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Published in:
Journal of Applied Econometrics

Publication date:
2007

[Link to publication in Tilburg University Research Portal](#)

Citation for published version (APA):
Kooreman, P., & Soetevent, A. (2007). A discrete choice model with social interactions; with an application to high school teen behavior. *Journal of Applied Econometrics*, 22, 599-624. <http://hdl.handle.net/10411/13622>

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A Discrete Choice Model with Social Interactions; with an Application to High School Teen Behavior

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Version October 2005

Abstract

We develop an empirical discrete choice interaction model with a finite number of agents. We characterize its equilibrium properties – in particular the correspondence between the interaction strength, the number of agents, and the set of equilibria – and propose to estimate the model by means of simulation methods.

In an empirical application, we analyze the individual behavior of high school teenagers in almost 500 school classes from 70 schools. In our baseline model endogenous social interaction effects are strong for behavior closely related to school (truancy), somewhat weaker for behavior partly related to school (smoking, cell phone ownership, and moped ownership) and absent for behavior far away from school (asking parents' permission for purchases). Intra-gender interactions are generally much stronger than cross-gender interactions. In a model with school specific fixed effects social interaction effects are insignificant, with the exception of intra-gender interactions for truancy.

Keywords: discrete choice; social interactions; equilibrium properties; teenage behavior

JEL classification: C35, D12

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We thank Rob Alessie, Ulf Bockenholt, Marco Haan, Yannis Ioannides, Joyce Jacobsen, Brian Krauth, Bertrand Melenberg, Bert Schoonbeek, Michel Wedel, and anonymous referees for helpful comments and discussions. In addition, we benefited from comments by seminar participants at ESEM2002, RAND Corporation, Tilburg University, University of Amsterdam, and University of California at Santa Barbara. Soetevent's research was supported by a grant from the MacArthur Research Network on Social Interactions and Economic Inequality, and by the Netherlands Organization for Scientific Research (NWO). Part of this paper was written while Soetevent was a visitor at the University of Wisconsin at Madison, whose hospitality he gratefully acknowledges.

1 Introduction

Early contributions by Veblen (1899), Duesenberry (1949), Leibenstein (1950), Pollak (1976), and others show that economists have recognized the potential importance of social interactions for a long time. The slow progress of empirical research in this area is to a large extent related to a number of methodological problems. As described by Manski (1993, 2000) and others, a major difficulty is to disentangle endogenous social interactions (which imply a social multiplier effect) from other types of social interactions (which do not imply a multiplier effect). Another problem is the endogeneity of reference groups. Recent years have shown an increasing number of empirical studies searching for credible empirical evidence on social interactions, in part by using data that are quasi-experimental in nature; see Sacerdote (2001), Durlauf and Moffitt (2003), and Duflo and Saez (2003) for examples.

The present paper focuses on methodological problems related to a specific but frequently encountered situation: social interactions in small groups when choice variables are discrete. In a discrete choice model with endogenous social interactions, the choices of other individuals are explanatory variables in the equation describing the choice behavior of a given individual. For estimation and other purposes, the reduced form (or “social equilibrium” or “solution”) of the model is required. While the reduced form is straightforwardly obtained in a linear model with continuous variables, its derivation is more complicated in the case of discrete variables. As already noted by authors analyzing the simultaneous probit model (see e.g. Heckman, 1978 and Maddala, 1983), such models may not have a solution or may have multiple solutions. This in turn may yield problems regarding the statistical coherency of the model.

In Section 2 we present the model and characterize its equilibrium properties, in particular the correspondence between the interaction strength, the number of agents, and the set of equilibria. Section 3 proposes to estimate

the model by means of simulation methods, assuming that observed choices represent an equilibrium of the static discrete game played by all interacting agents. Section 4 is devoted to an empirical application. We analyze a sample of 485 high school classes with detailed information on the individual behavior of the students within each class. As all students in a sampled class are interviewed in principle, the data set has rich information on the behavior of potentially important peers of each respondent. We estimate the model for five types of discrete choices made by teenagers: Smoking, truancy, moped ownership, cell phone ownership, and asking parents' permission for purchases. To control for sorting into schools and omitted variables that induce a positive correlation between peers, we also estimate versions that allow for within-class correlation of error terms and for school specific fixed effects. We find strong social interaction effects for behavior closely related to school (truancy), somewhat weaker social interaction effects for behavior partly related to school (smoking, moped and cell phone ownership) and no social interaction effects for behavior far away from school (asking parents' permission for purchases). Intra-gender interactions are generally much stronger than cross-gender interactions. Once we control for school specific fixed effects social interaction effects become insignificant, with the exception of intra-gender interactions for truancy.

A number of recent papers have analyzed social interactions in a discrete choice framework. Brock and Durlauf (2001a and 2003) use a random fields approach to study aggregate behavioral outcomes in an economy in which social interactions are imbedded in individual decisions. Equilibrium properties of this model are derived by imposing a rational expectations condition on the subjective choice probabilities of the agents and by assuming that the number of agents is sufficiently large that each agent ignores the effect of his own choice on the average choice level. In contrast, the present paper describes behavior in relatively small groups of a given size

in which choices of other individuals can be assumed to be fully observable. For this reason, it is more appropriate to model the interactions as a non-cooperative game, by making an individual's payoff dependent on the actual choice of others in his group. In the analysis, we will focus on the one-shot pure Nash equilibria of this game. In a recent paper Tamer (2003) proposes a semiparametric estimator which allows – under certain conditions – for consistent point estimation of the model in the $N = 2$ case without making assumptions regarding nonunique outcomes. Its extension and empirical implementation to $N \gg 2$ have not been fully developed as yet. Gaviria and Raphael (2001) analyze school-based peer effects in the individual discrete choice behavior of tenth-graders. However, their econometric model ignores multiplicity of equilibria.

2 Discrete Choice Interactions and Multiple Equilibria

2.1 Preliminaries

Consider a population of N individuals indexed by i , $i = 1, 2, \dots, N$. Each player i faces a binary choice and these choices are denoted by an indicator variable y_i which has support $Y_i = \{-1, 1\}$.¹

Y_i is the strategy set of player i and $Y = \times_{i=1}^N Y_i$. Elements of Y are called *strategy profiles* or *choice patterns*. A strategy profile is denoted by $\mathbf{y} = (y_i, \mathbf{y}_{-i})$, where $\mathbf{y}_{-i} = (y_1, y_2, \dots, y_{i-1}, y_{i+1}, \dots, y_N)'$. Note that the number of elements in Y is 2^N . Each individual makes a choice in order to maximize a payoff function $V : Y \rightarrow \mathbb{R} \cup \{-\infty\}$. For ease of exposition we will sometimes refer to $y = 1$ as “smoking” and to $y = -1$ as “non-smoking”, although we will also consider other types of behavior in the empirical part

¹As long as the model has an intercept, the specific support used is immaterial: Working with $Y_i = \{-1, 1\}$ gives qualitatively the same answers as working with $\tilde{Y}_i = \{0, 1\}$. When no intercept is added, the difference is that when using $\tilde{Y}_i = \{0, 1\}$, one implicitly assumes that only positive choices have a social effect. We thank Brian Krauth for helpful discussions on this matter.

of the paper.

In the standard economic approach, the payoff function is dependent on individual characteristics. Following the notation in Brock and Durlauf (2001b), we assume that these characteristics can be divided into an observable vector \mathbf{x}_i and a random shock $\epsilon_i(y_i)$ that is unobservable to the modeller but observable to agent i . Moreover, in interactions-based models explicit attention is given to the influence of the behavior of others on each individual's choice. Each choice is then described as

$$(1) \quad \max_{y_i \in Y_i} V(y_i, \mathbf{x}_i, \mathbf{y}_{-i}, \epsilon_i(y_i)).$$

Similar to Brock and Durlauf (2001b), we assume that the payoff function V can be additively decomposed into three terms:

$$(2) \quad V(y_i, \mathbf{x}_i, \mathbf{y}_{-i}, \epsilon_i(y_i)) = u(y_i, \mathbf{x}_i) + S(y_i, \mathbf{x}_i, \mathbf{y}_{-i}) + \epsilon_i(y_i),$$

where the first term $u(y_i, \mathbf{x}_i)$ denotes deterministic private utility, $S(y_i, \mathbf{x}_i, \mathbf{y}_{-i})$ denotes deterministic social utility and ϵ_i denotes random private utility. In this paper we assume the social utility term to have the following form

$$S_i \equiv S(y_i, \mathbf{x}_i, \mathbf{y}_{-i}) = \frac{\gamma}{2(N-1)} y_i \sum_{j \neq i} y_j.$$

Define $\mathbf{y}_{-ij} = \mathbf{y} \setminus \{y_i, y_j\}$ so that $(y_i, \mathbf{x}_i, \mathbf{y}_{-i}) = (y_i, \mathbf{x}_i, y_j, \mathbf{y}_{-ij})$. Note that

$$(3) \quad \begin{aligned} & \{V(1, \mathbf{x}_i, 1, \mathbf{y}_{-ij}, \epsilon_i(y_i)) - V(-1, \mathbf{x}_i, 1, \mathbf{y}_{-ij}, \epsilon_i(y_i))\} - \\ & \{V(1, \mathbf{x}_i, -1, \mathbf{y}_{-ij}, \epsilon_i(y_i)) - V(-1, \mathbf{x}_i, -1, \mathbf{y}_{-ij}, \epsilon_i(y_i))\} = \\ & \{S(1, \mathbf{x}_i, 1, \mathbf{y}_{-ij}) - S(-1, \mathbf{x}_i, 1, \mathbf{y}_{-ij})\} - \\ & \{S(1, \mathbf{x}_i, -1, \mathbf{y}_{-ij}) - S(-1, \mathbf{x}_i, -1, \mathbf{y}_{-ij})\} = \\ & \frac{2\gamma}{N-1}. \end{aligned}$$

Thus, for $\gamma > 0$ the utility of smoking (versus non-smoking) when another person smokes as well is larger than the utility of smoking (versus non-smoking) when another person does not smoke. In this case the parameter γ measures the strategic complementarity between the choice of any pair of individuals; for $\gamma < 0$ it measures the extent to which the choices are

strategic substitutes.² In fact, for $\gamma > 0$ ($\gamma < 0$), the model falls into the class of supermodular (submodular) games. Supermodular (submodular) games are games in which each player's strategy set is partially ordered and the marginal returns to increasing one's strategy (in this paper moving from $y = -1$ to $y = 1$) rise (decrease) with increases in the competitors' strategies.³

Conditional on the choice by individual i , deterministic private utility is assumed to be a linear function of exogenous characteristics \mathbf{x}_i , i.e. $u(1, \mathbf{x}_i) = \beta'_1 \mathbf{x}_i$ and $u(-1, \mathbf{x}_i) = \beta'_{-1} \mathbf{x}_i$.

The best response function of individual i given the choices of the other individuals can now be represented as

$$(4) \quad \begin{cases} y_i^* = \beta'_1 \mathbf{x}_i + s_i + \epsilon_i \\ y_i = 1 & \text{if } y_i^* > 0 \\ y_i = -1 & \text{if } y_i^* \leq 0 \end{cases}$$

where

$$s_i = \frac{\gamma}{N-1} \sum_{\substack{j=1 \\ j \neq i}}^N y_j$$

and where y_i^* denotes the difference between the utility individual i derives from choosing $y_i = 1$ and the utility he derives from choosing $y_i = -1$, conditional on \mathbf{y}_{-i} , that is,

$$y_i^* = V(1, \mathbf{x}_i, \mathbf{y}_{-i}, \epsilon_i(1)) - V(-1, \mathbf{x}_i, \mathbf{y}_{-i}, \epsilon_i(-1)),$$

with $\beta \equiv \beta_1 - \beta_{-1}$; $\epsilon_i \equiv \epsilon_i(1) - \epsilon_i(-1)$.

Define $\mathbf{x} \equiv (\mathbf{x}'_1, \mathbf{x}'_2, \dots, \mathbf{x}'_N)'$ and $\epsilon \equiv (\epsilon_1, \epsilon_2, \dots, \epsilon_N)'$. A strategy profile \mathbf{y} is a pure Nash equilibrium profile if and only if it is consistent with (4) for all i , i.e. if after substitution of these values of y_i in s_i we have $y_i^* > 0$ for all i with $y_i = 1$, and $y_i^* \leq 0$ for all i with $y_i = -1$.

²When $\gamma = 0$, the model reduces to the standard binary choice formulation without externalities.

³Milgrom and Roberts (1990, p. 1255). See also Vives (1990) and the textbook treatments of Topkis (1998) and Vives (1999).

Let $Q(\beta, \gamma, \mathbf{x}, \epsilon, N)$ denote the number of pure Nash equilibria given $\{\beta, \gamma, \mathbf{x}, \epsilon\}$ and the population size N . That is, for $N \geq 2$,

$$(5) \quad Q(\beta, \gamma, \mathbf{x}, \epsilon, N) = \sum_{t=1}^{2^N} \left[\prod_{i=1}^N I \left(\epsilon_i > -\beta' \mathbf{x}_i - \frac{\gamma}{N-1} \sum_{j \neq i} y_{jt} \right)^{\frac{1+y_{it}}{2}} I \left(\epsilon_i \leq -\beta' \mathbf{x}_i - \frac{\gamma}{N-1} \sum_{j \neq i} y_{jt} \right)^{\frac{1-y_{it}}{2}} \right]$$

with $I(\cdot)$ an indicator function.⁴ In the model without social interactions (i.e. $\gamma = 0$) each combination of $\{\beta, \gamma = 0, \mathbf{x}, \epsilon\}$ obviously defines a unique equilibrium, and thus $Q(\beta, 0, \mathbf{x}, \epsilon, N) = 1$.

An important feature of the model with social interactions is that, for a given combination of $\{\beta, \gamma \neq 0, \mathbf{x}, \epsilon\}$, several strategy profiles may be consistent with (4). For example, if $N = 2, \gamma = 1$, and $\beta' \mathbf{x}_1 + \epsilon_1 = \beta' \mathbf{x}_2 + \epsilon_2 = -\frac{1}{2}$, profiles $\mathbf{y} = (1, 1)'$ and $\mathbf{y} = (-1, -1)'$ are both consistent with (4). In the left panel of figure 1, equilibrium profiles for this two-person game are drawn in ϵ -space. The shaded area is the area with multiple equilibria.

2.2 Equilibrium properties

This section provides three propositions on the equilibrium properties of model (4). Proposition 1 guarantees the existence of an equilibrium in pure strategies. It turns out that the situation with strategic complements ($\gamma > 0$) is characterized by fundamentally different equilibrium behavior than the one with strategic substitutes ($\gamma < 0$). Moreover, in the latter case it makes a difference whether the population has an even or an odd number of

⁴We follow the convention $0^0 = 1$. Note that the expression between brackets checks for each entry y_{it} of a given strategy profile \mathbf{y}_t whether the choice is consistent with the value of the latent variable. If $y_{it} = 1$, the first indicator function contains the relevant comparison, and for $y_{it} = -1$ the second. If consistency holds for all entries of a given profile \mathbf{y}_t , the expression between brackets has a value of 1 (and zero otherwise). By aggregating over all 2^N possible strategy profiles, one obtains the number of equilibria. If the disturbances are i.i.d. with cumulative distribution function $F(\cdot)$, the expected number of equilibria can be expressed as

$$E[Q(\beta, \gamma, \mathbf{x}, N)] = \int Q(\beta, \gamma, \mathbf{x}, \epsilon, N) dF(\epsilon) = \sum_{t=1}^{2^N} \left[\prod_{i=1}^N \left(1 - F \left(-\beta' \mathbf{x}_i - \frac{\gamma}{N-1} \sum_{j \neq i} y_{jt} \right) \right)^{\frac{1+y_{it}}{2}} F \left(-\beta' \mathbf{x}_i - \frac{\gamma}{N-1} \sum_{j \neq i} y_{jt} \right)^{\frac{1-y_{it}}{2}} \right].$$

See Soetevent (2004) for some properties of $\partial E[Q(\beta, \gamma, \mathbf{x}, N)]/\partial \gamma$.

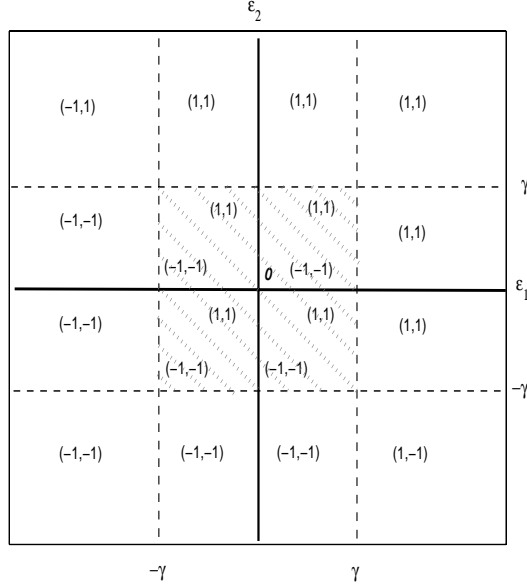


Figure 1: Multiple equilibria in ϵ -space ($N = 2, \gamma > 0, \beta' \mathbf{x}_1 = \beta' \mathbf{x}_2 = 0$).

members. Propositions 2 and 3 provide strict upper bounds on the number of equilibria, for the case with strategic complements and for the case with strategic substitutes, respectively.

Define $z_i \equiv \beta' \mathbf{x}_i + \epsilon_i$ and $k \equiv \sum_{i=1}^N y_i$, that is, k is the net number of agents choosing $y = 1$.⁵ Rank observations on basis of the values of z_i . Denote the ordered values as $z_{[1]} \geq z_{[2]} \geq \dots \geq z_{[N]}$. Denote the corresponding values of y for the agent with $z_{[j]}$ as $y_{[j]}$. Note that the latter are not ordered, such that it is not precluded that e.g. $y_{[j]} < y_{[j+1]}$.

Proposition 1 Existence of an equilibrium in pure strategies

For every combination $\{\beta, \gamma, \mathbf{x}, \epsilon\}$ there exists at least one vector $\mathbf{y} \equiv (y_1, y_2, \dots, y_N)'$ for which (4) holds.

Proof: See the Appendix.

⁵Note that given N , only those values of k for which $N + k$ is an even number are possible. This follows from the observation that $k = a \cdot 1 - (N - a), a \in \{0, 1, \dots, N\}$ can be rewritten as $N + k = 2a$.

Proposition 2 Maximum number of equilibria (strategic complements)

For every combination $\{\beta, \gamma > 0, \mathbf{x}, \epsilon\}$, the discrete interaction model (4) with N agents can have at most $d(N)$ distinct equilibria, with

$$(6) \quad d(N) = \lfloor \frac{N}{2} + 1 \rfloor.$$

Moreover, for every number N , there exists a combination of $\{\beta, \gamma > 0, \mathbf{x}, \epsilon\}$ for which $Q(\beta, \gamma, \mathbf{x}, \epsilon, N) = d(N)$.

Proof: See the Appendix.

The first part of proposition 2 states that in case of strategic complements the maximal number of equilibria grows linearly in N . The second part ensures that the upper bound on the number of equilibria is strict.

Proposition 3 Maximum number of equilibria (strategic substitutes)

For every combination $\{\beta, \gamma < 0, \mathbf{x}, \epsilon\}$, the discrete interaction model (4) with N agents can have at most $d(N)$ distinct equilibria, with

$$\begin{aligned} d(N) = d^e(N) &= \frac{N!}{(N/2)!(N/2)!} && \text{if } N \text{ is even, and} \\ d(N) = d^o(N) &= \frac{N!}{\{(N+1)/2\}!\{(N-1)/2\}!} && \text{if } N \text{ is odd.} \end{aligned}$$

Moreover, for every even (odd) number N , there exists a combination of $\{\beta, \gamma < 0, \mathbf{x}, \epsilon\}$ for which $Q(\beta, \gamma, \mathbf{x}, \epsilon, N) = d^e(N)$ ($Q(\beta, \gamma, \mathbf{x}, \epsilon, N) = d^o(N)$).

Proof: See the Appendix.

Proposition 3 states that for the situation with strategic substitutes, the maximal number of equilibria grows exponentially in N . As in the case with strategic complements, the upper bound on the number of equilibria is strict. Note that $\frac{d^e(N)}{d^o(N-1)} = 2$ for all even N and $\lim_{N \rightarrow \infty} \frac{d^o(N)}{d^e(N-1)} \uparrow 2$ for N

odd. That is, in the limit adding one agent to the population doubles the upper bound on the number of equilibria.

It is also worth mentioning that with strategic substitutes $|k| = |\sum_{i=1}^N y_i|$ decreases monotonically to 0 (1) as $\gamma \rightarrow -\infty$ for N even (N odd). In fact, this result holds more generally: in equilibrium, the difference between the number of agents choosing $y = 1$ and the number of agents choosing $y = -1$, is smaller when γ is more negative, other things equal.

2.3 Extension to more general interactions

The model considered so far only allows for identical interactions between all individuals in the group. One can think more general interactions, where the degree of interaction between two given individuals depends on e.g. their socio-economic characteristics. In this section, we briefly discuss the consequences of one particular extension of the model given by (4) in which the degree of interaction is made gender-dependent. This leads to four different interaction parameters: γ_{GB} measures the effect of boys on girls; γ_{BG} from girls on boys, and γ_{GG} and γ_{BB} the intra-gender effects between girls and boys, respectively. Specify

$$(7) \quad \begin{cases} y_i^* = \beta' \mathbf{x}_i + S_i + \epsilon_i \\ y_i = 1 & \text{if } y_i^* > 0, \\ y_i = -1 & \text{if } y_i^* \leq 0. \end{cases}$$

where

$$S_i = \begin{cases} (\gamma_{GG} \sum_{j=1, j \neq i}^N y_j^G + \gamma_{GB} \sum_{j=1}^N y_j^B) / (N-1) & \text{if } i \text{ is a girl,} \\ (\gamma_{BG} \sum_{j=1}^N y_j^G + \gamma_{BB} \sum_{j=1, j \neq i}^N y_j^B) / (N-1) & \text{if } i \text{ is a boy,} \end{cases}$$

with $y_j^G \equiv y_j \cdot I(j \text{ is a girl})$ and $y_j^B \equiv y_j \cdot I(j \text{ is a boy})$, $\forall j$.

Corollary 1 *For every combination $\{\beta, \gamma_{BB} \geq 0, \gamma_{GG} \geq 0, \gamma_{GB}, \gamma_{BG}, \mathbf{x}, \epsilon\}$ there exists at least one vector $\mathbf{y} \equiv (y_1, y_2, \dots, y_N)'$ for which (7) holds.*

Proof: See the Appendix.

The equivalent of proposition 2 for the extended model follows automatically:

Corollary 2 *For every combination $\{\beta, \gamma_{BB} > 0, \gamma_{GG} > 0, \gamma_{GB}, \gamma_{BG}, \mathbf{x}, \epsilon\}$, the discrete interaction model given by (7) with N_G girls and N_B boys can have at most $d^*(N_B, N_G)$ distinct equilibria, where*

$$d^*(N_B, N_G) = \lfloor \frac{N_B}{2} + 1 \rfloor \cdot \lfloor \frac{N_G}{2} + 1 \rfloor.$$

Moreover, for all N_G and N_B , there exists a combination of $\{\beta, \gamma_{BB} \geq 0, \gamma_{GG} \geq 0, \gamma_{GB}, \gamma_{BG}, \mathbf{x}, \epsilon\}$ for which the maximum number of equilibria is obtained.

It is noteworthy that the values of the cross-gender interaction parameters γ_{GB} and γ_{BG} do not play a role in the derivation of the upper bounds for the number of equilibria.

3 Estimation by simulation

To estimate the model by maximum likelihood we require the probability $P(\mathbf{y})$ that we observe \mathbf{y} , for any given set of parameter values.

A choice pattern \mathbf{y} observed for a particular group is either a single equilibrium or one of multiple equilibria. The support in ϵ -space for choice pattern \mathbf{y} is

$$(8) \quad \begin{cases} \epsilon_i > -\beta' \mathbf{x}_i - s(\mathbf{y}_{-i}) & \text{if } y_i = 1 \\ \epsilon_i \leq -\beta' \mathbf{x}_i - s(\mathbf{y}_{-i}) & \text{if } y_i = -1 \end{cases}$$

where

$$s(\mathbf{y}_{-i}) = \frac{\gamma}{N-1} \sum_{\substack{j=1 \\ j \neq i}}^N y_j,$$

for all $i, i = 1, \dots, N$. Denote the region in ϵ -space defined in (8) by $W(\mathbf{y}, \theta)$, with θ being the parameters to be estimated. Since $W(\mathbf{y}, \theta)$ may also support equilibria other than \mathbf{y} , we have $P(\epsilon \in W(\mathbf{y}, \theta)) \geq P(\mathbf{y})$.

Following Bjorn and Vuong (1983) and Kooreman (1994) we make a randomization assumption in case of multiple equilibria: whenever the model generates multiple equilibria we assume that one of them will occur with probability equal to one over the number of equilibria. To determine the number of equilibria in the various subregions of $W(\mathbf{y}, \theta)$ we use a simulation based method. Consider R random draws (indexed by r , $r = 1, \dots, R$) from the joint distribution of $(\epsilon_1, \dots, \epsilon_N)$ on $W(\mathbf{y}, \theta)$. For each draw, we calculate the number of equilibria. Recall that by construction of $W(\mathbf{y}, \theta)$, \mathbf{y} is either the single equilibrium or one of the multiple equilibria. Let Ω_r be the set of equilibria corresponding to draw r and let E_r denote the number of elements in Ω_r (i.e. E_r is the number of equilibria at draw r). Then the probability $P(\mathbf{y})$ that choice pattern \mathbf{y} will be observed is consistently estimated by the frequency simulator

$$(9) \quad P_1(\mathbf{y}) = P(\epsilon \in W(\mathbf{y}, \theta)) \cdot \frac{1}{R_1} \sum_{r=1}^{R_1} \frac{1}{E_r}$$

This procedure guarantees the statistical coherency of the model, i.e. $\sum_{t=1}^{2^N} P_1(\mathbf{y} = \mathbf{y}_t) = 1$, where $\mathbf{y}_t, t = 1, \dots, N$ is the enumeration of all elements in Y . Note that since $E_r \geq 1$ we have $\frac{1}{R_1} \sum_{r=1}^{R_1} \frac{1}{E_r} \leq 1$.

Alternatively, $P(\mathbf{y})$ could be estimated directly using

$$(10) \quad P_2(\mathbf{y}) = \frac{1}{R_2} \sum_{r=1}^{R_2} \frac{I(\mathbf{y} \in \Omega_r)}{E_r}$$

with R_2 the number of draws from the joint distribution of $(\epsilon_1, \dots, \epsilon_N)$ on \mathfrak{R}^N . However, this would require the number of draws to be of a much larger magnitude to achieve the same precision as achieved when using (9).⁶

We assume that $(\epsilon_1, \dots, \epsilon_N)$ is independently normally distributed (the independence assumption will be relaxed in section 4.4). We have used values for R_1 of 100 and 1000. These values may induce some simulation

⁶The reason is that in (9), (exact) analytical information on the probability of $W(\mathbf{y}, \theta)$ is used. In (10), this probability is estimated together with the probability of actually observing \mathbf{y} conditional on a draw of ϵ being in $W(\mathbf{y}, \theta)$.

variance in both the estimated parameters and the estimated standard errors. However, the estimated probabilities are sufficiently precise as inputs in a likelihood maximization algorithm, and experiments in which we increased the value of R_1 , other things equal, suggest that using larger values for R_1 would not substantially change our empirical results. The likelihood functions were maximized using a Newton-Raphson type of algorithm with numerically evaluated derivatives.⁷ The standard errors were obtained by inverting the approximate Hessian based on the outer products of class specific score vectors.

The characterization of the equilibria in propositions 1, 2, and 3 and their proofs turns out to be extremely helpful in developing an algorithm for estimation. Let $M = \sum_{i=1}^N I(y_i = 1)$, i.e. M denotes the number of individuals choosing $y = 1$. Then $\sum_{i=1}^N y_i = k$ implies $M = \frac{1}{2}(N + k)$. From the proof of proposition 2 it follows that, with $\gamma > 0$, the M agents with $y_i = 1$ are those with the M largest values of z_i . To determine whether there exists an equilibrium with $\sum_{i=1}^N y_i = k$, we therefore first rank observations on the basis of the values of z_i , for a given draw of $(\epsilon_1, \dots, \epsilon_N)$. An equilibrium with $\sum_{i=1}^N y_i = k$ exists if and only if the inequalities

$$(11) \quad \begin{aligned} z_{[N]} + \frac{k+1}{N-1}\gamma &\leq \dots \leq z_{[M+1]} + \frac{k+1}{N-1}\gamma \leq 0 < \\ z_{[M]} + \frac{k-1}{N-1}\gamma &\leq \dots \leq z_{[1]} + \frac{k-1}{N-1}\gamma, \end{aligned}$$

with $1 \leq M = \frac{1}{2}(N + k) \leq N - 1$, are satisfied. An equilibrium with $M = 0$ occurs if and only if $z_i - \gamma \leq 0$ for all i ; an equilibrium with $M = N$ occurs if and only if $z_i + \gamma > 0$ for all i . The proof of proposition 2 also shows that two vectors \mathbf{y} and $\tilde{\mathbf{y}}$ that differ in only one element cannot both be equilibria. As a result, we only have to check $d(N) = \lfloor \frac{N}{2} + 1 \rfloor$ out of the 2^N choice patterns as possible equilibria.

⁷Write the loglikelihood function as $\log L(\theta) = \sum_k \log p_k(\theta) + \sum_k \log r_k(\theta)$, where $p_k(\theta)$ and $r_k(\theta)$ are the first and second right hand side term in (9), respectively, for class k . To increase computational speed, we set $\partial r_k(\theta)/\partial \theta = 0$ in the initial phase of likelihood maximization; i.e. we calculate the term $\frac{1}{R_1} \sum_{r=1}^{R_1} \frac{1}{E_r}$ in (9) only once for a given iteration-class combination, and keep it constant when evaluating the numerical derivatives.

Suppose that model (7), with all γ 's positive, has an equilibrium with M_G smoking girls and M_B smoking boys. It is straightforward to show that the smoking girls are those with the largest values of z_i in the subset of girls, and that the smoking boys are those with the largest values of z_i in the subset of boys. As a result, we only have to check $d^*(N_B, N_G) = \lfloor \frac{N_B}{2} + 1 \rfloor \cdot \lfloor \frac{N_G}{2} + 1 \rfloor$ out of the 2^N choice patterns as potential equilibria.

Proposition 3 implies that with one or more negative γ 's estimation is computationally more demanding. In an analysis of a large number of teenage behaviors - based on the same data and using a continuous version of the model in the present paper - Kooreman (forthcoming) did not find any significant negative γ 's. In this paper we impose nonnegativity of γ 's in the estimation procedure.

From an empirical perspective it is important to note that in the estimated models the probability of a single equilibrium usually turns out to be larger than 80 percent, i.e. we usually have $\frac{1}{R_1} \sum_{r=1}^{R_1} \frac{1}{E_r} > 0.8$. The estimation results in this paper's application also appear to be only moderately sensitive with respect to the assumptions regarding the treatment of multiple equilibria. For example, maximizing a quasi-loglikelihood based on $P(\epsilon \in W(\mathbf{y}, \theta))$ yields estimates similar to those based on $P_1(\mathbf{y})$.

4 Empirical application

4.1 The data: the Dutch National School Youth Survey

We will estimate the model outlined in the previous sections using data from the Dutch National School Youth Survey (NSYS) from the year 2000.⁸

The data set contains information on the teenagers' individual character-

⁸Previous surveys were conducted in 1984, 1990, 1992, 1994, and 1996. The NSYS is a joint effort of the Social and Cultural Planning Office of The Netherlands (SCP) and the Netherlands Institute for Family Finance Information (NIBUD). In each survey year a random sample of high schools in The Netherlands is drawn. A participating school is compensated by means of a report summarizing the survey results for that school. The series of surveys is not a panel, although some schools have participated more than once.

istics, time use, income and expenditures, subjective information on norms and values, and information on various behaviors and durable goods ownership. There is only limited information on the parents (including education and working hours) and no information on siblings.

Although in principle all pupils in a sampled class participate in the survey, some pupils are excluded from the data. In some cases this is because a pupil was absent when the questionnaires were filled out, in other cases because information on some of the variables is missing. We exclude classes with more than 24 students. The resulting data contains information on 7534 students in 485 classes in 70 schools.

All information is self-reported. Thus, strictly speaking, our analysis measures social interactions in how teenagers report on their behavior. The results for “asking parents’ permission for purchases” may provide some insight in potential differences between social interactions in reported behavior and in actual behavior. Asking parents for permission before making a purchase is an aspect of out-of-class behavior. Since this primarily concerns the relationship between a pupil and his or her parents, we expect very weak or no endogenous social interaction effects in this type of actual behavior. However, if pupils copy each others’ responses to the survey questions when filling out the questionnaire, spurious social interaction effects might be found.⁹

⁹A US data set which is comparable to the present one is the National Education and Longitudinal Study (NELS), see *e.g.* Gaviria and Raphael (2001). Both the Dutch NSYS and the NELS focus on non-cognitive outcomes within schools. The NELS is a biannual survey, first held in 1988, and samples students within roughly 1000 schools. An important difference with the Dutch NSYS is that the NELS surveys only a relatively small group of students within each school. For example, in the 1990 sample used by Gaviria and Raphael, the mean sample size per school was 13.3 students. While the NELS contains information on school averages, these are not available per class, grade, or gender. This limits the possibilities for an analysis of interactions within schools (for example, it is impossible to allow for a school specific fixed effect) and it precludes any analysis of social interactions within classes. Two other US data sets on teenagers with peer group information are the Teenage Attitudes and Practices (TAPS) and the National Longitudinal Survey of Youths (NLSY). However, the TAPS only contains subjective information on a respondent’s four best same-sex friends, whereas the NLSY only has subjective peer information based on questions of the type “*What percentage of kids in your grade...?*”.

4.2 Specification of the empirical model

Given the cross-sectional nature of the data we will not be able to fully account for the identification problems that characterize the empirical analysis of social interactions. In order to provide a proper perspective for the interpretation of the empirical results to be presented, we briefly discuss the identification issues in relation to the present data set: *i)* the definition of the reference group, *ii)* endogenous versus contextual effects, and *iii)* non-random selection into reference groups.

The definition of the reference group

As in any empirical analysis on social interaction we require an assumption regarding the definition of the reference group – Who interacts with whom? A number of empirical papers have defined the reference group of an individual as the group of all persons in the population within the same age group and with the same education level, using the sample analogues as an approximation; see *e.g.* Kapteyn *et al.* (1997) and Aronsson *et al.* (1999). This is a crude definition, largely motivated by data limitations. A more attractive alternative is to use subjective information on an individual's reference group, as in Woittiez and Kapteyn (1998). However, the information on the reference group of a sampled individual is often limited as these reference group members are not themselves included in the sample. The data in the current analysis can be viewed as a *reference group based sample* as all students within a sampled class are interviewed in principle. While teenage behavior is obviously also influenced by persons outside the class, classmates are likely to play a dominant role in shaping teenagers' preferences and behavior. On a weekday, the average student in the sample spends about six hours in his or her school class. The total time spent on school related activities (including homework and commuting) is about eight hours per weekday, more than fifty percent of the daily waking time.

Teenagers within the same school or class therefore form social groups that are more clearly defined and delineated than in many other situations in which social interactions are likely to play a role. Obviously, the definition of the reference group could be extended to allow for interactions with students outside the class. Also, one could in principle refine the specification of social groups within the class beyond the boy-girl distinction, for example on the basis of ethnicity, or by allowing the effect of younger and of older classmates to be different. These extensions are left for future research.

Endogenous versus contextual effects

Gaviria and Raphael (2001) argue that students are less exposed to the family background of their school peers than they are exposed to the family background of peers residing in the same neighborhood. They conjecture that in an analysis of interactions through schools contextual effects are less important than in an analysis of interactions through neighborhoods. In their empirical analysis they assume that contextual effects are absent. Kawaguchi (2004) invokes subjective information about the perception of peer behaviors to achieve full identification.¹⁰ He finds that the absence of contextual effects cannot be rejected. The empirical results presented below are based on the assumption that there are no contextual effects. The estimates on the endogenous social interaction effects should therefore be interpreted as upper bounds on the true effects.

Non-random selection into reference groups

To control for non-random selection into schools to some extent we will also estimate a version of the model including school specific fixed effects. To control for selection into classes conditional on selection into schools we also allow for within-class correlation of error terms. This correlation coefficient

¹⁰Identification is based on the problematic assumption that perceived behavior is not determined by actual behavior.

is identified by the nonlinearity of the model and the implicit imposition of equal within-class correlation coefficients across classes.

The vector \mathbf{x} includes age, and dummy variables for gender, for being non-Dutch (based on the question “*Do you consider yourself to be Dutch?*”), for the type of education (MAVO (lower level), HAVO (intermediate level), and VWO (higher level), with ‘vocational’ as reference category), for Catholic, for Protestant, and for living in a ‘single parent family’ (based on the question “*Do you live in a family with father and mother?*”). Unfortunately, a large proportion of teenagers do not know their parents’ education level (41 and 36 percent for father’s and mother’s education level, respectively). We therefore choose not to include parents’ education levels as explanatory variables. However, we do include the father’s working time and the mother’s working time (for a pupil with a single parent the working time of the missing parent is set equal to the sample average).¹¹ Table 1 provides sample statistics for both the endogenous and exogenous variables in the model.

4.3 Estimation results

Table 2 presents four versions of the estimated model for smoking. The first column contains estimation results for the model without social interactions (i.e. with $\gamma_{GG} = \gamma_{GB} = \gamma_{BB} = \gamma_{BG} = 0$). The probability of smoking strongly increases in age. The effect of gender is insignificant. The higher the level of the type of education, the smaller the probability that a pupil smokes. We also find that pupils from single parent households and pupils whose mother has a paid job have a significantly larger probability to smoke. The variables non-Dutch, Catholic, and Protestant negatively affect pupils’ smoking behavior. The effects are largely consonant with earlier empirical

¹¹A number of studies have reported indicators for self-esteem to be important explanatory variables in the analysis of teenage behavior; see *e.g.* Smetters and Gravelle (2001). We choose not to include such a variable because of its potential endogeneity.

studies on smoking behavior; see for example, Gruber and Zinman (2001) and Gruber (2001).

Column two presents results for the model with social interactions. All social interaction coefficients are positive and highly significant. The largest one is γ_{BB} , measuring the boy-boy interaction, followed in size by γ_{GG} , measuring the interaction between girls. The coefficients γ_{GB} and γ_{BG} , measuring the cross-gender interactions are smaller in size and not significant. Note that the inclusion of the social interaction coefficients hardly affects the other parameters.

We have also estimated the model for truancy, moped ownership, cell phone ownership, and asking parents' permission for purchases.¹² Table 3 reports the results. (For ease of comparison the first column in table 3 repeats the second column from table 2).

For truancy, the intra-gender effects are stronger than for smoking. Moreover, we now also have significant cross-gender interactions. The probability of truancy sharply increases in age, is larger for non-Dutch pupils, and is lower for students in VWO, the highest education level in high school.

Moped ownership is the only type of behavior where we find a large gender effect: The probability of moped ownership is much larger for boys than for girls. It strongly increases in age (the legal minimum age for riding a moped in The Netherlands is 16) and decreases in the level of education. It is also the only type of behavior where we have a clear asymmetry in social interactions between genders. For a boy, the probability of moped

¹²The variable 'truancy' in the empirical analysis is based on the question "*How often have you been playing truant during the last (school)month?*". As truants have a larger probability of being absent when the questionnaire is being filled out, there is a potential selection bias. The effect on the estimated social interaction coefficients, however, is likely to be small. The absence of a group of truants with strong mutual interactions might bias the estimated γ 's towards zero, but the presence of a group of non-truants with strong mutual interactions will have the opposite effect. Moreover, tentative calculations indicate that the probability of a student truanting on a random schoolday is in the order of one percent.

ownership is strongly affected by moped ownership of other boys and, to a somewhat lesser extent, of girls. Moped ownership for girls, on the other hand, is not affected by social interactions.

For cell phone ownership we again find an increasing effect of age and a decreasing effect of education. Teenagers from a single parent family have a much larger probability of owning a cell phone. All social interaction coefficients are significant, with the girl-girl effect being largest in magnitude.

The probability of asking parents' permission before purchasing something strongly decreases in age, and is smaller for non-Dutch pupils and for pupils in a single parent household. It also significantly decreases in father's and mother's working time. The four social interaction coefficients are (jointly) insignificant. This suggests that students do not copy each other's responses when filling out the questionnaire.

4.4 Correlated within-class error terms

Clearly, a more flexible specification would be obtained by allowing for class specific fixed effects. With the current data, the estimation of class specific fixed effects is infeasible. Apart from the dependence of identification on functional form assumptions, estimation would have to be based on a much smaller number of observations since classes with non-smokers only (or with smokers only) cannot be used. However, we can estimate the model with class specific random effects.¹³ We assume the covariance matrix Σ of $(\epsilon_1, \dots, \epsilon_N)$ to be a 'one-factor' matrix such that $\Sigma = \{\rho_{ij}\}$ with $\rho_{ij} = \rho$ if $i \neq j$ and $\rho_{ij} = 1$ if $i = j$. To calculate the probabilities $P(\epsilon \in W(\mathbf{y}, \theta))$ we use a decomposition simulator which effectively depends on only a one-dimensional random variable; cf. Stern (1992).¹⁴

¹³As we assume that the within class correlation coefficient between error terms does not vary across classes, this random effects model calls for the estimation of only one additional parameter.

¹⁴Let the random variables u_1, \dots, u_N , and v be independently normally distributed with zero means; $\text{var}(u_i) = 1 - \rho$, $i = 1, \dots, N$ and $\text{var}(v) = \rho$. (We require $\rho > 0$; the procedure for $\rho < 0$ is slightly different. Note, however, that the positive definiteness of Σ

We first estimated this version of the model for smoking without social interaction effects. We found the estimated ρ to be small but significant ($\hat{\rho}=0.098$, t -value 4.5), with the other parameters largely unaffected. When estimating the model with social interaction effects, the estimated ρ is virtually equal to zero and insignificant, with the other parameters being identical to those in the second column of table 2. This seems to indicate that the results in table 2 are not driven by unobserved variables at the class level.

4.5 The magnitude of the social interaction effects

In order to gain some insight in the magnitude of the social interaction effects implied by the estimated γ 's consider a reference class (largely based on median values of exogenous variables). This is a hypothetical MAVO class composed of 8 girls and 8 boys; all of them are aged 14, Dutch, non-Protestant, non-Catholic, and come from a two-parent household with a father working 36 hours per week and a mother working 16 hours per week. Using the estimated parameters from table 3, we find that in equilibrium the expected number of truants is 3.14 (the probability of truancy is 0.191 for girls and 0.201 for boys).¹⁵

Now suppose that a surely truanting girl is added to this class (i.e. we add a girl with characteristics such that her probability of truancy is virtually equal to 1, irrespective of the behavior of others). Without social interaction effects, the expected fraction of truants would rise from 0.196 (3.14/16) to 0.244 (4.14/17), a 24 percent increase. Taking social interaction effects into account, the new equilibrium fraction of truants rises to 0.278 (4.73/17), an increase of 41 percent compared to the original level. If a surely non-

implies $-\frac{1}{N-1} < \rho < 1$.) Let $\epsilon_i = u_i + v$, $i = 1, \dots, N$. Then $Cov(\epsilon) = \Sigma$, with Σ defined in the main text. Now $P(\epsilon_1 < z_1, \dots, \epsilon_N < z_N) = P(u_1 < z_1 - v, \dots, u_N < z_N - v) = \int \Phi\left(\frac{z_1 - v}{\sqrt{1 - \rho}}\right) \dots \Phi\left(\frac{z_N - v}{\sqrt{1 - \rho}}\right) \cdot f(v) dv$, with $\Phi(\cdot)$ the standard normal cumulative distribution function and $f(v)$ a $N(0, \rho)$ density function. The integral is simulated by drawing v from $f(\cdot)$ and then evaluating $\Phi\left(\frac{z_1 - v}{\sqrt{1 - \rho}}\right) \dots \Phi\left(\frac{z_N - v}{\sqrt{1 - \rho}}\right)$ conditional on v .

¹⁵All numbers are based on simulations with R=100000.

truanting girl is added to this class, the expected fraction decreases from 0.196 (3.14/16) to 0.185 (3.14/17) without social interaction effects (a 6 percent decrease), and to 0.169 (2.88/17) with social interaction effects (a 16 percent decrease).

The model also implies that a change in the value of an exogenous variable of only one of the pupils in principle affects the behavior of all pupils in class. Suppose, for example, that the mother of one of the girls in the reference class increases her working hours to 46 per week. Then the equilibrium truancy probability of her daughter increases from 0.191 to 0.210. However, it also changes the equilibrium truancy probabilities of the other girls (from 0.1909 to 0.1915) and boys (from 0.2002 to 0.2012). As a result, the expected number of truanters in class increases not by only 0.019 (0.210-0.191), but by 0.031.

4.6 School specific fixed effects

Smoking behavior in all classes of a given school is likely to be affected by a number of unobserved school specific factors, like smoking behavior of teachers, the school's policy regarding smoking, and proximity of tobacco outlets. Similar effects are likely to be present for the other behaviors. Unobserved school specific factors may also be related to a non-random assignment of pupils to schools. For example, parents who smoke themselves may be less likely to send their children to a school in which smoking is strictly prohibited. Significant social interaction coefficients may then merely reflect the failure to control for these unobserved effects. While the estimation of class specific fixed effects is infeasible with the current data, we estimate in this section a version with school specific fixed effects.

The inclusion of school specific fixed effects amounts to estimating 69 additional parameters (one school is reference category) for truancy, cell phone ownership, and asking permission. For smoking two other schools

are omitted because they have non-smokers only; for a similar reason five schools are omitted in the moped ownership model. For smoking the results are reported in the fourth column of table 2 (the third column reports the results for the model without social interaction but with fixed effects). All social interaction coefficients are now smaller in magnitude, and none of them is significant; a χ^2 -test shows that the γ 's are also jointly insignificant ($p = 0.216$).

Table 4 reports the results for all discrete choice behaviors. (For ease of comparison the first column in table 4 repeats the fourth column from table 2). In addition to smoking, the social interaction coefficients are also jointly insignificant for moped ownership, cell phone ownership, and asking permission, and several γ 's – in particular those related to cross-gender interactions – reached their lower bound.

Truancy is the exception. Both intra-gender interaction coefficients are still highly significant. Although smaller than in Table 3, the effects are still substantial in magnitude, in particular the girl-girl interaction.

In all cases, the fixed effects are jointly significant at the 5 percent significance level.

5 Conclusion

We derived a number of equilibrium properties for the binary choice interaction model with a finite number of agents. Both for the case with strategic complements and strategic substitutes, equilibrium existence was proved and tight upper bounds were derived for the size of the set of equilibria, given the number of agents and the degree of interaction between them. We also briefly discussed the consequences for the set of equilibria when the model is extended to allow for gender-dependent interactions. The main finding here is that the cross-gender parameters are irrelevant in the derivation of the upper bounds.

In our application to teenagers' discrete choices, we found that most of the social interaction coefficients become insignificant once the model allows for school specific fixed effects. An exception is truancy, for which both intra-gender social interaction coefficients remain significant. The fact that we do find significant social interaction effects for a type of behavior closely related to school (truancy) and do not find such effects for behaviors farther away from school strongly suggests that our model measures genuine endogenous social interaction effects rather than unobserved social group effects.

The work presented in this paper indicates various possible extensions for future research. An example is to allow for more general interaction structures, for example by making interaction parameters dependent on socio-economic characteristics. Another, more general issue – typically neglected in the empirical social interactions literature to date – is the question which type of equilibrium concept is appropriate. The fact that classmates interact daily, usually for many years, and often become friends suggests that non-cooperative Nash equilibria may not always be plausible.

While the present data set has a number of important advantages in terms of information on reference group members, the empirical results are subject to the usual qualifications regarding inferences about social interactions based on cross-section data. Future steps toward increasing our understanding of social interactions will require more informative data and models characterized by a tight link between game theory and econometrics.

Appendix: Proofs

Proof of Proposition 1: Equilibrium existence

The case for $\gamma = 0$ is obvious. We prove proposition 1 for the game with strategic complements ($\gamma > 0$) and the game with strategic substitutes ($\gamma < 0$) separately. For the first case, existence can be readily proved by showing that the game belongs to the class of supermodular games. Existence then immediately follows from using Theorem 5 in Milgrom and Roberts (1990, p. 1265). In this appendix however, we will follow for both cases the alternative route of proving equilibrium existence through finding an explicit equilibrium for all combinations of $\{\beta, \gamma, \mathbf{x}, \epsilon\}$. This procedure may give more insight into some of the peculiarities of the model.

Every possible combination of $\{\beta, \gamma > 0, \mathbf{x}, \epsilon\}$ clearly falls into one of the three following categories

$$(i) \quad z_{[1]} \leq 0;$$

$$(ii) \quad z_{[N]} > 0;$$

$$(iii) \quad z_{[1]} > 0, z_{[N]} \leq 0;$$

We show that for each \mathbf{z} in every category there is an associated \mathbf{y} for which (4) holds, for all values $\gamma > 0$.

$$(i) \quad z_{[1]} \leq 0:$$

$y_i = -1, i = 1, 2, \dots, N$ ($k = -N$) is an equilibrium solution, since $y_{[1]}^* = z_{[1]} - \gamma \frac{N-1}{N-1} \leq 0$. This implies that $y_{[i]}^* \leq 0 \forall i$ since $\gamma \frac{N-1}{N-1}$ is a constant and $z_{[i]}$ weakly decreases with i .

$$(ii) \quad z_{[N]} > 0:$$

$y_i = 1, i = 1, 2, \dots, N$ ($k = N$) is an equilibrium solution, since $y_{[i]}^* = z_{[i]} + \gamma \frac{N-1}{N-1} > 0, \forall i$.

(iii) $z_{[1]} > 0, z_{[N]} \leq 0$:

Define $M \equiv 0$ if $z_{[j]} \leq -\gamma \frac{(2j-N-1)}{N-1}, \forall j, j \in \{1, 2, \dots, N\}$ and $M \equiv \arg \max_i \left(z_{[j]} > \gamma \frac{(2i-N-1)}{N-1}; \forall j \leq i \right)$ otherwise. Five examples of sequences of $z_{[i]}$ with $N = 6$ and $\gamma = 1$ are plotted in figure 2 together with the corresponding values of M . The solid line represents the equation $z_{[i]} = -\gamma \frac{(2i-N-1)}{N-1}$.

If $M = 0$, $y_{[i]} = -1, i = 1, 2, \dots, N$ is an equilibrium solution, since $y_{[i]}^* = z_{[i]} - \gamma \leq z_{[1]} - \gamma \leq 0, \forall i$. (See the +-sequence in figure 2.)

If $M > 0$, $y_{[i]} = 1$ for $i = 1, 2, \dots, M$ and $y_{[i]} = -1$ for $i = M + 1, M + 2, \dots, N$ ($k = M - [N - M] = 2M - N$) is an equilibrium solution, since $y_{[i]}^* = z_{[i]} + \gamma \frac{2M-N-1}{N-1} > 0$ for $i = 1, 2, \dots, M$ and $y_{[j]}^* \leq y_{[M+1]}^* = z_{[M+1]} + \gamma \frac{2M-N+1}{N-1} = z_{[M+1]} + \gamma \frac{2(M+1)-N-1}{N-1} \leq 0$ for all $j = M + 1, M + 2, \dots, N$.

Note that for sequences of $z_{[i]}$'s for which $M = N$ (like the sequence of circles and x-es in figure 2), $y_{[i]} = -1, i = 1, 2, \dots, N$ is another equilibrium solution iff. $z_{[1]} \leq \gamma$. In figure 2, this condition holds for the sequence of x-es but not for the sequence of circles. \square

Strategic substitutes ($\gamma < 0$)

In this case, we distinguish between the case where the number of subjects N is even and the case where this number is odd.

N even Let $\gamma < 0$. Define $m \equiv \arg \max_i (z_{[i]} > 0)$. Suppose that $m > N/2$, that is, the majority of the subjects have a value of z greater than zero. Define the non-overlapping non-empty intervals $I_0 \equiv \left[0, \frac{z_{[m]}(N-1)}{2m-N-1} \right)$; $I_{m-N/2} \equiv \left[\frac{z_{[N/2+1]}(N-1)}{2(N/2+1)-N-1}, \infty \right) = [z_{[N/2+1]}(N-1), \infty)$ and, if $m > N/2 + 1$, $I_r \equiv \left[\frac{z_{[m-r+1]}(N-1)}{2(m-r+1)-N-1}, \frac{z_{[m-r]}(N-1)}{2(m-r)-N-1} \right)$, for $r = 1, 2, \dots, m - N/2 - 1$.

First consider the case $m > N/2 + 1$. Since the intervals are non-

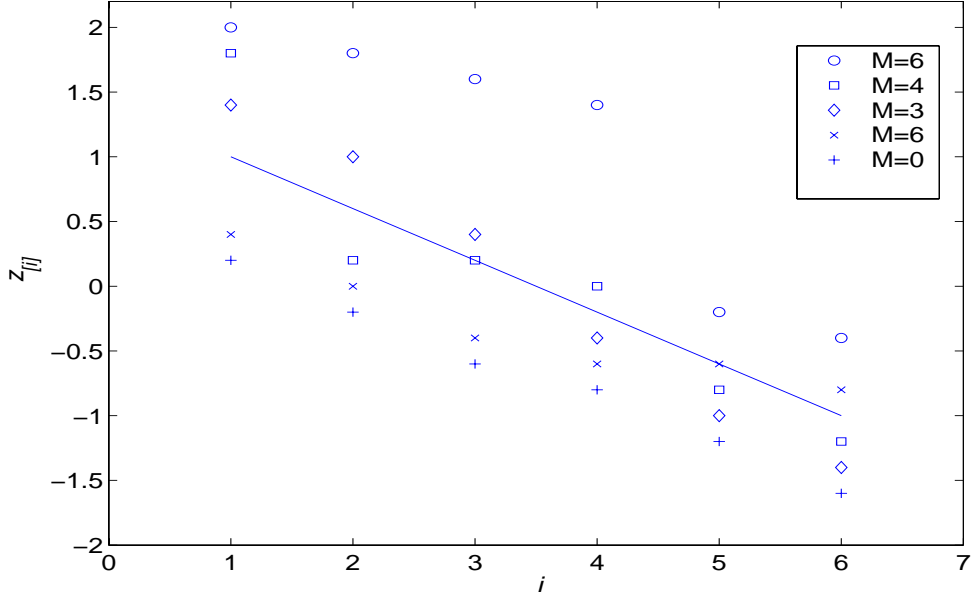


Figure 2: Five examples of $z_{[j]}$ -sequences and the corresponding solutions for $M \equiv \arg \max_i \left(z_{[j]} > \gamma \frac{(2i-N-1)}{N-1}; \forall j \leq i \right)$ for the case with $N = 6$ and $\gamma = 1$.

overlapping and since $I_0 \cup I_1 \cup \dots \cup I_{m-N/2} = [0, \infty)$, $-\gamma$ is in one and only one of these intervals. If $-\gamma \in I_0$, $\mathbf{y} = (1, 1, \dots, 1_m, -1, \dots, -1)'$, ($k = 2m - N$) is an equilibrium, since for this solution $y_{[1]}^* \geq \dots \geq y_{[m]}^* = z_{[m]} + \gamma \frac{2m-N-1}{N-1} > 0$ and $y_{[N]}^* \leq \dots \leq y_{[m+1]}^* = z_{[m+1]} + \gamma \frac{2m-N+1}{N-1} \leq 0$. If $-\gamma \in I_r$, for $r = 1, 2, \dots, m-N/2-1$, $\mathbf{y} = (1, 1, \dots, 1_{m-r}, -1, \dots, -1)'$ ($k = 2(m-r) - N$) is an equilibrium, since for this solution $y_{[1]}^* \geq \dots \geq y_{[m-r]}^* = z_{[m-r]} + \gamma \frac{2(m-r)-N-1}{N-1} > 0$ and $y_{[N]}^* \leq \dots \leq y_{[m-r+1]}^* = z_{[m-r+1]} + \gamma \frac{2(m-r)-N+1}{N-1} \leq 0$. If $-\gamma \in I_{m-N/2}$, $\mathbf{y} = (1, 1, \dots, 1_{N/2}, -1, \dots, -1)'$ ($k = 0$) is an equilibrium, since for this solution $y_{[1]}^* \geq \dots \geq y_{[N/2]}^* = z_{[N/2]} + \gamma \frac{-1}{N-1} > 0$ and $y_{[N]}^* \leq \dots \leq y_{[N/2+1]}^* = z_{[N/2+1]} + \gamma \frac{1}{N-1} \leq 0$.

If $m = N/2 + 1$, then $I_0 \cup I_{m-N/2} = I_0 \cup I_1 = [0, \infty)$. Applying similar reasoning, one can verify that $\mathbf{y} = (1, 1, \dots, 1_{N/2+1}, -1, \dots, -1)'$, ($k = 2$) is an equilibrium when $-\gamma \in I_0$ and that $\mathbf{y} = (1, 1, \dots, 1_{N/2}, -1, \dots, -1)'$ ($k = 0$) is an equilibrium when $-\gamma \in I_1$.

If $m = N/2$, then $\mathbf{y} = (1, 1, \dots, 1_{N/2}, -1, \dots, -1)'$ is an equilibrium for all $-\gamma \in (0, \infty)$, since $y_{[1]}^* \geq \dots \geq y_{[N/2]}^* = z_{[N/2]} + \gamma \frac{-1}{N-1} > z_{[N/2]} > 0$ and $y_{[N]}^* \leq \dots \leq y_{[N/2+1]}^* = z_{[N/2+1]} + \gamma \frac{1}{N-1} < z_{[N/2+1]} \leq 0$.

Due to symmetry, the above argument can be applied for $m < N/2$ with m replaced by $\tilde{m} \equiv N - m \geq N/2$ and the roles of the outcomes $+1$ and -1 interchanged.

N odd The above argument can also be applied for odd N . Suppose that $m > (N+1)/2$ and define $I_0 \equiv \left[0, \frac{z_{[m]}(N-1)}{2m-N-1}\right)$, $I_{m-(N+1)/2} \equiv \left[\frac{z_{[(N+1)/2+1]}(N-1)}{2\left(\frac{N+1}{2}+1\right)-N-1}, \infty\right) = \left[\frac{z_{[(N+1)/2+1]}(N-1)}{2}, \infty\right)$ and, if $m > (N+1)/2+1$, $I_r \equiv \left[\frac{z_{[m-r+1]}(N-1)}{2(m-r+1)-N-1}, \frac{z_{[m-r]}(N-1)}{2(m-r)-N-1}\right)$, for $r = 1, 2, \dots, m - (N+1)/2 - 1$.

Taking the case that $m > (N+1)/2 + 1$, it follows that for $-\gamma \in I_0$, $\mathbf{y} = (1, 1, \dots, 1_m, -1, \dots, -1)'$ ($k = 2m - N$) is an equilibrium; for $-\gamma \in I_r$, $r = 1, 2, \dots, m - (N+1)/2 - 1$, $\mathbf{y} = (1, 1, \dots, 1_{m-r}, -1, \dots, -1)'$ ($k = 2(m-r) - N$) is an equilibrium; and for $-\gamma \in I_{m-(N+1)/2}$, $\mathbf{y} = (1, 1, \dots, 1_{(N+1)/2}, -1, \dots, -1)'$ ($k = 1$) is an equilibrium.

If $m = (N+1)/2 + 1$, then $I_0 \cup I_{m-(N+1)/2} = I_0 \cup I_1 = [0, \infty)$. Applying similar reasoning, one can verify that $\mathbf{y} = (1, 1, \dots, 1_{(N+1)/2+1}, -1, \dots, -1)'$ ($k = 3$) is an equilibrium when $-\gamma \in I_0$ and that $\mathbf{y} = (1, 1, \dots, 1_{(N+1)/2}, -1, \dots, -1)'$ ($k = 1$) is an equilibrium when $-\gamma \in I_1$.

If $m = (N+1)/2$, then $\mathbf{y} = (1, 1, \dots, 1_{(N+1)/2}, -1, \dots, -1)'$ is an equilibrium for all $-\gamma \in (0, \infty)$, since $y_{[1]}^* \geq \dots \geq y_{[(N+1)/2]}^* = z_{[(N+1)/2]} + \gamma \cdot 0 > 0$ and $y_{[N]}^* \leq \dots \leq y_{[(N+1)/2+1]}^* = z_{[(N+1)/2+1]} + \gamma \frac{2}{N-1} < z_{[(N+1)/2+1]} \leq 0$. Again, the case with $m < (N+1)/2$ follows from symmetry. \square

Proof of Proposition 2: Maximum number of equilibria (strategic complements)

The proof for strategic complements uses the following lemma:

Lemma 1 *Let $\gamma > 0$. Suppose model (4) has an equilibrium \mathbf{y} . Then*

$$\min_{\{i|y_i=1\}} z_i - \max_{\{i|y_i=-1\}} z_i > \frac{2\gamma}{N-1},$$

where $z_i \equiv \beta' \mathbf{x}_i + \epsilon_i$.

Proof of Lemma 1

Consider an agent i with $y_i = 1$ and an agent j with $y_j = -1$. Suppose $z_j \geq z_i - \frac{2\gamma}{N-1}$. Then $y_j^* = z_j + \gamma \left(\frac{k+1}{N-1} \right) \geq z_i + \gamma \left(\frac{k-1}{N-1} \right) = y_i^*$. But since $y_i = 1$ and $y_j = -1$ implies $y_i^* > 0 \geq y_j^*$, we have a contradiction. \square

The lemma's effect is that it restricts the maximum number of potential equilibria to $N + 1$. The following observation is an immediate consequence of lemma 1:

- 1 *In any equilibrium the agents with $y_i = 1$ are those with the largest values for z_i .*

Now consider two vectors \mathbf{y} and $\tilde{\mathbf{y}}$ that differ in one element only. Without loss of generality, assume that $y_i = 1$ and $\tilde{y}_i = -1$ for some i . Define $\mathbf{y}_{-i} \equiv (y_1, y_2, \dots, y_{i-1}, y_{i+1}, \dots, y_N)'$ and $\tilde{\mathbf{y}}_{-i} \equiv (\tilde{y}_1, \tilde{y}_2, \dots, \tilde{y}_{i-1}, \tilde{y}_{i+1}, \dots, \tilde{y}_N)'$. Since $\mathbf{y}_{-i} = \tilde{\mathbf{y}}_{-i}$, it follows that $y_i^* = z_i + \frac{\gamma}{N-1} \sum_{j \neq i} y_j = z_i + \frac{\gamma}{N-1} \sum_{j \neq i} \tilde{y}_j = \tilde{y}_i^*$ given a combination of $\{\beta, \gamma, \mathbf{x}, \epsilon\}$. This implies that $y_i = \tilde{y}_i$ and we arrive at a contradiction. Note that this result holds irrespective of γ being positive or negative. The following observation is thus obtained:

- 2 *Two vectors \mathbf{y} and $\tilde{\mathbf{y}}$ that differ in only one element cannot both belong to the set of equilibria.*

From the observations 1 and 2 it follows that the number of equilibria for a given combination of $\{\beta, \gamma > 0, \mathbf{x}, \epsilon\}$ can be at most $d = \lfloor \frac{N}{2} + 1 \rfloor$, where $\lfloor w \rfloor$ denotes the largest integer not larger than w . To give an example: When the number of agents $N = 8$, the maximum number of equilibria can be at most $\lfloor \frac{N}{2} + 1 \rfloor = 5$. Due to statements 1 and 2, the strategy profiles of

these equilibria must be strictly ordered and differ in at least two elements.

This leaves the following five strategy profiles as the only candidates:

$$(1, 1, 1, 1, 1, 1, 1, 1)' ; (1, 1, 1, 1, 1, 1, -1, -1)' ; (1, 1, 1, 1, -1, -1, -1, -1)' ; \\ (1, 1, -1, -1, -1, -1, -1, -1)' ; (-1, -1, -1, -1, -1, -1, -1, -1)' .$$

This proves the first part of proposition 2. The proof of the second part – the upper bound on the number of equilibria is strict – runs as follows.

Denote the d equilibria that are to be sustained as¹⁶

$$\begin{aligned} \mathbf{y}^1 &= (1, 1, \dots, 1)' \\ \mathbf{y}^2 &= \begin{cases} (1, \dots, 1, -1, -1)' & \text{if } N \text{ is even,} \\ (1, \dots, 1, -1, -1, -1)' & \text{if } N \text{ is odd.} \end{cases} \\ &\quad \vdots \\ \mathbf{y}^j &= \begin{cases} (1, \dots, 1_{N-2(j-1)}, -1_{N-2(j-1)+1}, \dots, -1)' & \text{if } N \text{ is even,} \\ (1, \dots, 1_{N-2(j-1)-1}, -1_{N-2(j-1)}, \dots, -1)' & \text{if } N \text{ is odd,} \end{cases} \\ &\quad \text{with } j = 3, \dots, d-1. \\ \mathbf{y}^d &= (-1, -1, \dots, -1)' . \end{aligned}$$

First note that \mathbf{y}^1 can be sustained as an equilibrium outcome if and only if $z_{[N]} > -\gamma$ and that \mathbf{y}^d can be sustained as an equilibrium outcome if and only if $z_{[1]} \leq \gamma$. Further note that \mathbf{y}^{d-i} , $i = 1, \dots, d-2$ can be sustained as equilibria if and only if $z_{[2i]} > \gamma \frac{N-4i+1}{N-1}$ and $z_{[2i+1]} \leq \gamma \frac{N-4i-1}{N-1}$. The fact that these necessary and sufficient conditions on the values of z can be satisfied simultaneously completes the proof.

Proof of Proposition 3: Maximum number of equilibria (strategic substitutes)

In order to prove proposition 3, we will use:

Lemma 2 *For a given combination $\{\beta, \gamma < 0, \mathbf{x}, \epsilon\}$, \mathbf{y} and $\tilde{\mathbf{y}}$ are both equilibria of (4), only if $\sum_{i=1}^N y_i = \sum_{i=1}^N \tilde{y}_i$.*

¹⁶When N is odd, there has to be one equilibrium that differs in at least three elements when compared to any of the other equilibria. Without loss of generality we assume the last three elements of \mathbf{y} to be the three elements that move together.

The proof of lemma 2 uses:

Lemma 3 *If for a given combination $\{\beta, \gamma < 0, \mathbf{x}, \epsilon\}$ there exists an equilibrium \mathbf{y} with $y_{[j]} = -1$ and $y_{[j+1]} = 1$, then there also exists an equilibrium $\tilde{\mathbf{y}}$ with $\tilde{y}_{[j]} = 1$ and $\tilde{y}_{[j+1]} = -1$ and $\tilde{y}_{[i]} = y_{[i]}$ for $i \neq j, j + 1$.*

Proof of Lemma 3

From the fact that \mathbf{y} is an equilibrium with $y_{[j]} = -1$ and $y_{[j+1]} = 1$, it follows that

$$\begin{aligned} y_{[j]}^* &= z_{[j]} + \gamma \frac{k+1}{N-1} \leq 0 \\ y_{[j+1]}^* &= z_{[j+1]} + \gamma \frac{k-1}{N-1} > 0. \end{aligned}$$

However, since $\gamma < 0$, we have

$$\begin{aligned} \tilde{y}_{[j]}^* &= z_{[j]} + \gamma \frac{k-1}{N-1} \geq z_{[j+1]} + \gamma \frac{k-1}{N-1} > 0 \\ \tilde{y}_{[j+1]}^* &= z_{[j+1]} + \gamma \frac{k+1}{N-1} \leq z_{[j]} + \gamma \frac{k+1}{N-1} \leq 0. \end{aligned}$$

It then follows that $\tilde{\mathbf{y}}$ with $\tilde{y}_{[i]} = y_{[i]}$ for $i \neq j, j + 1$ and $\tilde{y}_{[j]} = 1$ and $\tilde{y}_{[j+1]} = -1$ is also an equilibrium. \square

Having proved lemma 3 we can now prove lemma 2.

Proof of Lemma 2

Suppose that \mathbf{y} with $\sum_{i=1}^N y_i = k$ and $\tilde{\mathbf{y}}$ with $\sum_{i=1}^N \tilde{y}_i = \tilde{k}$ and $\tilde{k} \neq k$ are both equilibria of (4), given a combination $\{\beta, \gamma < 0, \mathbf{x}, \epsilon\}$. From lemma 3 it follows that this is true only if $\mathbf{y}^k = (1_1, 1_2, \dots, 1_{\frac{N+k}{2}}, -1_{\frac{N+k+2}{2}}, \dots, -1_N)$ and $\mathbf{y}^{\tilde{k}} = (1_1, 1_2, \dots, 1_{\frac{N+\tilde{k}}{2}}, -1_{\frac{N+\tilde{k}+2}{2}}, \dots, -1_N)$ are both equilibria given $\{\beta, \gamma < 0, \mathbf{x}, \epsilon\}$. Assume without loss of generality that $\tilde{k} > k$, that is: $\tilde{k} - k \geq 2$. Let ν be the first subject whose choice is -1 in equilibrium \mathbf{y}^k and $+1$ in equilibrium $\mathbf{y}^{\tilde{k}}$. Then, for this subject

$$z_{[\nu]} + \gamma \frac{k+1}{N-1} \leq 0 \text{ and } z_{[\nu]} + \gamma \frac{\tilde{k}-1}{N-1} > 0.$$

But also

$$z_{[\nu]} + \gamma \frac{\tilde{k} - 1}{N - 1} = z_{[\nu]} + \gamma \frac{\tilde{k} - k + k + 1 - 2}{N - 1} = \underbrace{z_{[\nu]} + \gamma \frac{k + 1}{N - 1}}_{\leq 0} + \underbrace{\gamma \frac{(\tilde{k} - k) - 2}{N - 1}}_{\leq 0} \leq 0,$$

and the contradiction follows. \square

The message of lemma 2 is that for a given value of $\gamma < 0$, two different equilibria \mathbf{y} and $\tilde{\mathbf{y}}$ can co-exist only if $\sum_{i=1}^N y_i = \sum_{i=1}^N \tilde{y}_i$. That is, both equilibria must have the same number of subjects with outcome +1 and with outcome -1.

Repeated application of lemma 3 shows that a strategy profile \mathbf{y} with $\sum_{i=1}^N y_i = k$ can only be an equilibrium if the ordered (with respect to the z_i 's) strategy profile $\mathbf{y} = (1_1, 1_2, \dots, 1_k, -1_{k+1}, \dots, -1_N)'$ is an equilibrium. This result will prove to be useful later on in deriving upper bounds for the number of equilibria that may be sustained for a given value of γ .

To complete the proof of Proposition 3, note that the first part of lemma 2 implies that the maximum number of possible equilibria subject to the condition $\sum_{i=1}^N y_i = k$ is obtained when k is chosen to equal 0 (+1 or -1) when N is even (odd). In that case, there are $N/2$ ($(N + 1)/2$ or $(N - 1)/2$) agents choosing +1 and the others choosing -1, giving the upper bounds on the number of possible equilibria as given by $d(N)$ in proposition 3.

What is left to show is that there exists a combination of $\{\beta, \gamma < 0, \mathbf{x}, \epsilon\}$ for which the maximum number of equilibria is obtained. From lemma 2 we know that, given a combination of $\{\beta, \gamma < 0, \mathbf{x}, \epsilon\}$, every element in the equilibrium set must have the same number of agents choosing $y = 1$. For N is even, the set can thus only have $d^e(N)$ elements when the set contains *all* strategy profiles for which the number of agents choosing $y = 1$ equals the number of agents choosing $y = -1$. For each of these profiles to be an equilibrium, it must be optimal for *each* agent i to choose $y_i = 1$ given that $\sum_{j \neq i} y_j = -1$ and to choose $y_i = -1$ given that $\sum_{j \neq i} y_j = 1$. In particular,

it must hold that for each element the number of agents splits

$$\begin{aligned} z_{[1]} + \gamma \frac{1}{N-1} &\leq 0 \text{ and;} \\ z_{[N]} + \gamma \frac{-1}{N-1} &> 0. \end{aligned}$$

For γ negative enough, this condition is satisfied irrespective of the values of $z_{[1]}, \dots, z_{[N]}$.

For N is odd, the equilibrium set can only contain $d^o(N)$ elements when the set contains all strategy profiles for which $\sum_{i=1}^N y_i = 1$ or all strategy profiles for which $\sum_{i=1}^N y_i = -1$. The necessary and sufficient conditions for each of the profiles for which $\sum_{i=1}^N y_i = 1$ to be an equilibrium, are

$$(A.1) \quad z_{[1]} + \gamma \frac{2}{N-1} \leq 0 \quad \text{and} \quad z_{[N]} > 0,$$

and the corresponding conditions for the strategy profiles with $\sum_{i=1}^N y_i = -1$ are

$$(A.2) \quad z_{[1]} \leq 0 \quad \text{and} \quad z_{[N]} + \gamma \frac{-2}{N-1} > 0.$$

From these conditions it follows that the equilibrium set with $d^o(N)$ elements for which $\sum_{i=1}^N y_i = 1$ ($\sum_{i=1}^N y_i = -1$) is only obtainable when all z values are positive (non-positive). Together this proves proposition 3. \square

Lemma 2 and the observation that for the equilibria in the proof of proposition 1 $|k| = |\sum_{i=1}^N y_i|$ monotonically decreases as $\gamma \rightarrow -\infty$, together lead to the following corollary¹⁷ that for all equilibria, $|k|$ decreases monotonically to 0 (1) as $\gamma \rightarrow -\infty$, given N even (odd). This result is consonant with intuition: variation in behavior increases when the utility derived from being different increases.

¹⁷The corresponding result for positive interactions is that $|\sum_{i=1}^N y_i| \nearrow N$ as $\gamma \rightarrow \infty$. That is, in the limit all agents conform to $y = 1$ or to $y = -1$ regardless their private utility such that variation in behavior is minimized.

Corollary 3 For the equilibria \mathbf{y} of the discrete choice interaction model given by (4),

$$\left| \sum_{i=1}^N y_i \right| \searrow 0 \quad \text{as } \gamma \rightarrow -\infty \text{ and } N \text{ is even,}$$

$$\left| \sum_{i=1}^N y_i \right| \searrow 1 \quad \text{as } \gamma \rightarrow -\infty \text{ and } N \text{ is odd.}$$

Proof of Corollary 1

Define $\forall i$, $z_i^G \equiv \beta' \mathbf{x}_i + \frac{\gamma_{GB} \sum_{j=1}^N y_j^B}{N-1} + \epsilon_i$ if i is a girl and $z_i^B \equiv \beta' \mathbf{x}_i + \frac{\gamma_{BG} \sum_{j=1}^N y_j^G}{N-1} + \epsilon_i$ if i is a boy. Denote the ordered values of z_i^G (z_i^B) as $z_{[i]}^G$ ($z_{[i]}^B$) such that $z_{[1]}^G \geq z_{[2]}^G \geq \dots \geq z_{[N_G]}^G$ ($z_{[1]}^B \geq z_{[2]}^B \geq \dots \geq z_{[N_B]}^B$), with N_G (N_B) denoting the total number of girls (boys) in the sample.

The line of reasoning used in the proof of proposition 1 now can be applied to the subset of girls (boys), with $z_{[i]}$ replaced by $z_{[i]}^G$ ($z_{[i]}^B$) and γ replaced by γ_{GG} (γ_{BB}). \square

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Table 1: Sample statistics at the individual level (7,534 observations)

	mean	median	st. dev.	min.	max.
girl	0.5157	1.0000	0.4998	0.0000	1.0000
age	14.21	14.0000	1.45	11.0000	21.0000
non-Dutch	0.091	0.0000	0.287	0.0000	1.0000
single parent hh.	0.084	0.0000	0.278	0.0000	1.0000
MAVO	0.336	0.0000	0.473	0.0000	1.0000
HAVO	0.182	0.0000	0.386	0.0000	1.0000
VWO	0.152	0.0000	0.359	0.0000	1.0000
working time father	35.95	36.0000	12.76	0.0000	46.0000
working time mother	15.29	6.0000	15.13	0.0000	46.0000
catholic	0.234	0.0000	0.423	0.0000	1.0000
protestant	0.185	0.0000	0.388	0.0000	1.0000
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smoking	0.090	0.0000	0.287	0.000	1.000
truancy	0.184	0.0000	0.387	0.000	1.000
asking for permission	0.863	1.000	0.344	0.000	1.000
moped	0.064	0.0000	0.245	0.000	1.000
cell phone	0.211	0.000	0.408	0.000	1.000
girls (3,885 observations)					
smoking	0.093	0.000	0.290	0.000	1.000
truancy	0.174	0.000	0.379	0.000	1.000
asking for permission	0.854	1.000	0.353	0.000	1.000
moped	0.029	0.000	0.167	0.000	1.000
cell phone	0.203	0.000	0.402	0.000	1.000
boys (3,649 observations)					
smoking	0.088	0.000	0.283	0.000	1.000
truancy	0.194	0.0000	0.396	0.000	1.000
asking for permission	0.873	1.000	0.333	0.000	1.000
moped	0.102	0.000	0.303	0.000	1.000
cell phone	0.219	0.000	0.414	0.000	1.000

Table 2: Estimation results; smoking (t-values in parentheses)

	with fixed effects			
	no SI	with SI	no SI	with SI
constant	-4.21 (-19.2)	-3.46 (-12.2)	-4.74 (-6.9)	-4.67 (-6.5)
girl	0.044 (1.0)	-0.037 (-0.2)	0.025 (0.5)	0.030 (0.1)
age	0.188 (12.3)	0.167 (9.7)	0.176 (7.7)	0.174 (7.4)
non-Dutch	-0.269 (-3.3)	-0.264 (-3.1)	-0.204 (-1.9)	-0.202 (-1.9)
single parent family	0.210 (3.2)	0.194 (2.9)	0.224 (3.0)	0.222 (2.9)
MAVO	0.167 (3.6)	0.182 (3.4)	0.245 (2.9)	0.247 (2.9)
HAVO	-0.052 (-0.9)	-0.060 (-1.0)	-0.102 (-1.1)	-0.105 (-1.1)
VWO	-0.198 (-3.2)	-0.145 (-2.1)	-0.266 (-2.6)	-0.263 (-2.4)
father's working time	0.002 (1.4)	0.002 (1.3)	0.002 (1.2)	0.002 (1.2)
mother's working time	0.005 (3.5)	0.005 (3.3)	0.005 (3.2)	0.005 (3.1)
catholic	-0.211 (-4.3)	-0.207 (-4.1)	-0.200 (-2.8)	-0.197 (-2.7)
protestant	-0.122 (-2.2)	-0.154 (-2.6)	-0.152 (-1.7)	-0.148 (-1.6)
γ_{BB}	—	0.722 (4.4)	—	0.125 (0.7)
γ_{BG}	—	0.389 (1.6)	—	0.015 (0.1)
γ_{GB}	—	0.336 (1.7)	—	0.041 (0.2)
γ_{GG}	—	0.575 (3.6)	—	0.113 (0.6)
log-likelihood function	-2163.7	-2151.3	-2109.5	-2106.9

Table 3: Estimation results (t-values in parentheses)

	smoking	truancy	moped	cell phone	permission
constant	-3.46 (-12.2)	-2.90 (-9.4)	-4.54 (-13.3)	-2.71 (-13.0)	4.39 (18.0)
girl	-0.037 (-0.2)	-0.013 (-0.2)	-0.978 (-3.4)	0.027 (0.3)	-0.036 (-0.2)
age	0.167 (9.7)	0.165 (9.8)	0.256 (14.2)	0.151 (10.8)	-0.211 (-14.9)
non-Dutch	-0.264 (-3.1)	0.131 (2.0)	-0.157 (-1.7)	0.184 (3.1)	-0.193 (-3.1)
single parent family	0.194 (2.9)	0.054 (0.9)	-0.031 (-0.4)	0.280 (5.0)	-0.266 (-4.6)
MAVO	0.182 (3.4)	0.120 (2.3)	-0.094 (-1.4)	0.082 (1.8)	-0.104 (-2.1)
HAVO	-0.061 (-1.0)	0.144 (2.3)	-0.200 (-2.7)	-0.051 (-0.9)	-0.159 (-2.9)
VWO	-0.145 (-2.1)	0.059 (0.9)	-0.377 (-4.1)	-0.249 (-3.9)	-0.071 (-1.1)
father's working time	0.002 (1.3)	-0.001 (-0.7)	0.002 (1.1)	-0.001 (-0.8)	-0.005 (-3.4)
mother's working time	0.005 (3.3)	0.002 (1.3)	0.002 (1.1)	0.002 (2.1)	-0.003 (-2.7)
catholic	-0.207 (-4.1)	-0.156 (-3.3)	0.004 (0.1)	-0.011 (-0.3)	0.246 (5.2)
protestant	-0.154 (-2.6)	-0.124 (-2.4)	-0.074 (-1.1)	-0.277 (-5.0)	0.286 (5.3)
γ_{BB}	0.722 (4.4)	0.826 (8.9)	0.544 (2.7)	0.495 (4.8)	0.168 (1.2)
γ_{BG}	0.388 (1.6)	0.518 (3.7)	0.424 (1.8)	0.332 (2.2)	0.073 (0.4)
γ_{GB}	0.336 (1.7)	0.442 (2.9)	0.238 (0.8)	0.400 (2.5)	0.000 (0.0)
γ_{GG}	0.575 (3.6)	1.110 (11.5)	0.012 (0.0)	0.673 (7.3)	0.036 (0.3)
log-likelihood function	-2151.3	-3236.7	-1562.0	-3626.3	-2776.6

Table 4: Estimation results; with school specific fixed effects (t-values in parentheses)

	smoking	truancy	moped	cell phone	permission
constant	-4.67 (-6.5)	-3.65 (-5.5)	-5.51 (-9.5)	-4.06 (-10.5)	4.34 (13.5)
girl	0.030 (0.1)	-0.010 (-0.1)	-0.724 (-2.1)	-0.041 (-0.9)	-0.116 (-2.8)
age	0.174 (7.4)	0.165 (7.9)	0.303 (11.7)	0.190 (10.6)	-0.200 (-10.3)
non-Dutch	-0.202 (-1.9)	0.172 (2.2)	-0.165 (-1.3)	0.079 (1.2)	-0.200 (-2.7)
single parent family	0.222 (2.9)	0.080 (1.2)	-0.049 (-0.5)	0.265 (4.3)	-0.246 (-3.8)
MAVO	0.247 (2.9)	0.344 (4.5)	-0.192 (-1.7)	0.022 (0.0)	-0.135 (-1.5)
HAVO	-0.105 (-1.1)	0.206 (2.6)	-0.292 (-2.4)	-0.213 (-2.5)	-0.121 (-1.4)
VWO	-0.263 (-2.4)	0.105 (1.3)	-0.481 (-3.8)	-0.511 (-5.3)	0.014 (0.1)
father's working time	0.002 (1.2)	-0.000 (-0.2)	0.003 (1.2)	-0.000 (-0.1)	-0.006 (-3.2)
mother's working time	0.005 (3.1)	0.002 (1.5)	0.002 (1.2)	0.002 (1.9)	-0.004 (-2.5)
catholic	-0.197 (-2.7)	-0.140 (-2.4)	-0.025 (-0.3)	-0.041 (-0.8)	0.221 (3.4)
protestant	-0.148 (-1.6)	-0.185 (-2.7)	-0.156 (-1.3)	-0.217 (-3.0)	0.249 (3.2)
γ_{BB}	0.125 (0.7)	0.285 (2.7)	0.031 (0.1)	0.000 (-)	0.000 (-)
γ_{BG}	0.015 (0.1)	0.089 (0.6)	0.004 (0.0)	0.000 (-)	0.000 (-)
γ_{GB}	0.041 (0.2)	0.023 (1.6)	0.000 (-)	0.000 (-)	0.000 (-)
γ_{GG}	0.113 (0.6)	0.542 (5.3)	0.000 (-)	0.032 (0.3)	0.000 (-)
log-likelihood function	-2106.9	-3183.2	-1517.9	-3499.5	-2729.7
Significance γ/s (p -values)	0.261	0.000	0.704	0.538	1.000
Number of students	7454	7510	7392	7513	7534
Number of classes	479	483	474	483	485
Number of schools	68	70	65	70	70