Structural change and demand analysis: 
a cursory review*

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Summary

We address the issue of structural change in demand analysis. After a brief discussion of the major problems and questions that arise in this context, the main body of the paper is devoted to a review of analytical methods that are relevant to investigating structural change in demand. This survey is organised within the broad categories of 'nonparametric' and 'parametric' methods. Along with the main theoretical contributions, we try to cover a rather large body of applied studies. We strive to offer a critical and unified treatment of this assorted set of contributions, stressing the pros and cons of alternative approaches and methods.

Keywords: demand models, flexible functional forms, nonparametric demand analysis, structural change tests.

1. Introduction

'Economists have traditionally been suspicious of changing tastes, and a profession's intellectual tastes change slowly'. (Robert A. Pollak, 1978)

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The discipline of economics has long endeavoured to be considered a science, but this aspiration often appears frustrated by a fundamental feature of economics as a social science, which sets it apart from physical and natural sciences. The laws of nature that are studied in physics today are arguably the same as those studied by Galileo, and this fact has allowed physicists to amass an impressive amount of knowledge. In economics, however, because it is human behaviour within social institutions that is studied, the 'world' that economists analyse is constantly changing. For example, production decisions rely on ever-changing techniques employing an increasing variety of constantly improved inputs; consumption choices span an increasing variety of goods and are carried out by a demographically and culturally changing population; the ability of economic agents and markets to deal with fundamental uncertainties of the economic system is constantly improved by the emergence of new institutions; and so on. The possibility that the very structure that generates economic data may be changing poses serious problems that lie at the heart of the empirical economist's quest. How and what do we learn from empirical analysis if we are in the presence of such 'structural' changes?

Of course, one could quibble with our opening remarks. Some, like McCloskey (1983), would argue that economics is best interpreted as a rhetorical discipline rather than a 'scientific' enterprise. Others, perhaps more to the point, could question the implicit assumption that empirical economics only learns from observing the real world (a presumption of much of econometric theory), and not by running controlled experiments. An in-depth analysis of these and related concepts is not attempted here. Our aim is simply to review analytical methods that are relevant to investigating structural change in demand analysis. We open with a brief discussion of the main structural change issues that arise in empirical demand studies. The survey of methods that follows is organised under the broad categories of 'nonparametric' and 'parametric' methods. Along with a reference to the main theoretical contributions, we try to cover the rather large body of applied studies that pertain to our topic. In doing so, we are mindful of the subjective bias and unintended omissions that an exercise like this inevitably entails. The hope is that these limitations will not reduce the usefulness of our review for the applied researcher.

2. Structural change in demand models

In order to delimit somewhat the scope of this review, it is important to define what is meant by 'structural change' in demand. Arguing for the likelihood that economic data typically used by most practitioners may not have been generated by a constant structure depends, of course, on a somewhat narrow definition of what is the relevant economic structure. The
relevant structure should be that implied by theory, but this characterisation
is not conclusive because economic theories are, by necessity, simplifications.
For example, and with a notation that suits the demand focus of what
follows, a theory may characterise a variable \( q \) in terms of a set of variables
\( p \) by the function \( q = f(p) \) while, at the same time, it may be known that a
more general characterisation involves another set of variables \( z \) as in the
function \( q = F(p, z) \). However, explicit modelling of the effects of the variables
in \( z \) may not be essential because they are only marginally interesting, or
quantitatively unimportant, or quite simply unobservable (at least to the
analyst). Under some plausible conditions, the effect of \( z \) can be subsumed
in the function \( f(p) \), which can serve well as a 'theoretical' relation, but in
other cases, say associated with considerable changes in \( z \), the concise
theoretical relation \( q = f(p) \) will also change. From the point of view of the
theory that explains \( q \) in terms of \( p \) alone, we would say that we are in the
presence of a structural change.¹

In demand analysis, the focus of this paper, \( q \) typically represents the per
capita aggregate consumption of one or more goods, and \( p \) is a vector of
prices deflated by per capita income. Abstracting from considerations of
exactly which quantities and which relative prices are explicitly considered,
\( f(p) \) can then represent a market demand model such as those in a great
many studies using time series data. In some cases, however, another set of
variables \( z \) may turn out to be important in explaining demand behaviour.
For example, \( z \) may include important demographic variables, or condition-
ing variables such as advertising, or a state variable capturing systematically
evolving preferences. The existence of structural change has important impli-
cations for demand analysis, generally affecting a variety of welfare and
policy evaluations that depend on elasticities and other estimates typically
of interest in empirical demand models.

In demand analysis, hypotheses of structural change are often framed in
terms of 'changing tastes and preferences', although different studies and
analysts may have different notions of what that means. In some cases, one
thinks of changes in the shape of individual utility functions of a stable
population of consumers, as brought about by health concerns and attention
to quality, possibly related to new information and improved scientific
knowledge. In others, one may think of a changing demographic composition
of a heterogeneous collection of consumers who have different preferences.
Alternatively, one may postulate changes in the preferences individuals
display, induced by firm strategies such as advertising and product innova-
tion. Alternatively, individual choices may be based upon their basic charac-
teristics (Lancaster, 1966 and 1991), and if the content of those characteristics
changes over time, individual preferences for goods may be affected. Whereas
the differences in these examples may call into question the loose character
of the notion of 'changing tastes and preferences', from an operational point
of view it is sufficient to realise that they can all be modelled under a general framework such as the one outlined above.

The possibility of variable preferences was considered earlier by Basmann (1956), who postulated that demand models derive from a utility function expressed as $u = u(q, z)$, where $q$ represents the consumption vector and $z$ represents any other variable affecting preferences over bundles of goods. In such a setting, the substitution effects between goods are clearly affected by the variables $z$. The notion that preferences underlying demand models may change over time has found its critics. For example, Stigler and Becker (1977) have argued that various phenomena that may indicate a change in tastes can otherwise be explained by stable preferences; often a change in preferences is invoked to justify the inappropriateness of some economic models in interpreting observed data. Others have questioned such a position (see Pollak, 1978), and considered changes in consumer preferences, both exogenous and endogenous, as an important aspect of demand analysis and empirical work (Pollak, 1976 and 1977).

Viewed in the light of our earlier discussion, however, much of the debate on whether it is acceptable and/or useful to postulate structural change in demand analysis is a matter of semantics, and depends on whether one thinks in terms of $q = f(p)$ or views the problem from the more general relationship $q = F(p, z)$.

From an operational point of view, more pressing issues are: (i) to determine when a model of the $q = f(p)$ type is appropriate and when a more general model is warranted; (ii) to find which model, among the many possible extensions of the $q = F(p, z)$ type, may be more appropriate; and (iii) to tie the selected empirical model to a theoretical framework so that a consistent interpretation of empirical findings may be possible. Many procedures are available to deal with these specification problems. Although these may already be familiar in some other fields of economic analysis, we will review many of them here in the light of their application to demand analysis.

### 3. The nonparametric approach

There are two basic ways of characterising consumer demand. Classical demand theory, moving from basic rationality axioms, assumes that consumers have preferences over goods which are described by a utility function. Demand behaviour is then seen as the result of the consumer maximising her utility (subject to a budget constraint). Alternatively, revealed-preference theory takes individual choices as primitive elements, and sets forth restrictions on these choices that parallel the rationality axioms of classical demand theory. Although much of the intellectual appeal of revealed preferences derives from the fact that it frees demand theory from the burden of a 'utility function', what is being exploited in modern nonparametric demand analysis
is, in fact, the equivalence of the restrictions that revealed preferences and utility maximisation impose on a finite set of observed consumer choices. Following the seminal contributions of Afriat (1967, 1973), Varian (1982, 1983) developed a series of operational procedures to check the consistency of a body of data with the theoretical properties of revealed preferences and/or utility maximisation. Specifically, these procedures entail testing for consistency of the data with the weak, strong or generalised axioms of revealed preference (WARP, SARP and GARP, respectively). Failure to meet requirements for these axioms may be interpreted as an indication of structural change in demand: if we maintain that consumers are, in fact, maximising utility, then a change in the structure of preferences could account for the observed violations.

To illustrate briefly the consistency implications of revealed preferences, using Varian's notation (Varian, 1992), WARP requires that if \( q^i R^D q^j \), then it is not the case that \( q^i R^D q^i \), where \( R^D \) denotes the directly revealed preference relation, and \( q^i \) and \( q^j \) are any two observed consumption vectors. Testing for consistency of the data with WARP requires searching for violations in pairwise comparisons; a violation is found when both \( C_{ij} > C_{ij} \) and \( C_{ji} > C_{ji} \), where \( C_{ij} \) indicates the expenditure with prices in time \( i \) of the bundle chosen in time \( j \), and \( C_{ii} > C_{ij} \) is equivalent to \( q^i R^D q^j \). A more stringent test for consistency requires ruling out intransitivities, i.e. checking the consistency of the data with SARP. This axiom requires that if \( q^i R q^j \), then it is not the case that \( q^i R q^i \), where \( R \) is the transitive closure of the relation \( R^D \). Applications of revealed preference procedures to test structural change in demand data include Landsburg (1981), Thurman (1987), Chalfant and Alston (1988), Burton and Young (1991), Sakong and Hayes (1993), and Dono and Thompson (1994).

The most important feature of this approach is that it allows one to draw inferences on the nature of a particular data set without making assumptions about the functional form of demand functions. This clearly eliminates one source of arbitrariness present in parametric procedures (see below). Unfortunately, the nonparametric approach has shortcomings of its own that make the interpretation of findings from such an approach somewhat difficult. One of the major concerns is the power and size of such tests, especially in view of their 'exact' nature [the fact that these tests are non-statistical (Epstein and Yatchew, 1985)].

3.1. Power and size of nonparametric tests

Under the view that nonparametric tests are exact, their size is zero; thus, even a single violation should be enough to invalidate the maintained hypothesis. Hence, in this setting, the only admissible concern is the power of such tests. In our case, the power of a nonparametric test relates to its capability of detecting violations of consistency when, in fact, there is
structural change. There are legitimate reasons for believing that such a power may not be great. For example, Chalfant and Alston's (1988) results based on a quarterly Australian data set, imply, among other things, the absence of seasonality in consumption, although seasonality is a fairly accepted feature of quarterly meat demand. The failure to detect at least some seasonality may lend support to Varian's (1982) and Landsburg's (1981) observation that nonparametric tests based on revealed preferences are likely to have little power with aggregate time series consumption data. This may be due to the fact that, as initially pointed out by Varian (1982), when income (or expenditure) growth is large compared to changes in relative prices, then it may be difficult to find comparable points: at the limit, every observed bundle is revealed preferred to all the previous ones, and there is no possibility of finding any violation, even if a strong shift in preferences may have occurred.9

A possible solution to this problem is that of adjusting the data. Ideally, in such cases, one would like to work with income-compensated demand bundles, but unfortunately they are not observable. Chalfant and Alston (1988) try to recover them by adjusting their data for expenditure growth under the assumption that all expenditure elasticities are equal to one. Clearly, such a procedure is admissible only when preferences are homothetic, a hypothesis that is systematically rejected by virtually any data set. Sakong and Hayes (1993), extending Chavas and Cox's (1990) linear programming technique to consumer demand analysis, adjust their data in a way that allows for non-unitary income elasticities. However, this approach essentially recovers Hicksian demand by a first-order approximation and, strictly speaking, there are no theoretical restrictions one should expect to be satisfied by such adjusted data. The bottom line is that compensated demands cannot be recovered from observed Marshallian consumption bundles unless one resorts to functional form assumptions of a nature typical of parametric models, thereby undermining the main distinguishing feature of nonparametric analysis.

An alternative tactic is to relax the 'exact' view of nonparametric tests. The proposed solution is to postulate that observed consumption patterns are measured with error. As it stands, this has to do both with the power and the size of the test. The approach is described in Varian (1985) and, in its original form, it is basically related to the size of the test: the idea is to minimise a 'distance' function of the observed data from the closest point that satisfies the null hypothesis.10 As common in the parametric approach, it is assumed that observed quantities are random variables, and acceptance (rejection) of the null hypothesis may simply be due to the impossibility of observing 'true' quantities.11 Thus data may be perturbed in order to eliminate (or induce) violations of consistency with revealed preference axioms, and some measure of this adjustment gives the level of significance of the nonparametric test.
3.2. **Limitations of the nonparametric approach**

The appealing features of the nonparametric approach, and its extension to testing for structural change, are challenged by the issues of power and size of these tests. The proposed solutions are not completely satisfactory. For instance, an example in Gross (1991) strongly undermines the usual test of WARP. Using a Cobb–Douglas utility function with two goods, he shows that a very large shift in preferences between two points, combined with no change in expenditure and a small change in prices, produces a small violation of WARP when measured in terms of $C_{ij}$. In particular, a slight modification of the example shows that, under large preference change, a small change in income (of less than 1 per cent) will make it impossible to detect the preference shift. Thus, simply showing that postulating a small measurement error can restore theoretical consistency in observed quantities has the potential of being quite misleading.

Gross (1991) proposed to test for consistency of the data by using the money metric utility or the direct compensation function, instead of the expenditure index (i.e. testing for WARP), by extending an idea of Varian (1990): under the assumption that preferences are stable, the direct compensation function provides a measure of the minimum expenditure at time $j$, given that preferences are unchanged with respect to time $i$, and that the individual is willing to attain the level of utility that his/her observed bundle would provide. Thus, if preferences are unchanged and the individual is maximising utility, the minimum expenditure will be the same as the actual expenditure. If preferences are unstable, then the difference between minimum and actual expenditures gives an indication of the hypothetical waste in expenditure when maximising utility in time $j$ with preferences of time $i$: the larger the difference, the more serious the shift in preferences between the two periods. Although, in principle, the adoption of the direct compensation function can increase the power of the test, its computation requires knowledge of the particular structure of preferences. However, that is typically not known, and use of the approximations of the direct compensation function discussed by Varian (1982) does not necessarily improve the power of the test.

Some final points should be kept in mind in evaluating the ability of these procedures to detect structural change. First, insofar as applications pertain to a subset of the goods comprising consumer's choice (say, three or four meat goods), there are virtually no restrictions that one can place on such a subset of data, unless the assumption of separability is invoked. Varian (1988) concludes that consistency of observed data must be interpreted only '... as tests for separability of the observed choices from other variables in the utility function rather than as a test of maximisation per se'. Hence, nonparametric tests on subsets of data are conditional on a correct assumption of separability. Put another way, the null hypothesis of a consistency
check is composite, and the problem remains of how to interpret consistency. To be sure, this is a specification problem that affects parametric and nonparametric applications alike. Still, it should suggest more caution in claiming that structural change has not occurred when the analysis is based on a handful of goods only. Second, the whole revealed theory apparatus pertains to one individual’s choices, but empirical applications typically rely on aggregate (market) data. The validity of this procedure would seem to depend on the exact aggregation conditions to be satisfied. Such conditions are known to be rather stringent (Deaton and Muellbauer, 1980a: Chapt. 6), but they are typically ignored in empirical applications of nonparametric methods.

4. The parametric approach

In this approach an explicit model to represent demand functions is specified, either directly or in terms of a primitive utility (direct or indirect) or expenditure function. Relative to the nonparametric approach just described, the analyst is required to make an assumption about the functional form relating the variables of interest. Whereas this concession to arbitrariness may be deemed undesirable, there is really no particular novelty here, as this step is required in virtually every econometric application. It is common to try and ensure that the arbitrariness of this step does not prejudge important aspects of the analysis by choosing a ‘general enough’ specification (see below). Having chosen a functional representation of preferences, there are at least three alternative (but related) ways of examining structural change issues: consistency analysis, parameter instability analysis and explicit modelling of structural change by a trend or other economic variables.

4.1. Consistency analysis

Given the chosen functional representation of preferences, the analysis could proceed as in the nonparametric approach. Specifically, one could test whether a body of data satisfies the theoretical restrictions of demand theory, such as homogeneity of degree zero in prices and income, and symmetry and negative semidefiniteness of the matrix of Slutsky substitution terms. Testing for these properties is, indeed, the parametric counterpart of checking the satisfaction of WARP, SARP, or GARP. This set of equivalences has been made explicit in the work of Kihlstrom et al. (1976), Hildenbrand and Jerison (1989) and John (1995), who show the relation between WARP and homogeneity, and the equivalence between a weaker version of WARP and the semidefinite negativeness (but not the symmetry) of the Slutsky substitution matrix. The relation of the nonparametric approach with integrability
of demand functions is also reviewed in Mas-Colell (1978), and related developments can be found in Chiappori and Rochet (1987).

Curiously, although the relationship between common nonparametric consistency checks and tests of homogeneity, symmetry, and negativity is obvious, few studies seem to have taken that approach. Perhaps it is due to the recognition that other sources of misspecification can affect the outcome of such tests, including separability assumptions, aggregation conditions, omitted variables, distributional assumptions, and functional form choice.\(^\text{16}\)

Although true, it is important to emphasise that all these limitations (with the exception of the functional form selection) also affect the nonparametric procedures described above. Perhaps more important, the fact that the parametric approach has followed other routes may be due to the relative richness of options that it offers. Thus, analysts have typically preferred to maintain the theoretical properties of demand theory as much as possible, and look for evidence of structural change in other ways.\(^\text{17}\)

4.2. Tests of parameter stability

A more common approach to detecting structural change originates from the observation that such changes will alter parameter values, given an unchanged functional form. Thus, testing for parameter instability has been a common way to test for structural change. Tests that can be used include the classical Chow test (Chow, 1960; Fisher, 1970) and the CUSUM test (Brown et al., 1975), with their modifications and generalisations (Dufour, 1982; Davidson and MacKinnon, 1993: Chapt. 11), the Farley-Hinich test (Farley and Hinich, 1970; Farley et al., 1975), the fluctuation test (Ploberger et al., 1989) and other tests (Andrews, 1993). Applications in demand analysis include Moschini and Meilke (1984), Martin and Porter (1985), Atkins et al. (1989), Chang and Kinnucan (1991), and Chen and Veeman (1991).

The relevant issues here are the size and power of the proposed tests. The size of the test is crucial, because the null hypothesis that we are typically testing is actually a set of hypotheses that are best grouped generically as a null hypothesis for misspecification (type-I errors). Again, the main problem is that parameter instability may arise from different sources, with structural change being only one of the possibilities. Hence, these tests are properly interpreted as tests for misspecification arising from any source of invalid conditioning. The problem has been widely recognised in the econometric literature, and it has received a great deal of attention in applied demand analysis (see Alston and Chalfant, 1991).

As for power, the performance of the tests for parameter instability proposed in literature often depends on the nature of the alternative hypothesis.\(^\text{18}\) Testing the null hypothesis that a parameter vector is stable over the sample period implies a comparison with an alternative hypothesis that can take different forms, like a one-time 'structural' change, with a known or
unknown change point, or smooth patterns of change, or other cases where no information is available on the timing of structural change (see Andrews, 1993). Thus, the particular nature of the structural change may be important, and therefore it is convenient to resort to tests that have high power against different alternatives of structural change: a priori information may be useful in choosing the appropriate test.\textsuperscript{19}

4.3. Explicit modelling of structural change

A related procedure consists of explicitly modelling the effect of structural change by introducing, in the estimating model, variables indexing taste shifters. The simplest version of this approach is to include a time trend or a (set of) dummy variable(s). One basic application of this approach is the use of dummy variables to account for seasonality in consumption when using frequent time series data (say, quarterly). Alternatively, under the assumption that preferences have changed smoothly over the observation period, a trend variable can provide a useful proxy for these effects, and following Stone (1954), Deaton (1975), and Jorgenson and Lau (1975), this approach has been adopted in a number of studies. Furthermore, a distinction can be made between systematic and random variations in parameters: systematic variations imply that a certain deterministic pattern of change for the parameter vector can be modelled, even the most general, while stochastic variations allow for a more flexible specification of the pattern of change.\textsuperscript{20} The statistical problem then reduces to that of the significance of the added variable(s). The relationship with parameter instability tests is obvious. For example, one can restate the Chow tests in terms of the significance of a set of dummy variables. Thus, our econometric discussion of parameter instability tests applies here as well.

Of course, modelling structural change by a time trend is a somewhat unpleasing shortcut, and the use of such a trend is often interpreted as an admission of ignorance of the true form of structural change. The alternative is to be more specific about what sort of structural change one has in mind, and model it accordingly. For example, under the assumption that US consumers' egg preferences were changing due to an increased concern about the health hazards of large intakes of cholesterol and saturated fats, Brown and Schrader (1990) constructed a 'cholesterol information index' from the number of articles in medical journals linking cholesterol in diet to heart disease. Whereas, in principle, this approach is attractive, it still involves rather arbitrary choices,\textsuperscript{21} or may turn out to be econometrically equivalent to a trend (for example, the correlation coefficient between Brown and Schrader's cholesterol index and a linear time trend is 0.986).

In some cases, direct modelling of preference shifters is clearly the preferred alternative, especially when dealing with issues of demographic or dynamic effects in demand. That individuals may have different preferences (and
therefore demands) is widely accepted. This diversity is supported by a number of cross-sectional studies showing the significance of demographic effects (such as household size, age of household members, region of residence, employment status, and others) in demand models. Insofar as relevant demographic variables change over time, market demand functions typically investigated in demand studies using time series will be affected and may display structural change.

Similarly, the importance of dynamic components in aggregate demand has long been recognised. One explanation for such dynamics postulates that individuals' consumption is sluggish due to their dependence on a state variable that can be interpreted as a 'stock of habits' (Houthakker and Taylor, 1970; Pollak, 1970). This 'habit formation' hypothesis is usually implemented in demand models by specifying preferences as depending on past consumption levels. The econometric problem of testing for this specific instance of structural change then reduces to that of the significance of the added lagged consumption variable(s). Alternatively, as in Anderson and Blundell (1983), one can evaluate how accounting for dynamics affects consistency tests (homogeneity and symmetry). Of course, dynamic considerations can be nested in other structural change issues. For example, one could consider testing for parameter instability within a dynamic model (Krämer et al., 1988).

Other variables that may play an important role at one time or another in explaining consumption are advertising, product innovation, quality, information and environmental changes, and many studies have tried to account for these effects in demand systems. However, some of them are measured (or proxied) by variables that display a strong time trend, especially when some index is used; thus, their effect is almost indistinguishable from a trend, and the interpretation of results from this model may still be misleading in attributing a role for some effects (see above).

### 4.4. The issue of functional form

Consistency, parameter instability and explicit modelling of structural change are all concerned with the issue of model specification. As such, they address the basic problem of structural change, which relates to both the parametric and nonparametric methods we have discussed. On the other hand, the parametric approach requires a few additional assumptions, which exposes it to some additional problems. First, one often needs to make a prior choice of endogeneity and/or exogeneity of prices, quantities and income in standard demand studies. Overlooking the endogeneity of some variables has the potential of introducing considerable biases in inference (LaFrance, 1991). Whereas preliminary tests may help in adopting a correct specification, it is clear that wrong assumptions may lead to spurious identification of structural change (Wahl and Hayes, 1990; Eales and Unnevehr,
For instance, structural change in supply, such as technological change, can appear as a demand shift. However, the most obvious shortcoming of parametric relative to nonparametric methods is that one typically needs to assume a specific functional form. Hence, inference in parametric models is usually conditional on the choice of the functional form. This has led to considerable controversy over the analysis of structural change with parametric models, typically centring on the interpretation of the results and questioning the possibility of ever concluding anything useful from a parametric analysis of structural change (Alston and Chalfant, 1991).

One can try to take some precautions against the limitations of an arbitrary functional form by selecting a sufficiently general functional form. For example, in a single equation framework, Moschini and Meilke (1984) and Martin and Porter (1985) test for structural change in flexible parameterisations based on the Box–Cox transformation. More generally, in a system's framework, it has become common to rely on the concept of flexible functional forms (FFFs), pioneered by Diewert (1971, 1974) and by Christensen et al. (1971), which centre on the approximation properties of a Taylor series expansion of the unknown true function. Systems of equations commonly used in demand analysis, such as the translog (Christensen et al., 1975), the almost ideal (Deaton and Muellbauer, 1980b), and the normalised quadratic (Diewert and Wales, 1988) satisfy this notion of flexibility; another commonly used system, the Rotterdam model (Barten, 1966; Theil, 1975 and 1976), satisfies an equivalent definition of flexibility.

Whereas this notion of flexibility is useful, it does not eliminate the arbitrariness of the functional form chosen. FFFs provide an accurate approximation only at a point, but not much can be said about their approximation properties away from that point; thus, Diewert's notion of flexibility is not sufficient to ensure that these second-order forms can approximate the underlying (true) function over the entire region of the price-income space. Therefore, if the approximation properties are only valid around part of a point, and there is great variability in the price-income space over the sample, then parameter instability can be detected. Because of this, it has long been recognised that estimation and hypothesis testing are sensitive to this choice (Gallant, 1981). The open issue, specifically in testing for structural change, concerns the extent of this sensitivity. In particular, work by Alston and Chalfant (1991) has shown that the performance of the test statistic for structural change can be heavily affected by the choice of the functional form. Specifically, in a simulation setting where the true function is known by construction, it is shown that the adoption of an incorrect functional form enormously increases the proportion of rejections of the (true) null hypothesis of stable preferences.

The point of Alston and Chalfant (1991) is well taken, but the results they actually present are too extreme and pessimistic because their Monte Carlo simulations do not account for the (arbitrary) choice of the signal-to-noise
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ratio (which turns out to be important when the explanatory variables are trended). To illustrate, consider their experiment using the General Electric (GE) data reported in Theil (1971: 296), which shows that when the data are generated by a linear model without structural change, a Chow test for structural change at the 5 per cent significance level will give the wrong answer 100 per cent of the time if carried out with the wrong functional form (double-log, semi-log, or square root functions). Crucial to this finding, however, is the fact that simulated samples are obtained by adding random terms with mean zero and unit variance, but a variance of one, given the design matrix at hand, corresponds to a population $R^2$ in excess of 0.999. Because a perfect fit is rarely a feature of typical empirical problems, it may be of interest to consider the same experiment with a more reasonable assumption on the error term. For example, one can repeat the experiment by fixing the variance at the level required to replicate the $R^2$ obtained by fitting the linear model with the GE data (which, by assumption, is the ‘true’ model), i.e., $R^2 = 0.705$. The results in this case are quite different: the wrong rejection of the hypothesis of no structural change (at the 5 per cent level) falls from 100 per cent to, respectively, 21 per cent (semi-log), 23 per cent (double-log), and 11 per cent (square root). It is clear that the fraction of wrong rejections of the true hypothesis of no structural change is dramatically affected by the signal-to-noise assumption, although for incorrect functions it is still greater than the nominal size.

In order to reduce the potential bias of the arbitrary choice of a functional form, one can test the validity of the maintained form, say by using Ramsey’s (1969) RESET test and its generalisations (Davidson and MacKinnon, 1993: Chapt. 6). An alternative strategy is that of specifying larger models that can encompass different functional specifications: structural change tests conducted on these larger specifications should reduce the initial conditioning. Along the same line is the idea of reducing misspecification effects by comparing and selecting different models. FFFs can be compared, but usually these models are not nested, and hence this strategy requires the use of appropriate procedures to test non-nested models.\(^{28}\)

5. The ‘econometric’ nonparametric approach

Whereas FFFs can offer a workable solution to the arbitrariness of specifying an explicit parametric model, and have become widely adopted in empirical applications, it is apparent from the foregoing that their use has come under some rightful criticism. In particular, because most FFFs are essentially Taylor series expansions of the unknown true function, these forms have the undesirable feature that their approximation properties are invariant to the sample size. An improved approximation was obtained by Gallant (1981) by adding trigonometric terms to the leading terms of a Taylor series

\(^{28}\)
expansion, which produces the Fourier functional form. The increased flexibility of this approach hinges on the requirement that the number of trigonometric terms tends to infinity as the sample size grows. An alternative approximation strategy relies on the use of nonparametric methods. Here, the term 'nonparametric' applies to the statistical method of density estimation (Silverman, 1986). Using this approach, one can estimate the regression function, or other function of interest, without making any parametric assumption about the true functional form (Hardle, 1990; Ullah, 1988). A parametric form can sometimes be retained for a portion of the model, and this leads to semiparametric specifications (Robinson, 1988).

Applications of these nonparametric methods in the study of structural change issues are clearly possible. The simplest application, again, would be to test for the consistency of a body of data with the properties of demand theory. For example, one could test the homogeneity property following the procedure used by Moschini (1990) to test for constant returns to scale. One could also test symmetry along the lines discussed by Stoker (1989). Alternatively, one could use the nonparametric approach to test for the significance of added variables meant to index structural change. Particularly useful here may be Robinson's semiparametric approach, as applied, for example, by Moschini (1991).

A distinctive feature of the nonparametric approach based on density estimation, as compared with other nonparametric methods discussed earlier, is that it has a solid statistical foundation which is appealing for empirical applications requiring formal tests of hypotheses. In a sense, therefore, nonparametric estimation of the regression function represents the obvious evolution of the framework of analysis based on parametric flexible functional forms. The main advantage is that it allows econometric modelling and hypothesis testing that do not depend on arbitrary (and possibly restrictive) parametric assumptions. However, there are also a number of limitations to this approach. For example, an important issue at the application stage is the choice of smoothing parameter (window width). This is crucial to estimation results as it corresponds to a sort of implicit parameterisation. Unfortunately, there is no widely accepted method for the choice of window width, and this introduces an element of arbitrariness in the estimation process.

Another issue concerns the statistical properties of the nonparametric estimators. Under certain assumptions, one can prove consistency and asymptotic normality for most nonparametric estimators. However, the rate of convergence in distribution is typically slower than that of parametric models. Also, this rate can be very slow if the number of regressors is large (the 'curse of dimensionality'). A workable solution may sometimes be found by using the semiparametric model, where the parametric portion can be estimated consistently and efficiently, or by using the method of averaging (Hardle and Stoker, 1989). In general, however, large samples and simple
models seem necessary for a reasonable application of nonparametric methods of estimation.

6. Concluding remarks

A number of explanations of certain features of market demand may fall under the heading of 'structural change'. Several methods are used to detect these situations in applied analysis, and to improve demand models typically used for welfare and policy analysis. In this paper, we have reviewed most of these procedures, grouping them under the broad categories of 'nonparametric' and 'parametric' methods. Nonparametric methods based on revealed-preference theory can be used to analyse the consistency of a body of consumption data with the assumption of utility maximisation. Because this can be accomplished with few accessory assumptions, nonparametric methods have the potential of yielding conclusions needing minimal qualifications. However, such methods are difficult to extend over the most basic framework of standard demand analysis, and are incapable of producing accurate quantitative predictions and response functions typically necessary for applied problems.

Parametric methods usually require one to specify a functional form, and thus conclusions are conditional on a degree of arbitrariness. However, such methods are typically easy to adapt and generalise in order to handle a greater variety of problems and questions, and the careful analyst can take precautions against the danger of being misled by a grossly incorrect functional form. Most of the parametric approaches that we have reviewed are, in fact, model specification tests. Whereas this is quite appropriate for a number of hypotheses concerning structural change in demand analysis, it does raise the issue of interpreting the results one obtains, and emphasises the fact that a carefully constructed theoretical model should always precede any empirical application.

We have, in addition, reviewed what we called the 'econometric' nonparametric approach. This is similar in spirit to the nonparametric methods discussed earlier, because it attempts to do away with arbitrary functional specification choices, but is also akin to the parametric methods in incorporating the explicit stochastic framework that constitutes the hallmark of econometrics. If this approach is taken as a good-faith effort to reconcile the two classes of methods discussed earlier, it offers a sobering message. In making explicit the large information requirements for its implementation, it suggests that overcoming the main limitations of parametric methods may be difficult, and that the potential advantages of nonparametric methods may prove hard to achieve in applied research.
Notes

1. One should not be misled into concluding that structural change issues can be assumed away by working only with models of the type \( q = F(p, z) \). Because the vector \( z \) potentially includes a great many things, virtually all of the economic models used for empirical analysis are of the concise type \( q = f(p) \), and which component of \( z \) will turn out to be important as a vehicle of 'structural change' may depend on circumstances or specific applications.

2. Endogenous tastes are defined as a preference ordering that depends on other people's consumption and/or on prices, such as in the 'snob' effect (see also Pollak and Wales, 1992).

3. Somewhat related to this, Bessler and Covey (1993) distinguish between associational and structural inference, and claim that results from observed data often show just prima facie causal relations, and drawing associational inference on the economic structure is incorrect and misleading.

4. Revealed-preference theory was developed by Samuelson (1938, 1948) and Houthakker (1950). Other contributions include Koo (1963, 1971) and Richter (1966).

5. Related results can be found in Diewert and Parkan (1985) and Chavas and Cox (1993).

6. As in Chalfant and Alston (1988), a test for WARP may be implemented by constructing the matrix \( \Phi \) whose elements are defined as \( \Phi_{ij} = C_{ij}/C_{ii} \). We have a violation of WARP if both \( \Phi_{ij} \) and \( \Phi_{ji} \) are less than one.

7. See Varian (1992) for more details. One important difference between WARP, SARP, and GARP is that the first two axioms assume that a unique bundle is chosen with each budget line (as implied by strictly convex preferences in utility theory), while GARP is consistent with multiple optimal bundles for any given price-income combination.

8. The power of the test is related to the probability of type-II errors, i.e. the probability of accepting the null hypothesis when it is false; the size of the test is the probability of type-I errors, i.e. the probability of rejecting the null hypothesis when it is true. Alston and Chalfant (1992) provide a discussion on the issue of power and size of nonparametric tests.

9. Bronars (1987) stresses the fact that useful information may be obtained from the observed data when budget lines cross, even if there are no comparable bundles. An application of this approach is found in Burton (1994).

10. See also discussion in Epstein and Yatchew (1985). This procedure is applied by Burton and Young (1991). Tsur (1989), working under some special assumptions, proposes a fast procedure to test for the significance of GARP violations. A discussion about the size and the power of the test under the provision that data can be measured with error can be found in Alston and Chalfant (1992).

11. In empirical work, it is common to assume that only quantities are observed with error, while prices and expenditure are taken as exact (a parallel assumption is usually made in parametric models). Of course, measurement errors are not the only possible source of randomness. Errors may arise in the budgeting process, and observed quantities may not be the maximising ones because of errors in expenditure allocation. Finally, as in Varian (1990), individuals may have a 'nearly' optimising behaviour: thus, the usual approach of analysing randomness in quantities, both in parametric and nonparametric models, may be misleading, since relatively large errors in quantities may be consistent with small departures from optimising behaviour.

12. Gross (1991) considers a Cobb–Douglas utility function of the form \( u = q_1^z q_2^{1-z} \), where \( z = 0.1 \) at time \( i \) and \( z = 0.9 \) at time \( j \). Expenditure in $10,000 in both periods, and prices are \( p_1 = 599 \) and \( p_2 = 5101 \) at time \( i \), and \( p_1 = 510 = 5100 \) at time \( j \). Given optimal budget shares, consumption at time \( i \) is 10.1 for \( q_1 \) and 89.11 for \( q_2 \), whereas at time \( j \) it is 90 for \( q_1 \) and 10 for \( q_2 \). This extremely large shift in preferences produces \( \Phi_{ij} = 0.992 \) and \( \Phi_{ji} = 0.992 \), which are very close to unity: thus, small adjustment in quantities could restore consistency. Alternatively, if expenditure at time \( j \) were equal to $9,915, then \( \Phi_{ij} = 0.984 \) and \( \Phi_{ji} = 1.001 \).
In this case there would be no violation, and thus a small change in income would imply
that the exact test does not detect structural change.

13. Gross (1991) shows that by computing the direct compensation at time \( j \) by solving
\[
\min_{q_i} \{ p'q : u_i(q) = u_i(q^*) \},
\]
one obtains a minimum expenditure of \$1,724.27, implying that
under the hypothesis of no structural change the consumer would have wasted about
83 per cent of her income.

14. One can analyse further the example in Gross (1991) by computing the overcompensation
function \( m^+(p, q) \) as in Varian (1982), where \( m^+(p, q) \) is defined as the solution to
\[
\min_{z \in Z} \{ \frac{p z}{z'q} \}.
\]
In our example \( m^+(p', q') = C_{ij} \), and the procedure proposed by Gross
collapses to the one used by Chalfant and Alston (1988).

15. For example, one may find that a separable group is not affected by structural change.
However, if the change of preferences takes place in the (typically untested) first stage, then
the consumption of the goods in the separable group is biased if the group is not homothetic
(Moschini, 1991).

16. For this reason, McGuirk et al. (1993, 1995) insist on the notion that the model must be
'statistically adequate' before one can meaningfully test hypotheses.

17. Using Japanese data, Maki (1992) finds that homogeneity and symmetry are satisfied when
taste change is allowed. A similar approach is used in Chen and Veeman (1991).

18. See Krämer et al. (1988), for a discussion on the power of the CUSUM test and its
extension to dynamic models; this test is usually affected by the local power problem, that
is, the power is dependent on the form of the alternatives. The types of tests proposed by
Andrews (1993) do not suffer from this problem, and may have power against several
alternatives. However, much of the work on the power of tests for structural change
is devoted to models where parameter instability is originated by structural change, thus the
issue of a composite null hypothesis may still be crucial in empirical applications. See also
Andrews and Fair (1988) for testing for structural change in nonlinear models.

19. The sample size may be a critical aspect here, since most of these tests have asymptotic
properties, and do not perform well in small samples (see Fachin, 1994, for a discussion of
this issue in the context of variable additional tests). For example, Wales (1984) has shown
the tendency towards over-rejection of tests for structural change based on the likelihood
ratio: this bias is more serious when the sample size is small.

20. Several applications of these techniques can be found. Moschini and Meilke (1989) adopted
a gradual switching regression model for structural change in a demand system (see also
Reynolds and Goddard, 1991; Burton and Young, 1992; Eales and Unnevehr, 1988; and
Björndal et al., 1992). A more complex gradual switching model, with stochastic cross-
equational constraints, has been proposed by Tsurumi et al. (1986), and adapted to meat
demand analysis by Goodwin (1992), using a Bayesian approach. Poirier (1976) studied
the use of spline functions in modelling structural change. Chavas (1983) estimated a
random coefficient model, and Leybourne (1993) a time-varying coefficient AIDS model,
both based on the Kalman filter. Other applications of systematic and stochastic changes
in parameters are in Kinnucan and Venkateswaran (1994). A slightly different application
is in Choi and Sosin (1990), who test for structural change using time-varying multiplicative
terms. Finally, for other applications, see Buse (1989).

21. For example, the cholesterol index developed by McGuirk et al. (1995) is quite different
from the cholesterol index constructed by Brown and Schrader (1990), and which of the
two is more appropriate is not clear.

22. Demographic effects have been widely incorporated in demand analysis [Pollak and Wales
(1981); Ray (1984); Lewbel (1985); Rossi (1988); Alessie and Kapteyn (1991); see also
Pollak and Wales (1992, Chapt. 3)]. Applications in food demand analysis include Kokoski

23. A general dynamic specification of demand systems, that includes habit formation as a
special case, can be found in Anderson and Blundell (1982, 1983).
24. This approach is found in Burton and Young (1992). Long-run dynamics are accounted for in Kesavan et al. (1993).

25. Scaling and translating, typically used for demographic effects, can also be applied for other effects, following Lewbel's (1985) generalisation. For a treatment of advertising in demand systems, see also Selvanathan (1989) and Duffy (1987). Applications can be found in Kinnucan (1987), Chang and Kinnucan (1991), Green et al. (1991), Brown and Lee (1993), Kinnucan and Venkateswaran (1994). Increasing attention has been devoted to the role of information and health concerns: see applications in Brown and Schrader (1990), Capps and Schmitz (1991), Chang and Kinnucan (1991), Jensen et al. (1992), Gould and Lin (1994). The treatment of quality variation is considered in the pioneering work by Houthakker (1952) and Theil (1952); see also Hanemann (1981), Cox and Wohlgenant (1986), Deaton (1989), and Nelson (1991). Other factors that have been accounted for are convenience (Capps et al., 1985), retailing (Bjornsdal et al., 1992), government intervention (Gould et al., 1991), and product innovation (Gould et al., 1994).


27. A possible solution to the problem may be to resort to FFFs with larger approximation properties. Gallant (1982) proposed a form, based on a multivariate Fourier series expansion, where a better approximation is obtained at the expense of an increased number of parameters. This approach has been applied in food demand estimation and testing for structural change by Wohlgenant (1985).

28. For an early review of non-nested testing procedures, see MacKinnon (1983). Several applications can be found in demand analysis since Deaton (1978); a recent application is Brester and Wohlgenant (1991). An alternative interesting approach, rooted in the model selection literature, is the likelihood dominance criterion proposed by Pollak and Wales (1991).

References


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