Marketing Letters 13:3, 195–205, 2002


# Context Dependence and Aggregation in Disaggregate Choice Analysis

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*Accepted February 7, 2002*

### *Abstract*

There is an emerging consensus among disciplines dealing with human decision making that the context in which a decision is made is an important determinant of outcomes. This consensus has been slow in the making because much of what is known about context effects has evolved from a desire to demonstrate the untenability of certain common assumptions upon which tractable models of behavior have generally been built. This paper seeks to bring disparate disciplinary perspectives to bear on the relation between context and choice, to formulate (1) recommendations for improvements to the state-of-the-practice of Random Utility Models (RUMs) of choice behavior, and (2) a future research agenda to guide the further incorporation of context into these models of choice behavior.

**Key words:** choice, context, random utility

## 1. Introduction

Over the past thirty years, the context dependence of choice behavior has become the focus of a large literature in psychology, marketing and economics. The literature started with Lichtenstein and Slovic's (1971) discovery of preference reversals—in comparing two gambles, subjects' preferences varied depending on whether the task involved choice or matching. Also influential was Tversky and Kahneman's (1981) demonstration of framing effects. In their "Asian disease" experiment, subjects, including physicians, reversed their preference for treatment strategies when the outcomes were framed in terms of the probability of surviving or the probability of dying.

Since those initial demonstrations, the phenomena of preference reversal, framing effects, and loss aversion have been documented in a wide variety of settings, both experimental and real-world, and their scope has been extended considerably (see Roth 1995 and Camerer 1995 for surveys). Many forms of context-dependent preferences have been identified (space considerations preclude references): (1) habit or experience dependence effects, (2) social interdependence, (3) accountability effects, (4) menu-dependence, (5) chooser-dependence, (6) mental accounting, (7) choice bracketing, (8) motivation effects, (9) decoy effects, (10) reference prices, and (11) complexity effects. This list is by no means exhaustive!

When preference reversals and framing effects were first demonstrated, the discussion in the literature often focused on the implied violation of individual rationality (Tversky and Kahneman 1981, 1986). However, as repeated efforts to discredit these effects failed, it became apparent that they were not mere artifacts but robust features of actual behavior that need to be taken seriously. Even in economics there is now a growing attempt to respond to this weight of evidence by lessening the dependence on idealized models of hyper-rationality and turning instead to more behavioral models of individual decision making (e.g. McFadden 2001).

Lack of knowledge about context's linkages to choice behavior may leave policy analysts blind to potential/unexpected effects on choice set formation, constraints, evaluation rules and decision rules. Hence, one should seek to explicitly incorporate appropriate aspects of context in model development by explicit manipulation of context (Payne, Bettman and Schkade 1999), whether in a sampling sense (e.g. stratification over respondents in different contexts) or in an experimental sense (e.g. placing randomly selected respondents in different information environments in an SP choice task). *A priori*, it would seem sensible not only that context must be incorporated in these ways, but also that some attempt must be made by the analyst to match the preference elicitation context with the prediction context (Payne, Bettman and Schkade 1999). The end result of such matching should be more robust models of choice behavior, better able to predict to a variety of contexts as well as permitting "averaging" over contexts to remove conditioning by context (more on this subsequently).

Some introspection on the issue of context effects and context manipulation gives rise to a Lucas-like "context critique" (Lucas 1976). That is to say, predictive models which ignore context may give rise to biased predictions because policy actions may also impact context, which in turn may impact any or all of the sub-processes of choice (to be defined below). Hence, the impetus for context manipulation and context inclusion in models of choice behavior is also to permit context itself to be policy sensitive. Ultimately, then, development of predictive models should aim not just at the incorporation of context effects, but the very modeling of context itself.

In choice behavior there exist distinguishable stages, including the initial cognitive representation of the decision problem, information acquisition and interpretation, information combination leading to an evaluation, and expression or mapping of the evaluation onto a response, which opens up the possibility of context impacting processes at each stage (Payne, Bettman and Schkade 1999). These closely parallel the stages identified by Tourangeau (1984), who used this model to account for many of the context effects documented in survey research by showing how the context of a survey item can affect each stage of the response process. The insight that context effects can be mapped, and this knowledge can be used constructively to obtain an improved understanding of individual behavior, has had a powerful influence on the field of survey research where it provided the conceptual underpinning for an interdisciplinary movement on Cognitive Aspects of Survey Methodology (CASM).

In choice modeling, we believe a shift in emphasis to mapping the psychological processes of an individual in comprehending and responding to the decision task at hand could bring some significant gains in terms of a richer insight into individual preferences, improved accuracy in predicting individual behavioral responses to economic changes or policy interventions, and a more realistic assessment of the impact of policy interventions on individual welfare. To realize these gains, one needs a conceptual framework to identify the sources of context dependence in individual decision processes, mathematical models to represent the context-dependence of choice behavior, empirical procedures to measure context-dependence in the field and econometric techniques to estimate these models from data. This is the focus of our paper—we offer suggestions for building context explicitly into models of individual choice behavior, and propose an initial research agenda for bringing this ambition to fruition.

## 2. A Model of Choice in Context

It is useful to begin by relating our approach to a framework common in the literature on psychological measurement and testing: observed response (B) is represented as a linear function of some unobserved "true" response (say, preference P) and measurement error $\varepsilon$ as in $\mathrm{B} = \mathrm{P} + \varepsilon$. To allow context to affect choice behavior, it is natural to extend the model by writing $\mathrm{B} = \mathrm{P} + \Omega + \eta$, where $\Omega$ is context. This decomposes the response error $\varepsilon$ into a context-dependent component, $\Omega$, and a component that it is independent of context, $\eta$ thus: $\varepsilon = \Omega + \eta$. Common assumptions are that (i) $\varepsilon$ has a zero mean, and $\varepsilon$ and $\Omega$ are independent and uncorrelated, or (ii) $\eta$ has a zero mean, and $\eta$, $\Omega$ and P are independent and uncorrelated. The implications of (i) and (ii) are that context is "noise," and its impact on choice behavior washes out in the aggregate. Given the empirical evidence of the abundance and persistence of context-dependence effects, we suggest an alternative stochastic specification in which $\eta = \mathrm{P} \cdot \Omega + \upsilon \cdot \Omega + \upsilon$; thus,

$$B = P + \Omega + P \cdot \Omega + \upsilon \cdot \Omega + \upsilon, \tag{1}$$

where (iii) $\upsilon$ has zero mean, and $\upsilon$, P and $\Omega$ are independent and uncorrelated. The implications of (1) and (iii) are that context can have a systematic impact on choice behavior, it can interact with preferences, and the effects of context need not wash out in the aggregate. In principle, context can be disentangled from preference on the basis of (1). In practice, however, (1) is likely to be too simple a formulation, so we now develop a more articulated model of how context may interact with preference to determine choice behavior.

### *2.1. A Formal Model of Choice*

To keep things simple, we will focus on a purely discrete choice as in McFadden (1974), as opposed to mixed discrete-continuous choices of the sort considered by Hanemann (1984). In a stylized model of decision making, let D represent the decision strategy, C represent the choice set, j index alternatives, n index individuals and t index time. Let V be an index of strength of preference (or utility) and $\varepsilon$ an error process that is assumed to arise from elements of the process unobserved by the researcher. The stylized decision structure can be framed as producing the chosen alternative $i^*_{nt}$ according to

$$i^*_{nt} \leftarrow \underset{j \in C_{nt}}{D_n} \{V_{jnt}, \varepsilon_{jnt}\}. \tag{2}$$

We now examine the many ways in which context can affect this decision structure.

***Choice Set Formation.*** Contextual factors affect the set of alternatives that are being actively considered, or those that can possibly be considered. The process of choice set formation can be considered one of initially identifying all known alternatives, then reducing the set to the final choice set used in decision making. Part of this process will involve information on structural restrictions on the choice set, while another part will be based on contextual factors (e.g. public vs. private consumption). At the extreme, people may consider only one or two options that happen to be salient because of context.

***Constraints.*** Constraints traditionally considered to be involved in the decision process include income, time and other (e.g. cognitive capabilities) resources. Context may affect the perception of available resources: if concepts of relative income are more important than absolute income, then income constraints are clearly affected by social group and related contextual factors (Frank and Sunstein 2000). The time horizon, or temporal bracketing, that individuals employ differs by context and will also affect the definition of income and time constraints (Read et al. 1999).

***Evaluation Rules.*** A common economic evaluation rule involves determining an aggregate index that allows compensatory evaluation of an alternative. In (2), V implies a utility function approach to evaluation. However, compensatory approaches can require significant cognitive effort to employ (Johnson and Payne 1985). Evaluation rules in contexts of perceived inconsequential decisions (e.g. arguably, purchasing ketchup) may be very simplified: "purchase what was purchased in the past." In such cases, utility arising from attributes, while embedded in previous decisions, has little impact on the current decisions. Context, in terms of choice history, also plays a role here: if there is no history, then the process cannot be based on previous choices and requires some evaluation of attributes. Thus, initial conditions and learning are important considerations for certain segments of a market, but not necessarily for others.

***Decision Rules.*** Optimization over all attributes and alternatives using a compensatory decision rule is a common assumption in economic analysis. Research in economics, psychology, marketing and other disciplines shows that a wide variety of decision rules appear to be used by individuals, often dependent on context. Increasing choice complexity, for example, appears to result in increased processing by dimensional reduction, or even avoiding making choices (Payne 1976; Swait and Adamowicz 2001b). Context variation may result in changes from near-utility optimization to elimination-by-aspects, to simplified dimensional reduction or majority-of-confirming-decision heuristics, among an infinity of other possibilities.

Context effects, then, can be categorized as those that influence choice sets, constraints, evaluation rules and decision strategies, any subset of which may be simultaneously affected by a specific context factor. As before, let $\Omega$ represent choice context, and rewrite (2) thus,

$$i^*_{nt} \leftarrow \underset{j \in C(\Omega)_{nt}}{D(\Omega)_n} \{V(\Omega)_{jnt}, \varepsilon(\Omega)_{jnt}\}. \tag{3}$$

This expansion of the decision framework illustrates the consensus of the workshop that context effects must be understood by examining across cases that have variation in $\Omega$ and where effects on the elements of choice (D, V, C and $\varepsilon$) can be *identified*. Identification will require formal model structures that provide for isolation of elements D, V, C and $\varepsilon$ and sufficient variation in $\Omega$ to identify effects of context.

Below we review prior work in two topic areas, choice set formation [$C(\Omega)$] and decision context complexity [$D(\Omega)$], to demonstrate that incorporation of context in choice models is an area where research has already begun, but where much remains to be done.

### 2.2. Examples of Context Modeling

The choice set formation literature builds upon the theory that choice follows a two-stage process: (1) selection of a subset of goods C from the universal set of alternatives M, followed by (2) choice of the most preferred good in C. In this literature (see, e.g. Swait and Ben-Akiva 1987 and Ben-Akiva and Boccara 1995), structural models of the two-stage process have been shown successful in capturing non-compensatory behavior, but suffer from the combinatorial complexity arising from the latent nature of the choice set formation process. More recently, reduced form representations of the two-stage process in a single-stage model have been done: e.g., classes in a latent class model that partially capture different choice set structures (Swait 1994), or the incorporation of personal and contextual constraints affecting choice set formation in a pseudo-Lagrangian utility function that summarizes both stages of choice (Swait 2001).

The psychology and consumer behavior literatures have identified complexity of the decision context as a major factor affecting the use of decision heuristics, and thus, a major factor in establishing decision accuracy and effectiveness. Swait and Adamowicz (2001a) extend the usual view in these literatures that complexity arises from number of alternatives, number of attributes and interattribute correlation, and propose an extension to the MNL model in which the variance of the error term is an endogenous function of entropy, which they show to be a useful uni-dimensional summary of contextual complexity. Swait and Adamowicz (2001b) also use entropy as a complexity measure to show, through an ordered latent class choice model, that decision difficulty and cumulative cognitive load lead respondents to switch from a full-information, compensatory evaluation strategy at the beginning of a SP task, to a simpler strategy ignoring some attributes towards the end of the task (see Louviere et al. 2002 for additional discussion of models of variance, task design and complexity).

## 3. Context, Choice and Their Measurement

### *3.1. Exploratory Techniques for Measurement of Context*

Psychologists have used a variety of tactics in trying to uncover the conceptual structures and cognitive processes that underlie many different behaviors, including choice behaviors. In this section we describe some of these methods and show how they might be applied to the discovery of the choice sets, attributes, decision rules, history and expectations that affect choice behavior. We emphasize that these techniques are exploratory in character and would typically be used to generate hypotheses rather than to test them. Nonetheless, we believe that many of them can be fruitfully applied to the problem of characterizing and measuring choice context.

***Identifying Choice Sets.*** Cognitive psychologists have used several techniques to get a better understanding of how everyday categories are structured; many of these techniques seem especially relevant to discovering how people construe choice sets. One simple method—card sorting—asks respondents to sort the possible members of a choice set into whatever groups make sense to them; in addition, the respondents are often asked to label the groups they form. The aim of this procedure is to discover the classes that people spontaneously use when given little guidance. The resulting data can be examined informally or analyzed rigorously via clustering algorithms. Related techniques ask respondents to rate the similarity of pairs of members of the choice set (ketchup and mustard, barbecue sauce and steak sauce); scaling procedures (e.g. INDSCAL) are useful to determine the dimensions underlying these ratings.

***Decision Rules and Attribute Use.*** Another exploratory tool is the retrospective probe: respondents are asked what they were thinking about as they made some judgment or solved some problem. For example, respondents might be asked what attributes came to mind as they made a decision. Such probes can be very broad ("Tell me everything you were thinking about as you made that decision") or more focused ("Did you consider price?"). Once a set of attributes has been identified in this way, the choices themselves can be examined to see whether they reflect consistent preferences over the attributes. A related strategy is to ask people how they arrived at their decisions. Again, either broad, open-ended probes ("How did you arrive at your choice?") or more focused ones ("Did you focus mostly on one thing as you considered the alternatives?") can be used to discover decision rules governing a set of choices.

***Past History.*** A crucial attribute of the decision-maker is his or her past history of similar choices, his or her personal context. Special probes might be crafted to assess whether the decision maker sees the current choice as relatively novel and unfamiliar or as familiar and routine ("Does this product remind you of similar products you bought in the past?"). If the choice is a recurring one, it may be possible to ask the person whether they have a regular policy or rule that governs their choices ("Do you always buy the same brand? Do you buy the cheapest brand? Do you deliberately vary your choices for the sake of variety?").

***Information Gathering and Processing.*** These same tactics can be applied to discover what information people seek as they make choices and how they use that information. For example, for important choices (car purchases) decision-makers may seek information from several sources (*Consumer Reports*, the Internet), and they may process and organize it in different ways (writing it down, discussing it with friends, putting it into a spreadsheet). Straightforward probing can identify the sources of information they tapped and how they processed it and thus identifies actions associated with the decision-making context.

While these ideas are intended simply as guides and suggestions to researchers, and are themselves subject to potential problems (Nisbett and Wilson, 1977), the important message to take away is that it is feasible to measure the likely shape of context effects on the components of choice. At that point, the choice model analyst faces the task of deciding which context effects must be included in the model framework being developed.

### *3.2. Choice Model Development, Testing and Prediction*

***Dynamics and Decision Sequencing.*** An essential feature of any model of choice is whether the choice is dynamic, in the sense that current choices affect future payoffs or opportunities, and the decision-maker is aware of this relationship. Many decisions are clearly dynamic—the decision to retire, for instance, or decisions about medical treatment. We are also led to distinguish between dynamic and sequential decisions: whereas dynamic decision making is more concerned with controlling the process over time, sequential decision making describes a situation where the decision-maker makes successive observations of a process before a final decision is made (e.g. price searching). Life is replete with decisions that may be dynamic but are nonetheless modeled by social scientists as static. We suspect two reasons for this discrepancy: (1) estimation of structural dynamic decisions remains a difficult task—the pioneering work of John Rust and others (see Rust 1994) provides some tractable structural dynamic models of choice, but even in these cases estimation remains a formidable undertaking; (2) economists have not seriously considered the possibility that contextual variables may cause apparently static decisions to be dynamic. For instance, in their discussion of choice bracketing, Read et al. (1999) discuss "mental" budgeting and cite experiments indicating that households are often quite strict about keeping money within distinct budget categories, which has implications for whether behavior is dynamic or static.

Casting behavior as static when it is dynamic will generate inaccurate forecasts and biased welfare estimates. Nonetheless, the difficulty of estimating such models suggests the need for a modest initial research agenda with the following three elements: (1) theoretical analysis that sheds light on how context induces or suppresses dynamic behavior; (2) the development of extended decision-level panel data conducive to exploring the existence and role of dynamics in the decision process; and (3) the development of simple diagnostics for detecting dynamic behavior. This last task is potentially difficult because behavioral models characterized by sequential static optimization often may fit observed behavior as well or better than their "true" dynamic counterparts. Perhaps direct querying of individuals in surveys about dynamic aspects of their choices will initially prove the best available and most sensible diagnostic.

***Econometric Estimation and Model Comparisons.*** Consider again the choice model in equation (3): decision rules, choice sets, the indirect utility function, and the error structure are all (potentially) a function of context. Some overarching version of a choice model would include all of these effects simultaneously. While this should be the eventual applied objective, we believe that substantial progress can be made by first considering sub-sets of the problem. Consider implementation of equation (4), which presents a simpler model where context may affect perceptions of attributes, preference weights, and error components.

$$U_{jn\Omega} = f_{\Omega}(X_{j\Omega}, \beta_{n\Omega}) + \varepsilon_{\Omega}, \tag{4}$$

Note that even this simpler model makes a distinction between context affecting error components (see Louviere et al. 2002), and context affecting structural aspects of choice (preference weights and attribute perceptions). The sophisticated econometrician might attempt to model the entire impact of context through the error term via a rich set of error components that could be a function of unobserved preference heterogeneity and other unobserved factors, both evolving temporally. This would result in a Random Utility model with a multivariate error structure (e.g. Keane 1997). It is important to determine the extent to which this error components strategy will succeed in capturing context effects. In a manner analogous to how ignoring state dependence will likely overstate the importance of unobserved preference heterogeneity (and vice versa) in discrete panel data, we expect that ignoring structural context effects will overstate the importance of error components, and conversely, ignoring context dependency in the error components will overstate the importance of structural context effects. Still, formal approaches need to be developed and applied studies examining these issues must be conducted. We describe one possible approach next.

To be specific, imagine a model with observable context effects and an IID Type I Extreme Value error structure, which we will term a Context Multinomial Logit (CMNL) model. To test models, conceptually it is a simple matter to add a multivariate normal error structure to a CMNL model. With this adjustment we would arrive at a Context MNP (CMNP) model nesting both the CMNL model (at least approximately) and the standard MNP model, thus allowing one to test for the presence of both context and unobserved heterogeneity. We suspect that both context and unobserved heterogeneity will be present in most applications. Modeling only the unobserved heterogeneity while ignoring context raises deep questions regarding the interpretation of MNP covariance matrices, not to mention means.

Moving from econometrics to prediction, one can predict conditional on given contexts, or average over the relevant contexts to form unconditional predictions. When context matters, averaging should result in better model fits and better predictions. Averaging over many contexts will also allow the researcher and consumers of research to better assess the robustness and relevance of the model.

## 4. Recommendations for Future Research

Two guiding principles animated our workshop discussions: (1) we had a clear objective of producing a research agenda for improving empirical modeling of disaggregate choice behavior based on richer models of consumer behavior, more sophisticated econometrics and better data collection methods to yield more information about consumer motivation and perceptions; and (2) we worked within the flexible framework of random utility models to help us through the (potentially) unending maze of context effects on choice.

During the course of the paper, we have mentioned a number of research and implementation initiatives that we believe are important. We list below the ones we consider most important.

***Data Collection.*** The development of improved models of choice that incorporate context effects only makes sense when allied to supporting data collection methods. A rich literature from the CASM movement in survey research (see, e.g., Tourangeau et al. 2000) is available as a starting point to guide research on data collection and on their practical implementation. Specifically, supporting the development of context modeling will require collection of data on (1) attitudes/perceptions, (2) dynamics (history, expectations), (3) mental models, (4) task and context complexity, and (5) context manipulation checks and debriefing protocols. The goal here should be to produce reliable and easy-to-use context measurement tools, as well as to characterize potential biases in tools.

***Context Modeling.*** Our goal here is particularly to urge the incorporation of what is already known about context effects into choice modeling practice, as well as calling for the continued development of knowledge about context effects and their incorporation into choice models. Some relevant topics for advancing choice models based on current knowledge are (1) reference dependence of preferences, (2) choice set formation, (3) taste heterogeneity, error components and heteroskedasticity, (4) choice dynamics and sequential decision making, and (5) prediction with context-sensitive models. Prior work has shown that several extensions to the RU framework are likely to prove fruitful in these endeavors: choice set formation (e.g. Swait and Ben-Akiva 1987), latent class (e.g. Dayton and Macready 1988) and error-components (see Louviere et al. 2002) models are among potential starting points for future research in this area. In addition, explicit manipulation of contexts in controlled experiments and econometric analysis using RU methods should be employed to assess systematic differences in context.

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