. Since there are an infinite number of points in $\boldsymbol{\psi}$, they cannot all be checked explicitly. The connectedness is approximated by a fine grid, denoted by the disconnected set $\boldsymbol{\psi}_g \subset \boldsymbol{\psi}$. Within the Gibbs or Metropolis Hastings chain an additional Accept-Reject algorithm is implemented to guarantee that $\forall \mathbf{b}^{(j)}$ the regularity conditions hold for any single grid point. This implies that $\mathbf{b}^{(j)} \in \Theta^R|\boldsymbol{\psi}_g \ \forall j$, whereby $\Theta^R|\boldsymbol{\psi}_g$ is the *approximated* regularity likelihood (or—in the Bayesian context—posterior) support, which will tend toward the actual set $\Theta^R|\boldsymbol{\psi}$ the finer the approximation grid $\boldsymbol{\psi}_g$.

Approximating $\boldsymbol{\psi}$

In the simplest setting, $\boldsymbol{\psi}^\square$ is a hypercube (the superscript \square refers to the cube approach): Let $z_i(\boldsymbol{\psi}_{\min})$ and $z_i(\boldsymbol{\psi}_{\max})$ represent the minimum and maximum of the i -th right hand side variable. The grid is constructed by selecting $F = 10$ equidistant values for each variable: $z_i^f = z_i(\boldsymbol{\psi}_{\min}) + (f-1)F^{-1}(z_i(\boldsymbol{\psi}_{\max}) - z_i(\boldsymbol{\psi}_{\min})) \ \forall f \in \{1, 2, \dots, F\}$ and using all possible $Q = 10^6 = F^{\dim(\mathbf{z})}$ combinations to generate the Q -grid $\boldsymbol{\psi}_g^\square \subset \boldsymbol{\psi}^\square$. In order to circumvent the approximate nature of this representation, Wolff *et al.* 2010 identified conditions under which checking a certain key point in $\boldsymbol{\psi}^\square$ guarantees regularity in well defined neighborhood. The purpose is then to

¹⁵ Let Θ be the K -dimensional parameter space. If all regularity conditions hold for all values of \mathbf{z} in $\boldsymbol{\psi}$, the regular parameter set is defined as $\Theta^R|\boldsymbol{\psi} = \{\boldsymbol{\beta} \in \Theta: \mathbf{i}(\mathbf{p};\boldsymbol{\beta}) \geq \mathbf{0} \ \forall \mathbf{z} \in \boldsymbol{\psi}\}$, hence $\Theta^R|\boldsymbol{\psi}$ is dependent on the choice of $\boldsymbol{\psi}$. The marginal prior on $\boldsymbol{\beta}$ is specified as an indicator function $p(\boldsymbol{\beta}|\boldsymbol{\psi}) = \mathbb{1}\{\boldsymbol{\beta} \in \Theta^R|\boldsymbol{\psi}\}$ where the prior equals 1 if regularity holds at the value $\boldsymbol{\beta} \ \forall \mathbf{z} \in \boldsymbol{\psi}$, and equals 0 otherwise. Throughout the paper we assume the standard ignorance prior for the $N \times N$ covariance matrix $|\boldsymbol{\Sigma}|^{-(N+1)/2}$. The posterior distribution for $\boldsymbol{\beta}$ is then derived by applying Bayes rule, $p(\boldsymbol{\beta}|\mathbf{y},\boldsymbol{\psi}) \propto [L(\boldsymbol{\beta},\boldsymbol{\Sigma}|\mathbf{y}) \cdot \mathbb{1}\{\boldsymbol{\beta} \in \Theta^R|\boldsymbol{\psi}\} \cdot |\boldsymbol{\Sigma}|^{-(N+1)/2}] d\boldsymbol{\Sigma}$, where $L(\boldsymbol{\beta},\boldsymbol{\Sigma}|\mathbf{y})$ is the normal likelihood function.

find a collection of such key points that guarantees overall regularity $\forall \mathbf{z} \in \Psi^{\square}$. These procedures lead to a reduction in regularity checks to a total of $Q^* = 343900 < Q = 10^6$. Notably, the new Q^* -grid, while improving the computational speed of the algorithm, maintains the same accuracy of approximation obtained from the original Q -grid.

This reduction of regularity checks can be further improved by constructing nonconvex sets: with $T = 25$ observations and, for example, if the number of out of sample forecasts $S=10$, the number of regularity checks is reduced to occur, at $316 = 1+(F-1)(T+S)$ grid points only in the string approach.

Point estimates and the relation to Maximum Simulated Normal Likelihood

As far as we are aware, most studies had defined the point estimate as the mean $E[\boldsymbol{\beta}]$ of the regularity posterior $p(\boldsymbol{\beta}|\mathbf{y},\boldsymbol{\Psi})$. This may result in regularity violations because in general $\Theta^R|\boldsymbol{\Psi}$ is not a convex set. Instead using the mode $\boldsymbol{\beta}^{(\text{mode})} = \arg \max_{\boldsymbol{\beta} \in \Theta^R|\boldsymbol{\Psi}_g} \{p(\boldsymbol{\beta} | \mathbf{y}, \boldsymbol{\Psi}_g)\}$ guarantees that the point estimate resides in the regular support $\Theta^R|\boldsymbol{\Psi}$. In order to approximate the solution based upon the MCMC outcomes $\{\mathbf{b}^{(j)}\}_{j=1}^J$, one can simply compare the values $p_u(\mathbf{b}^{(j)}|\mathbf{y}) \forall j$ resulting from the MHARA as $\mathbf{b}^{(\text{mode})} = \underset{\mathbf{b}^{(j)}}{\operatorname{argmax}} \left\{ |(N-L)\boldsymbol{\Sigma}(\mathbf{b}^{(j)})|^{-N/2} \right\}$. This point estimate is used in our application in case of the mode estimate. The proposed technique can be applied to the Bayesian and to the Classical frameworks. In the Classical framework one would maximize a likelihood function subject to the inequality constraints and the numerical point estimate of the maximum simulated likelihood is the mode. This Classical mode is exactly identical to the above defined Bayesian point estimate $\boldsymbol{\beta}^{(\text{mode})}$ if, as we have done above, an uninformative prior distribution on $\Theta^R|\boldsymbol{\Psi}$ is employed.

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