Demand Dynamics with Socially Evolving Preferences

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In this work we, first, identify a few stylized facts concerning microconsumption acts. Second, building on them, we develop a simple model of 'boundedly rational' consumers who endogenously evolve their preferences via both innovation and social imitation. Third, we explore some statistical properties of the demand patterns generated by the model which, despite its simplicity, are surprisingly in line with the empirical evidence. These results, we suggest, bring encouraging support to microfoundations of demand theory based on cognitive and behavioral foundations more in tune with the psychological and sociological evidence, based on heterogeneous agents who are much less 'rational' and much more social than in standard theory, and who collectively discover 'along the way' what they like within a growing universe of available commodities.

1. *Introduction*

In this work we begin to explore some aggregate dynamic properties of demand patterns when preferences are shaped by the cognitive structures of consumers and evolve in socially embedded fashions.

After setting the general framework of the discussion (Section 2), in Section 3 we identify some 'stylized facts' stemming from the 'state of the art' of different social disciplines such as cognitive and social psychology and marketing. We employ them as the reference points for the model developed in Section 3, analyzing the dynamics of consumption with heterogeneous, 'boundedly rational' agents which are nonetheless able to endogenously evolve their preferences, innovate and imitate the others. Finally, the statistical properties of the model are discussed in Section 4.

2. *Consumption Acts and Demand Patterns: Some Interpretation Frameworks*

A while ago, one of the authors of this paper witnessed at a seminar the horror of most colleagues when Werner Hildenbrand, presenting some further development on his theory of demand (Hildenbrand, 1994) provocatively suggested more or less that 'preferences and choices are matters for psychiatrists and not for economists,' while the task of the latter should be primarily to establish some statistical conditions under which basic propositions of economic theory—such as downward sloping demand curves, etc.—hold in the aggregate, in presence of heterogeneous, and possibly 'irrational' consumers.

In a nutshell, the provocation highlights, first of all, a major divide cutting across the economic discipline—as well as other social sciences—namely, how seriously should one take standard utility theory (with or without its more recent refinements) and the associated 'rational' theory of decision making as the foundation of a descriptive theory of demand?[1]

Needless to say, the majority of the economic profession seems to take that type of microeconomic foundation of decisions very seriously indeed, entrenched as they are with deep ('anthropological') views on the nature of 'rationality' and self-seeking behaviors, passed through successive generations via conventional teaching tools such as 'indifference curves' and the like, and further justified by their purported role in bridging descriptive and normative analyses (welfare theorems, etc.).

However, admittedly minority views in economics (but nearly 'mainstream' in other social disciplines) claim that classic decision theory has little to offer by way of the interpretation of what people actually do and that one should turn in fact to cognitive and social psychology, sociology (and—why not?—psychiatry) in order to derive empirically sound theories of how people behave and choose the way they do.

Note that the appeal to inductive generalizations—in this perspective—does not concern solely the nature and origins of preferences [which could, as such, nicely complement rather than upset 'rational' decision-theoretic views; after all, in the latter, as reminded by Stigler and Becker (1977), '*de gustibus non est disputandum* . . .']. More profoundly, it relates to both the procedures by which decisions are taken and the interactions (possibly at a collectively level) between decisions, outcomes and preferences themselves.

First, at a procedural level, as Legrenzi *et al.* (1993, pp. 37–8) put it,

> the classical theory of decision-making, whatever its status as a

[1] Another major problem concerns the aggregate properties of diverse demand schedules, no matter how constructed. We shall come to that below.

> specification of rationality, does not begin to explain the mental processes underlying decisions. . . . On the one hand, the theory is radically incomplete: it has nothing to say about when one should decide to make a decision, or how one should determine the range of options, or how one should assess the utilities of various outcomes. On the other hand, the theory conflicts with the evidence on how people reach decisions in daily life.

The literature on this subject is immense: see, among others, Slovic (1990), Payne *et al.* (1992), Tversky and Kahneman (1986), Thaler (1992) and the companion paper by Devetag (1999).[2] In economics, the emphasis on the 'bounds' of rationality, and the related analytical requirement, so to speak, to 'open up the cognitive black-box,' has found a good deal of inspiration in the path-breaking work of Herbert Simon (1959, 1986, 1988). Indeed, the empirical departures from the canonic procedures prescribed by rational decision theory are likely to be even deeper than those envisaged by Simon, in that human agents might not only be bound away from 'substantive' rationality, but often also display systematic biases in the procedures themselves for judgment and choice.[3]

Moreover, as Shafir *et al.* (1993, p. 34) conclude, also on the grounds of the cited Payne *et al.* (1992),

> in contrast to classical theory that assumes stable values and preferences, it appears that people often do not have well-established values, and that preferences are actually constructed—not merely revealed—during their elicitation . . .[4]

Finally, the literature on cognitive dissonance reveals another, symmetric, source of endogeneity of preferences, namely the post-decisional adjustment of goals in order to rationalize counter-intentional behaviors and outcomes (Fastinger, 1956; Wicklund and Brehm, 1976; for an economic application, see Akerlof and Dickens, 1982).

All this *lato sensu* 'cognitive' evidence suggests that, first, we should primarily call in psychologists rather than decision-theorists in order to explain goal formation, deliberation and choice. Second, other pieces of evidence hint that we should call in social psychologists and sociologists, too. More precisely, one finds widespread occurrences of social endogeneity of preferences, including social imitation, formation of relatively homogeneous

[2] A rather balanced assessment of the merits and limitations of standard utility theory from an economist's point of view is in Schoemaker (1982).

[3] Dosi *et al.* (1996) discusses some of them with an eye on their implications for evolutionary theories of learning in economics.

[4] See also Tversky and Simonson (1993).

'lifestyles' within specific social groups, 'snob effects,' authority-induced changes in values and choices, and many others.[5] In these domains, T. Veblen is one of the outstanding early contributors of plenty of conjectures and 'appreciative theories,' notwithstanding their sometimes irritating analytical fuzziness.[6]

As already mentioned, it is worth recalling the caveat that under certain conditions the endogeneity of preferences as such does not pose any overwhelming challenge to standard decision theory. That includes those circumstances whereby (i) the timescale of preference evolution is of orders of magnitude greater than the timescale of decisions themselves (so that, for example, the 'disutility of eating pork' might have evolved over millennia, but for all practical purposes that can be taken as a given and stable preference trait of any practicing Jew or Muslim while selecting meat); (ii) preferences are not context-dependent, so that, in James March's language, they fulfil the conventional 'logic of consequences' rather than a 'logic of appropriateness' ('what is appropriate for anyone with my identity and my social role in those circumstances to do?'; cf. March, 1994); (iii) future changes in preferences are fully anticipated by forward-looking intertemporally utility maximizers (cf. Becker, 1976);[7] and (iv) the collective distributions of preferences, at each time, are not among the arguments of individual decision algorithms (i.e. 'like to do what my neighbors do,' etc.). Here and throughout, we refer to 'social endogeneity' to mean those circumstances—in our view, quite frequent indeed—whereby those conditions are violated.

The two sets of evidence—related, broadly speaking, first, to the cognitive and behavioral processes of choice, and, second, to their social embeddedness—strongly militate in favor of inductively disciplined theories of microeconomic behaviors, in general, and—as far as this work is concerned—final consumption, in particular, grounded in the relevant 'phenomenological' generalizations drawn from, for example, cognitive and social psychology, sociology, etc. It is a view certainly shared by those breeds of economists who might label themselves 'behaviorist,' 'institutionalist' and 'evolutionary'.[8]

However, even granted all that (a point by no means uncontroversial

[5] A thorough discussion of a few of these issues with respect to consumption patterns is in Earl (1986). Relatedly, within an enormous literature, see also, e.g. Milgram (1974), Maital and Maital (1993), Hirschman (1965), Kuran (1987), all the way to the suggestive conjectures on the historical dynamics of social adaptation and rebellion in Moore (1978).

[6] Cf. Veblen (1899, 1919) and, later, along somewhat similar lines, Duesenberry (1949), Leibenstein (1950, 1976); see also Katona (1975, 1980).

[7] Cf. also Gary Becker (1996) who tries to derive 'endogenous' preferences from a sort of invariant 'meta-utility functions'.

[8] For quite germane developments of this argument, see Nelson and Winter (1982), Coriat and Dosi (1998), Hodgson (1988) and Earl (1986).

among economists), why should we not leave this domain of micro-investigation to psychologists and sociologists (and psychiatrists), and limit our attention as economists to much more general, and, so to speak, 'minimal' statistical restrictions on the characteristics of the populations of, for example, consumers which are sufficient for aggregate propositions on demand patterns to hold?[9] If we understand correctly, this is the perspective underlying the pioneering works of Trockel (1984) and especially Hildenbrand (1994), whereby one attempts to establish the requirements for aggregate shapes of demand curves as functions of prices, entirely disposing of dubious psychological constructs based on 'utilities,' etc. and explicitly overcoming the aggregation problems undermining the extrapolation of the purported behavior of single consumers to pseudo-behavioral entities like 'the representative agent'.[10]

In order to illustrate this point, let us just recall the very basics which most undergraduates learn in Economics 101.

When dealing with demand, one starts with the intuition that when prices of any one commodity are higher, demand is lower, and, conversely, when prices are lower demand is higher. Next, one easily draws on the blackboard a standard demand curve relating prices and quantities with its familiar downward slope, and that remains as one of the most profound imprints of the discipline thereafter.

But, on second thoughts, what does that demand curve mean (even in a partial equilibrium setting)? After all, at any point in time, one only observes *one* actual combination between a certain price and a certain quantity of a good or a bundle of them. Keeping to the static framework, the curve must necessarily imply some sort of counterfactual experiment, namely *what would have happened if* prices were higher or lower (holding everything else constant—including initial endowment and preferences).

In turn, that counterfactual exercise either applies at the level of the individual consumer or, alternatively, of collections of them. In the former case, the hypothetical experiment basically concerns the degrees of coherence in microeconomic preference structures. This belongs to the first domain of analysis mentioned above. So, for example, we know—from Samuelson

[9] Of course, matter would look in any case quite different in fields like marketing or applied industrial economics, but for the time being we shall confine our discussion to those more general properties of demand which one typically finds in any intermediate economics textbook.

[10] The fundamental inconsistencies of such a notion have been thoroughly discussed by Kirman (1989, 1992). One of the points, among others, is that, even admitting individual maximizers, with well-behaved utility functions, etc., aggregation does not carry over any restriction on the shape of the aggregate demand functions (i.e. the demand functions attributed to the 'representative agent') without further *ad hoc* assumptions on the nature of preferences themselves. Complementarily, on the lack of isomorphism between microbehavioral rules and aggregate dynamics of the corresponding time-series, see Lippi (1988).

(1938) all the way to Varian (1982)—that 'revealed preferences,' under different consistency restrictions, may be, so to speak, 'mapped back' to an underlying (and unobservable) utility function of a maximizing consumer (cf. also Sippel, 1997). In the opposite counterfactual experiment, the focus is upon the statistical robustness of the demand curves one routinely draws—irrespective of any greater knowledge on microdecision processes. In the latter approach, one is entirely agnostic on the ways preferences are formed (and whether they obey the consistency requirements of standard decision theories); rather, distributional invariances, together with budget constraints, account for the aggregate patterns one is meant to explain.[11]

We do indeed believe that this is a highly promising route that is just beginning to be investigated. However, we also believe that the 'agnosticism' on behavioral microfoundations can go only part of the way in explaining observed 'stylized facts' on demand. First, the question why distributions of revealed preferences are what they are seems to us an interesting one in its own right. Second, one might wonder how and when those distributions change—under the influence of, for example, introduction of new products, social interactions, etc.—and what implications all this has for aggregate demand properties.

Note that both points are likely to be particularly relevant when one increases the number of empirical phenomena one tries to account for, e.g. in addition to the question of why demand schedules tend to be downward sloping, one investigates, together, the determinants of diffusion patterns of new commodities, the conditions of occurrence of Engel-type demand profiles over time, or—even more complicated—the emergence of particular 'norms of consumption' within a population of consumers or subgroups of them.

It is in these domains where we see a profound complementarity between behaviorally parsimonious statistical approaches—'à la Hildenbrand'—on the one hand, and constructive micro-theories in a 'Simonesque' and 'Veblenesque' spirit, which indeed build upon what cognitive scientists, sociologists and psychologists tell us about choices and behaviors, on the other. In order to build that bridge, of course, we must undertake the difficult task of constructing micro-founded models which respect the spirit of the behavioral findings and, at the same time, are 'abstract' enough to generate stylized statistical properties of the ensuing aggregate demand profiles. This is indeed what we shall begin to do in the following.

The basic rationale of the exercise is to show how social processes of 'preference learning' and innovation, in the presence of stochastically growing

[11] An early modeling attempt to derive the sign of demand adjustments to price changes solely from budget constraints is in Sanderson (1974).

incomes, can generate patterns of demand, and also diffusion patterns of new goods, which are statistically similar to those observed empirically. We are far from claiming that, by that token, this is 'explaining' the evidence. More modestly, we take it as an 'exercise in plausibility,' whereby, notwithstanding heroic modeling assumptions, a few observed statistical properties of consumption can be constructively generated on foundations built on heterogeneous agents who are much less 'rational' and much more social than in standard theories, and who discover collectively 'along the way' what they like and what they demand within a growing universe of available commodities.

3. *Toward a Descriptive Theory of Consumption: Some Building Blocks*

It is obviously impossible to provide here any fair account of the diverse pieces of evidence on the processes leading to consumption choices; a whole book would not be enough to adequately cover the findings, which range from marketing to cognitive sciences.[12]

Here, we shall just try to abstract some properties which appear sufficiently general to be candidates for building blocks of modeling efforts.

1. *The coherence criteria prescribed by decision-theoretic models are systematically violated by empirical agents* (i.e. by most of us human beings) *even under utterly simple experimental circumstances.*

Given its inherent double nature—normative and descriptive—the standard theory of consumer behavior requires, as a bottom line of rationality, that beliefs and preferences obey some set of coherent formal rules.

However, as experimental evidence suggests, consumers tend often to act in ways that are inconsistent with standard decision-theoretic tenets in that many widely accepted *normative* principles appear indeed to be pervasively and systematically violated as *descriptive* laws of consumer behavior, both in real life and experimental setups.[13]

For instance, as far as generic decisions under uncertainty are concerned, *framing effects* often imply that actual choices not only depend on the 'objective' characteristics of the options at hand but also on the ways the choice setup is perceived and represented by the agents. In particular, *preference*

[12] See anyhow Earl (1986) for an ambitious overview and interpretation, Devetag (1999), this volume, and Robertson and Kassarjian (1991).

[13] Cf. Devetag (1999), this volume, for a thorough discussion.

reversal phenomena have been shown to systematically arise in consumer choices. Moreover, in all circumstances where agents face an alternative between certain (or apparently certain) gains and uncertain lotteries, the emergence of the so-called *certainty* (or *pseudo-certainty*) *effects* leads to the violation of basic axioms, such as *dominance* (i.e. if option A is better than B in every respect, then A should always be preferred to B), *cancellation* (i.e. the choice between two options depends upon the states in which they yield different outcomes) and *substitution*, and also dramatically challenges the *sure-thing principle* and the *independence axiom*. The very notion of *utility* as commonly depicted by the theory is also questioned by experimental evidence, as it turns out that, even though utility should be assigned to states (e.g. *levels* of wealth), agents systematically assign utility to events (e.g. *variations* of wealth) relative to a reference point (the *status quo*), and, more seriously, tend to evaluate the same objective output as a gain or a loss depending on the framing of the reference state. As a consequence, indifference curves cannot be drawn without references to current endowments (*endowment effect*). In addition, as shown, for example, by Ellsberg (1961) in his well-known paradox, the subjective probabilities which should be employed in weighting the utility of a given outcome are not generally independent of the origin of the uncertainty, so that people, when faced with ambiguity, choose as if they have assigned the 'true' probabilities to the events, making on average the wrong choice.

Even more dramatically, choices made in (nearly) *deterministic* situations often imply strong conflicts with basic assumptions of economic theory as well. For example, a large body of work has singled out situations in which consumers' choices exhibit strong discrepancies between willingness to pay and willingness to sell (even in the absence of any income effects and transaction costs) and between marginal costs and marginal benefits. Moreover, systematic evidence has been presented in favor of the statement that fixed, sunk, costs *do* indeed matter in economic decisions. Finally, consumers tend to frame their purchase decisions—and consequently their way of perceiving costs, losses and the value of money—by their *mental accounting systems*, so that, in many deterministic situations, *money illusion* and the emergence of *reference prices* are often reported.

In many respects, the foregoing systematic inconsistencies between normative prescriptions and evidence, whether formally accounted or not, should also help in establishing some loose boundary between those decision incidents where 'coherence' of some kind should be plausibly imputed to consumption acts and where it should not (with that bound being indeed quite restrictive). However, this same evidence can be taken as the starting point for the identification of relatively invariant behavioral patterns consistent with alternative theories.

2. *Consumption acts (as well as other economic behaviors) are nested into cognitive categories and 'mental models' of the actors.*

As argued at some greater length in Dosi *et al.* (1996), any theory of choice, behavior and learning in complex and changing environments is most likely bound at some point to take explicitly on board the cognitive structures by which people frame the interpretations of their experience and their expectations. And consumption activities are no exception (cf. Devetag, 1999, this volume). Works from cognitive and social psychology and artificial sciences, including Holland *et al.* (1986), Tversky and Kahneman (1986), Lakoff (1987), Johnson-Laird (1983, 1993) and Goffman (1974), are painstakingly making timid inroads into economics; and, with reference to consumption theory, Earl (1986) makes extensive use of Kelly's Personal Construct Psychology (cf. Kelly, 1955) and Steinbrunner's 'cybernetic' approach (see Steinbrunner, 1974).

Notwithstanding the enormous diversity across these cited approaches, it seems to us that what they have in common for our rudimentary purposes is the general acknowledgement of the importance of diverse and possibly evolving mental models, cognitive categories and 'frames' shaping perception and deliberation.

3. *The relationships between 'mental models', preferences and consumption behaviors are to some extent implicit and, possibly, also partly inconsistent with each other.*

The fact that 'models' provide a structure through which people 'make sense' of what they do (and, together, what they want) is likely to entail the emergence and reproduction of recognizable lifestyles (cf. Earl, 1986).

However, these structures tend to be fuzzy and ridden with inconsistencies in terms of both actual choices and mapping between the latter and perceived goals (cognitive dissonance relates precisely to this phenomenon). Conflicting preference structures and criteria for choice might precariously (and sometimes painfully) coexist within the same agent.

'Models' offer satisficing inferential machineries for choice (Legrenzi *et al.*, 1993; Johnson-Laird, 1993). However, given their 'satisficing' nature and their blurred links with (possibly conflicting) goals, first, they leave open 'reason-based' decision-procedures:

> decisions . . . are often reached by focusing on the reasons that justify the

> selection of one option over another. Different frames, contexts and elicitation procedures highlight different aspects of the options and bring forth different reasons and considerations that influence decisions. (Shafir *et al.*, 1993, p. 34)

This implies a sort of inseparability between preference-formation and preference-revelation (through the choices act): in a sense, preferences are constructed through the very process of deliberation. An implication, in this perspective, is that one cannot innocently separate some unequivocal objective [e.g. max $U(\, . \, , \, . \, , \, \ldots \,)$] from the algorithms for its implementation. Rather, mental and behavioral models are (rough) templates for the elicitation of both the choice procedures and what is to be preferred.

Second, the choice process is often guided by heuristic criteria which might not bear any rigorous mapping into any underlying coherent structure of preferences. This point finds ample support from what in various models of consumer's behavior are called noncompensatory criteria of choice (heuristics often based on hierarchical filtering procedures, 'focusing' upon salient aspects of the choice context, exercises of comparison with prototypical expectations, etc.) (cf. Earl, 1986; Devetag, 1999, and references therein).[14]

Conversely, the 'compensatory' archetype of choice is a necessary condition for maximization over convex combinations of attributes (or goods) and prices. Attempts to hold together standard decision-theoretic assumptions and the acknowledgement of some nonconvexities in the purported utility sets have been made through the so-called 'multi-attribute utility theory' (cf. Dyer *et al.*, 1992; see also Fishburn, 1974).

4. *Habits, routines and explicit deliberative processes coexist to varying degrees as determinants of most consumption acts.*

As Olshavsky and Granbois (1979) put it (also cited in Earl, 1986):

> For many purchases a decision process never occurs, not even on the first purchase. . . . Purchases can occur out of necessity; they can be derived from culturally mandated lifestyles or from interlocked purchases; they can reflect preferences acquired in early childhood; they can result from simple conformity to group norms or from imitation of others; purchases can be made exclusively on recommendations from personal or non-personal sources; they can be made on the basis of surrogates of various types; or they can even occur on a random or superficial basis. . . . Even

[14] Interestingly, this literature mainly from marketing or from experimental studies has drawn relatively little attention from the scholars more directly inspired by standard economic theory: cf., for example, the otherwise thorough and balanced discussions of models and statistical evidence of Brown and Deaton (1972) and Deaton and Muellbauer (1980b).

> when purchase behavior is preceded by a choice process, {the latter} is likely to be very limited. It typically involves the evaluation of few alternatives, little external search, few evaluative criteria, and simple evaluation models. (Olshavsky and Granbois, 1979, pp. 98–99)

Clearly, the evidence on routinization of behavioral patterns is quite in tune with that taken on board and theorized upon, in other domains of economic activity, by various evolutionary approaches—cf. in particular Nelson and Winter (1982) and Cohen *et al.* (1996). And, of course, it fits well with the ample sociological evidence on adaptation to specific social roles.[15]

More generally:

5. *Consumption habits and routines, and, dynamically, their formation and acquisition, are embedded in the processes of socialization and identity-building.*

The 'social embeddedness' notion of economic behaviors is obviously near the spirit of a lot of sociological thinking and evidence.[16] Taken seriously, that view implies also that one should be wary of assuming any individual preference structures (or, for that matter, individual behavioral patterns) as sole 'primitives' of micro-founded theories of economic behaviors.

Rather, one ought to account for explicit dynamics of collective adaptation from the start. Multiple factors support this view. Some of them underlie the possibility of social bandwagon effects (see Leibenstein, 1976). Freely citing from Granovetter and Soong (1986, pp. 84–5), they include interpersonal correlations of preferences nested in (i) status seeking; (ii) consumption externalities of whatever kind; and (iii) the revealed outcome of other people's experiences as surrogate for one's own search.[17]

Even more profoundly, social adaptation also in consumption patterns is likely to be part of fundamental processes of identity-building, involving (imperfect) adaptation to the habits and norms of specific social groups. In this respect, many of the works of Bourdieu are suggestive illustrations of how the social context contributes to structure social behaviors and revealed preferences (cf. Bourdieu, 1976, 1979; see also Berger and Luckman, 1967).[18]

[15] Incidentally, note that in the early works of G. Becker, one finds the possibility of explanations of economic behaviors based on habits rather utility maximization: cf. Becker (1962).

[16] For appraisals relevant for the current discussion, see, among others, Granovetter (1985), Barron and Hannan (1994), Hodgson (1988); see also Dosi (1995) and Coriat and Dosi (1998) on the background of some of the ideas put forward here.

[17] Conversely, differentiation effects may emerge as well, such as 'snob' inclinations to distinguish oneself from the revealed majority {and also more complex—'cognitively dissonant'—attitudes such as those summarized by Marx (Groucho), unwilling to 'join any club which would accept him as a member . . .'}.

[18] Straightforwardly, this point links with the previous ones on 'mental models' and 'lifestyles': in this perspective, the evolution of the latter is dynamically coupled with a social context framing the meanings and also the reinforcements (the 'pleasures and pains') of individual experiences.

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However, at least in contemporary capitalist economies, adaptation to social roles is rather imperfect, ridden with conflicts and with multiple (possibly contradictory) archetypal identities, with these archetypes themselves changing rather quickly over time.[20]

As a consequence:

6. *Habits and routines-formation hold varying and precarious balances with search and innovation.*

Pushing it to an extreme, the idea is that a good part of the complement to one of routinized, relatively automatic and repetitive consumption patterns is not any canonically 'rational' deliberative choice, but rather some wilder process of search/experimentation, whereby also some 'utility' (whatever that means) is drawn from the very exploratory process—whether or not one subscribed to the general anthropological conjecture of Scitovsky (1992) on the intrinsic stimuli and pleasure brought about by novelty.[21] As with routines, we find here some loose analogy with the exploratory patterns of producers, which has been investigated much more in the literature on the economics of technological innovation (cf. Freeman, 1982, Nelson and Winter, 1982; Rosenberg, 1982; Dosi, 1988).

7. *(Imperfect) social adaptation, learning—on both preferences and consumption 'technologies'—and search, all entail path-dependencies (at the very least at individual level).*

By now, it is, at last, generally acknowledged that both collective externalities and dynamic increasing returns generally involve dependence of dynamic

[19] Incidentally, note that the importance of the social context in determining judgements and behaviors is also revealed by *accountability effects* which can be detected in the choice process: cf. Tetlock (1985) and Dalli and Tedeschi (1997).

[20] For insightful discussions on potentially 'multiple selves' pertinent to different domains of experience, cf. Elster (1986). A subtle issue, which cannot be pursued here, is the relative 'rational' coherence of each of the purported 'selves,' however, as should be clear from the foregoing argument, we are inclined to depict a 'self' (i.e. an identity) with a good deal of internal inconsistencies in both goals and procedures in order to achieve them.

[21] With a robust body of evidence from experimental psychology supporting it, notwithstanding equally robust examples of reinforcements to social adaptation, there is certainly strong empirical grounds for the idea that, at least in a few circumstances, consumers 'experiment,' 'explore,' 'discover,' develop novel 'consumption technologies' and lifestyles, etc. (cf. Earl, 1986; Bianchi, 1997).

paths upon initial conditions (or, in richer stochastic formulations, the dependence of limit states upon early fluctuations). However, in a strange paradox, the relevance of this widespread phenomenon has been much more emphasized on the supply side of production and technological innovation (see, among others, David, 1985; Arthur, 1988; Dosi, 1997), rather than on the final demand side.

It is some paradox because on the supply side, microeconomic path-dependencies (e.g. regarding the learning patterns of individual firms) might not exert long-term collective influences insofar as selection environments (e.g. markets) remain test-beds for different innovative trial-and-errors on the grounds of unchanged selection criteria (i.e. insofar as the 'selection landscape' remains unchanged).

Conversely, on the final demand side, agent-specific and collective path-dependencies are even more likely to arise, since there is no 'selection environment' to speak of (after all, everyone agrees that, except for ethical considerations, '*de gustibus non est disputandum*').

In its essence, the point had been already made by Duesenberry when taking issue against the assumptions that, first, 'every individual's consumption behavior is independent of that of every other individual, and [second], the consumption relations are reversible in time' (Duesenberry, 1949, p. 1).

Since then, a lot of corroborating evidence on consumer behaviors has indeed supported both of Duesenberry's counter-assumptions (cf. Earl, 1986), without, however, any appropriate acknowledgement in terms of demand theory.

8. *Micro-consumption patterns are likely to be characterized by: (a) complementarities among multiple goods within lifestyle-shaped consumption-systems; and (b) (roughly) lexicographic patterns of consumer's selection over hedonic attributes and goods.*

At least as a first cut, let us assume that (socially shaped) 'mental models' link together multiple—and, possibly, partly contradictory—goals, heuristics perceived to be appropriate to their achievement, and particular types of goods. After all, if different 'lifestyles' exist, they ought to involve discretely different maps across these sets of variables. In turn, collectively shared models and behavioral patterns are likely to involve proximate complementarities in preference structures over both hedonic attributes of goods and goods themselves. (In an illustrative caricature, one is not very likely to find

Ferrari drivers wearing chainstore shoes; or Mozart fanatics content to listen to music on a Walkman.)

Complementarities are, of course, enormously reinforced by 'harder' social interdependencies—like those linking patterns of spatial mobility, uses of leisure time, ownership of cars, service stations, the presence of infrastructures like highways—and so on. And, relatedly, mental models and social lifestyles add up to more mundane 'physical' hierarchies of needs in determining rough lexicographic orders of consumption priorities.

Hence, on top of rather predictable hierarchies from basic necessities (such as food) to more discretional expenditures, socially acquired norms and visions tend to drive proximate rankings over commodities, or classes of them well above the sheer physiological constraints.

This does not mean, of course, that discretionality, 'choice,' price-dependent substitution, etc., are ruled out. On the contrary, cognitive and behavioral structures can be seen as a sort of basin of attraction allowing for a good deal of stochastic fluctuations where both explicit deliberations and path-dependent influences play major roles.

However, we still maintain the hypothesis that while 'compensatory choices' might hold locally for butter versus vegetable oil, etc., broader changes in consumption patterns are largely nested into deeper, discrete, changes in cognition and socialization models (and in ways possibly independent from any change in relative prices).

To sum up: a descriptive theory of consumption, in our view, should in principle encompass relatively ordered 'models' and 'lifestyles,' routines, explicit deliberations held together with 'imperfect coherence,' all of which path-dependently evolve through both (partial) social imitation and innovation. Can one capture at least some elements of this view in a formal model? This is the question we shall try to answer in the next section.[22]

4. *The Model*

The starting point is utterly simple agents whose (lexicographic) preference structure is represented through a modified version of *genetic alghorithms* (GAs).[23]

In essence a GA is based on the reproduction and modification of information coded on strings of finite length. In an analogy with DNA coding, think of a sequentially ordered set of elements (genes in the biological

[22] Other models which attempt to tackle at least part of the foregoing 'stylized facts' are discussed in Dosi *et al.* (1999).

[23] Much more on this is in Holland (1975) and Goldberg (1989).

interpretations; demanded goods in this application). Each element can take two or more alternative forms (or 'alleles'): below straightforwardly it can have two states, 1 or 0, i.e. the good is either demanded or not by any one consumer.[24]

Hence, for example, the string {01010} encodes the fact that the consumer is going to demand only—reading from left to right—the second and the fourth good. GAs evolve through two operators, namely crossover and mutation.

Crossover entails a recombination over two 'parent' strings. For example, given two strings, say, {01010} and {10011}, a random draw of an integer K (in the case, $1 \leq K \leq 5$) determines, so to speak, the 'cutting point' (say, 3). In this case the recombined strings will consist of the first three alleles of the first one and the last two of the second one, {01011}, and vice versa for the second 'child': {10010}, i.e. the first three of the second 'parent' and the last two of the first one.

Mutation involves the change of state of any one random element on the sequence (from 0 to 1 or vice versa).

In the standard formulation, strings are in turn selected over time according to their relative 'fitness' as revealed by the environmental payoffs that they obtain. This will not be so in the model which follows. As already mentioned, there is no reason to think that some consumption pattern may be intrinsically 'better' than another one, and, in any case, there is no collective mechanism (thank God!!) to check it. Therefore, more technically, our strings evolve over a flat selection landscape, solely driven by crossover and mutation. The death process (of strings) in our model is only determined by the (time-lagged) effects of budget constraints ('Once upon a time, I desired to have a villa at Cap Ferrat, five servants and caviar every day . . . however, I have now forgotten all that, and I am quite content with my little apartment and meat twice a week . . .').

In the model that follows each element of the string encodes, as mentioned, one particular commodity (which might or might not be supplied at any particular time t).[25]

For our purposes here, GAs provide a simple (albeit inevitably rough) account of an evolving lexicographic order over the desired commodities, whose structure is indeed a proxy for the 'lifestyle' of the consumer.[26]

[24] For our purpose here we can neglect the element (*) of the GA alphabet, meaning 'wildcards' whose specification does not affect the overall performance of the string itself.

[25] In the latter case, of course, the corresponding value of that element will be zero for all consumers.

[26] Here and throughout, there is a major, and admittedly unresolved, ambiguity between preferences over 'attributes' versus preferences over commodities. While we share with Earl (1986), and, before, Lancaster (1971), the idea that some underlying (hedonic) attributes and not commodities themselves are the object of consumption acts, our very simple model avoids any explicit account of the 'cognitive' mappings between the former and the latter, and their evolution in the minds of consumers.

Needless to say, the model of consumer behavior that we propose is highly stylized and 'abstract'—possibly as 'abstract' as the standard utility-based model. However, the assumptions that it incorporates are radically different from the latter in that it tries to capture (i) the social nature of preference formation; (ii) the role of individual and collective history; (iii) the formation (and change) of consumption habits; and (iv) the permanent possibility of innovation. Contrary to the canonic decision model, we assume agents with extremely limited computational capabilities, but with the possibility of 'learning their preferences' through the very process by which they select their consumption patterns.

Representation of Consumers

At any time t each consumer j is characterized by:

- $y_j(t)$, its income level (in monetary terms);
- $r_j(t)$, the income class to which it belongs (these classes endogenously change as income grow—see also below);
- $L_j^{\tau}(t)$, a binary string of length ℓ (with ℓ = number of actual and eventually possible goods), where each element $i \in \{1, \ldots, \ell\}$ takes the value of 1 or 0 depending on whether the corresponding good appears or not in the consumption pattern of consumer j. Note also that goods are further distinguished according to their product group g (below $g = 1, \ldots, 5$), metaphorically standing for different basic functions, so that—reading the strings from left to right—one goes from 'basic' to more 'luxury' categories of expenditures;
- $S_j^{\tau}(t)$, a string of length ℓ coding the actual expenditures (in monetary terms) on each good i (clearly, taking value zero for all goods which have a zero on the $L_j^{\tau}(t)$ string);
- $L_j^f(t)$, a binary string of length ℓ, which we call 'frustrated memory', where element $i \in \{1, \ldots, \ell\}$ takes value 1 if that good has been selected to be part of one's own consumption pattern but no purchase has yet been made due to the budget constraint. Note that whenever a purchase occurs on any i in $L_j^f(t)$, that i will start to appear as '1' on the string of actual consumption patterns $L_j^{\tau}(t)$, and correspondingly disappear from the 'frustrated memory' (a '1' will turn into a '0'). We shall see below how the frustrated memory emerges, as indirect outcome of innovation and social imitation; moreover, it stochastically decays as an exponential function of time (so that, '1's turn 'radioactively' into '0's as time goes by);

- $S_j^f(t)$, a string of length ℓ, listing the desired expenditures (in monetary terms) corresponding to the items which appear on the 'frustrated memory'.

This description of the consumers, together with the string $P(t)$, which is the system-level vector of unit prices $p_i(t)$ is sufficient to determine the actual quantities purchased by each j.[27]

Income Dynamics

The logs of (monetary) incomes of individual consumers are random walks with a reflecting barrier, so that:

$$y_j(t) = y_j(t-1)\left[1 + \varepsilon_j(t)\right] \tag{1}$$

where $\varepsilon_j(t)$ is an i.i.d., serially uncorrelated, random variable drawn from a truncated normal $\sim N(\mu,\sigma^2)$ and truncation is such to prevent, for simplicity, negative income changes.[28]

Consumers do not save (except possibly for some residual involuntary saving, see below); hence in general income is equal to total expenditure (correspondingly, all commodities ought to be rigorously considered as 'nondurable').

Income Classes

We define $r = 20$ income classes, initially set so that the higher value of the class exceeds the lower one by some given $\eta\%$ (obviously, near the very beginning of the simulation most of the classes are going to be empty: see below on 'initial conditions'). As incomes growth, the 20 classes are endogenously redefined so that they will continue to partition the whole population in 20 groups of log-identical sizes.

[27] In the model we assume indivisibility of the first unit purchased, but divisibility over any amount above 1 (one might want to consider that as a very rough proxy of quality-related differentiation, albeit totally unspecified on the supply side, so that, for example 'one and a half' unit of a commodity might be metaphorically understood as one unit plus added gadgets and optionals). We further add the convention that any commodity i which is not actually produced at t has price zero and obviously cannot be bought by any consumers.

[28] Throughout the simulations presented here we assume $\mu = 0.03$.

Old and New Products

At the beginning of 'history' (i.e. at $t = 0$), available commodities are very few, and mainly concentrated in product group one (the metaphorical equivalent of 'basic necessities'). Hence also most elements in the strings $L_{(\cdot)}^{\tau}(\cdot)$ and $P(\cdot)$ have value zero. However, at each time point new commodities stochastically arrive, whose number is drawn from a Poisson distribution.

Given that number, each virtual i (i.e. each commodity which takes at $t - 1$ a value zero on the price vector) has a uniform probability of coming into existence. Consider all that as a simplified version of some unspecified dynamics of innovation on the supply side. Note that whenever a new commodity is born, it appears with a positive price in the $P(\cdot)$ vector. That, however, does not automatically imply that it is bought by any one consumer (see below on 'innovation'). A commodity unsold for more that t^* periods (in our simulations $t^* = 3$) becomes 'dead'.

Commodity Unit Prices

When a commodity is introduced it is associated with a random price $p_i(0)$, drawn from a uniform distribution defined on a finite support (in our simulations, $1 \leq p_i(0) \leq 100$). We experimented with two versions of price dynamics. In version 1,

$$p_i(t) = p_i^{(0)}\left[1 + \nu_i(t)\right] \tag{2}$$

where $\nu_i(t)$ is an i.i.d., serially uncorrelated, random variable drawn from a truncated normal distribution with zero mean, defined over $-1 < -a \leq \nu_i \leq +a$.

In version 2,

$$p_i(t) = p_i^{(0)}\left[\sum_{\tilde{t}} q_i(\tilde{t})\right]^{\alpha_i} \tag{3}$$

where $\alpha_i \leq 0$ and $q_i(t)$ stands for total quantities of the commodity sold at each t. In a nutshell, in version 1, prices are subject to uncorrelated random shocks, while in version 2, they fall as a function of cumulated sales, in a fashion similar to what is often suggested in the literature on 'learning curves' and dynamic increasing returns.

Dynamics of Individual Consumption

At each 'period' after individual incomes have been updated, each consumer *j* faces four stochastic alternatives:

1. *Leave unchanged the consumption basket, with probability* θ_j^{u}. In the following we have assumed θ_j^{u} identical for all *j*'s and experimented with different parametrizations, ranging from 0.2 to 0.8). Under this option, all budget items are identically increased in proportion to income growth.[29]
2. *Access the 'frustrated memory' with probability* θ_j^{f}. In this case, all income increase is in principle devoted to the purchase of one or more items which, as mentioned, had been acquired as part of the chosen 'lifestyle' but could not be bought due to the budget constraint. (Note that despite income growth, the addition of new items to the actual consumption basket is not necessarily guaranteed: see below on 'adjustment algorithms'.)
3. *Change (part) of the consumption patterns via innovation or imitation with probability* $(1 - \theta_j^{u} - \theta_j^{f})$. In our model, quite in tune with the evidence on innovation diffusion,[30] we have assumed that, once the consumer has stochastically 'decided' to change, the innovative option (i.e. adopt a new product) is a function of its income class, r_j.[31] The complement to one is the effort to imitate, which, we assume, is restricted to one's own income class and higher ones (if any). Imitation has clearly to do also with phenomena of social integration, formation of (partially) homogeneous lifestyles within similar social groups or, conversely, efforts to sanction upward social mobility. A rough way to capture all that is to assume that the consumer to be imitated is drawn from a Poisson-type distribution with mean 1 (for the purposes of this draw we reclassify income classes, so that we indicate with zero the class to which the consumer belongs, with 1 that immediately higher, etc.).[32]

[29] That hypothesis amounts to assuming, under this option, a homothetic demand function with unitary price elasticities of demand. It is an extreme assumption, running counter to a lot of evidence on different price- and income-elasticities of different goods. We made it just in order not to in-build any possible emergent properties of the model into the assumptions. Hence, for example, if Engel-type patterns in budget coefficients were to emerge, they ought to be solely due to the dynamics of preference evolution and not to some preimposed preference structure differently weighting different goods as incomes grow. Of course, the conclusions would hold *a fortiori* in a more realistic model that would allow for both preference evolution and 'intrinsic' propensities, e.g. to trade off 'inferior' and 'superior' goods.

[30] See, for example, Rogers (1983). Discussions of evidence and models of innovation diffusion from different angles are in Mahajar *et al.* (1989), Dosi (1991) and Stoneman (1995).

[31] We assume that the probability of innovating is distributed as an exponential function of the income classes.

[32] Since the distribution will have a truncation corresponding to the highest income class, probabilities are proportionally reassigned to the relevant income classes.

3a. *Innovation.* If the consumer has opted, so to speak, for the 'exploration' route, it randomly draws (within a uniform probability distribution) one of the 'new' products which have become available (see above) but are not included in its desired consumption patterns of that particular consumer.

3b. *Imitation.* Conversely, after having selected the income class to be imitated through the above procedure, a consumer is randomly selected in that class, and, together, a random product group from g. Next, the crossover operator from GAs is applied to the substring corresponding to that product aggregate and that consumer.[33] In that way, the imitator 'borrows,' so to speak, part of the preference structure of the imitated agent, and, in a first approximation, also its budget allocation to the corresponding items (i.e. the relevant parts of the strings $L_k^{\tau}(t-1)$ and $S_k^{\tau}(t-1)$, with k being the imitated agent).[34]

Adjustment Algorithms

Given the indivisibility of the first unit of any item of consumption (cf. footnote 27) changes in the consumption patterns—no matter whether due to access to the 'frustrated memory,' innovation or imitation—do not necessarily fulfill the budget constraint. If they do, the new consumption profile will be implemented (with any possible income residual being subject again to the same stochastic allocation process described so far, i.e. between 'no change,' memory-activation, imitation, innovation). If the new consumption profile, on the contrary, violates the budget constraint, an iterated procedure of adjustment is implemented, checking whether relatively 'local' adjustments can accommodate for the new desired expenditures. The steps are the following:

(a) check if reductions of expenditures over up to five goods within the same product group are sufficient to make up to the novel desired expenditure (under the requirement of a minimal unitary expenditure on the former);
(b) same as sub (a) plus the reduction of desired quantities of new items to one unit each;

[33] Out of the two substrings so obtained, the imitator is assumed to retain that which has on the right-hand the preferences of the imitated consumer. (Recall that the whole string can be read from left to right as going from 'old' to 'new' products, and in terms of product aggregates, from necessities to more discretional items of expenditure.)

[34] In fact, we allow also with small probability a sort of 'involuntary innovation' to occur through the imitation process, in so far as the relevant part of the $L_k^{\tau}(\cdot)$ string is imperfectly copied (with a '0' instead of '1' or vice versa).

(c) same as (b), but with the added possibility of giving up entirely up to two 'old' goods;
(d) same procedure as (a) and (b), but with the expenditure reduction applicable to the *whole consumption string* (up to a maximum of 10 items);
(e) same procedure as (c), again applied to the whole string.

We assume that the corresponding changes in consumption patterns always occur when either steps (a) or (b) generate budget-consistent schedules, while they happen only in probability in cases (c)–(e) (with the probability falling from the former to the latter).[35]

This algorithm, as simple as it is, is meant to capture the relative inertia and path-dependency of 'models of consumption' and related 'lifestyles'. Moreover, note that when only part of the new desired expenditures can be fulfilled, in the spirit of our earlier considerations on lexicographic hierarchies in consumption, the order of priorities goes 'from left to right' on the string, in terms of product groups. Whenever, after the mentioned adjustment iterations, some (or all) desired new expenditures remain unfulfilled, they transit to the 'frustrated memory'.

Initial Conditions

At time zero, we assume consumers (1000 in the following) with an identical (and low) income and identical preferences over a small number of initially available commodities (five goods, of which three are within group 1, i.e. 'necessities').[36]

One of the purposes of the model is precisely to see whether, notwithstanding these initial conditions and the quite simple dynamics described above, the model can generate as sorts of *emergent properties*[37] some of the regularities that one generally detect in the empirically observed consumption patterns.

5. *A Preliminary Look at Some Statistical Properties*

Let us begin by noting that the model endogenously generates differentiation

[35] In order to prevent nearly infinite recursions, we stipulate that whenever the income to be allocated is $<5\%$ of the total disposable income, that will be added to next period income as a sort of 'involuntary saving'.

[36] In the simulations presented below, we set the notional number of commodities which can be explored by the system at $\ell = 223$.

[37] For a detailed discussion of this notion, see Lane (1993).

in individual consumption patterns, and, at the same time, entails processes of social imitation which prevent such diversity from exploding.

Despite totally uniform initial conditions, as incomes stochastically grow, both patterns of consumption and 'preferences' evolve in ways that are path-dependent and socially embedded. Path-dependency appears at two levels: first, the individual consumption patterns at any time depend also on the sequence of past 'preferences' and consumption acts; second, indirectly, they depend on the whole collective history of the latter. Relatedly, the social embeddedness of the dynamics is straightforward, in that preferences and revealed purchasing patterns emerge from collective mechanisms of social imitation, which represent also ordering mechanisms, possibly accounting for the relative predictability of aggregate patterns over time[38]. In the present model, almost entirely focused on the demand side, this implies that implicit dynamics on the supply side provides coevolving opportunities of innovation.[39] Given all that, an important 'exercise in plausibility' (although not a rigorous validation of the model itself) is, as mentioned in Section 2, the analysis of both qualitative and statistical properties of the patterns of consumption generated by the model, our goal being to assess the extent to which they are able to replicate actual properties of empirically observed (cross-section and time-series) expenditure patterns.[40]

Diffusion Patterns

Figure 1(a,b) depicts two quite typical diffusion profiles that the model generates, displaying the usual S-shape generally found in the empirical diffusion patterns (see e.g. Rogers, 1983; Mahajar *et al.*, 1989; Grübler and

[38] Incidentally, note that our model does not appear to display, under the parameterizations which we explored, those phenomena of sudden 'regime transitions' and possibly chaotic behavior predicted by the model of social imitation of Granovetter and Soong (1986). Our intuition is that this does not happen here, first, because of the higher path-dependency, and thus 'inertia' in-built in our model. Second, here consumers tend to imitate consumption bundles and not individual items, implying also a slower and more imperfect drive to social uniformity (since the imitated bundles are generally different from each other). However, it does not seem unlikely that Granovetter and Soong's properties could emerge in modified versions of this model allowing for, e.g., 'fashion' goods, faster rates of imitation on them and sampling mechanisms for the imitation with respect to the imitated population. Finally, the model allows the persistent exploration of new items of consumption—and through that, an everlasting evolution of 'lifestyles'.

[39] Note, also, that empirically testing restrictions on a purported (and unobservable) 'utility function' does not have a much different epistemological status.

[40] The simulations discussed in the following are based on 500-period runs with 1000 agents. Unless otherwise specified the results which we present hold for the whole range of parametrizations on the 'inertia' consumption patterns (i.e. the probability of sticking to the past basket composition) which we varied from 0.2 to 0.8. Similarly, they hold under both versions of price dynamics (see above).

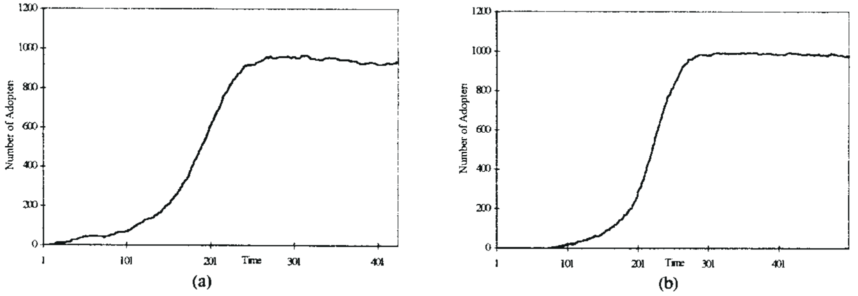

FIGURE 1. Two typical examples of diffusion patterns.

Nakicenovic, 1991). With regard to empirical data, one often finds in the literature estimates of the rate equations of the diffusion process as a (nonlinear) function of the number of potential adopters and of the total number of consumers who have already adopted the commodity in their consumption basket. A typical model is some discretization of a rate equation such as

$$\frac{\mathrm{d}N(t)}{\mathrm{d}t} = a\overline{N} + (b-a)N(t) - \frac{b}{\overline{N}}\left[N(t)\right]^2 \tag{4}$$

where $N(t)$ stands for the total number of adopters at t, $\overline{N}$ is the number of potential adopters, the parameter a is meant to capture the 'autonomous' (i.e. in our language, 'innovation-related') adoption choices and b governs 'imitation-related' choices—nonlinearly dependent on N (cf. Mahajar *et al.*, 1989). (Note also that in our model as well as in reality, 'older' commodities may be driven out of the consumption baskets by the arrival of new ones.)

For sake of illustration, we report in Appendix 1 one of the estimates of the discrete reformulation of (4)

$$S(t) = \alpha + \beta N(t-1) + \delta\left[N(t-1)\right]^2 \tag{5}$$

where $S(t)$ is the net arrival of new adopters at t.

Notwithstanding their widespread use, however, estimates of models like (5) are ridden with serious econometric problems (see Appendix 1). Hence, we do not want to make much out of it. Let us simply state primarily as a conjecture—apparently not contradicted by the data—that 'autonomous' innovation in consumption, as well as social imitationm do not only appear in the 'microscopic' description of how agents evolve their consumption patterns, but seem to carry over to the 'macroscopic' description of system dynamics.

Cross-section Engel Curves

For a wide range of parameters, the model is able to generate cross-section Engel curves whose shapes are very similar to the empirically observed ones.

Recently collected evidence on the shape of the relationship between commodity expenditure and income (or total expenditure) seems to suggest that, cross-sectionally, standard linear logarithmic expenditure-share models[41] are robust in describing the observed behavior for certain classes of goods (e.g. food and, more generally, 'basics'), but should be generalized when one turns to more 'luxury' categories of expenditures (e.g. alcohol and clothing), so as to allow for nonlinearities in total expenditure.[42]

As briefly reported in Appendix 2, when expenditure shares are plotted against the log of total individual (real) expenditure (for a given, sufficiently large, *t*), both standard OLS and nonparametric kernel regressions show that, no matter the level of aggregation of goods into product groups, 'basics' (respectively, 'luxury') budget shares tend to be negatively (respectively, positively) correlated with log of income, as expected.

Strong evidence for nonlinearities is furthermore displayed by non-parametric kernel regressions (in line with, e.g., Banks *et al.*, 1997), suggesting the need for higher-order terms in the Engel curve relationships (see Figure A1).

Quantitative support for this conjecture is further obtained by testing convenient specifications of the general (cross-section) expenditure system:

$$w_j^g = b_{0g}(\mathbf{p}) + \sum_{h=1}^{L} b_{hg}(\mathbf{p}) g_h\left(\log m_j\right) \tag{6}$$

where w_j^g is the budget share of consumer j for commodities belonging to group $g = 1, \ldots, 5$; $g_h(\cdot)$ are polynomials in the (log of) real consumer j's income m_j; and $\mathbf{p}$ is the price-vector (time-subscripts have been omitted for clarity). Thanks to its interesting properties, the class of expenditure systems (6) has been recently employed in both *theory-driven* and *data-driven*

[41] For example, the Almost Ideal (AI) model of Deaton and Muellbauer (1980a).

[42] Cf. Banks *et al.* (1997), Blundell and Ray (1984), Blundell *et al.* (1993), Hardle and Jerison (1990), Hildenbrand (1994) and Hausman *et al.* (1995). See, however, Bierens and Pott-Buter (1990) for a quite distinct point of view.

analyses.[43] Note, first, that (6) is indeed general enough to nest, as special cases, linear expenditure models as Working-Leser (cf. Deaton, 1986; Blundell, 1988) and Deaton and Muellbauer's (1980a) Almost-Ideal demand systems, while preserving (exact nonlinear) aggregability.[44] Second, Gorman (1981) and Banks *et al.* (1997) have shown that: (i) in order to be theory-consistent, the rank of demand systems such as (6) cannot be higher than 3, i.e. $L \leq 2$; and (ii) the rank-3 conditions forces, so to speak, $g_h(\log m_j)$ to be $(\log m_j)^2$, as long as one also desires to preserve exact aggregability. As a consequence, the special case:

$$w_j^g = b_0^g(\mathbf{p}_t) + b_1^g(\mathbf{p}_t)\log m_j + b_{2,t}^g(\mathbf{p}_t)\left(\log m_j\right)^2 \tag{7}$$

also known as QUAIDS model, turns out to be an 'as general as we can go,' theory-consistent, model (Deaton, 1981, p .3), which is, at the same time, well supported by recently collected empirical evidence.

Quite in tune with Banks *et al.* (1997), results reported in Appendix 2 (cf. Table A2) seem to suggest that, once (7) is tested against other functional specifications in a 'general-to-specific' framework, it appears as the *sole* correctly specified model explaining the cross-section relationships between individual budget shares and the log of individual (real) incomes generated by our model for a wide range of parameters. Even more importantly, the model seems to be able to simulate cross-section expenditure patterns which, independently of the level of aggregation over commodities, indirectly support Gorman's rank-3 assumption, even though individual consumption behaviors are of course designed to be at odds with those postulated by the standard utility-based model of rational choice.[45]

[43] At one extreme, a totally *data-driven* approach would imply fitting (either parametrically or not) statistical models to cross-section or time-series data and finding the 'preferred' ones according to a battery of econometric tests involving functional form mispecification, normality, heteroscedasticity, etc. In this case, very few restrictions are needed *ex ante*, so that, provided the model does not display any evidence for mispecification and allows for meaningful testing, it is possible to check *ex post* the plausibility of any theory of consumer behavior by performing appropriate econometric tests. On the other hand, a *theory-driven* approach prescribes that the model employed in the estimation of separate (or systems of) commodity demand functions should be consistent, generally speaking, with some theory of household expenditure behavior. Specifically, as long as this theory is the standard *utility-based model of rational choice*, one requires that (i) the functional form of demand equations to be estimated is generated by constrained maximization of a well-defined utility function; (ii) the unknown parameters involved in the estimation satisfy all derived restrictions, e.g. adding-up, homogeneity, symmetry: cf. Deaton and Muellbauer (1980b).

[44] That is, the aggregate Engel curve (i.e. weighted averages of budget shares) has the same coefficients of the individual one.

[45] This evidence, at the very least, casts some doubts on the robustness of the results obtained, among others, by Hausman *et al.* (1995) and Banks *et al.* (1997), who try to find empirical evidence agreeing with Gorman's rank-3 result.

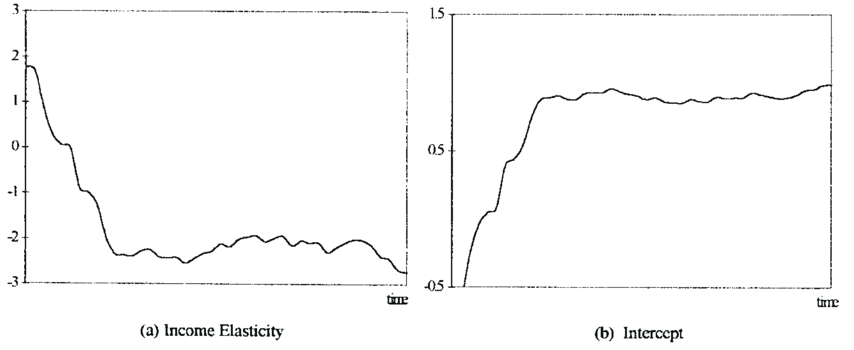

FIGURE 2. Evolution over time of income elasticity and intercept for commodity group 1.

The Evolution of Income Elasticities over Time

As far as repeated cross-section analyses of individual expenditure patterns are concerned, an interesting question is whether income elasticities for different commodities groups display any meaningful intertemporal patterns. For example, recent empirical evidence (cf. Anderson and Vahid, 1997) appears to show that the (average) individual income elasticity for food-like commodities has declined over time.

This empirical finding is robustly confirmed by the data generated for group 1 commodities by our model under different parametrizations (see Figure 2). Moreover, our results also display a general tendency for increasing intercepts over time. However, this pattern of behavior is not so clear for other (less 'basic') commodity groups.

Engel-type Dynamics of Consumption Patterns and Structural Instability

As mentioned earlier, in order not to bias by construction our results, we have made the extreme (and unrealistic) hypothesis that, when consumers opt for the reproduction over time of their past consumption patterns, they do so in a way that amounts to assuming a homothetic demand with unitary price elasticity. It is interesting to check whether, despite this assumption, long-term changes in budget coefficients emerge, driven by social innovation and imitation, jointly with stochastically growing incomes.

More generally, one wants to investigate whether some stable, parameter-constant, relationship between aggregate budget shares and aggregate real income and prices would exist in simulated data, displaying Engel-type patterns of evolution in the share of different product groups.

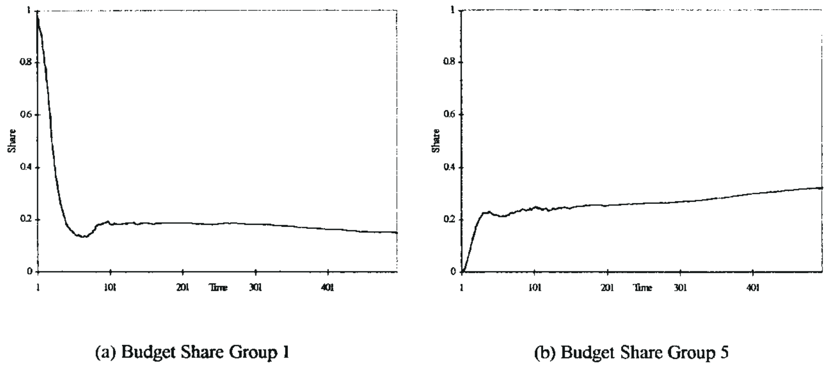

FIGURE 3. Budget shares time series.

An important *caveat*, however, applies. The presence of nonlinearities in log-linear cross-section Engel curves (see above) will *per se* destroy any isomorphisms between individual and aggregate functional forms; hence, it must be stressed that, even though such a stable time-series relationship would be found over subsamples, its functional specification will in general be very complicated. Moreover, additional 'aggregation errors' which are likely to be detected in the data (e.g. income distribution might not be *mean-scaled*, income-dependent heteroscedastic errors might arise), can in principle lead to aggregated, correctly specified time-series models whose functional form is so convoluted to prevent any interpretation of macro-parameters in terms of individual ones.[46]

In line with recent studies on food-like commodities, we found (see Appendix 3) that the data generated by the model are indeed characterized also by, in addition to the nonlinearities in cross-section relationships already singled out, other 'aggregation errors' [income is not mean-scaled (cf. Lewbel, 1992), and income-dependent heteroscedastic errors are detected (cf. Anderson and Vahid, 1997)].

Nevertheless, as Figure 3 shows, budget shares *do* display, remarkably, the expected long-term changes. This type of dynamics appears most evidently in the case of group 1 (a metaphorical proxy for 'basics') and group 5 (which,

[46] Cf. Stoker (1986), Lewbel (1992) and Anderson and Vahid (1997). If one is primarily interested in preserving some isomorphisms between aggregate (time-series) and individual (cross-section) parameters (e.g. consumption/income elasticity), so as to be able to interpret macro-estimates as micro ones in a 'representative-agent' account, many overly restrictive assumptions are essential—both on the aggregate functional form to be tested, on its dynamic specification and on the distributional properties of the involved variables. Since the available empirical evidence clearly shows that those conditions are hardly met in reality, a *data-driven* approach which does not impose any *a priori* functional forms (either at the individual or at the aggregate level) is then strongly suggested. See Deaton and Muellbauer (1980a), Deaton (1992), Tobin (1950), Stoker (1980, 1982).

being on the right-hand part of the consumption string is, in probability, 'filled up' after more basic necessities have been satisfied).

More rigorously, as reported in more detail in Appendix 3, we are in general able to select (over subsamples) preferred, correctly specified, VAR models as:

$$\Delta w_t^g = \alpha_0 + \sum_{i=1}^{k} \alpha_i^g \Delta w_{t-i}^g + \sum_{j=0}^{n} \beta_j \Delta \log m_{t-j} + \sum_{h=0}^{m} \gamma_h p_{t-h} + \varepsilon_t^g, \quad g = 1,\ldots,5 \tag{8}$$

displaying Engel-type patterns of evolution in the share of different product groups.[47]

Price-coefficients, although they are negative, are not generally significant (neither in the estimates shown here nor in most other tests that we have carried out)—which is not too surprising given our extreme assumptions. What is much more interesting is the significant effect of lagged incomes, yielding Engel-type patterns which are purely an aggregate emergent property, driven by the collective exploration of new consumption opportunities, together with the progressive relaxation of budget constraints.

Moreover, in empirical time prices, one often detects evidence of important and generalized structural breaks in the patterns of consumption within and across product groups.[48] Remarkably, notwithstanding our rather rudimentary behavioral assumptions, structural instability most often emerges with respect to both commodity groups and within groups shares of individual commodities. When applying the usual tests for structural stability (Chow, CUSUM and CUSUMSQ), one generally finds (especially with regards to groups $g = 1$ and $g = 5$) significant structural change, intertwined with rather long periods of structural stability. At the risk of some overinterpretation, these patterns might suggest the easy emergence of punctuated discontinuities in historically shaped, collectively shared, 'models of consumption,' which, however, display a 'metastable' character (in the sense that they persist on timescales of orders of magnitude greater that those of the processes which generated them, but nonetheless tend to vanish with probability one as time goes on).[49]

[47] All simulations have been carried out under the stationary/stochastic price version. Moreover, note that to avoid singularity of regression matrices entailed by the identity between total expenditure and total income, we have chosen to model $g = 1, \ldots, 4$ (the results hold irrespective of this choice). Finally, first differences are employed because of nonstationarity of the corresponding levels. See Appendix 3 for further details.

[48] On the former, cf. Combris (1992); more generally on changes in consumption patterns, cf. Houthakker (1957), Kuznets (1962), Gardes and Louvet (1986), Deaton and Muellbauer (1980b).

[49] A stimulating discussion of meta-stability notions in the domain of evolutionary models in economics is in Lane (1993). Conversely, on the recurrence and economic importance of specific social 'norms of consumption,' cf. the broad historical interpretations in Aglietta (1979) and Boyer (1986).

'Demand Laws' with Innovative Exploration and Social Adaptation

As emphasized in Section 2, a crucial question concerns the robustness of aggregate economic propositions, such as 'demand laws,' well beyond those circumstances whereby aggregate dynamics is presumed to map exactly into corresponding behavioral patterns of some purported 'representative' (most often, utility-maximizing) agent. A major advantage of a model such as that presented here is that one is bound to specify the microscopic decision algorithms, which, in our case, are clearly at odds with any assumption of both (i) statistical invariance in some 'revealed preferences,' and, at least equally important, (ii) algorithmic coherence in the choice process. Do well-established pieces of conventional economic wisdom—such as downward sloping demand schedules for individual commodities—hold in these cases too?

As mentioned in the introduction, this is precisely the question addressed by Hildenbrand (1994), in a perspective which is on purpose much more agnostic about microeconomic decision rules. Here, having constructed the data-generating process, we may also try to establish the nature of the underlying microconditions under which 'demand law' type propositions apply. As a premise, note that we have already touched on the issue, from a dynamic point of view, hinting that, for commodity aggregates, seemingly 'well-behaved' demand schedules might (often but not always) emerge out of the interactions between price changes, dynamic income effects, social imitation, relaxation of budget constraints, and so on

However, 'laws of demand,' as mentioned above, imply a major static (with respect to time) thought-experiment. That is, despite the fact that at any given time one obviously observes only one price–quantity combination, what would happen if the price of the commodity at hand were higher/lower—holding constant all other system parameters and microdecision rules? Hildenbrand (1994) proves indeed some sufficient conditions for standard demand-law propositions (and weaker versions thereof) to hold, which carry observationally testable implications concerning the distribution of demand patterns, at any t, conditional on different income classes (cf. Appendix 4).

One of the basic ideas is that if the distribution of preferences—irrespective of how they formed (or, for that matter, of how coherent they are)—is sufficiently homogeneous across income cohorts, one can establish sufficient conditions to guarantee non-upward-sloping notional demand curves (at each t), whose fulfillment can be detected from the statistical properties of actual demand conditional on different income classes.

In brief, a 'law of demand' (LD) is verified [i.e. the demand function $F_t(\mathbf{p})$ is strictly monotonically decreasing] if for any pair of price vectors $\mathbf{p}$ and $\mathbf{p}'$, $\mathbf{p} \neq \mathbf{p}'$:

$$(\mathbf{p} - \mathbf{p}') \cdot [F_t(\mathbf{p}) - F_t(\mathbf{p}')] < 0$$

A weaker version is represented by the so-called Wald axiom (WA), that is

$$(\mathbf{p} - \mathbf{p}') \cdot F_t(\mathbf{p}') \leq 0 \quad \text{implies} \quad (\mathbf{p} - \mathbf{p}') \cdot F_t(\mathbf{p}) \leq 0 \tag{9}$$

or in the strict formulation,

$$(\mathbf{p} - \mathbf{p}') \cdot F_t(\mathbf{p}') \leq 0 \quad \text{implies} \quad (\mathbf{p} - \mathbf{p}') \cdot F_t(\mathbf{p}) < 0 \tag{10}$$

The 'law of demand' satisfies the WA but the converse is not true. The bottom line is how to establish the conditions under which the LD and the WA are verified without imposing corresponding restrictions on (unobservable) individual demand schedules. These conditions turn out to be related to various measures of dispersion of demand patterns across income cohorts (cf. Appendix 4).

In Appendix 4 we show that, indeed, under some parametrizations of our model the conditions for the WA (and also for the LD) are satisfied. Note, again, that this is another emergent property of the model which does not necessarily find any direct isomorphism into microbehavioral rules. It is also interesting to observe under which specifications of the model these properties hold. The results presented in Appendix 4 apply under the stationary-price version, with relatively high inertia in individual consumption patterns.[50] However, an admittedly preliminary exploration of different parameter values shows that the LD and WA properties tend to be lost as one increases the probability of innovating (and this is so, above some threshold, also if one correspondingly increases the probability of imitating, too).

Our conjecture is that in fact the fulfillment of the conditions for the LD and WA to hold are ultimately determined by (imperfect) social imitation, so that the distribution of notional 'preferences'—or 'desired lifestyles'—are not too different across income classes, together with the different impact that budget constraints exert on actual expenditures of consumers (so that, loosely

[50] In the simulations analyzed there the probability of sticking to the past is 0.8.

speaking, with higher incomes, the 'cloud' of commodity combinations corresponding to each consumer tend to be more dispersed).[51]

However, if innovative behaviors acquire a major role in the evolution of individual consumption patterns the relative homogeneity of the distribution of 'preferences' across income classes [i.e. what Hildenbrand (1994) calls 'metonymy' of demand schedules] tends to be lost, and with that also the aggregate statistical properties sufficient for the validation of the LD and of the WA. Let us state this conjecture in a more extreme and provocative way: (i) whenever one abandons the assumptions of well-behaved micropreference functions together with rather demanding and quite *ad hoc* restrictions on their distributions, aggregate LD and/or WA properties might continue to hold as statistical collective properties (these are Hildenbrand's results); however, (ii) what basically determines these aggregate properties are ultimately phenomena of social imitations, together with budget constraints; and, relatedly, (iii) sufficiently fast processes of 'autonomous' consumer innovation might also imply the breakdown of conventional assumptions on (static) inverse relations between prices and demanded quantities.

6. *Conclusions*

In this work, building on what we consider to be some general empirical properties of consumption decisions and their evolution, we have developed a simple model which tries to capture—albeit in a very rudimentary form—phenomena like the existence of recognizably different 'lifestyles,' lexicographic orders on consumption acts, (limited) path-dependency of individual and collective consumption patterns, innovation and social imitation. It turns out that, despite its simplicity, the model generates emerging aggregate patterns of consumption with statistical properties quite in tune with empirically observed regularities, such as S-shaped diffusion of new commodities, Engel-type dynamics of budget shares, and, under quite a few microparametrizations, distributions of consumption coefficients yielding in the aggregate notional downward sloping demand curves. Of course, one can think of several improvements upon both the model and the exploration of the statistical properties of the data it generates.

Concerning the model, one can easily imagine two complementary directions. On the one hand, one might gain many insight from models

[51] Note that the two propositions are not in conflict with each other. The first one claims that 'desired lifestyles' are relatively similar across income groups (of course one assumes on that several such 'lifestyles' coexist at any t). The second proposition holds that as one goes from one income cohort to a higher one, the dispersion of actual consumption baskets will increase because under a relaxed budget constraint more of those desired (and cross-sectionally diverse) 'lifestyles' will be satisfied.

which, paraphrasing Malerba *et al.* (1996), are more 'evidence-friendly,' in that they take on board much more detailed phenomenological specifications on, for example, cognitive processes shaping the formation of 'lifestyles' and decision rules, different characteristics of commodities, different 'consumption technologies,' etc. (For example, it is obvious that the distribution between durable versus nondurable, necessities versus discretionary items, etc. are likely to map also into different decision rules.) In the same vein, sooner or later, one will have to tackle the challenge of providing more rigorous accounts of coevolutionary processes among consumption acts, preferences and cognitive representations.[52] In the other direction, one might want to explore the properties of even more reduced form models with some hope of studying analytically some generic invariances in the ensuing statistical properties.[53] With respect to statistical follow-ups, what we have tried here are just a few and rather naive attempts to check the coherence between the properties of the data generated by the model and those observed in actual history. Ahead, there are obviously more rigorous exploration of the robustness of the results (including Monte Carlo-type exercises holding parametrizations constant, and systematic comparisons across sample paths generated under different parametrizations and behavioral assumptions). Moreover, one may envisage—as mentioned earlier—promising interactions between analyses establishing parsimonious sufficient statistical conditions for aggregate economic propositions to hold {such as those, discussed above, proved by Hildenbrand (1994) on notional 'demand laws'} and explicitly microfounded models that might illuminate the classes of data-generating processes yielding certain aggregate statistical outcomes.

Increasing numbers of scholars are coming to appreciate the importance of nesting the interpretation of economic phenomena into microfoundations different from coherent self-seeking monads with well-behaved 'utility functions' and extraordinary calculating capabilities. In this perspective, the foregoing work is hopefully moving some modest steps forward in the direction of an evolutionary (and socially grounded) theory of demand, still to come.

[52] As pleaded by Devetag (1999), this volume, and, with reference to other economic domains, by Marengo and Tordjman (1996) and Dosi *et al.* (1996).

[53] In this mode, one can intuitively see fruitful overlapping with much simpler (and more elegant and analytically tractable) models of socially evolving preferences, such as Brock and Durlauf (1995). Relatedly, note that, in principle, our consumption model might be possibly be reformulated as some Markov process in some high-dimensional (or infinitely dimensional) state space.

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Appendix 1

The basic model of diffusion explains the variation of the number of adopters at time t, i.e. $S_t = \Delta N_t$, as a function of the lagged number of total adopters, i.e. N_{t-1}, and its square, i.e. N_{t-1}^2. However, if we consider subsamples of the

TABLE A1

Variable	Coefficient	SE	t-value	HCSE	PartR^2	Instability
Constant	–3.3328	1.0740000	–3.103	0.9226700	0.0895	0.06
N_{t-1}	0.0625	0.0064673	9.670	0.0064453	0.4883	0.04
${N_{t-1}}^2$	–0.0001	0.0000072	–8.507	0.0000076	0.4248	0.03

Variables: 3	Var. instab. test: 0.65403*	AR 1–2 $F(2,96) = 0.41165$ [0.6637]
Observations: 101	Joint instab. test: 0.935403	ARCH 1 $F(1,96) = 0.20172$ [0.6543]
$R^2 = 0.53859$	Information criteria:	Normality $\chi^2(2) = 1.4576$ [0.4825]
$F(2,98) = 57.196$ [0.0000]	SC = 2.52722;	${X_i}^2$ $F(3,94) = 2.2337$ [0.0894]
$\sigma = 3.35397$	HQ = 2.48099;	$X_i{*}X_j$ $F(4,93) = 1.6595$ [0.1661]
DW = 2.14	FPE = 11.5833	RESET $F(1,97) = 3.3138$ [0.0718]
RSS = 1102.414139		

whole observation period (e.g. $t = 200, \ldots, 300$), both a graphical analysis and ADF tests on the order of integration of the above series suggest that N_t and ${N_t}^2$ are both $I(2)$, so that S_t turns out to be I(1). It is well known that if we try to estimate a linear regression:

$$S_t = \alpha + \beta N_{t-1} + \gamma N_{t-1}^2 + \varepsilon_t \quad \text{with } \varepsilon_t \approx NI\left(0, \sigma^2\right) \qquad \text{(A1.1)}$$

by computing OLS estimates of α, β, γ when the variables involved are not $I(0)$, they no longer have standard asymptotic properties (as normality) and standard significance tests (as the t-statistics) are useless. Furthermore, before testing equation (A1.1) with OLS, we should test whether weak exogeneity of N_{t-1} and ${N_{t-1}}^2$ for the parameters of interest is fulfilled. Despite these serious econometric problems, we report in Table A1, as an illustration, the outcomes stemming from a crude estimation of the model (A1.1). As already stressed in the text, our principal aim is just to check whether our results match those typically found in the literature although we do not want to infer much from the following analysis.

As one can easily see, the model is well specified (apart from a very low evidence of parameter nonconstancy). The data are well fitted by the chosen linear form and, despite a very low coefficient on ${N_{t-1}}^2$, both coefficients of interest are significant with the expected sign.

The above results are also confirmed, albeit not so strongly, for a second model of diffusion, namely:

$$N_t = \alpha' + \beta' C_{t-1} + \gamma' C_{t-1}^2 + \varepsilon_t \quad \text{with } \varepsilon_t \approx NI\left(0, \sigma^2\right) \qquad \text{(A1.2)}$$

where C_{t-1} is the cumulated number of adopters up to $t - 1$ and $C_{t-1}{}^2$ is its square. Typically, both C_t and $C_{t-1}{}^2$ appear to be $I(3)$ (in the same subsample) so that a crude estimate of (A1.2) displays the same difficulties.

Appendix 2

In order to try to assess the shape of cross-section Engel curves, we have first performed a descriptive analysis of the Working–Leser model:

$$w_j^g = \alpha^g + \beta_t^g \log m_j^g$$

where w_j^g is the budget share of agent j in commodity group g and m_j is total real income (expenditure) of agent j. As for aggregation in commodity groups, we considered two different setups, namely (i) goods are aggregated into the original five groups, $g = 1, \ldots, 5$; and (ii) goods are aggregated into two groups, i.e. $g = \{B,L\}$, where $B = 1 \cup 2$ stands for 'basics' and $L = 4 \cup 5$ stands for 'luxury'. For every commodity group, and for different points in time, we carried out cross-plots of w_j^g versus ($\log m_j^g$) and we performed both para- metric (OLS) and non-parametric (Kernel) regressions.

As a general pattern (see Figure A1), one is likely to find a low correlation between budget shares and log of income. Despite that, irrespective of the aggregation setup, budget shares and log of individual incomes seem to be correlated with the expected signs [cf. panels (a) and (b) with (c) and (d)]. Moreover, quite in line with the results of Banks *et al.* (1997), nonlinearities appear throughout, suggesting the need for higher-order terms of $\log m_j^g$ in cross-section Engel curves.

We then estimated by standard OLS in both aggregation setups the alternative specifications:

$$\begin{aligned} M1\text{:} \quad w_j^g &= \alpha^g + \beta_{1t}^g \log m_j^g + \beta_{2t}^g \left(\log m_j^g\right)^2 + \varepsilon_j^g \\ M2\text{:} \quad w_j^g &= \alpha^g + \beta_t^g \log m_j^g + \varepsilon_j^g \end{aligned}$$

Estimation results for an archetypal case [with an aggregation setup as in (ii) above] are reported in Table A2. Although the R^2s for all cross-section regressions are very low, both 'basics' and 'luxury' expenditure shares display non-linearities in the log of income. Tests for autoregressive conditional (ARCH) and income dependent heteroscedasticity (F-test, not reported) failed to find any evidence for heteroscedastic residuals. Nevertheless, functional form mispecification arises in all estimated log-linear models: both the equivalent reset F-test and LM tests—performed to assess whether the

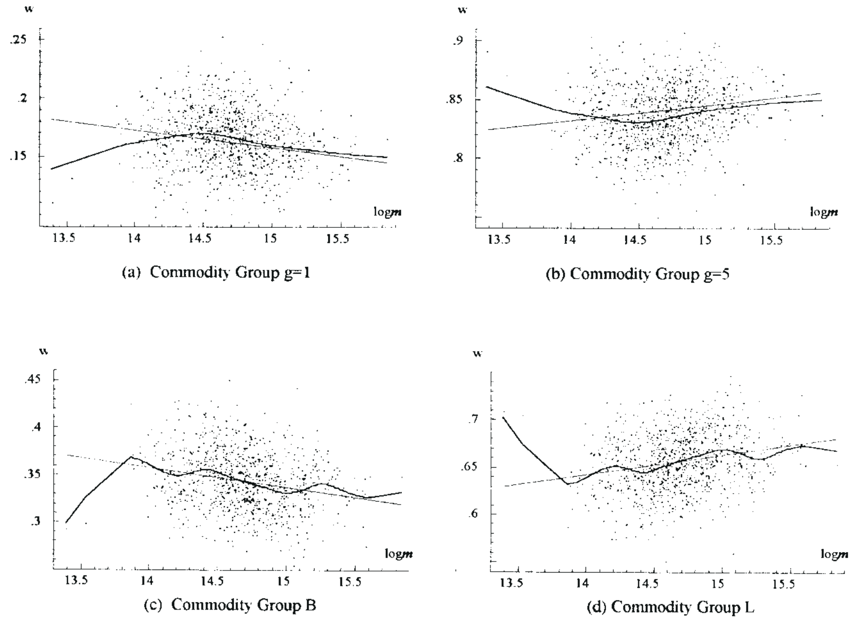

FIGURE A1. Linear regression (thin lines) and nonparametric kernel estimates of Engel curves.

variable (log $m_{j,t}$)^2 has been omitted—strongly reject the null hypothesis. However, once the square of the log of income is introduced into the regression, no mispecifications are reported, even though the R^2s still remain very low. Finally, further nonlinear terms appear not to be significant in explaining budget shares, as the $X_i \cdot X_j$ F-tests show (see M1 column in Table A2).

Evidence of nonlinearities in Engel curve specifications also arises from the OLS estimation of the log-linear specification:

$$\log C^g_{j,t} = \alpha^g_t + \beta^g_t \log m_{j,t} + \varepsilon^g_{j,t}, \quad \varepsilon^g_{j,t} \approx N\left(0, \sigma^2\right) \tag{A2.1}$$

where $C_{j,t}{}^g$ is time-t (total) real expenditure of agent i in commodity group g = 1,2, . . .,5, $m_{j,t}$ is real income and $t \in \{200, 250, 300, \ldots, 500\}$. In Figure A2 we show an example (period t = 500) of the cross-plots (log $C_{j,t}{}^g$, log $m_{j,t}$) for each commodity group. The shape of the cross-plots is robust across time and through different levels of aggregation over commodities.

Moreover, in Table A3 we report the results of the comparison of the regression for commodity group 1 ('basics') and that for the aggregate group L (i.e. 'luxury', g = 4 $\cup$ 5). Income elasticities are all significant and the R^2 are very high. However, the widespread, strong evidence for functional-form

TABLE A2. An Example of OLS Estimation Results of Cross-section Engel Curve Regressions ($t = 500$)

	Model M1: $w_j^g = \alpha_t^g + \beta_{1t}^g \log m_j^g + \beta_{2t}^g (\log m_j^g)^2 + \varepsilon_j^g$		Model M2: $w_j^g = \alpha_t^g + \beta_{1t}^g \log m_j^g + \varepsilon_j^g$	
	Group $g = 1$	Group $L = 4 \cup 5$	Group $g = 1$	Group $L = 4 \cup 5$ +
Estimated coefficients				
Constant				
Est.	–1.8393	3.3321	0.3404	0.4421
σ	0.9944	1.2555	0.0321	0.0405
t	1.850	2.654	10.602	10.903
t-pr	0.0647	0.0081	0.0000	0.0000
$\log m_j{}^g$				
Est.	0.3562	–0.4740	–0.0144	0.0175
σ	0.1691	0.2134	0.0027	0.0034
t	2.107	–2.221	–5.291	5.0691
t-pr	0.0353	0.0266	0.0000	0.0000
$(\log m_j^g)^2$				
Est.	–0.0157	0.0209	–	–
σ	0.0072	0.0091		
t	–2.193	2.303		
t-pr	0.0285	0.0215		
Diagnostics				
R^2	0.1312	0.1303	0.1273	0.1251
F-test	16.455 [0.0000]	15.556 [0.0000]	27.995 [0.0000]	25.696 [0.0000]
σ	0.0244	0.0308	0.0245	0.0309
AR 1–2	1.331 [0.2648]	0.0787 [0.9242]	1.429 [0.2400]	0.0872 [0.9165]
ARCH 1	0.069 [0.7918]	1.8712 [0.1716]	0.117 [0.7323]	1.3868 [0.2392]
Norm. χ^2	1.372 [0.5036]	1.2526 [0.5346]	1.726 [0.4220]	0.9459 [0.6232]
X_i^2	0.076 [0.9896]	0.6426 [0.6322]	0.124 [0.8831]	0.6725 [0.5107]
RESET	0.087 [0.7677]	2.4372 [0.1188]	4.809 [0.0285]**	5.3046 [0.0215]**
X_i*X_j	0.400 [0.8484]	1.3312 [0.2485]	–	–

mispecifications (cf. the large value of the F-test for omitted variables) suggests the incluson of (at least) the square of log of income in the regressions. As to other kind of mispecifications (not reported in Table A4), one often finds evidence for non-normality.

After having introduced the additional explanatory variable $(\log m_{j,t})^2$ in the regression (A2.1), RESET tests fail to display functional form mispecifications—see Table A4. This, however, is not completely true for group 1, suggesting that, after all, the linear specification for 'basic' commodities is not completely wrong (see Banks *et al.*, 1997).

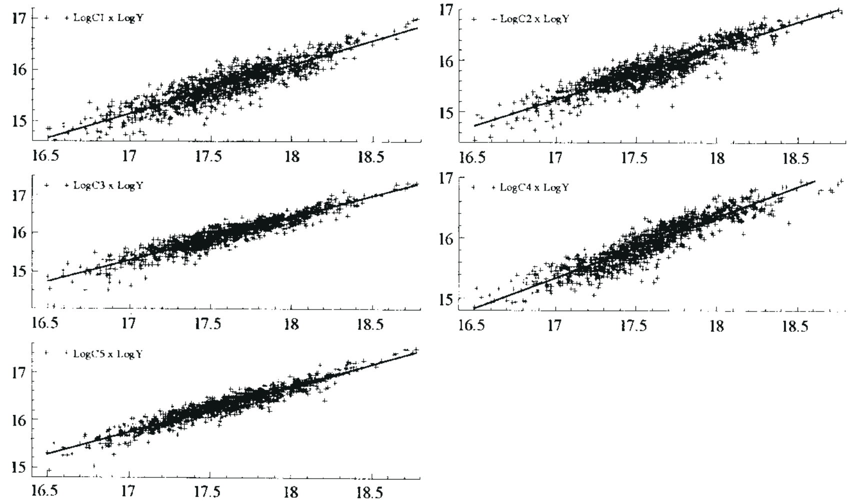

FIGURE A2. Cross-plots of log (C_g) versus log (m) at time t = 500, g = 1, 2, . . ., 5.

TABLE A3. Output of the Regressions: $\log C_{j,t}^{g} = \alpha_t^{g} + \beta_t^{g} \log m_{j,t} + \varepsilon_{jt}^{g}$

	α_t^g	β_t^g	SE of β_t^g	t-value H_0: $\beta_t^g = 0$	R^2	LM test for omitted $(\log m_{jt})^2$
Commodity group 1						
t = 200	–0.2498	0.8293	0.3847	19.064 [0.0000]**	0.27	7.0917 [0.0079]**
t = 250	–0.1628	0.8446	0.0250	33.721 [0.0000]**	0.53	2.1374 [0.1441]
t = 300	–0.5754	0.8978	0.0162	55.316 [0.0000]**	0.75	2.2440 [0.1344]
t = 350	–1.0496	0.9446	0.0141	66.731 [0.0000]**	0.81	6.8328 [0.0091]**
t = 400	–1.0251	0.9461	0.0143	66.359 [0.0000]**	0.82	16.030 [0.0001]**
t = 450	–1.0058	0.9474	0.0152	62.354 [0.0000]**	0.80	8.4432 [0.0037]**
t = 500	–0.9558	0.9475	0.0149	63.196 [0.0000]**	0.81	3.3934 [0.0822]*
Commodity groups 4 and 5 (aggregated)						
t = 200	–0.4585	1.0294	0.0096	107.66 [0.0000]**	0.92	4.7358 [0.0298]*
t = 250	–0.4774	1.0277	0.0052	198.02 [0.0000]**	0.97	4.8723 [0.0402]*
t = 300	–0.3919	1.0174	0.0033	308.54 [0.0000]**	0.99	4.6806 [0.0307]*
t = 350	–0.3400	1.0116	0.0028	356.32 [0.0000]**	0.99	7.0823 [0.0079]**
t = 400	–0.3414	1.0110	0.0027	367.72 [0.0000]**	0.99	16.033 [0.0001]**
t = 450	–0.3041	1.0081	0.0028	362.38 [0.0000]**	0.99	17.215 [0.0000]**
t = 500	–0.3411	1.0098	0.0027	367.92 [0.0000]**	0.99	4.6001 [0.0318]*

The results suggest, first, that nonlinear terms (square of log of income) matter in Engel curve specifications, and, secondly, that Gorman's rank 3 assumption is satisfied by our computer-simulated data. This conjecture is further supported by jointly testing a demand system for four out of the five commodity groups (avoiding singularity of the dependent variables matrix)

TABLE A4. Reset Test for Functional Form Specification in the Extended Regression: $\log C_{j,t}^{g} = \alpha_t^{g} + \beta_t^{g} \log m_{j,t} + (\log m_{j,t})^2 + \varepsilon_{j,t}^{g}$

Time period	Reset test $F(1,996)$	
	Commodity group 1	Commodity groups 4 and 5 (aggregated)
200	0.37068 [0.5428]	0.29995 [0.5840]
250	0.67287 [0.4122]	0.15043 [0.6982]
300	0.00980 [0.9211]	0.00083 [0.9769]
350	5.95680 [0.0148]*	2.31770 [0.1282]
400	8.50660 [0.0036]**	2.67330 [0.1024]
450	4.76523 [0.0293]*	2.65432 [0.1035]
500	0.15582 [0.6931]	0.89528 [0.3443]

and employing χ^2 statistics to test nonlinear restrictions implied by the determinants of the matrices of estimated parameters (not reported).

Appendix 3

Concerning the estimation of time-series models relating total consumption levels (suitably disaggregated into commodity groups), aggregate income and prices, it is common practice to employ a log-linear specification so as to keep some isomorphism with the correspondent individual functional form widely employed in cross-section analyses.

However, as shown by, among others, Tobin (1950), Stoker (1986), Lewbel (1992), and Anderson and Vahid (1997), aggregation preserves the cross-section functional form purported at the individual level only if some restrictive conditions are satisfied. Among the others, three such necessary conditions for log-linearity to hold in the aggregate (and hence for macro-estimates of consumption–income elasticities to be interpreted as micro ones) are: (i) absence of nonlinear terms (in the log of individual incomes) in cross-section log-linear regressions; (ii) (cross-section) real income distributions must be mean-scaled, i.e. changes in the mean of real income distributions have to be independent of changes in its *relative* distribution;[54] (iii) the errors in the log-linear cross-section regressions must not display income-dependent heteroscedasticity.[55]

[54] More precisely, if $F(m_{h,t};M_t,\zeta t)$ is the distribution of real income across agents h at time t (where ζt is a vector of parameters and M_t is aggregate real income), then F is 'mean scaled' if: $F(m_{h,t}|M_t,\zeta t) = M_t^{-1}\cdot G'(m_{h,t}/M_t|\zeta t)$, i.e. if changes in the parameters ζt are independent of M_t, cf. Lewbel (1992).

[55] Given the simple cross-section log-linear regression: $\log q_{h,t} = \alpha_t + \beta_t \log m_{h,t} + \varepsilon_{h,t}$, where $q_{h,t}$ is time-t real consumption of agent h, then $\varepsilon_{h,t}$ display income-dependent heteroscedasticity, if for some function κ, we have $\varepsilon_{h,t}|m_{h,t} \sim N(0,\kappa(\log m_{h,t}))$, cf Anderson and Vahid (1997).

TABLE A5. Mean Scaling

(a) Correlation coefficients, slopes and t-tests (with related two-tail probabilities) in the linear regression between λ_{qt} and m_t^{a}

Quantile	Correlation coefficients	Slope	Intercept	t–test (H_0: slope = 0)	t–prob
0.05	–0.48434	–0.02701	0.931281	–26.4454	2.87E–30
0.10	–0.49381	–0.0233	0.95172	–29.7429	1.4E–32
0.15	–0.48586	–0.02054	0.965446	–31.2597	1.44E–33
0.20	–0.48467	–0.01792	0.975194	–31.5544	9.4E–34
0.25	–0.50168	–0.01574	0.984421	–36.3622	1.36E–36
0.30	–0.5158	–0.01339	0.990982	–40.8192	6.27E–39
0.35	–0.50572	–0.0109	0.995992	–41.6818	2.36E–39
0.40	–0.5456	–0.00887	1.003407	–54.91	5.55E–45
0.45	–0.57435	–0.00667	1.008879	–43.11	4.88E–40
0.50	–0.64344	–0.00399	1.010857	–22.0775	8.71E–27
0.55	–0.7525	–0.0013	1.014056	–6.10536	1.73E–07
0.60	0.007196	0.001201	1.01882	4.644559	2.67E–05
0.65	0.362836	0.00375	1.024419	11.36428	3.27E–15
0.70	0.356507	0.006315	1.032558	14.48989	3.75E–19
0.75	0.430486	0.009965	1.036768	19.30651	2.87E–24
0.80	0.47293	0.014504	1.038847	23.58233	4.78E–28
0.85	0.500399	0.020081	1.040037	28.57797	8.63E–32
0.90	0.517477	0.029452	1.026954	37.13548	5.12E–37
0.95	0.534887	0.043081	1.015893	48.10711	2.84E–42
1.00	0.551493	0.107345	1.002358	27.31886	6.64E–31

(b) Correlation coefficient, slope and t-test in the linear regression between m_t^{a} and m_t^{g}

	Correlation coefficient	Slope	R^2	t-test (H_0: slope = 0)	t-prob
Statistics	–0.6008	–1.2629E–09	0.36	–5.1553	4.7404E–06

Following Lewbel (1992), we first tested whether our model is able to generate mean-scaled cross-section real income distributions.[56] The results reported in Table A5 strongly reject mean-scaling. This is in line with the evidence reported by Lewbel (1992) about the income distribution in the US

[56] To that end, we performed two different kinds of computations. First, given a sufficiently long time-period sample T, let s_{qt} be the qth quantile of the distribution of individual real income m_t. Next, define by m_t^{a} and m_t^{g}, respectively, the arithmetic and geometric average of the time-t income distribution. Finally, let $\lambda_{qt} = s_{qt}/m_t^{a}$ and $\omega t = m_t^{a}/m_t^{g}$. It is easy to show that the distribution of m_t is mean-scaled if and only if λ_{qt} and m_t^{a} are independent over time for every q. Moreover, the condition that ω_t and m_t^{a} are independent over time is necessary for the distribution of m_t to be mean-scaled. In our computations, see Table A5(a), we considered $T = 10, 20, 30, \ldots, 500$ and $q = 0.05, 0.10, \ldots, 0.95$. Second, in order to test the independence over time of the pairs of time-series (λ_{qt}, m_t^{a}), for every q, and (m_t^{a}, m_t^{g}), we performed a t-test on the slope of the related linear regression (after having checked for mispecifications), cf. Table A5(b).

Current Population Reports data 1947–83 and allows one to conclude that, even though a log-linear model relating consumption and income is assumed in cross-section regressions, the same specification cannot arise from aggregation. Second, we detected strong evidence of income-dependent heteroscedasticity, which is often present in simulated cross-section data both at different levels of aggregation over commodities (in particular, for 'luxury' goods) and across time (see Table A6).[57]

The foregoing evidence, in addition to that suggesting the presence of nonlinearities in cross-section log-linear models, led us to revert to a more data-driven approach, the goal being the selection of well-specified, time-series VAR (and single-equation) models relating aggregate budget shares (w_t^g) to (some functions of) real total expenditure (m_t) and commodity groups price indices (p_t^g).[58] All five budget shares, as well as real income, appear to be stochastically nonstationary in the selected sample simulation period, i.e. $t = 250, \ldots, 500$ (see also Figure 3[59]). Therefore, all subsequent analyses have been carried out on differences in budget shares and real income. We estimated—both simultaneously and separately—models of the form:

$$\begin{aligned} \Delta w_t^g \quad = \quad & \alpha_0 + \sum_{i=1}^{k} \sum_{g'=1}^{5} \alpha_i^{g'} \Delta w_{t-i}^{g'} + \sum_{j=0}^{n} \beta_j \Delta \log m_{t-j} \\ & + \sum_{h=0}^{m} \gamma_h p_{t-j} + [\text{other terms}] + \varepsilon_t^g \end{aligned} \tag{A3.1}$$

As a general result, we get that in the equation for Δw_t^g neither lagged terms of Δw_t^g nor (contemporaneous and lagged) terms of $\Delta w_t^{g'}$, $g' \neq g$, are statistically significant (i.e. $\alpha_i^{g'} = 0$, all i and $g' \neq g$). Therefore, one can revert to a single-equation analysis, since both income and price indices are (weakly

[57] To test for income-dependent heteroscedasticity, we considered the regression: $\log q_{h,t} = \alpha_t + \beta_t \log m_{h,t} + \varepsilon_{h,t}$, and we assumed that $\varepsilon_{h,t}^g | m_{h,t} \sim N(0, \kappa(\log m_{h,t}))$. Then, we ran an auxiliary regression to test whether the specification: $\kappa(\log m_{h,t}) = \omega_0 + \omega_1 \log m_{h,t} + \omega_2 (\log m_{h,t})^2$ correctly explains the variance of the errors.

[58] In testing VAR specifications, one has to face two important issues. Indeed, our data are characterized by (i) endogeneity of consumption and income (i.e. total expenditure approximately equals total income); and (ii) prices and income are exogenous (independent) stochastic processes, while, of course, the series C_t^g are not, because consumption choices in our model are taken simultaneously. Therefore, one should model together the series $\{w_t^g, g = 1, \ldots, 5\}$ and assume—by (ii) above—weak (and strong) exogeneity of both prices and (log of) income. However, because of the identity between total expenditure and total income, one can only model simultaneously up to four budget shares' series so as to avoid singularity of the matrices involved in the regressions. In the following, we have chosen to model w_t^g for $g = 1, \ldots, 4$ (even though our main results hold irrespective of that choice).

[59] In the model, prices are generated by two alternative data-generating processes (stationary versus non-stationary). The results we present in this section are examples of the case in which price indices are $I(0)$.

TABLE A6. χ^2 and F-tests for Income Dependent Heteroscedasticity (Auxiliary Regression: $\varepsilon_{h,t}^{g} = \omega_0 + \omega_1 \log m_{h,t} + \omega_2(\log m_{h,t})^2 + \nu_{h,t}^{g}$)

Time	Commodity group 1		Commodity groups 4 and 5 (aggregated)	
	χ^2 (2) test	F-form $F(2,995)$	χ^2 (2) test	F-form $F(2,995)$
200	1.4007 [0.4964]	0.6978 [0.4979]	17.030 [0.0002]**	8.6190 [0.0002]**
250	0.1052 [0.9488]	0.0523 [0.9423]	14.965 [0.0006]**	7.5582 [0.0006]**
300	4.0997 [0.1288]	2.0480 [0.1295]	7.826 [0.0199]*	3.901 [0.0202]*
350	3.3612 [0.1863]	1.6778 [0.1873]	5.9344 [0.0514]*	2.9700 [0.0518]*
400	5.9352 [0.0514]*	2.9704 [0.0517]*	5.2625 [0.0720]*	2.6319 [0.0724]*
450	1.4154 [0.4928]	0.7051 [0.4943]	1.7359 [0.4198]	0.8651 [0.4213]
500	8.4578 [0.0146]*	4.2437 [0.0146]*	14.468 [0.0007]**	7.3034 [0.0007]**

and strongly) exogenous for the parameters to be estimated. Following a 'general to specific' modeling strategy, we can in general select preferred models with no mispecifications displaying Engel-type patterns of evolution in the share of different product groups. Our preferred expenditure schedules are of the form:

$$\begin{aligned}\Delta w_t^g &= \alpha_0 + \sum_{i=1}^{k} \alpha_i^g \Delta w_{t-i}^g + \sum_{j=0}^{n} \beta_j \Delta \log m_{t-j} \\ &\quad + \sum_{h=0}^{m} \gamma_h p_{t-j} + \varepsilon_t^g\end{aligned} \tag{A3.2}$$

In Table A7, two examples of OLS estimates of (A3.2) are reported for commodity groups 1 and 5. We found significant lagged values for both $\Delta\log m_t$ and p_t very far from time t (even for the lags $t-j, j > 20$), despite our extreme modeling assumptions and the stationarity of the price-generating process.

As to the required dynamic specification, a dynamic analysis of the lag structure generally suggests that the choice of $k \approx 10$, $n \approx 20$ and $m \approx 10$ is the one which optimally trades-off the goodness of fit and correct specification. Solving for the static long-run equations allows us to get statistically significant coefficients which have the 'right' expected sign. Moreover, a Wald test for the joint significance of all the variables (excluding the constant) in the long-run solution (see Table A7) strongly rejects the null hypothesis, suggesting that in the long run (i.e. when the means of the independent variables have remained at a constant level for long enough and the dependent one has reached its long-run solution) the influences of income and prices on budget shares are similar to the empirically observed ones.

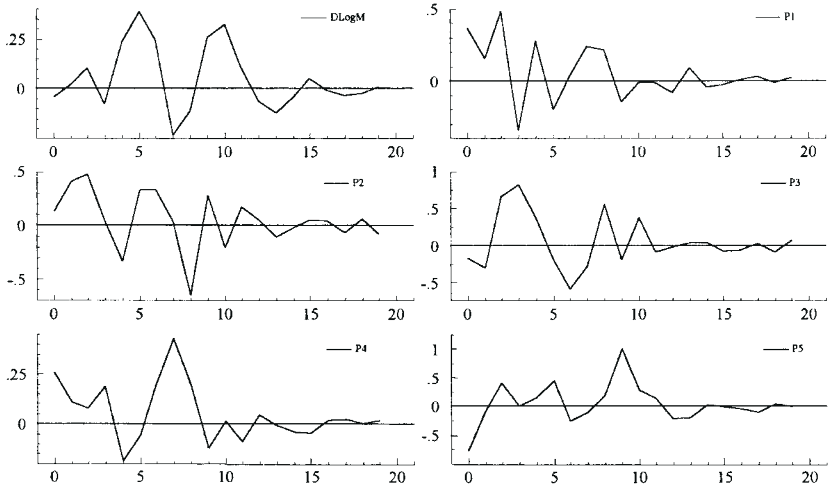

FIGURE A3. Plots of the normalized lag weights (lags $t + 1, t + 2, \ldots$ on the x-axis) for the regression:

$$\Delta w_t^g = \alpha_0 + \sum_{i=1}^{k} \alpha_i^g \Delta w_{t-i}^g + \sum_{j=0}^{n} \beta_j \Delta \log m_{t-j} + \sum_{h=0}^{m} \gamma_h p_{t-j} + \varepsilon_t^g, \quad g = 1$$

However, even after the dynamics has reached its static long-run solution, in the short-run there appear to be a sort of cycles in the response of the change of budget shares to the impulses of a change in (the log of) real income and price indexes. This can be clearly seen if we take a look at the plots of the normalized lag weights (see Figure A3 for an example concerning group 1), which give the responses of the dependent variable at time $t + 1$, $t + 2$, etc., when one slightly perturbs the level of an explanatory variable at time t.

Tests on other simulation results conducted on the 'version 2' of price dynamics (i.e. price falling along with 'learning curves'), not shown here, show that, while in general Engel-type patterns continue to emerge, prices (both the price index of the group in question and of the others) appear to exert a significantly greater influence of the dynamics of budget shares (up to the fifth lag, and mostly but not always with the expected sign). However, note that, again, this should be considered as an emergent property which does not bear any isomorphism with microscopic behavior: in fact, by construction, individual agents either have unit price elasticities when acting 'business-as-usual' or do not look at all at prices when imitating or innovating—except insofar as prices affect budget constraints. Indeed, what appears in the aggregate as the dynamic influence of prices upon shares rests in fact on the process by

TABLE A7. Estimation Results for Budget Shares of Groups 1 and 5

Modelling ΔW^1 by OLS; sample: 250–491

Variable	Coefficient	SE	t-value	t-prob	PartR^2
Constant	0.014399	0.017400	0.828	0.4091	0.0041
DW1_1	0.067477	0.080796	0.835	0.4048	0.0042
DW1_2	0.072266	0.078136	0.925	0.3564	0.0052
DW1_3	–0.13778	0.079565	–1.732	0.0852	0.0178
DW1_4	–0.12425	0.078185	–1.589	0.1139	0.0151
DW1_5	0.0081782	0.079610	0.103	0.9183	0.0001
DW1_6	0.041917	0.081683	0.513	0.6085	0.0016
DW1_7	–0.093529	0.079630	–1.175	0.2419	0.0083
DW1_8	–0.11975	0.077689	–1.541	0.1251	0.0142
DW1_9	0.11576	0.076248	1.518	0.1309	0.0138
DW1_10	–0.037119	0.077013	–0.482	0.6305	0.0014
DLog m	–0.0079119	0.034163	–0.232	0.8171	0.0003
DLogm_1	0.0055317	0.034025	0.163	0.8711	0.0002
DLogm_2	0.020731	0.033492	0.619	0.5368	0.0023
DLogm_3	–0.018563	0.034391	–0.540	0.5901	0.0018
DLogm_4	0.045341	0.034535	1.313	0.1910	0.0103
DLogm_5	0.077241	0.034523	2.237	0.0266	0.0294
DLogm_6	0.039277	0.035487	1.107	0.2700	0.0074
DLogm_7	–0.051060	0.034684	–1.472	0.1429	0.0130
DLogm_8	–0.0069982	0.035748	–0.196	0.8450	0.0002
DLogm_9	0.074726	0.034452	2.169	0.0315	0.0277
DLogm_10	0.057994	0.034924	1.661	0.0987	0.0164
P1	–0.0040681	0.0022155	–1.836	0.0681	0.0200
P1_1	–0.0014405	0.0022903	–0.629	0.5303	0.0024
P1_2	–0.0049606	0.0023072	–2.150	0.0330	0.0273
P1_3	0.0038150	0.0023237	1.642	0.1025	0.0161
P1_4	–0.0037049	0.0023212	–1.596	0.1124	0.0152
P1_5	0.0012277	0.0023123	0.531	0.5962	0.0017
P1_6	–0.00018341	0.0023001	–0.080	0.9365	0.0000
P1_7	–0.0029585	0.0023352	–1.267	0.2070	0.0096
P1_8	–0.0027406	0.0024003	–1.142	0.2552	0.0078
P1_9	0.0018748	0.0023725	0.790	0.4305	0.0038
P1_10	–0.00032785	0.0023565	–0.139	0.8895	0.0001
P2	0.00085988	0.0022112	0.389	0.6979	0.0009
P2_1	0.0026362	0.0021606	1.220	0.2242	0.0089
P2_2	0.0028655	0.0022212	1.290	0.1988	0.0100
P2_3	–3.1874e–005	0.0022014	–0.014	0.9885	0.0000
P2_4	–0.0019596	0.0022060	–0.888	0.3757	0.0048
P2_5	0.0030341	0.0022523	1.347	0.1798	0.0109
P2_6	0.0025096	0.0022884	1.097	0.2744	0.0072
P2_7	–0.00037745	0.0022475	–0.168	0.8668	0.0002
P2_8	–0.0041533	0.0022574	–1.840	0.0676	0.0201
P2_9	0.0031807	0.0022966	1.385	0.1679	0.0115

TABLE A7. *Continued*

Modelling ΔW^1 by OLS; sample: 250–491

Variable	Coefficient	SE	t-value	t-prob	PartR^2
P2_10	–0.00064465	0.0022645	–0.285	0.7762	0.0005
P3	–0.00075375	0.0021648	–0.348	0.7281	0.0007
P3_1	–0.0012626	0.0020942	–0.603	0.5474	0.0022
P3_2	0.0031266	0.0021020	1.487	0.1388	0.0132
P3_3	0.0034611	0.0021262	1.628	0.1055	0.0158
P3_4	0.00095185	0.0021348	0.446	0.6563	0.0012
P3_5	–0.0010036	0.0020987	–0.478	0.6331	0.0014
P3_6	–0.0017712	0.0020423	–0.867	0.3871	0.0045
P3_7	–0.00038312	0.0020183	–0.190	0.8497	0.0002
P3_8	0.0025405	0.0020090	1.265	0.2078	0.0096
P3_9	–0.0013308	0.0019754	–0.674	0.5015	0.0027
P3_10	0.0018484	0.0020330	0.909	0.3646	0.0050
P4	–0.0032225	0.0019425	–1.659	0.0990	0.0164
P4_1	–0.0011197	0.0019668	–0.569	0.5699	0.0020
P4_2	–0.00061173	0.0019426	–0.315	0.7532	0.0006
P4_3	–0.0026184	0.0019550	–1.339	0.1823	0.0108
P4_4	0.0019880	0.0019309	1.030	0.3047	0.0064
P4_5	0.00047779	0.0018993	0.252	0.8017	0.0004
P4_6	–0.0029956	0.0019146	–1.565	0.1196	0.0146
P4_7	–0.0054100	0.0019310	–2.802	0.0057	0.0454
P4_8	–0.0020209	0.0019950	–1.013	0.3126	0.0062
P4_9	0.0020014	0.0019600	1.021	0.3087	0.0063
P4_10	–0.0015133	0.0019722	–0.767	0.4440	0.0036
P5	0.0040710	0.0024694	1.649	0.1011	0.0162
P5_1	0.00015334	0.0025030	0.061	0.9512	0.0000
P5_2	–0.0025588	0.0024199	–1.057	0.2919	0.0067
P5_3	0.00064062	0.0023429	0.273	0.7849	0.0005
P5_4	–7.1316e–005	0.0023095	–0.031	0.9754	0.0000
P5_5	–0.0026849	0.0023655	–1.135	0.2580	0.0077
P5_6	0.0010634	0.0022633	0.470	0.6391	0.0013
P5_7	0.00091247	0.0022652	0.403	0.6876	0.0010
P5_8	–0.00093153	0.0022951	–0.406	0.6854	0.0010
P5_9	–0.0060717	0.0023336	–2.602	0.0101	0.0394
P5_10	–0.00094319	0.0024006	–0.393	0.6949	0.0009

R^2 = 0.374521; $F(76,165)$ = 1.3 [0.0839]; σ = 0.000248291; DW = 1.98
RSS = 1.017200123E–005 for 77 variables and 242 observations

AR 1-2 $F(2,163)$ = 1.1594 [0.3162]
ARCH 1 $F(1,163)$ = 0.32107 [0.5717]
Normality $\chi^2(2)$= 3.053 [0.2173]
X_i^2 $F(152,12)$ = 0.13954 [1.0000]
RESET $F(1,164)$ = 1.0579 [0.3052]

TABLE A7. *Continued*

Solved static long-run equation (SE in parentheses)

$\Delta W^1 =$	$+0.01193$	$-0.1958\Delta \log m$	$-0.01116P^1$
	(0.01485)	(0.09559)	(0.006759
	$+0.006562P^2$	$+0.004494P^3$	$-0.01247P^4$
	(0.005806)	(0.005267)	(0.006793)
	$-0.00532P^5$		
	(0.007467)		

Wald test on the joint significance of the regressors in the static long-run equation:
$\chi^2(6) = 12.14$ [0.0589]*

Modelling ΔW^5 by OLS; sample: 250–491

Variable	Coefficient	SE	t-value	t-prob	PartR^2
DW5_1	–0.082185	0.077074	–1.066	0.2878	0.0068
DW5_2	0.071646	0.076488	0.937	0.3503	0.0053
DW5_3	–0.0096307	0.077876	–0.124	0.9017	0.0001
DW5_4	0.055801	0.077361	0.721	0.4717	0.0031
DW5_5	0.033120	0.078369	0.423	0.6731	0.0011
DW5_6	–0.051880	0.076937	–0.674	0.5011	0.0027
DW5_7	–0.035467	0.076054	–0.466	0.6416	0.0013
DW5_8	0.00098872	0.076691	0.013	0.9897	0.0000
DW5_9	–0.12282	0.075094	–1.636	0.1038	0.0159
DW5_10	0.022530	0.075979	0.297	0.7672	0.0005
DLog m	0.012063	0.047117	0.256	0.7983	0.0004
DLogm_1	0.030212	0.046187	0.654	0.5139	0.0026
DLogm_2	–0.043489	0.046183	–0.942	0.3477	0.0053
DLogm_3	–0.036847	0.047890	–0.769	0.4427	0.0036
DLogm_4	0.029431	0.047730	0.617	0.5383	0.0023
DLogm_5	0.079272	0.048522	1.634	0.1042	0.0158
DLogm_6	–0.036480	0.048421	–0.753	0.4523	0.0034
DLogm_7	0.050134	0.047122	1.064	0.2889	0.0068
DLogm_8	–0.024313	0.047179	–0.515	0.6070	0.0016
DLogm_9	0.010077	0.046147	0.218	0.8274	0.0003
DLogm_10	–0.041547	0.046244	–0.898	0.3703	0.0048
P1	–0.0027548	0.0029610	–0.930	0.3535	0.0052
P1_1	0.0026985	0.0029956	0.901	0.3690	0.0049
P1_2	0.0036776	0.0030099	1.222	0.2235	0.0089
P1_3	0.0013651	0.0030325	0.450	0.6532	0.0012
P1_4	0.0011860	0.0030519	0.389	0.6981	0.0009
P1_5	–0.0055964	0.0030561	–1.831	0.0689	0.0198
P1_6	0.0025663	0.0030818	0.833	0.4062	0.0042
P1_7	0.00062041	0.0030890	0.201	0.8411	0.0002
P1_8	0.0017759	0.0031212	0.569	0.5701	0.0019
P1_9	–0.00069218	0.0031232	–0.222	0.8249	0.0003

TABLE A7. *Continued*

Modelling ΔW^5 by OLS; sample: 250–491

Variable	Coefficient	SE	t-value	t-prob	PartR^2
P1_10	0.00086999	0.0030791	0.283	0.7779	0.0005
P2	–0.0032273	0.0030453	–1.060	0.2908	0.0067
P2_1	–0.0023747	0.0029514	–0.805	0.4222	0.0039
P2_2	0.0010171	0.0029625	0.343	0.7318	0.0007
P2_3	–0.0036754	0.0029815	–1.233	0.2194	0.0091
P2_4	0.0021103	0.0030270	0.697	0.4867	0.0029
P2_5	–0.0048765	0.0031438	–1.551	0.1228	0.0143
P2_6	1.3506e–005	0.0032066	0.004	0.9966	0.0000
P2_7	–0.0033518	0.0031482	–1.065	0.2886	0.0068
P2_8	–0.0040231	0.0031632	–1.272	0.2052	0.0097
P2_9	0.00076303	0.0031769	0.240	0.8105	0.0003
P2_10	–0.0020661	0.0030912	–0.668	0.5048	0.0027
P3	0.0015409	0.0029322	0.525	0.5999	0.0017
P3_1	0.0028598	0.0027970	1.022	0.3081	0.0063
P3_2	0.0029338	0.0027934	1.050	0.2951	0.0066
P3_3	0.0018003	0.0028435	0.633	0.5275	0.0024
P3_4	–0.0041426	0.0028621	–1.447	0.1497	0.0125
P3_5	–0.00081055	0.0028010	–0.289	0.7726	0.0005
P3_6	–0.0031370	0.0027469	–1.142	0.2551	0.0078
P3_7	–0.0016872	0.0028079	–0.601	0.5487	0.0022
P3_8	–0.0026356	0.0027974	–0.942	0.3475	0.0053
P3_9	0.0059293	0.0027877	2.127	0.0349	0.0265
P3_10	–0.0030227	0.0028883	–1.047	0.2968	0.0066
P4	–0.00096590	0.0025289	–0.382	0.7030	0.0009
P4_1	0.0020119	0.0025429	0.791	0.4300	0.0038
P4_2	0.0061854	0.0025650	2.411	0.0170	0.0338
P4_3	0.0027090	0.0026503	1.022	0.3082	0.0063
P4_4	–0.0015558	0.0026208	–0.594	0.5536	0.0021
P4_5	0.0023941	0.0026267	0.911	0.3634	0.0050
P4_6	0.0010877	0.0026446	0.411	0.6814	0.0010
P4_7	0.00078059	0.0026301	0.297	0.7670	0.0005
P4_8	0.0020296	0.0026642	0.762	0.4473	0.0035
P4_9	–0.0030548	0.0026582	–1.149	0.2521	0.0079
P4_10	0.0030617	0.0026875	1.139	0.2563	0.0078
P5	0.0012626	0.0033587	0.376	0.7075	0.0009
P5_1	–0.0030755	0.0033403	–0.921	0.3585	0.0051
P5_2	0.0032968	0.0032282	1.021	0.3086	0.0062
P5_3	–0.00097235	0.0031370	–0.310	0.7570	0.0006
P5_4	0.0029049	0.0030984	0.938	0.3498	0.0053
P5_5	–0.0044821	0.0031865	–1.407	0.1614	0.0118
P5_6	0.0011213	0.0031122	0.360	0.7191	0.0008
P5_7	0.00068764	0.0030605	0.225	0.8225	0.0003

TABLE A7. *Continued*

Modelling ΔW^5 by OLS; sample: 250–491

Variable	Coefficient	SE	t-value	t-prob	PartR^2
P5_8	–0.0017455	0.0030233	–0.577	0.5645	0.0020
P5_9	0.00081573	0.0030821	0.265	0.7916	0.0004
P5_10	–0.00097498	0.0031339	–0.311	0.7561	0.0006

$R^2 = 0.346397$; $\sigma = 0.000343694$
DW = 1.99RSS = 1.960882911E–005 for 76 variables and 242 observations

AR 1–2 $F(2,164) = 0.077785$ [0.9252]
ARCH 1 $F(1,164) = 1.4758$ [0.2262]
Normality $\chi^2(2) = 0.9086$ [0.6349]
X_i^2 $F(152,13) = 0.085042$ [1.0000]
RESET $F(1,165) = 0.23458$ [0.6288]

Solved static long-run equation (SE in parentheses)

$$\Delta W^5 = \underset{(0.1359)}{+0.02551\Delta\log m} \; \underset{(0.008066)}{+0.005113P^1} \; \underset{(0.007964)}{-0.01761P^2}$$

$$\underset{(0.007537)}{-0.0003325P^3} \; \underset{(0.008583)}{+0.01313P^4} \; \underset{(0.0095)}{-0.001039P^5}$$

Wald test on the joint significance of the regressors in the static long-run equation:
$\chi^2(6) = 20.006$ [0.0028]**

which the fall in the former helps relaxing budget constraints (a sort of dynamic version of an income effect) and that in turn makes innovation, imitation and fulfillment of 'frustrated' options easier.

Appendix 4

As already mentioned in the text, Hildenbrand (1994) establishes sufficient conditions under which the Wald Axiom and the Law of Demand hold.

Let us start with the Wald Axiom and define $\upsilon(p \mid x)$ as the (observable) distribution of the x-households' demand, where by x-household we mean a 'household with income x'. Each household is completely characterized by: (i) the short-run demand function f; (ii) the current level of the disposable income x. Hence, the market demand function $F(p)$ is defined as the mean of individual demand functions f with respect to the distribution μ of the space of the households' characteristics (f,x). Moreover, let the (cross-sectional) demand function $\bar{f}(p,x)$ be the mean of the individual demand functions f with respect to the conditional distribution $\mu|x$. Finally, let the income distribution be given by $\rho(x)$ and define $\upsilon(p) = \upsilon(p|x)\rho(x)$.

Hypothesis 1* (increasing dispersion of *x*-households' demand): The (unobservable) distribution $\widetilde{\upsilon}(x + \Delta, x, p)$ (i.e. the distribution of x-households' demand under the hypothesis that their income were $x + \Delta$) is more 'dispersed' than the distribution $\widetilde{\upsilon}(x,x,p) = \upsilon(p|x)$, all $\Delta > 0$, in the sense that the matrix

$$\widetilde{C}_{1*}(\Delta, x) = \left[\operatorname{cov}\widetilde{\upsilon}(x+\Delta, x, p) - \operatorname{cov}\upsilon(p|x)\right]$$

is positive semi-definite for all $\Delta > 0$, all x.

Hypothesis 1 (average increasing dispersion of *x*-households' demand): The matrix

$$\widetilde{C}_1(\Delta) = \int\left[\operatorname{cov}\widetilde{\upsilon}(x+\Delta, x, p) - \operatorname{cov}\upsilon(p|x)\right]\rho(x)\,\mathrm{d}x$$

is positive semi-definite for all $\Delta > 0$.

Hypothesis 2 (increasing dispersion of all households' demand): For all directions υ orthogonal to the market demand $F(p)$, the unobservable distribution $\widetilde{\upsilon}(\Delta,p)$, obtained assuming that the income of every household is increased by $\Delta > 0$, is more dispersed that the (observable) distribution $\upsilon(p)$ for all $\Delta > 0$, in the sense that the matrix

$$\widetilde{C}_2(\Delta) = \left[\operatorname{cov}\widetilde{\upsilon}(\Delta, p) - \operatorname{cov}\upsilon(p)\right]$$

is positive semi-definite, all $\Delta > 0$.

Under standard assumptions on the distribution μ, Hildenbrand (1994) shows that if Hypothesis 1* (respectively Hypothesis 2) is fulfilled, then $\bar{f}(p,x)$ {respectively the demand function $F(p)$} satisfies the Wald Axiom. Under an additional regularity condition (see p. 86), Hypothesis 1 implies that the demand function $F(p)$ satisfies the strict version of the Wald Axiom.

Clearly, the above hypotheses are not empirically verifiable, since the distributions denoted by $\widetilde{\upsilon}$ are not observable. However, they can be easily replaced by observable proxies of them, allowing to formulate empirical counterparts of Hypotheses 1*, 1 and 2, namely:

Property 1* (increasing dispersion of conditional demand): The conditional distribution $\upsilon(p\,|\,x)$ is increasing in all x such that $\rho(x) > 0$, i.e. the matrix

$$C_{1*}(\Delta, x) = \left[\operatorname{cov} \upsilon\left(p \middle| x + \Delta\right) - \operatorname{cov} \upsilon\left(p \middle| x\right)\right]$$

is positive semi-definite for all $\Delta > 0$, all x: $\rho(x) > 0$.

Property 1 (average increasing dispersion of conditional demand): The matrix

$$C_1(\Delta) = \int \left[\operatorname{cov} \upsilon\left(p \middle| x + \Delta\right) - \operatorname{cov} \upsilon\left(p \middle| x\right)\right] \rho(x) \mathrm{d}x$$

is positive semi-definite for all $\Delta > 0$.

Property 2 The Δ-shift of the distribution $\upsilon(p)$—denoted by $\upsilon(p,\Delta)$ and obtained from the (observable) distribution $\upsilon(p) = \upsilon(p\,|\,x)\rho(x)$ replacing $\rho(x)$ by $\rho(x - \Delta)$—is more dispersed than the distribution $\upsilon(p)$, all $\Delta > 0$, in the sense that the matrix

$$C_2(\Delta) = \left[\operatorname{cov} \upsilon(\rho, \Delta) - \operatorname{cov} \upsilon(p)\right]$$

is positive semi-definite for all $\Delta > 0$.

Hildenbrand (1994) shows that, if the demand behaviour of the x-households is sufficiently homogeneous (i.e. they satisfy the property called 'conditional covariance metonymy', see p. 116), Properties 1*, 1 and 2 imply the corresponding hypotheses above.

The matrices $C_i(\Delta)$, $i = 1^*, 1, 2$ involved in the above properties can be easily computed using the outcomes of our model (see Section 4). In particular, consider $g = 5$ product groups, $x = 1, \ldots, 8$ income classes (obtained by aggregating the initial 20 classes) and discrete shifts $\Delta = 1, \ldots, 7$. Note that all the following results refer to a period well down the road of our simulation histories ($t = 500$), in order to let the mechanisms of innovation, imitation, income differentiation, etc., work their way through. For convenience, the positive semi-definiteness of C_i matrices (which are 5×5) is checked by computing their five principal minors instead of their smallest eigenvalue. We report here only the results coming from a 'representative' simulation, with stationary prices and a small probability of innovation. Some preliminary Monte Carlo-type studies about the robustness of the outcomes and 'response surfaces' analyses have been carried out, with encouraging results throughout.

In Table A8 the kind of definiteness of the matrices $C_i(\Delta,x)$, $x = 1, \ldots, 8$ and $\Delta = 1, \ldots, 7$ is reported. Apart from negative definite matrices for the

TABLE A8. Definiteness of Matrices $C_{1*}(\Delta,x)$: Property 1*

Income class	Shift							Income distribution
	$\Delta = 1$	$\Delta = 2$	$\Delta = 3$	$\Delta = 4$	$\Delta = 5$	$\Delta = 6$	$\Delta = 7$	
1	–	–	–	–	–	–	–	0.106
2	POS	–	–	–	–	–	–	0.422
3	POS	POS	–	–	–	–	–	0.262
4	POS	POS	POS	–	–	–	–	0.141
5	POS	POS	POS	POS	–	–	–	0.055
6	?	?	POS	POS	POS	–	–	0.011
7	NEG	NEG	NEG	NEG	NEG	NEG	–	0.002
8	?	NEG	NEG	NEG	NEG	NEG	NEG	0.001

TABLE A9. Principal Minors of the matrices $C_1(\Delta)$: Property 1

Minors	$\Delta = 1$	$\Delta = 2$	$\Delta = 3$	$\Delta = 4$
1st	2.97E+11	6.08E+11	8.64E+11	6.06E+11
2nd	1.28E+21	4.46E+21	8.89E+21	3.17E+21
3rd	9.8E+30	6.81E+31	1.84E+32	3.13E+31
4th	9.53E+40	1.34E+42	5.06E+42	3.04E+41
5th	2.71E+50	6.69E+51	2.29E+52	6.09E+50

TABLE A10. The Matrix $C_2(1)$ and its Principal Minors

Matrix					Principal minors
1.72E+10	5.48E+09	5.7E+09	6.69E+09	5.17E+09	1.72E+10
5.48E+09	1.82E+09	1.89E+09	2.26E+09	1.82E+09	1.23E+18
5.7E+09	1.89E+09	2E+09	2.31E+09	1.87E+09	4.04E+25
6.69E+09	2.26E+09	2.31E+09	2.92E+09	2.35E+09	2.85E+33
5.17E+09	1.82E+09	1.87E+09	2.35E+09	1.99E+09	7.43E+40

income classes where $\rho(x) \approx 0$ (not to be considered, see Property 1*), we can conclude that the (cross-section) demand function $\bar{f}(p,x)$ generated by the model satisfy the Wald Axiom in the weak form.

Moreover, Table A9 shows that the market demand function $F(p)$ also satisfies the Wald Axiom in the weak form, since at least for $\Delta = 1,2,3,4$ the matrices $C_1(\Delta)$ are positive definite. Finally, Table A10 reports the matrix $C_2(\Delta)$ for $\Delta = 1$ and its principal minors. Again, Property 2 and consequently

TABLE A11. The Matrix $C_3(1)$ and its Principal Minors

Matrix					Principal minors
7.14E+10	2.86E+10	2.64E+10	2.88E+10	2.89E+10	7.14E+10
2.86E+10	1.17E+10	1.07E+10	1.17E+10	1.2E+10	1.74E+19
2.64E+10	1.07E+10	9.86E+09	1.07E+10	1.09E+10	7.34E+26
2.88E+10	1.17E+10	1.07E+10	1.18E+10	1.2E+10	1.43E+35
2.89E+10	1.2E+10	1.09E+10	1.2E+10	1.24E+10	–2.3E+43

Hypothesis 2 are satisfied, so that the market demand function $F(p)$ satisfies the Wald Axiom also in its strong form.

Let us turn now to the Law of Demand. The corresponding hypothesis involves the second moments matrices (denoted by m^2) of the distributions υ. More precisely:

Hypothesis 3 (increasing spread of household demand): The unobservable distribution $\widetilde{\upsilon}(\Delta,p)$, obtained assuming that the income of every household is increased by $\Delta > 0$, is more spread than the (observable) distribution $\upsilon(p)$ for all $\Delta > 0$, in the sense that the matrix

$$\widetilde{C}_3(\Delta) = \left[m^2\widetilde{\upsilon}(\Delta,p) - m^2\upsilon(p)\right]$$

is positive semi-definite for all $\Delta > 0$.

The empirical counterpart of the latter is given by:

Property 3 (average increasing spread of conditional demand): The observable distribution $\upsilon(\Delta,p)$ is more 'spread' than the distribution $\upsilon(p)$ for all $\Delta > 0$, in the sense that the matrix

$$C_3(\Delta) = \left[m^2\upsilon(\Delta,p) - m^2\upsilon(p)\right]$$

is positive semi-definite, all $\Delta > 0$.

Again, we computed the matrix $C_3(1)$ for our 'benchmark' simulation and it turns out to be positive definite, as the principal minors show (see Table A11). Hence, we can conclude that the market demand $F(p)$ satisfies the Law of Demand.