Discrete Choices with Social Interactions: An Application to Consumer Recycling*

Gorm Kipperberg

Department of Agricultural and Resource Economics
University of California, Davis

February, 2005

*This is work in progress, which means all results are preliminary. Please ask permission before citing. The current version of this paper has benefited particularly from discussions with Charles Mason and comments from Michael Caputo. Useful feedback was also provided by participants in the AERE sessions of the 2004 AAEA meeting and participants of the ERE Discussion Group at the ARE-UCD. All errors are mine. I can be contacted at gorm@primal.ucdavis.edu and updates are posted to http://www.frisch.uio.no/cv/frisch_kipperberg.html.

1. Introdction

The classical *Homo economicus* brings exogenous money prices and money budgets into its preference domain and makes maximizing decisions accordingly. This simplified view of the 'economic man' has long stood as the dominant basis for applied work in economics.

Some economists, however, have begun to develop richer and more realistic conceptual models of consumer behavior. For example, the notion that time prices and time budgets are important was formalized in Becker (1965). This choice aspect has found its way into applied research as well, particularly in the work on non-market valuation.

Another side of economic behavior is the *social* aspect of homo economicus. Clearly, consumers are not isolated beings making decisions without regards to the actions of their fellow humans. They care about how they are perceived in their social environment and pay attention to the economic behavior of others. The idea that interactions, other than those mediated by market mechanisms, are important to consumer choice and welfare has been discussed by economists as far back as Adam Smith himself. Nevertheless, little applied research has attempted to treat this aspect in a serious manner.

In this paper we build on a rapidly emerging body of literature that incorporates the notion of social interactions into economic models [see Brock and Durlauf (2001b) for a good introduction]. This literature relaxes the atomistic view of the consumer that is embedded in standard economic models.

The broad type of choice context that we have in mind is one in which individual consumers can choose between an environmentally friendly (*green*) action and some less environmentally friendly (*brown*) actions. Modern-day consumers frequently find themselves in such choices situations, e.g., in selecting between automobiles with varying fuel efficiencies, in choosing travel modes, and in every-day supermarket shopping, where a wide-range of conventional products now have environmentally friendly counter-parts (such as eco-detergents, organic foods, products made from re-processed materials, and so on).

The specific choice context of this study is consumers' decisions on how to handle bi-products from their household production and consumption activities. We conceptualize individuals as being faced with a discrete choice of whether or not to recycle various material items. The alternative to recycling is disposing of them as waste. Recycling is referred to as the *green* alternative and waste disposal as the *brown* alternative, because the former is generally considered more environmentally friendly than the latter. For example, recycling is a way to conserve scarce resources and extend their useful lives. Moreover, making new products from recycled materials reduces reliance, on and hence negative externalities from, virgin-material production. Lastly, recycling is considered an effective way to avoid common environmental problems associated with landfills and incineration facilities.

A central dilemma individuals face in these choice contexts is that taking the environmental course of action often comes at some kind of cost-premium, either in terms of costing them more money or requiring a greater time effort on their part. Yet, one can find in many instances that a significant number of individuals voluntarily incur these costs. From the perspective of the 'classical economic man' this would seem counter-intuitive and individualistically irrational.

The insight that both time and money are important to consumers is reflected in recycling-related public policies. The two most popular waste management policies are the pricing of waste removal and the provision of convenient recycling options. The former policy works through the consumers' money budgets while a desired consequence of the latter policy is to reduce the impact of recycling on time budgets. Despite the fact that policymakers and planners generally agree that these policies are effective incentive tools, both casual real-life observations and formal empirical inquiry reveal ambiguities and apparent paradoxes. For example, high levels of recycling are often achieved in social environments where these policies are absent. In contrast, some social environments are associated with low recycling outcomes, despite high incentive levels. The existence of such phenomena has been noted by several researchers; see, for example, Akerman (1997), and Kinnaman and Fullerton (1999).

One way to explain wide-spread recycling in the absence of primary budgetary incentives is to invoke one of several the new voluntary public good contribution 'stories'. Contrary to predictions of the standard public good contribution 'story', complete free-riding need not be the rational outcome. Provided consumers perceive recycling as contributing to environmental quality and environmental quality to be a public good, their actions could be driven by intrinsic, non-pecuniary motivations. This idea is demonstrated in the warm-glow-giving model of Andreoni (1990) and the moral motivation model of Brekke et al. (2003). The latter model can be viewed as a generalization of the former. More importantly, it brings into the analysis a specific rationale for the dependence of an economic agent's behavior on the public good contributions of others. Other related strands of economic research, investigating what might be called *specific types of social interactions*, are the social norms literature (e.g., Kreps, 1997) and the identity literature (e.g., Akerlof and Kranton, 2000).

In this paper, we provide an econometric analysis of the determinants of consumer recycling, with particular emphasis on the role of social interactions. The model that we investigate is capable of describing large variation in outcomes across social groups, allowing for both the possibility of low levels of recycling in social groups exposed to strong recycling incentives ('vicious' outcomes) and high levels of recycling in social groups with low recycling incentives ('virtuous' outcomes).

The analytical framework that we employ was developed by Brock and Durlauf (2001a). This framework extends the classical random utility model (RUM) to permit preferences to be defined over the actions (or expected actions) of an individual's social group members. Furthermore, these authors show how this framework links naturally to empirically estimable discrete choice models.

In our choice context, the consumer chooses to recycle or dispose of material items according to maximization of a utility function, which depends on the behavior of other individuals. As usual, the deterministic portion of the individual utility function is assumed to have a *private* component, decreasing in money costs and expected time expenditures, and generally a function of characteristics of the individual. As a generalization of the standard RUM framework, total utility is extended to incorporate a *social* utility component, which is modeled as a function of the individual's expectation of the mean recycling behavior of other group members.

We implement this model with a rich dataset on consumer recycling in Norway, where the relevant social group is taken to be an individual's local community. The richness of the dataset permits us to explore a wide range of factors that may influence individual behavior. We are also able to make a clean distinction between (i) exogenous factors that could induce a group of individuals to behave similarly, and (ii) true social interaction effects arising from direct dependence of an individual's utility on aggregate community behavior. The dataset contains six recycling choices for each individual, namely drinking cartons, paper, glass, metals, plastics, and food wastes. We incorporate the panel nature of the data and latent preference heterogeneity via estimation of a panel mixed logit model.

Preliminary estimation results lend support to the hypothesis that social interactions play a role in the recycling choice context. The sample individuals are found to have strong preferences for conforming, rather than standing apart, from the choices made by other community members, at least in the choice context of this analysis. We also corroborate common results in the recycling literature. Policies, such as a monetary disincentive on waste disposal and convenient recycling options, generally increase the likelihood that the environmentally friendly action will be taken. The importance attached to these policies or incentives is found to vary, suggesting significant degrees of consumer heterogeneity. Finally, individuals with higher perceived time costs are more likely to favor waste disposal over recycling, although again, our estimation results suggest that consumers are highly heterogeneous.

The remainder of this paper is organized as follows: Section 2 offers the unfamiliar reader a brief review of the social interaction literature. Section 3 gives an exposition of the social interaction-random utility model and illustrates some of its complex features with two numeric examples. Section 4 provides the back-drop for our empirical application and motivates the potential relevance of the model by investigating some summary statistics on recycling behavior throughout the Norwegian communities. Section 5 discusses empirical specification issues and some econometric concerns that are commonly raised in the social interaction literature. Section 6 offers a brief exposition of the empirical model while section 7 reports preliminary estimation results. A few concluding remarks are made in section 8.

2. A Brief Literature Review

The literature on social interactions and its potential role in economics is too vast for complete review here. For good places to start, the interested reader can see Brock and Durlauf (2001a, 2001b) and Manski (2000). Historically, the importance to consumer choice and welfare of interactions other than those mediated by market mechanisms has been pointed out by several economists, including Adam Smith, Torsten Veblen, and Alfred Marshall. Pioneering work giving serious attention to this aspect of behavior can be found in Dusesenberry (1949) and Leibenstein (1950). In more recent times, Schelling (1971), Becker (1974), and Akerlof (1980) demonstrate the potential roles of social interactions in decision-making processes. One of the major points of dispute in assessing whether social interaction effects should be brought into the domain of economic models is the extent to which meaningful empirical models can be formulated and estimated. A major concern is econometric identification. The "reflection problem" was formalized in a seminal paper by Manski (1993). The same author discusses other serious (related) challenges to empirical research into social interactions in Manski (2000). A seminal paper by Pollak (1976) shows how standard demand models can be augmented to account for preference interdependence. An interesting recent application to demand systems can be found in Kapteyn et al. (1997). Key work on social interactions in the context of discrete choices is found in Brock and Durlauf (2001a, 2001b). Several authors have sought to estimate discrete choice models with social interactions. For example, Kooreman and Soetvent (2002) investigate several types of high school teen behavior. They estimate a model that explicitly incorporates peer group choices by maximum likelihood procedures. Yang and Allenby (2001) estimate a hierarchical Bayes autoregressive mixture model, which implicitly accounts for preference interdependence in the context of consumer automobile choices.

3. A Social Interaction-Random Utility Model (SI-RUM)

Our theoretical framework follows Brock and Durlauf (2001a, 2001b, **2001c, 2003**).[1] This framework extends a standard RUM to explicitly account for social interactions.

Basic Set-Up

Consider discrete choices made by I individuals within a single reference group.[2] Individuals are indexed by i and the choice alternatives are indexed j, where $j \in \{0,1\}$ for the binary case. Utility U_{ij} from a choice alternative is modeled as a function of (i) a private component V_{ij}, (ii) a social component S_{ij}, and (iii) a random component ε_{ij}. The latter can be viewed as arising from the researcher's inability to fully observe all factors that influence utility. Total utility is represented by the single-index function

$$U_{ij} = U_{ij}(V_{ij}, S_{ij}, \varepsilon_{ij})\,. \tag{1}$$

We make three assumptions regarding this utility index. First, as is common, we assume that it is additively separable in the three components. Second, we approximate the private component by a linear function of observable factors Z_{ij} whose importance is reflected in a conformable vector of preference weights β_j. These factors include both individual-specific factors X_{ij} and group-specific factors Y_j such that $Z_{ij} \equiv (X_{ij}, Y_j)$ and $\beta_j \equiv (\beta_j^X, \beta_j^Y)$. Third, we assume that the social utility component can be represented by $S_{ij} = \gamma P_{ij}^e$, where P_{ij}^e represents individual *i*'s belief (or expectation) of the portion of group members choosing the *j*th alternative and γ is a social interaction parameter measuring the strength of social influence. Given these assumptions we express equation (1) as[3]

$$U_{ij} = Z_{ij}\beta_j + \gamma P_{ij}^e + \varepsilon_{ij}\,. \tag{2}$$

This social interaction specification is a so-called *global interaction* specification because individuals are seen as being influenced by the (expected) average group behavior instead of by particular group members.[4] Note that when the social interaction parameter is zero an individual's behavior does not depend on the behavior of others and the model collapses to the standard RUM. A positive social interaction parameter reflects preferences for conformity (*fitting-in*) while a negative parameter implies preferences for non-conformity (*standing-apart*).

In order to describe the individual choice problem let us denote the actual choice of an individual by ω_i, $\omega_i \in \{0,1\}$. Under the standard utility maximization assumption, an individual makes choices that obey

$$\omega_i = \arg\max\{U_{ij} = Z_{ij}\beta_j + \gamma P_{ij}^e + \varepsilon_{ij} \mid j = 0,1\}. \tag{3}$$

This choice-rule can be expressed probabilistically. We assume that ε_{ij} is iid extreme value, which leads to a multinominal logit specification.[5] The probability that individual *i* will choose alternative *k* is

$$\Pr(\omega_i = k) = \frac{e^{Z_{ik}\beta_k + \gamma P_{ik}^e}}{\sum_j e^{Z_{ij}\beta_j + \gamma P_{ij}^e}} \tag{4}$$

Given the independence assumption, the joint choice probabilities for the group of individuals take the simple form

$$\Pr(\omega_1 = k, \omega_2 = k, .., \omega_I = k) = \prod_i \left[\frac{e^{Z_{ik}\beta_k + \gamma P_{ik}^e}}{\sum_j e^{Z_{ij}\beta_j + \gamma P_{ij}^e}} \right]. \tag{5}$$

Group Equilibrium

The model can be "closed" by specifying how individuals form beliefs about the group's behavior. One possibility is to impose the so-called *rational expectation* or *self-consistent belief* condition. This specification is equivalent to assuming common knowledge of (i) the choice-rule (including the preference weights); and (ii) the distribution of factors that affect private utility among group members. Under this assumption, individuals' beliefs P_{ik}^e coincide with the mathematical expectation of equation (4). Denoting the mathematical expectation simply by P_k gives the following equilibrium condition

$$P_{ik}^e = P_k = \int \left[\frac{e^{Z_{ik}\beta_k + \gamma P_k}}{\sum_j e^{Z_{ij}\beta_j + \gamma P_j}} \right] dF_Z \, . \tag{6}$$

At this point, let us make several notes about equation (6). First, the expression can be regarded as a rational expectation equilibrium condition for a non-cooperative game played by the group members with pay-offs described by equation (2) and corresponding decision-rule in equation (3). One way to see this is to view P_k as the expected market or group share for alternative *k*. In the binary case, solving the equation for one of the alternatives, say P_1, immediately characterizes the equilibrium, since $P_0 = 1 - P_1$. Second, if the group size is sufficiently large, a given individual's impact on the expected group-share choosing either alternative is negligible. In other words, there are no feedback effects in the sense that one individual can unilaterally alter the pay-offs of others via that individual's choice. Thusly, each individual takes the expected group shares as given in making a choice. Moreover, the rational expectation assumption implies that the beliefs of all group members are the same.[6] Third, the mathematical expectation is taken over a distribution function F_Z for the factors influencing the private utility component. Since Y is group-invariant we have that $F_Z = F_{X|Y}$.[7] Lastly, since the term P_k appears both on the left-hand-side and in the non-linear expression on the right-hand-side, equation (6) does not have a closed-form solution. By Brower's fixed point theorem, at least one solution exists. In general, there could be multiple solutions. The possibility of multiple equilibria with respect to average choices arises from the presence of the social utility component. Specifically, multiple equilibria are possible if the social interaction parameter is positive and sufficiently large (more on this below). When this parameter is zero the social utility component is absent from the pay-off function and the right-hand-side of the equation immediately gives the average group choice, that is, the expected share of group members choosing alternative *k*. This is the standard RUM model.

Model Properties

Many of the properties and features of this model are investigated formally and comprehensively in Brock and Durlauf (2001b). Here, we focus informally on two features that are believed to be of particular interest to the ensuing empirical application, to wit, multiple equilibria and multiplier effects versus "sticky" aggregate behavior.

The possibility of multiple equilibria is a complexity feature that makes social interaction models very appealing. Intuitively, this property suggests that it could be possible to observe groups of people, which are otherwise identical (or close to it), displaying large variations in their aggregate behaviors. For this reason, social interaction models may be regarded as promising in explaining or resolving several phenomena that appear counter-intuitive from a standard economic perspective, e.g., heterogeneous policy responsiveness and crowding-effects as in Frey and Oberholzer-Gee (1997), occurrences of *vicious/virtuous* economic cycles, see, **Brekke et al. (2004)**, and voluntary public good contributions (Andreoni, 1990).[8]

When are multiple equilibria possible? Unfortunately, the conditions giving rise to multiple equilibria are known only for simplified versions of equation (6) [see Brock and Durlauf (2001a, 2003)]. For instance, it can be shown that in the absence of private utility ($V_{ij} = 0$) there exists a unique equilibrium ($P_k = \{0.5\}$) if $\gamma \leq 2$ and three equilibria ($P_k = \{0, 0.5, 1\}$) otherwise. When the difference between the private utility from the two alternatives is non-zero but the same for all individuals ($\tilde{V} \equiv V_{i1} - V_{i0}$, $\tilde{V} \neq 0$) and $\gamma \leq 2$, a unique equilibrium exists, with the share choosing alternative 1 greater than 0.5 if $\tilde{V} > 0$ and less than 0.5 if $\tilde{V} < 0$. In the case when $\tilde{V} \neq 0$ and $\gamma > 2$, and more generally, when private utility varies across individuals, whether there is a unique or multiple equilibria cannot be easily determined.

A second feature of the model is that the presence of social interactions could make it difficult to predict the effects of policies. At one extreme we have the concept of *social multiplier* effects. When some (or all) group members are subjected to an exogenous pay-off "shock" (such as a price change or a tax/subsidy), a dramatically different group-equilibrium could emerge. The reason for this is that the policy has two effects, namely, a direct effect and an indirect effect. First, it may cause some group members to find it individually rational to switch their choices in the face of new private incentives. Second, provided a non-trivial number of individuals alter their behaviors, the social utility incentives will change, which in turn induces more individuals to re-assess their choices, and so on. This multiplication (or *cascading*) effect suggests that a moderate policy may result in a large change in aggregate behavior. Importantly, policymakers who ignore this effect are likely to device policies that "overshoot" their objectives.

In contrast to the concept of multiplier effects, aggregate behavior could instead be "sticky" or non-responsive with respect to policy intervention. This is most likely to be the case when the social utility component is dominant relative to the private utility component (and when multiple equilibria are possible). Such a situation would require substantial or non-marginal changes to private pay-offs to create a non-trivial change in aggregate behavior. Policymakers who ignore the presence of social interactions in such choice contexts may overestimate responsiveness to policy intervention, which is likely to lead policies to fall short of their objectives.

Below, we illustrate these properties through two examples. As a general set-up, and in anticipation of the empirical application to follow, think of a choice context in which individuals choose between two commodities (or actions), where one is more *environmentally friendly* than the other, i.e., they choose between a *green* alternative and a *brown* alternative. We index the more environmentally friendly alternative by 1 and its alternative by 0. For further concreteness, we may think of the brown alternative as a commodity that has associated production externalities or an action that negatively impact others. To make the examples interesting, we assume that the *green* alternative is socially more desirable but privately more costly. The first example considers a unique equilibrium case while the second example explores a case where multiple equilibria exist. In both examples, we investigate the required subsidy to the green alternative that would be needed to induce a desired behavioral change.

Example 1:

Suppose that the utility function in equation (2) has the following simplified form

$$U_{ij} = \beta C_{ij} + \gamma P_{ij}^{e} + \varepsilon_{ij},$$

where C_{ij} can be thought of as a scalar measure of monetary costs.

Assume that the preference weighs are $\gamma = 2$ and $\beta = -0.1$. The positive social interaction parameter means that individuals have preferences for conformity and the negative cost parameter means that utility is decreasing in money costs. For simplicity, all individuals are assumed to face the same cost structure with the *green* alternative costlier than the *brown* ($C_{i1} - C_{i0} = \overline{C} > 0$). Assume that $\overline{C} = 3$ (e.g., \$3).

By equations (3) and (6), the unique rational expectation equilibrium for the *green* alternative, denoted P_1^{RE}, is given by the implicit expression

$$P_1^{RE} = \frac{e^{-0.1\overline{C}+2.0P_1^{RE}}}{e^{-0.1\overline{C}+2.0P_1^{RE}} + e^{2.0(1-P_1^{RE})}}.$$

Solving this expression numerically yields a low-level equilibrium for the more environmentally friendly alternative, namely, $P_1^{RE} \approx 0.1595$. This implies that a little less than 16% of the group members choose the green alternative. Figure 1 illustrates this equilibrium graphically. This figure graphs the right-hand side of equation (6) for different values of P_1 under the given parametric assumptions. The 45 degree line intersects the probability function at the fixed point (the permissible equilibrium).

Now suppose that a policy agency wants more individuals to choose the *green* alternative due to its relative social desirability. For concreteness, suppose that the policy agency seeks to devise a policy that would achieve a green market share of 0.6. Let us denote this policy objective by $\hat{P}_1$. In principle, this objective could be achieved equivalently by means of a subsidy to the *green* alternative or a tax on the *brown* alternative. Let us consider a subsidy and denote it by τ. What does the policy agency know about the individuals? Suppose the agency knows (i) that individuals choose alternatives based on maximization of a random utility function, (ii) the value of $\overline{C}$, (iii) the distribution of ε_{ij}, and (iv) the aggregate outcome in the absence of policy intervention. However, it ignores (or, is not aware of) the social utility component. Given this information set, the agency makes an inference about the cost parameter β by solving

$$0.1595 = \frac{e^{\beta\overline{C}}}{1+e^{\beta\overline{C}}},$$

which yields $\beta \approx -0.3278$. Note that this, in absolute terms, is an overstatement of the utility weight of the money cost component. Subsequently, it sets the subsidy intended to achieve the policy objective by solving

$$0.6 = \frac{e^{-0.3278(\overline{C}-\hat{\tau})}}{1+e^{-0.3278(\overline{C}-\hat{\tau})}},$$

which implies that $\hat{\tau} \approx 3.7318$. However, this subsidy would not achieve its intended objective. Specifically, it overshoots the policy objective. By plugging this subsidy into the true model to re-solve for the rational expectation equilibrium it can be shown that a green market share of about 73% instead of the targeted 60% would be achieved. The reason for the overshoot is that the policy agency failed to account for the multiplier effect arising from the presence of social interactions. The subsidy that would achieve a green market share of 60%, denoted by $\hat{\tau}^{RE}$, is the solution to the following implicit expression

$$\hat{P}_1 = \frac{e^{-0.1(\overline{C}-\hat{\tau}^{RE})+2.0\hat{P}_1}}{e^{-0.1(\overline{C}-\hat{\tau}^{RE})+2.0\hat{P}_1} + e^{2.0(1-\hat{P}_1)}},$$

which yields $\hat{\tau}^{RE} \approx 3.0547$.

Example 2:

Next, consider the same example as above with the exception that the conformity effect is more dominating. Specifically, assume that $\gamma = 3$. By using the same approach as in the previous example, it is possible to solve equation (6) under the current parametric assumptions. Now there are three possible non-cooperative, rational expectation equilibria, namely, $P_1^{RE} \approx \{0.0465, 0.6621, 0.8763\}$, illustrated graphically in Figure 2. Brock and Durlauf (2001b) and Blume and Durlauf (2002) discuss the stability of a dynamic version of this model. Under the maintained assumptions, they find that the extreme (low and high) equilibria are locally stable whereas the mid-level equilibrium is locally unstable.

To explore the effect of policies, let us assume that the realized equilibrium is the low-level equilibrium $P_1^{RE} \approx 0.0465$. Again, assume that the policy agency wants to achieve a green market share of 60%. As in the previous example, the agency would make a mistake by failing to account for social interactions. It would infer that the private incentives can be characterized by a cost parameter of negative 0.6526 and subsequently sets a subsidy of 3.4026.

Given the true model, it can be shown that such a re-balancing of money incentives supports three new equilibria ($P_1^{RE(\hat{\tau})} \approx \{0.0753, 0.4799, 0.9335\}$), which means that the policy has the potential to either cause a mere perturbation, a moderate effect, or a very dramatic effect. If the equilibrium changed from 0.0465 to 0.0753 one could say that the presence of a relatively dominant social pay-off component in the individual utility function makes aggregate behavior "sticky" or non-responsive with respect to policy intervention. Which equilibrium is more likely to be realized? The mid-level equilibrium is dynamically unstable and therefore a less likely outcome according to Brock and Durlauf (2001b) and Durlauf and Blume (2002). Between the two extreme equilibria, it seems reasonable to think that the subsidy would cause some individuals to switch to the *green* alternative. However, it seems unlikely that there would be sufficient behavioral re-assessment to set in motion a large multiplier (or cascading) effect moving the group to the high equilibrium.

Would it be possible to devise a policy that yields the desired policy objective of this example? The answer is "probably not". There exists a particular subsidy which would support the policy objective. However, this subsidy also supports two other aggregate behavioral outcomes. For this subsidy, the 60% green market is a mid-level equilibrium, which is unstable in a dynamic sense and therefore less likely to be observed. This example demonstrates the challenges of determining optimal polices in choice contexts with social interactions. Moreover, it demonstrates how it is possible for apparently similar groups, facing the same private incentives, to display radically different aggregate behaviors.

4. Empirical Application: Consumer Recycling in Norwegian Communities

We implement the social interaction-random utility model in an analysis of consumer recycling behavior in Norway. Individuals are assumed to make discrete choices whether or not to recycle various bi-products from their household production and consumption activities. The alternative to recycling material items is to dispose of them as waste.

From the society's point of view, recycling is one way to conserve or extend the useful life of scarce resources. Moreover, a well developed recycling industry can reduce reliance on and hence the negative externalities from virgin-material production. Lastly, recycling is an effective way to avoid common environmental problems associated with landfills and incineration facilities. For these reasons, we consider recycling to be the environmentally friendly or *green* waste handling alternative, while waste disposal is the *brown* alternative.

From the individual's point of view, recycling activities can often be more costly, particularly because it requires an additional effort on their part. In the remainder of this paper, we seek to analyze individuals' recycling choices and investigate whether community-level recycling outcomes, in terms of the shares of community members choosing to recycle, are subject to social interactions within the communities. This would be true if individuals are influenced by choices made by others within their respective community.

The empirical strategy that we employ is to estimate an econometric model for individual choices that explicitly incorporates a social utility component. The social interaction hypothesis is tested by evaluating the statistical significance of the social utility preference parameter. In order to make the analysis tractable, we only consider interactions that are *global* within communities, meaning that individuals are assumed to be affected by the aggregate (average) recycling behavior within their community, not the behavior of specific individuals. Furthermore, the aggregate outcome in one community is treated as independent that in other communities.

Individual Recycling Behavior

Data for the analysis come from a national household survey conducted on a quarterly basis by Statistics Norway. The overall purpose of these quarterly surveys is to obtain basic information on the economic and demographic status of individuals throughout the 435 Norwegian communities (or municipalities). The fourth quarter 1999 survey questionnaire included a non-standard section on household recycling behavior [Statistics Norway (1999)].[9] A total of 2000 individuals were selected for this survey and it achieved a response rate of about 58%. After eliminating observations with *item non-response* for key variables, we end up with a dataset consisting of 1039 individuals from

125 different communities. Each individual reported recycling choices for six types of recyclable materials: drinking cartons, paper, plastics, glass, metal, and food waste, yielding a panel-type dataset with a total of 6234 observations.[10]

Table 1 summarizes the recycling choices of the sample individuals. Overall, 67% of the observations are classified as "recycling" choices while 33% are classified as "non-recycling/disposal" choices. The most commonly recycled material was paper, with 94% of the respondents reporting to recycle this material. Plastic items were the least commonly recycled material at 38%.

Community-Level Waste Management Policies

The national goal, set by the Norwegian government, is to reduce the fraction of total waste generated that goes to landfills and incineration facilities to 25% by the year 2010. An important aspect of achieving this goal is to encourage consumers to recycle material items that arise from their household consumption and production activities, instead of disposing them in the trash. *Waste disposal fees* and *curbside recycling programs* are the two most common waste management policies targeted at consumers. A third policy, provision of *drop-off recycling centers* is an alternative to curbside recycling programs. This recycling option generally provides less of an incentive than curbside recycling.[11] In Norway (as well as in most other countries) these policies are implemented at the local community level. Table 2 summarizes the exposure of the sample individuals to these policies.

Waste disposal fee schemes are designed in a variety of ways. Most commonly, fees are volume based and incremental rather than marginal. Typically, a household chooses its preferred size of trash can from a discrete set of options. The bigger the trash can, the more it has to pay on its monthly utility bill. In Norway, there are several variations on this system, one in which there is a single can size, but household can share a subscription with its neighbor. Under all fee schemes, households have at least some incentive to reduce the amount of trash produced as a way to lower their monthly utility payments. At the time of the survey about 60% of the participants lived in communities with waste disposal fees.

In contrast to waste disposal fees, which provide a broad incentive to recycle, curbside recycling programs are generally material-specific. As can be seen in table 2, curbside collection of cartons, paper, and food waste is much more common than curbside collection of glass, metals, and plastics. At the time of the survey the average availability of curbside recycling (across materials) was 36%.

The general consensus is that these waste management policies have been highly successful in Norway (and elsewhere). By 1998 over 50% of all consumption and production bi-products (from households, businesses, and industry) were diverted away from landfills and incineration facilities. This constitutes an increase in the diversion rate from about 39% in 1993, before these policies started gaining popularity (see, Statistics Norway, 2001). Despite the apparent success, not much is known about how the policies have performed locally. This question is important particularly because recycling programs can be expensive for communities to implement and operate.

Though the purpose of our paper is not to provide community-level cost-benefit assessments, as part of our analysis of social interactions, we do seek to shed light on how well waste management policies perform at the local community-level. As suggested before, when individuals' decisions are influenced by others, the effect of policies on aggregate outcomes could become highly complex and vary greatly from community to community.

Waste Management Policies and Community-Level Recycling Outcomes

In the following, we define as a community outcome (or equilibrium) the share of community members recycling a given material. Given this definition, our dataset represents 750 outcomes, one for each of the six materials in the 125 sample communities.

As an initial assessment of policy effectiveness, table 3 reports correlation coefficients between the share of community members recycling and the two major waste management policies. Aggregating across all materials, the correlation coefficient between community recycling shares and the presence of a curbside program is 0.28 and the correlation coefficient between these shares and the presence of a waste disposal fee is 0.13. These coefficients suggest that the policies have a positive impact on community recycling outcomes, but perhaps not that large of an impact.

For specific materials, the highest correlation (0.5) is observed between recycling and the presence of curbside recycling of food waste. Several low coefficients can also be observed with the lowest one (-0.03) that between glass recycling and waste disposal fees.

Table 4 reports on average outcomes classified according to four policy "regimes" or policy exposure intensities. These are outcomes associated with (1) absence of a major policy, (2) presence of waste disposal fees, (3) presence of curbside recycling, and

(4) presence of both disposal fee and curbside recycling. Overall, the lowest average recycling shares can be found, as expected, in communities with no policy (see also figure 3). However, this average is very high at 0.59, implying that on average 59% of community members recycle even when both policies are absent. This should be considered a counter-intuitive result. Moreover, this statistic is only slightly smaller than the average outcome in communities that had implemented a waste disposal fee. This outcome was about 0.65. Similarly to the correlation coefficients above, the statistical results in table 4 suggests that curbside recycling programs might be more effective than waste fees. With curbside recycling only, the average outcome was about 0.76 and with both waste fees and curbside recycling the average outcome was 0.86.[12]

At the material-level, additional puzzling observations can be made. For example, there is no discernable difference in the average recycling outcomes for glass and paper under no policy exposure versus the disposal fee-policy regime. Secondly, food waste recycling outcomes appear to be lower in the presence of a fee compared to the situation with neither policy in place. Curbside recycling programs for cartons and paper items, while apparently effective in conjunction with a waste fee, seem ineffective alone. These observations put into question the community-level effectiveness of these policies.

Finally, figure 4 plots each of the 750 community outcomes against their associated policy regime. This figure demonstrates the dramatic variation in community-level recycling outcomes, even across communities that apparently share similar policy environments. As a crude classification, one might say that plot-points in the upper left corner represent *low incentive-high recycling* outcomes while plot-points in the lower right corner represent *high incentive-low recycling* outcomes (‘virtuous’ versus ‘vicious’ outcomes respectively). Clearly, there are a non-trivial number of such outcomes. Such outcomes cannot be easily reconciled with the standard economic story of how individual consumers decide how to deal with household production and consumption bi-products.

These statistical observations do not constitute *prima facie* evidence of social interactions. Nevertheless, they are generally consistent with complex features of the theoretical model presented in section 3. The following sections implement a more formal econometric analysis. But first we briefly discuss several other control variables included to analyze determinants of recycling behavior.

The social interaction literature typically seeks to differentiate between two types of variables that may impact individual behavior and whose effects must be distinguished from genuine social interactions, namely, (i) *individual-specific* variables, and (ii) *group-specific variables*. The effects of these variables are often called *correlated effects* and *contextual effects* respectively; see Manski (1993) for an extensive discussion. The former type of effect arises when a group of individuals tend to behave similarly because they share similar characteristics. The latter arise when individuals display converging behaviors simply due to their shared contextual environment. The waste management policies that we have discussed hitherto are examples of group-specific variables.

Next, we discuss three important types of factors that are individual-specific: (i) socioeconomics and demographics, (ii) attitudes and motivations, and (iii) the price (or cost) of recycling.

Individual-Specific Factors

Socioeconomics and Demographics

Descriptive statistics for socioeconomic and demographic variables are presented in table 5. About 25% of the sample individuals had at least a college degree, the average respondent was 42 years old and the average household size was 2.8. About 77% owned the home they lived in and 60% lived in a single family residence. A priori, we anticipate that such factors may affect individual choices. For example, individuals with higher education may be more aware of waste-related problems and therefore be more inclined to engage in recycling. However, the Norwegian population is generally very homogeneous. Therefore, it seems unlikely that any systematic variation in socioeconomic and demographic factors across communities would helpfully explain variation in the community-level outcomes discussed above.[13]

Attitudes and Motivations

Several questions included in the survey sought to identify recycling attitudes and motivations. The participants were presented with various statements and asked to indicate their extent of agreement with each. A summary of responses to these questions are also reported in table 5.[14] The maximum possible agreement score is 3 while a score of zero signals complete disagreement. For example, *I think recycling is a pleasant activity in itself* captures the extent to which recycling might be a utility-generating activity (vis-à-vis waste disposal or other household chores). The average agreement with this statement was 1.1, indicating that participants typically did not agree with it. The statement *I find recycling a government imposed requirement* had an average agreement score of 1.8. The highest agreement score of 2.5 was received by the statement *I would like to do what I want others to do*. Such a statement, as well as the statement *I would like to think of myself as a responsible person*, might be consistent with an internal moral motivation for recycling (Brekke et al., 2003). The combination of *I would like to contribute to a better environment* and *I think recycling is good for the environment* also received a high agreement score. This might be interpreted as a measure of warm-glow motivation (Andreoni, 1990). We include these attitudinal/motivational measures in our estimation specifically to differentiate genuine social interactions from what might otherwise be purely intrinsic motivations.

The price of Recycling

An economic choice model must incorporate variables that capture all relevant primary budget affects. Previously, we pointed out that a waste disposal fee provides a monetary inducement to recycle instead of disposing of material items as waste. This is not, however, the only budget impact relevant to our analysis. While it is true that communities generally do not charge a monetary fee for recycling options, choosing the recycling alternative does not come *gratis* to individuals and their households. Here, we focus on the implied costs associated with the efforts to recycle various materials.[15] As part of the survey, participants gave assessments of their time use in recycling-related activities, such as sorting, cleaning, storing, and transporting recyclable items. Overall, the average time spent per week on these activities was about 28 minutes (which is about 24 hours per year). Provided consumers have binding time constraints such time use is costly and therefore has a money-equivalence. We obtain measures of this price (cost) by combining results from two auxiliary econometric estimations. The first of these estimated individual-specific money values of time and yielded an average of approximately \$1.5 per hour (about 1/10 of the average earnings rate in Norway). The second analysis derived material-specific time prices (or time requirements) and yielded minutes per week estimates of 9.6 (cartons), 7.0 (paper), 10.3 (glass), 5.9 (metals), 6.3 (plastics) and 1.1 (food waste). Combining these analyses provide measures of what might be called *expected* recycling prices. This 'imputed' variable is included in estimations, along with the community-specific waste disposal fee variable, to control for primary budget impacts. Further details are provided in the appendix.

5. Empirical Specification Issues

In specifying an empirical model, we want to expand the section 3 model in several ways. First, we want to account for multiple-choice occasions by each individual. Seeing as there are L material types that each individual chooses to either recycle or dispose, we treat each type of material, denoted l, as a "choice occasion". Next, we want to recognize that, regardless of social environments and any social influences, each individual may place different weights on factors that affect utility. We conceptualize such *preference heterogeneity* by a random parameter specification. Specifically, we allow for the parameter on the price of recycling, the policy parameters, and the social interaction parameter to vary in the sample population. We collect these parameters compactly in $\theta_i \equiv (\beta_i^C, \beta_i^Y, \gamma_i)$ where β_i^C is a random parameter on the price of recycling, β_i^Y are random parameters on the policy variables, and γ_i is a random social interaction parameter. In order to construct a measure of the individual's belief (or expectation) about the mean community behavior, we assume that a specific belief is formed for each choice occasion. Moreover, we do not impose rational expectations. Instead, as a ‘first cut’, we take the view that individuals’ beliefs have adapted to, and therefore approximately correspond to, the actual or realized outcomes in their respective community.[16] Since we do not know of any richer and more reliable source of data on Norwegian community recycling, we construct these outcomes or belief measures directly from the sample data.[17]

A non-trivial concern in any econometric analysis is concern for omitted variable bias. Such bias could render the distributional assumption on the error structure suspect and potentially lead to biased or inconsistent parameter estimates. Discrete choice models require that the error terms are iid. Omitted variable bias in a discrete choice model with social interactions could be particularly problematic. For example, as an extreme case, suppose that the presence of curbside recycling programs constitute a central determining factor in individuals’ recycling choices, but data on these programs were unavailable. This leads to an immediate violation of the iid assumption because the error term would vary systematically across individuals within the same community (since they are exposed to the same policies).

Even more troublesome is the following. By affecting individual behavior, curbside recycling programs also influence aggregate community behavior. Hence, the variable that was originally constructed to capture individuals’ beliefs about community behavior, and subsequently identify the model’s social interaction parameter econometrically, would likely be tainted by the impact of curbside recycling programs. This constitutes a *spurious regression* problem and may result in failure to reject the social interaction hypothesis when it really should be rejected. More generally, it leads to an identification problem in the sense that it is not possible to distinguish contextual effects, i.e., the impact on individual behavior of exogenous group-specific factors, from true social interaction effects [see Manski (1993) for a seminal treatment of this problem].

An advantageous mark of our application is its reliance on a rich dataset, which helps reduce exposure to the above specification problems. Specifically, the dataset permits us to explore the social interaction hypothesis while controlling for both (i) economic primitives that directly impact individuals' money and time budgets, (ii) individual idiosyncratic factors, and (iii) the exogenous policy environment of the individuals' respective community. Furthermore, the unique richness of the dataset permits us to incorporate latent preference heterogeneity while taking advantage of its panel-nature. Lastly, we include two additional sets of control variables. First, while we conceptualize the recycling decision generically as a binary choice between a *green* alternative and a *brown* alternative, it is possible that individuals systematically evaluate this choice differently across the different material types. We account for this by including material indicator variables in the estimations.[18] Second, each community in Norway belongs to one of twenty larger county regions. Though waste policies are implemented at the community level, it is possible that some systematic influence is exerted on communities within the same county. We account for this possibility by including county indicator variables in the estimations.

6. Empirical Model

We estimate the social interaction-RUM as a *panel mixed logit* [see Train (2001) for details and Revelt and Train (1998) for a seminal application]. The vector of random parameters θ_i is unobservable to the researcher but assumed to follow a density $f(\theta_i \mid \theta^*)$ in the population, where θ^* represents moments of this distribution. Conditional on θ_i, the fixed parameters, and the data, the error component is assumed iid extreme value. The *conditional* probability that individual i will recycle material l is given by

$$\Pr_{il}(\omega_{il} = 1, \theta_i) = \frac{\exp[V_{il1} + S_{il1}]}{\exp[V_{il0} + S_{il0}] + \exp[V_{il1} + S_{il1}]}.$$

The *unconditional* probability can be expressed as

$$\Pr_{il}(\omega_{il} = 1 \mid \theta^*) = \int \Pr_{il}(\omega_{il} = 1, \theta_i) f(\theta_i \mid \theta^*) d\theta_i .$$

Accounting for multiple choice occasions and denoting the probability assessment of the choice individual i actually made with respect to material l by $\Pr_{il}(\omega_{il}, \theta_i)$, the joint probability of the multiple choices, conditional on θ_i is

$$\Pr_i(\theta_i) = \Pi_l \Pr_{il}(\omega_{il}, \theta_i) .$$

The unconditional probability of the choices is

$$\Pr_i(\theta^*) = \int \Pr_i(\theta_i) f(\theta_i \mid \theta^*) d\theta_i \, .$$

This estimation model is called a panel mixed logit because it permits random parameters (*mixed*) while accounting for multiple choice occasion observations for each individual (*panel*) under the usual maintained error distribution assumption of a multinomial logit model. The model does not have a closed-form solution but can be estimated by simulated maximum likelihood. For our application, we adopt the procedures from Train (1996) to our data.

7. Preliminary Estimation Results

Table 6 provides preliminary estimation results. Only direct effects of variables are estimated. There are two estimated coefficients, central tendency and dispersion, for each variable with random preference weight. The parameter on the price of recycling was specified as log-normally distributed. All other random parameters were specified as normally distributed. The material-specific dummy variables and the county-specific dummy variables were jointly significant, but coefficient estimates are of secondary interest and subsequently not reported. However, it should be noted that the qualitative nature and statistical significance of the other parameter estimates, which are of primary interest here, were robust with respect to inclusion or exclusion of these dummy variables.

The Effects of Individual-Specific Control Variables

Several of the *correlated effects* parameters are significant. First, the price of recycling is found to influence recycling choices. The coefficient estimates for this variable must be transformed for meaningful interpretation since the estimated coefficients are the mean and standard deviation of the natural log of the price parameter. The implied median, mean, and standard deviation for the price parameter is 0.018, 0.025, and 0.025, respectively. Because the variable was entered negatively, the signs of the mean and median are correctly positive. The interpretation is as expected. A higher price on recycling reduces utility from recycling and hence increases the probability that waste disposal will be chosen over the recycling alternative. Figure 5b provides a graphical representation of the estimated parameter distribution.

Second, several of the socioeconomic and demographic factors are significant. Recycling probabilities appear to be positively correlated with individuals' age, whether they live in single-family house and their household size (although the age coefficient is only significant at a 90% level of confidence). Somewhat surprisingly, having attained at least a college degree appears not to have a positive influence on recycling probabilities.

Third, three of the attitudinal variables are significant explanatory factors. Finding recycling pleasurable, desire to be a socially responsible person, and wanting to contribute to the quality of the environment, are positively correlated with choosing the recycling alternative over trash disposal. This suggest that, social interactions aside, some non-pecuniary considerations, or motivations operating outside the primary budgets of time and money, are important facets of consumer behavior in the recycling choice context.

The Effects of Group-Specific Control Variables

Among the *contextual effects* the results suggest that, “on average”, waste disposal fees and curbside recycling have positive effects on the likelihood that a consumer will choose recycling over the disposal alternative. But the results fail to demonstrate that drop-off recycling locations constitute a positive inducement for recycling. The estimated mean of the random parameter for this variable is not statistically discernable from zero.

Figures 5c and 5d provide graphical representations of parameter distributions for curbside recycling programs and waste disposal fees respectively. These figures reveal large degrees of consumer heterogeneity, with both parameters having non-trivial probability mass supported by negative parameter values. At face value, one interpretation of this is that a portion of consumers react negatively to what is generally believed and intended to constitute positive recycling incentives. The robustness of this finding was tested by estimating the model with alternative distributional assumptions. Uniform and triangular distributions yielded similar results. Log-normality, which forces parameter distributions to be supported by either positive or negative values, did not fit well.

This finding may lend some credence to the claim that policies sometimes *crowd-out* other incentive mechanisms (e.g., internal motivation and/or social motivations) and therefore sometimes reverse the intended effects of policies; see for example Frey and Oberholzer-Gee (1997) and Nyborg and Rege (2003) for discussions of the crowding phenomena.

The Social Interaction Hypothesis

The estimated parameter on the *mean choice of others* is significant, lending support to the social interaction hypothesis. Moreover, the mean of the parameter distribution is positive and the standard deviation is small, suggesting consumers have strong preferences for conformity (fitting-in) as opposed to non-conformity (standing-apart). As can be seen from figure 5a, most of the estimated probability mass is supported by strictly positive parameter values. In this case, the result that some probability mass (albeit small) has negative support is clearly an artifact of the parameter's normality assumption. When the model was estimated instead with triangular or uniform distributional specification, the probability mass was completely supported by positive values, again suggesting preference for conformity.

8. Concluding Remarks

In this paper we specified a social interaction-random utility model. Our specification accounted for both multiple choice occasions and latent preference heterogeneity. Care was taken in specifying the model such that social interaction effects could be entangled from other factors that may cause individuals to behave similarly. This was made possible largely through the use of a rich dataset on waste management choices made by consumers throughout Norwegian communities. Panel mixed logit results provided evidence that social interactions play a role in this choice context and that consumers have preferences for conformity. The estimation also revealed substantial consumer heterogeneity. The main message of this paper is that social interactions may explain why aggregate outcomes differ across communities, often in seemingly counter-intuitive ways.

References

Akerlof, George. 1980. "A Theory of Social Custom, of Which Unemployment may be One Consequence." *Quarterly Journal of Economics.* 84: 488-500.

Akerlof, George A., and Rachel E. Kranton. 2000. "Economics and Identity." *The Quarterly Journal of Economics.* CXV (3): 715-753.

Ackerman, Frank. 1997. Why Do We Recycle? Markets, Values, and Public Policy. Island Press.

Andreoni, J. 1990. "Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow-Giving." *The Economic Journal*. 100: 464-477.

Becker, Gary. 1965. "A Theory of the Allocation of Time." Economic Journal. 40(299): 493-508.

Becker, Gary. 1974. "A Theory of Social Interactions." *Journal of Political Economy.* 82: 1063-1093.

Blume, Lawrence, and Steven Durlauf. 2002. "Equilibrium Concepts for Social Interaction Models." Mimeo. Cornell University.

Brekke, K.A., Kverndokk, S., and K. Nyborg. 2003. "An Economic Model of Moral Motivation." *Forthcoming in Journal of Public Economics.*

Brock, William A., and Steven N. Durlauf. 2001a. "Discrete Choice with Social Interactions." *Review of Economic Studies.* 68: 235-260.

Brock, William A., and Steven N. Durlauf. 2001b. "Interaction Based Models," in J. Heckman and E. Leamer, eds., Handbook of Econometrics 5. Amsterdam: North-Holland.

Brock, William A., and Steven N. Durlauf. 2003. "Multinomial Choice with Social Interactions." Working Paper. University of Wisconsin at Madison.

Bruvoll, A., Halvorsen, B., and K. Nyborg. 2002. "Household's Recycling Efforts." *Resources, Conservation, and Recycling*. 36(4):337-354.

Duesenberry, J. 1949. Income, Savings and the Theory of Consumer Behavior. Harvard University Press, Cambridge, MA.

Frey, Bruno S., and Felix Oberholzer-Gee. 1997. "The Cost of Price Incentives: An Empirical Analysis of Motivation Crowding-Out." *American Economic Review.* 87(4): 746-755.

Halvorsen, Bente, and Gorm Kipperberg. 2003. "Household recycling of different materials in Norwegian municipalities." Selected Paper for the Twelfth Annual Conference of the European Association of Environmental and Resource Economists. June 28-30, Bilbao, Spain.

Manski, Charles. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *Review of Economics Studies.* 60: 531-542.

Manski, Charles. 2000. "Economic Analysis of Social Interactions." *Journal of Economic Perspectives.* 14: 115-136.

Nyborg, Karine, and Mari Rege. 2003. "Does Public Policy Crowd Out Private Contributions to Public Goods." *Public Choice*. 115(3): 397-418.

Kapteyn, A., de Geer, S. V., de Stadt, H. V, and T. Wansbeek. 1997. "Interdependent Preferences: An Econometric Analysis." *Journal of Econometrics.* 12: 665-686.

Kinnaman, Thomas C., and Don Fullerton. 1999. "The Economics of Residential Solid Waste Management." National Bureau of Economic Research. Working Paper 7326. *Forthcoming in The International Yearbook of Environmental and Resource Economics 2000/2001, edited by Henk Folmer and Tom Tietenberg.*

Kooreman, P., and A. R. 2002. "A Discrete Choice Model with Social Interactions: An Analysis of High School Teen Behavior." Working Paper, University of Groningen.

Kreps, David M. 1997. "Intrinsic Motivation and Extrinsic Incentives." *American Economic Review.* 87(2): 359-364.

Leibenstein, H. 1950. "Bandwagon, Snob, and Veblen Effects in the Theory of Consumer's Demand." *Quarterly Journal of Economics.* 64: 183-207.

Pollak, Robert. 1976. "Interdependent Preferences." *American Economic Review.* 66(3): 309-321.

Revelt, David, and Kenneth Train. 1998. "Mixed Logit with Repeated Choices: Household's Choices of Appliance Efficiency Level." Review of Economics and Statistics. LXXX(4): 647-657.

Schelling, Thomas. 1971. "Dynamic Models of Segregation." *Journal of Mathematical Sociology.* 1: 143-186.

Statistics Norway. 1999. OMNIBUS 04/99. Quarterly Survey of Norwegian Households.

Statistics Norway. 2001. *Statistical Analyses. Natural Resources and the Environment 2001. Norway.*

Train, Kenneth. 2001. Discrete Choice Methods with Simulation. Draft version dated December 7, 2001.

Train, Kenneth. 1996. Mixed Logit Estimation Routine for Panel Data. Available on the Internet at http://elsa.berkeley.edu/Software/abstracts/train0296.html.

Yang, Sha, and Greg M. Allenby. 2001. "Modeling Socially Dependent Preferences." Working Paper, UC Riverside.

TABLE 1: Summary of Recycling Behavior, Overall and by Material Type

Recycling Participation	*Sample Mean*	*Sample Range*	*Observations*
Cartons	0.7276	0-1	1039
Paper	0.9355	0-1	1039
Plastics	0.3831	0-1	1039
Glass	0.8595	0-1	1039
Metals	0.5881	0-1	1039
Food Waste	0.5313	0-1	1039
Overall Recycling	**0.6708**	**0-1**	**6234**

TABLE 2: Summary of Sample Individuals' Exposure to Community-Level Policies

Policy Exposure	*Curbside Recycling*	*Drop-Off Center*	*Waste Disposal Fee*
Cartons	0.88	0.42	0.60
Paper	0.88	0.42	0.60
Plastics	0.02	0.24	0.60
Glass	0.03	0.92	0.60
Metals	0.02	0.62	0.60
Food Waste	0.58	0.08	0.60
Overall Exposure	**0.36**	**0.40**	**0.60**

TABLE 3: Correlations between Community-Level Recycling Shares and Waste Policies

Correlation Coefficients	*Community Recycling Share & Curbside Recycling Program*	*Community Recycling Share & Waste Disposal Fee*
Cartons	0.0597	0.3134
Paper	0.0285	0.1520
Plastics	0.1768	0.1959
Glass	0.1211	-0.0277
Metals	0.0739	0.0573
Food Waste	0.4964	0.2047
Overall Correlations	**0.2832**	**0.1350**

TABLE 4: Average Shares of Community Members Recycling by Policy Regime

Community Share of Recyclers	*No Curbside or Fee*	*Curbside Recycling*	*Waste Disposal Fee*	*Both Curbside & Fee*
Cartons	0.64	0.63	0.76	0.81
Paper	0.91	0.88	0.91	0.95
Plastics	0.33	1.00	0.46	0.67
Glass	0.88	1.00	0.87	0.97
Metals	0.59	0.83	0.64	0.60
Food Waste	0.42	0.70	0.37	0.83
Overall Average Shares	**0.59**	**0.76**	**0.65**	**0.86**

TABLE 5: Descriptive Statistics for Individual-Level Explanatory Variables

Variables	*Sample Mean*	*Sample Range*
Socioeconomic and Demographics		
0/1 Indicator for College Degree or Above	0.2502	0-1
Age of Respondent	42.4148	15-79
Household Size	2.8114	1-13
0/1 Indicator Variable for Home Ownership	0.7661	0-1
0/1 Indicator for Single Family House	0.6006	0-1
Attitudinal/Motivational Agreement		
"Think recycling is a pleasant activity in itself"	1.1126	0-3
"Find recycling a government imposed requirement"	1.7440	0-3
"Would like to think of myself as a responsible person"	1.9788	0-3
"Would like to do what I wants Others to do"	2.4860	0-3
"Would like to contribute…" & "thinks recycling is good for the environment"	2.4850	0-3

TABLE 6: Panel Mixed Logit Estimation Results

Parameter Description	*Coeff. Est.*	*St. Error*	*A-T*	*P-Value*
Individual-Specific Control Variables:				
Negative of Price of Recycling: Central Tendency	-4.0352	0.5140	-7.8510	0.0000
Negative of Price of Recycling: Dispersion	0.8335	0.3500	2.3820	0.0086
College Degree or Above	0.0022	0.1203	0.0180	0.4928
Age of Respondent	0.0454	0.0344	1.3200	0.0934
Household Size	1.1501	0.3987	2.8850	0.0020
Home Ownership	0.0156	0.1731	0.0900	0.4642
Single Family House	0.3322	0.1460	2.2760	0.0114
"find recycling pleasurable"	2.5804	0.4992	5.1690	0.0000
"find recycling a government imposed requirement"	0.1553	0.4533	0.3430	0.3659
"would like to think of him/herself as a responsible person"	0.7638	0.4860	1.5720	0.0580
"would like to do what one wants others to do"	0.7532	0.6501	1.1590	0.1233
"..contribute to environment" & "..recycling important..”	2.4907	0.5184	4.8040	0.0000
Group-Specific Control Variables:				
Waste Disposal Fees: Central Tendency	0.2938	0.1309	2.2440	0.0124
Waste Disposal Fees: Dispersion	1.2806	0.1129	11.3450	0.0000
Curbside Recycling: Central Tendency	0.5686	0.1508	3.7700	0.0001
Curbside Recycling: Dispersion	0.7161	0.2419	2.9600	0.0015
Drop-Off Recycling Location: Central Tendency	0.0116	0.1291	0.0900	0.4641
Drop-Off Recycling Location: Dispersion	1.4035	0.1592	8.8170	0.0000
Social Interaction Variable:				
Mean Choice of Others: Central Tendency	2.3480	0.1324	17.7360	0.0000
Mean Choice of Others: Dispersion	0.9517	0.1770	5.3750	0.0000
Other Control Variables:				
Material-Specific Dummy Variables	Yes			
Region-Specific Dummy Variables	Yes			
Mean LL @ Convergence:	-0.4254			
Number of Cases:	6234			

Figure 1: Pre-Policy Intervention Equilibrium for Example 1

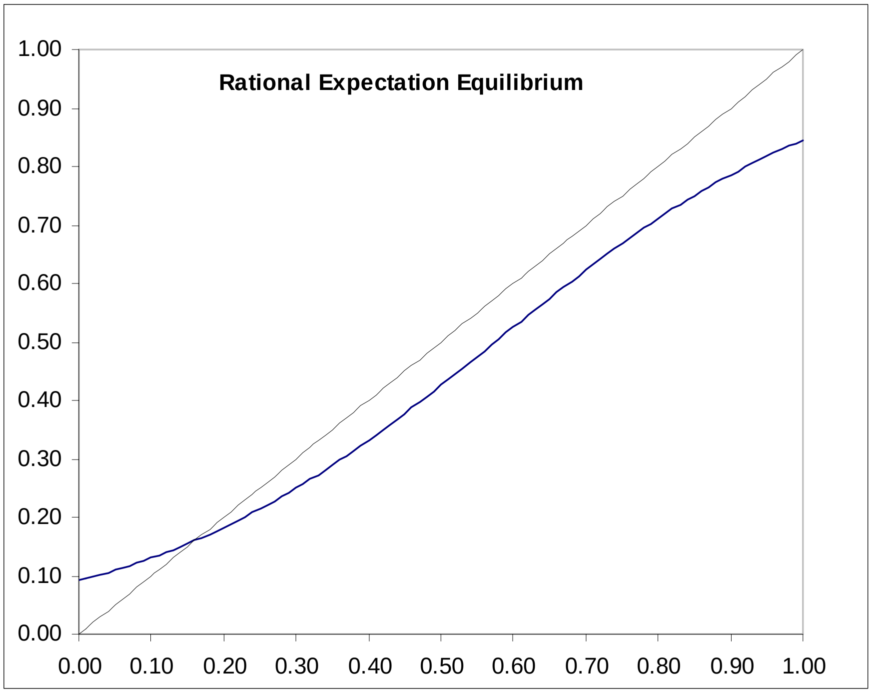


Figure 2: Pre-Policy Intervention Equilibria for Example 2

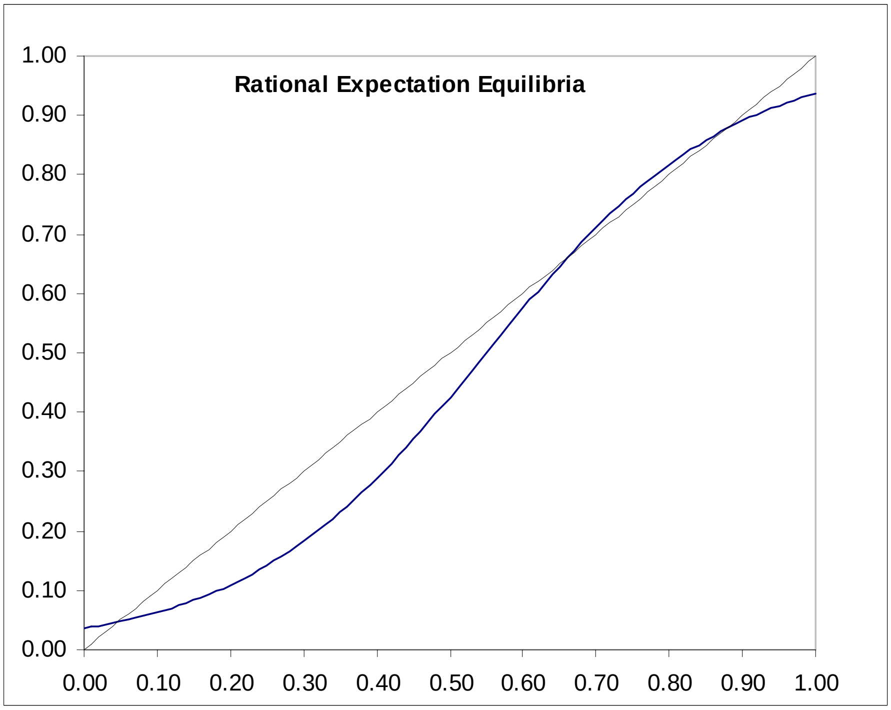


FIGURE 3: Average Outcome by Policy Regime

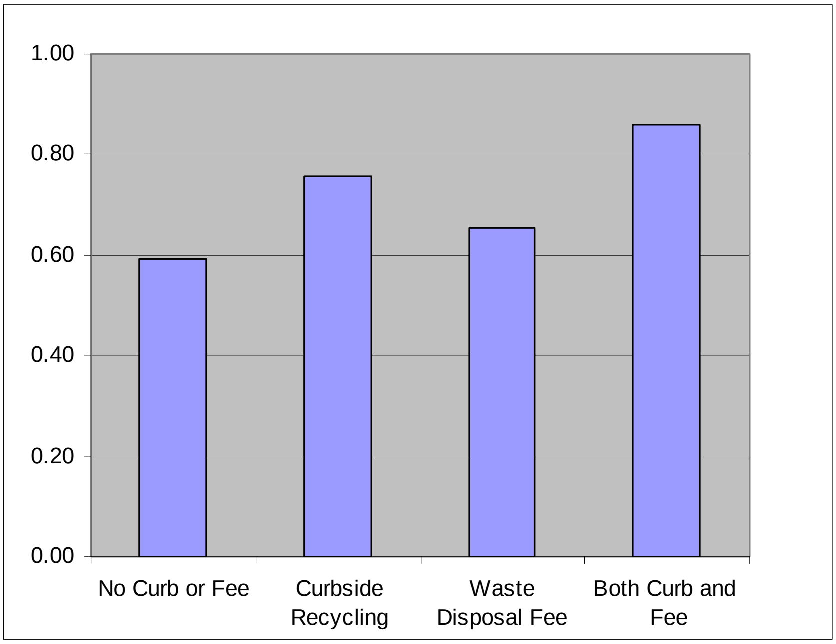


FIGURE 4: Recycling Outcomes by Policy Regime

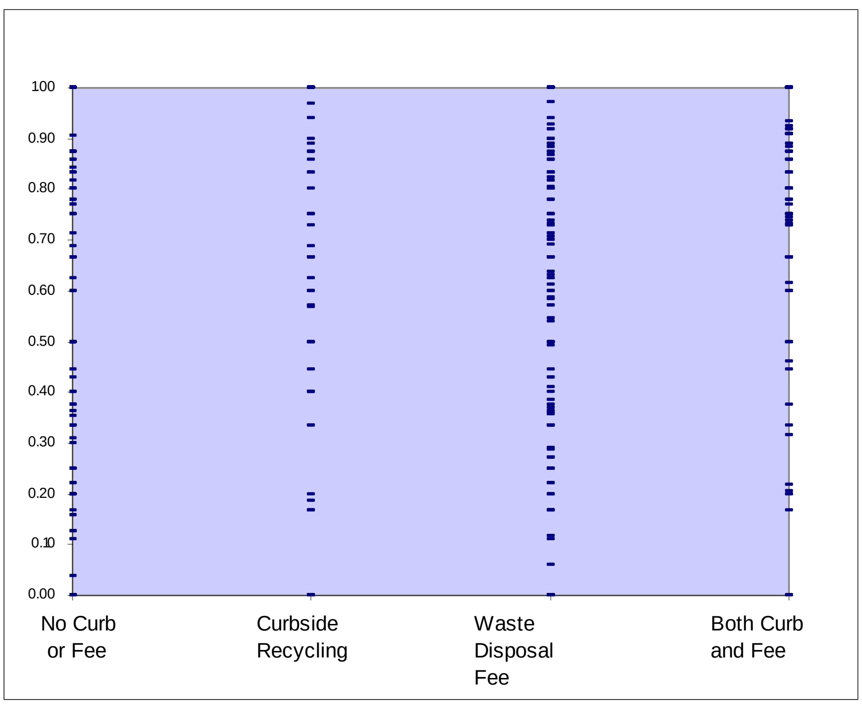
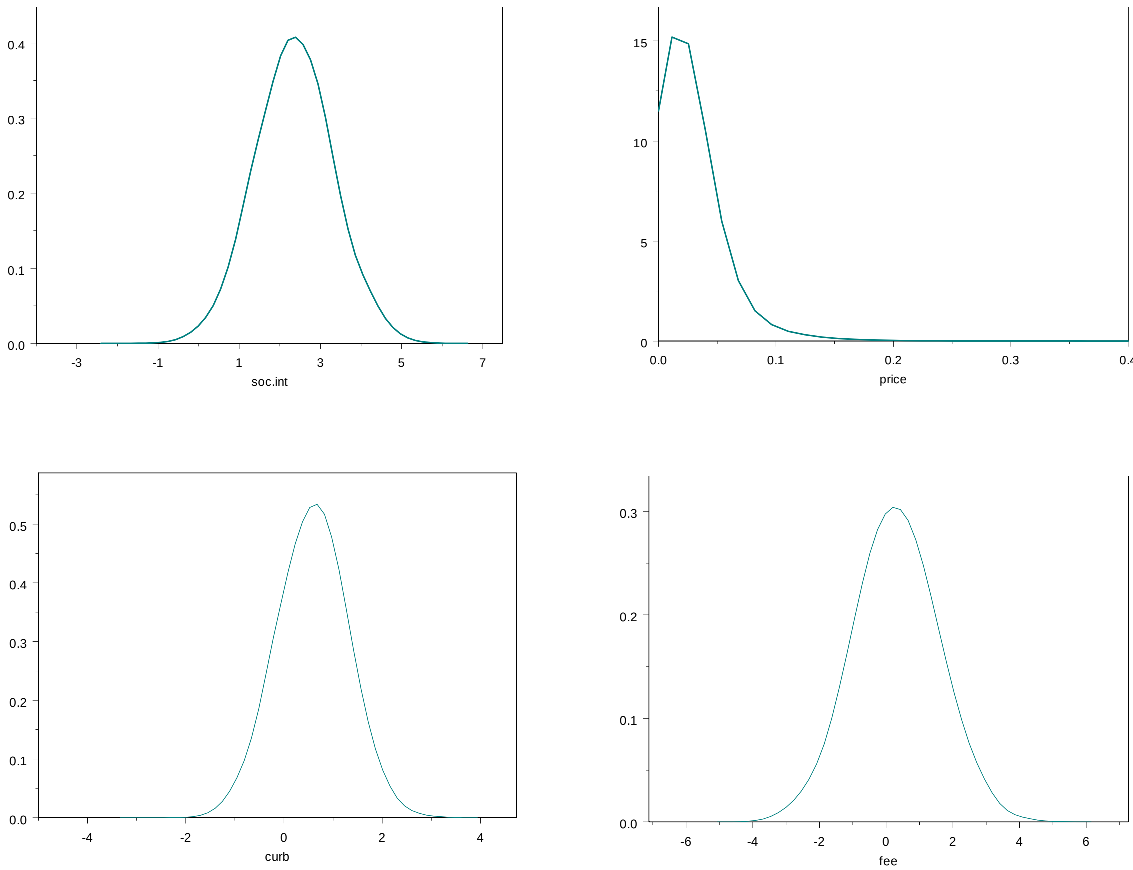


FIGURE 5: Density Plots for Random Parameters

5a: Social Interaction Parameter **5b: Recycling Price Parameter**



5c: Curbside Recycling Parameter **5d: Waste Disposal Fee Parameter**

Appendix 1: Derivation of Expected Recycling Prices

The goal of this analysis is to obtain price or cost measures for recycling that are consistent with the discrete choice model from section 3. We anticipate that recycling of different materials have different time prices (or time requirements). We denote these time prices by t_l, where l subscripts the material type, $l = 1,2,...,L$ (in our case L = 6). We also anticipate that individuals place different money values on their time. We denote the money values of time by ρ_i. The price measures are given by $p_{il} = \tilde{\rho}_i \tilde{t}_l$, where time prices and money values a converted into conformable units of measurement. We obtain these prices measures by combining the results of two auxiliary econometric analyses.

Individual-Specific Money Value of Time

A contingent valuation question asked survey participants their maximum annual willingness to pay to have a company take over the recycling responsibility on behalf of their respective household (WTP_i). This hypothetical system was described to result in the same levels of recycling, and the same environmental impact, as the current recycling system. Survey participants were also asked how much time they typically spend on recycling-related activities (T_i^R). Under the assumption that individuals are utility-neutral between their current recycling system and the hypothetical system, and after accounting for the cost of their recycling efforts, the ratio of these two can be regarded as a measure of the money value of time, i.e. $\rho_i = WTP_i / T_i^R$ [see Halvorsen and Kipperberg (2003) for a more formal treatment].

While this ratio could potentially be used directly in the construction of the recycling price measures, two survey issues prevent this from being possible in our case. First, participants who reported that they did not recycle any of the materials were not asked these questions. Second, these survey questions, especially the contingent valuation question, suffered from non-trivial item non-response. To deal with this we adopted the strategy of estimating an econometric model for the money value of time using data on the subset of individuals for whom it was possible to construct the ratio of willingness to pay to total time spent recycling. We then use the estimated model to predict values of time for each individual in our full sample.

The money value of time is estimated as a function of demographic variables, including variables characterizing the respondent's labor market situation. We adopt a log-linear functional form, which ensures that predicted values are strictly positive, consistent with the belief that time constraints are generally binding. We estimate the model by ordinary least squares. Results are reported in the following table.

Ordinary Least Square Regression for Log Marginal Money Value of Time

Variable	**Est. Coef.**	**St. Error**	**P-Values**
Constant	2.8081	0.2717	0.0000
Earnings Rate	0.0004	0.0005	0.3317
Age of Respondent	-0.0145	0.0056	0.0093
Household Size	-0.1174	0.0422	0.0057
(0,1) Indicator for College Degree or Above	0.0399	0.1359	0.7690
(0,1) Indicator for Management Position	0.4069	0.1529	0.0081
(0,1) Indicator for Private Sector	0.0617	0.1403	0.6603
(0,1) Indicator for Unemployed	0.1241	0.5042	0.8057
(0,1) Indicator for Staying at Home	-0.6442	0.4151	0.1214
(0,1) Indicator for Retired and Living off Pension	-0.2775	0.2468	0.2614
(0,1) Indicator for Student	0.5238	0.2050	0.0109
(0,1) Indicator for Unskilled	-0.4550	0.2285	0.0471
(0,1) Indicator for Male Respondent	0.1632	0.1211	0.1785
Number of observations: 441. Adjusted R-Squared=0.11, P-Value=0.0000			

The results indicate absence of a correspondence between a person's earnings rate and his or her opportunity cost of time. Unfortunately, we did not have information to distinguish between respondents working flexible hours versus fixed hours. Intuitively, the value of time for people working flexible schedules is more likely to be connected to their earnings rate. The significant variables are age, household size, and whether the respondent works in management, is a student, or unskilled labor. Age, household size, and being an unskilled laborer appear to have a negative impact on the money value of time. Managers and students seem to have higher values of time. For example, a one-year increase in age is associated with a 1.45% decline in the time value. Being a manager increases the value of time by about 41%. The mean predicted money value of time for the entire sample is about $1.5 per hour, which is less than 1/10 of the mean hourly earnings rate in Norway.

Material-Specific Time Price of Recycling

A limitation of the survey is that it did not ask participants how much time they spent (or would expect to spend) on recycling each material. If that were the case, we would immediately have measures of the time prices of recycling. Furthermore, these prices would be material-specific as well as potentially individual-specific. The latter would be true to the extent that time requirements depend on factors such as household characteristics (which might affect the composition and quantities of materials that arise as bi-products of household production and consumption), the type of recycling options available in the individuals' respective community, and so on.

In order to overcome this limitation and obtain measures of the time prices, we decompose econometrically the total time spent on recycling as a function of which materials were reported to be recycled using a linear approximation. Specifically, we assume that $T_i^R = \alpha + \sum_l t_l d_{il} + e_i$, where α is an intercept capturing time spent recycling materials that the survey did not ask about, d is an indicator for recycled material, and e_i is a random error term assumed iid normal with mean zero. The time prices are estimated as parameters on the indicator variables by ordinary least squares. The table below reports the estimation results.

<u>Ordinary Least Square for Total Time Spent Recycling</u>

Variable	**Est. Coef.**	**St. Error**	**P-Value**
Constant	3.9175	1.0886	0.0003
Cartons	9.5596	0.8483	0.0000
Paper	6.9734	1.1541	0.0000
Glass	10.3485	1.0016	0.0000
Metals	5.8719	0.9478	0.0000
Plastic	6.3286	0.9575	0.0000
Food Waste	1.1339	0.8564	0.1855
Number of Observations: 990. Adjusted R-Square=0.13, P-Value=0.0000			

All coefficients, except that for food waste, are statistically significant at least at a 0.99 level of confidence. In terms of interpretation, for instance, the coefficient on paper suggests that the average time requirement (or the expected time price) for paper recycling is 6.97 minutes per week. This decomposition seems broadly reasonable. The two material types that often require cleaning, cartons and glass, have the highest time prices. Food waste does not appear to require a significant effort in terms of time. This could be because the most commonly way to recycle food waste is to merely put it into a separate container for weekly home collection.

We also made several attempts to extend the above specification by conditioning the overall amount of time spent recycling on household characteristics and the type of recycling programs available. For example, a priori, one would think that the time requirement for a given material would depend on whether the community had implemented a curbside collection program for that material. However, we were unable to find statistically discernable differences in the decomposition by such extensions. Hence, for the purpose of this paper, we combine the results of the above table with the estimation results for the money values of time to construct recycling price measures.

[1] Brock and Durlauf (2001a, 2001b, and 2001c) provide various expositions and discussions of a binary discrete choice model with social interactions. Here, we adopt the notational convention from Brock and Durlauf (2003), which is a generalization of this model to cases with more than two choice alternatives. In order to align the notation closer to the notation of the standard RUM literature, we make some slight modifications (for example, we use U instead of V to represent total utility and V instead of h to represent the observable (deterministic) component of the indirect utility function).

[2] We assume that social (reference) groups are not overlapping in the sense that some individuals belong to multiple groups. This implies that social groups do not influence each other and that an individual is only influenced by the behavior of other individuals within his/her specific group. Empirical implementation requires that data are available for multiple groups, with observations on I individuals belonging to one out of N groups such that $I = I_1 + I_2 + \ldots + I_N$.

[3] We have omitted subscript i on the preference parameters. However, as a generalization, these parameters could be thought of as individual-specific, reflecting that the weights placed on specific factors in the utility function may vary across individuals. We incorporate the notion of such *preference heterogeneity* in our empirical specification and estimation.

[4] A different interpretation is that the individual choices of others matter but are weighted equally by a given individual in making his/her decision.

[5] The issue of scale always emerges in discrete choice models. Here, simply think of all parameters as re-scaled such that the variance of the error component is unity. Due to the identification issues, such assumption is commonly made for practical purposes in estimation.

[6] This is a strong implication. Later we discuss the possibility of relaxing this assumption. We also discuss the practical matter of how to model these expectations empirically, when the number of sampled individuals from groups is relatively small.

[7] For empirical implementation, the invariance of Y within a group (as well as the self-consistency of belief assumption) means that a researcher must have data on individuals from multiple groups in order to identify the contextual parameters (β_Y) and the social interaction parameter (γ).

[8] See Akerlof and Kranton (2002) for many examples of seemingly counter-intuitive behaviors. See Brock and Durlauf (2001a) and Manski (2000) for further discussions of the applicability of social interaction models to many choice contexts.

[9])]. Detailed descriptions of the survey data can be found elsewhere; see e.g. Bruvoll et al. (2002) or Halvorsen and Kipperberg (2003).

[10] The survey asked the participants to indicate whether they typically recycle "none", "some", "most" or "all" of each material type. Here, we only distinguish between whether the individuals recycled or did not recycle a particular material. Hence, we treat recycling as a binary, discrete choice. The reported efforts in the first response category were re-classified as "non-recycling" choices and efforts in the latter three categories as "recycling" choices. One reason for making this simplification is that the large majority of participants selected either the "none" response category or the "all" category. This was true for all six material types. This seems to indicate that recycling is often an "all or nothing" decision. Also, it seems more reasonable to think that individuals form beliefs about the share of community members that are recycling rather than the distribution of community efforts. A response category such as "some" may be interpreted differently, in terms of what actual effort level underlies it, by different individuals.

[11] Drop-off recycling centers may make more sense in sparsely populated communities where curbside recycling programs are less likely to be technically feasible and/or economically viable.

[12] However, when statistical noise is taken into account, one cannot draw unambiguous conclusions.

[13] Other variables were available as well. Firstly, the survey collected data on both individual and household income. But, as is well known from the discrete choice literature, income, interpreted as an economic primitive, drops out when a linear utility function is specified. Alternatively, income could be interpreted as a general preference shifter. However, both income variables performed poorly in preliminary regressions and further exasperated problems of item non-response. Consequently, we choose not to use income in further econometric explorations. Secondly, the survey collected detailed characteristics of each individual's labor market situation. We do not use these variables in our recycling choice models. However, we use several of these variables in the recycling price derivation (see appendix).

[14] Original verbal response categories have been converted to numeric values.

[15] See Bruvoll et al. (2002) for a discussion of other costs, such as expenses associated with water and energy usage in cleaning recyclable items and expenses associated with transportation of sorted materials to drop-off centers.

[16] In future extensions of this research, we intend to explore alternative specification strategies. One possibility is to treat individuals' beliefs as a latent variable that follows a certain structure, rational expectation or other. This would suggest the application of a *full-information* estimation procedure, where the expectation formation 'process' is estimated simultaneously with the recycling choices.

[17] This approach is arguably naive. For one, it presumes that consumers are well informed with respect to the actions of their community members. This does not, however, work in favor of the social interaction hypothesis. Provided individual beliefs bear little or no correspondence to actual community outcomes, including such a variable in the makes it more likely that the hypothesis is rejected. Hence, we feel justified in making this assumption. Secondly, it presumes that the sample responses for each community represent well the actual behavior of the community population. With 1139 individuals from 125 communities, we have on average less than ten representatives from each community. We are not specifically concerned about what might be called "avid-recycler" selection bias. Since, the recycling questions only constituted a small portion of the survey questionnaire we do not believe that our sample data suffer from such bias. Nevertheless, ideally we would have liked to have more observations for each community. As one test of whether this would affect hypothesis testing, the model was estimated both using data from all 125 communities and using data from the 60 communities with the most observations per community. The estimation results we report in this paper were found to be robust in this respect.

[18] This is akin to treating the material type as an attribute of the choice occasion.