Nurture vs. Nurture: Endogenous Parental and Peer Effects and the Social Transmission of Preferences

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First Version: July. 2010
This Version: Oct 2011

Abstract

I study the social formation of preferences in an environment in which children interact strategically with each other and choose their preferences with the desire to conform, and parents purposefully socialize their children to their own attitudes. To this end I use religious and alcohol consumption data from the Add Health Study. I first find that conditional on child and school-specific controls, a childs behavior is a weighted average of her peers and parental attitudes, suggesting that the main driving force in the transmission process is the desire to conform. Using longitudinal data for a period of seven years, I then show that these effects are enduring, with no signs of fading out. Finally, I show that parental effects can be decomposed into exogenous, role-model effects, and endogenous parental nurturing choices.

*Email: dv465@nyu.edu. Department of Economics. New York University and NYUAD. I thank first and foremost Alberto Bisin for his continual guidance and support. I also thank Raquel Fernández, Boyan Jovanovic, Kevin Thom, David Cesarini and Chetan Dave; their critical comments helped to considerably improve and redirect several parts of the paper. Finally, I benefitted from discussions with Alejandro Corvalán, Emanuel Vespa, Kemal Akoz and assistants to the Micro Student Workshop at NYU, Graduate Student Workshop at the University of Washington in Saint Louis (2010) and seminar series at Universidad de los Andes, Universidad del Rosario, and NYUAD. As usual, all remaining errors are mine.

1 Introduction

The question of *Nature vs. Nurture*— the relative importance of genetic and environmental factors explaining outcomes— has received a considerable amount of attention from social scientists in recent years,[1] largely due to the wider availability of the specific data sets needed for such an enterprise. Generally relying on twins and adoptees data, this literature shows that under certain assumptions one can decompose the total variance of a specific outcome of interest— eg. political participation, religious preferences, health issues, etc.— into its genetic, family and environment components, and finds that on average, genetic effects account for half of the variance of any given outcome, behavior or attitude.[2]

Due to the generality of these results, it is often taken for granted that genetic effects are nontrivial, a phenomenon that could be called *The Nature Assumption*.[3] The related term, the "Nurture Assumption", was coined by Harris (1999) in her critical assessment of evidence coming from developmental psychology research, arguing that parental nurturing practices are of critical importance in a child's future behavior. Her basic claims are that (i) parental nurturing effects are not important, (ii) peers and genes play important roles, with a preponderance of the former, and (iii) that researchers that fail to account for genetic differences may overstate any parental effects ascribed to a given behavior.

In this paper I argue that for a possibly small class of preferences the fundamental tension is between *Nurture* vs. Nurture, and specifically, between parental and peer effects.

My objective is mainly empirical and threefold: first, I seek to estimate parental and peer effects for a specific class of outcomes or preferences. Second, I argue that parental effects can be decomposed into exogenous and endogenous components, the former associated with a role-model effect, and the latter with endogenous parental socialization choices by the parents. Third, I will argue that these effects are enduring in time.

In order to attain the first and second objectives, I build a model of social interactions and endogenous parental effects that is perfectly suited for the use of the new econometric methods for identification of peer effects. I assume that in the critical stage of preference formation, children strategically choose their preferences with the desire to fit in, balancing the tradeoff between being like their parents and being like their peers, i.e. their only desire is to conform to their social environment. Building on the economics literature on cultural transmission, I further assume that parents prefer children with preferences closer to their own, and they rationally choose socialization schemes in order to guarantee so.[4] Each component in the model

[1] Pinker (2004) provides a large list of recent references on the debate in the social sciences. A historical review in psychology applications can be found in Kimble (1996).

[2] A methodological review on twin studies and behavioral genetics can be found in Neal and Maes (2004).

[3] See Turkheimer (2000).

[4] See Bisin and Verdier (2000) or Bisin and Verdier (2001).

serves a specific role to attain my main empirical objectives: while the children's component of the model maps neatly to the econometric literature on peer effects, the parental socialization component generates testable predictions from where I am able to find evidence of endogenous parental effects.

To estimate peer and parental effects I use religious and alcohol consumption data from the Add Health Study, a longitudinal survey that interviewed children and parents three times from 1994 to 2002.[5] Since I do not have data on twins, I cannot say anything about genetic effects, and as emphasized by Harris, this also challenges the interpretation I give to parental effects. However, three different findings allow me to argue that the latter is correct, and suggests that genetic effects are unlikely to be a cause of concern from an identification point of view.

First and foremost, I show that for the outcomes under study, marginal peer and parental effects add up to one, i.e. after conditioning for individual and school-level effects, children outcomes are a weighted average of their parents' and peers' outcomes. This finding is remarkable because it depends crucially on the assumed functional form of the children's utility functions, and I show several natural examples where it fails to hold. For instance, if genetic effects are also present, or if children are forward-looking, marginal effects add up to *less* than one. Moreover, it is robust to the choice of peer group (school level vs. grade level) and to school-level measurement error. I consistently find it across all waves of information, ethnic groups and dependent variables. Using results from related ongoing research I show that this is not caused by the particular choice of technique used to estimate peer effects: using schooling data from the National Educational Longitudinal Study and a large array of political values from the Student-Parent Socialization Study, I show that for the former, peer and parental effects add up to less than unity, as expected when there are genetic effects (ability) or when children have concerns other than fitting in (as in the standard human capital approach to education). With the latter I show that for some outcomes peer and parental effects add up to one, but for the majority they add up to less than one, as expected when other effects are present (eg. oblique effects caused by adults different from their parents).[6] Results from these papers suggest that one can construct a typology of preferences depending on which effects are present.

Second, I show that parental and peer effects are stable across the seven years spanned by the data, in contrast with the extensive empirical literature in behavioral genetics showing that the *heritability* of preferences and attitudes increases in importance as a child matures into adulthood.[7,8]

Third, the comparative statics analysis derived from the parental socialization problem allow me test for the endogeneity of parental effects using reduced-form regressions.

[5] I use the public-use dataset that only includes the first three waves of information.
[6] See Vaughan (2011d) and Vaughan (2011b).
[7] *Heritability* of a trait is broadly defined as the fraction of phenotypical variance explained by genetic effects.
[8] See McGue, Bouchard, Iacono, and Lykken (1996)

Also, as observed by Kremer (1997) and Borjas (1995), the study of peer and parental effects naturally raises questions on ethnic assimilation.[9] I show that in the absence of genetic effects, the social environment is sufficient to generate blending among different ethnic groups as long as children from different ethnic groups interact with each other. This *local Melting Pot* property is further explored theoretically by Vaughan (2011a), but here it is a natural byproduct of the result that peer and parental effects add up to one. The empirical corollary is that within each school, children of different ethnic groups blend with each other. The assimilation hypothesis has been empirically validated in the economics literature, but some sociologists are less optimistic about its general validity.[10] The results here show one possible explanation for such contrasting results.

This paper contributes to the literature that studies the process of preference transmission. Researchers borrowing the methods of behavioral genetics have shown the importance of genes in explaining the variation in economic outcomes and preferences.[11] Peer and neighborhood effects are also now part of a dynamic research agenda, motivated by the discussion of identification problems in Manski (1993).[12] Finally, direct parental socialization effects have also been studied extensively and independently, mainly in the psychology and sociology literatures, and by researchers interested in the economics of cultural transmission.[13] In contrast to the behavioral genetics literature, my emphasis is on the *social environment*. Building on the literature on peer effects and parental socialization, I put some structure on this environment in order to disentangle the social transmission of preferences channel. Doing so, I also contribute methodologically to each of these literatures.

First, while silent on genetic effects, this paper shows that the analysis can be enriched by explicitly modeling the incentives that children and parents have. Moreover, the problem for the children is set up in a way that corresponds closely to the linear, additive methods used in behavioral genetics. The finding that parental effects can be decomposed into exogenous and endogenous effects, and that the two enter multiplicately shows clearly how the behavioral

[9]To be sure, neither of these papers considers direct parental effects but rather, neighborhood effects where *other* adults also affect a child's outcome.

[10]In economics, see for example Blau (1992); Blau and Kahn (2007); Borjas (1998); Duncan and Trejo (2008); Lazear (2007); Rosenfeld (2002). In sociology, Portes and Zhou (1993) among others, have argued that in contrast to previous waves of immigrants, the new immigrants are following a path of segmented assimilation.

[11]See for example Wallace, Cesarini, Lichtenstein, and Johannesson (2007), Cesarini, Dawes, Johannesson, Lichtenstein, and Wallace (2009), Cesarini, Dawes, Fowler, Johannesson, Lichtenstein, and Wallace (2009), Holmlund, Lindahl, and Plug (2011), Sacerdote (2002) and Sacerdote (2011).

[12]On peer effects, see for example Brock and Durlauf (2001), Epple and Romano (2011), Gaviria and Raphael (2001), Glaeser and Scheinkman (2003), Graham (2008), Blume, Brock, Durlauf, and Ioannides (2011), Kremer and Levy (2008), Moffitt (2001), Bramoullé, Djebbari, and Fortin (2009). On neighborhood effects see Borjas (1995), Borjas (1998), Patacchini and Zenou (Forthcoming), Goux and Maurin (2007), Kremer (1997) and Topa (2001)

[13]In sociology and psychology see Corsaro (2011) and Harris (1999), respectively. A recent survey on theoretical and empirical results in economics can be found in Bisin and Verdier (2010).

genetics analysis can be enriched by the use of economics.

By emphasizing the importance of parental effects, I contribute to the literature on peer effects in three ways: first, I show that parental and peer effects are systematically negatively correlated, at least for the outcomes under study. Second, I show how parental effects can be used to escape Manski (1993) reflection problem: if peers' parents do not act as role models for the children, endogenous interaction effects can be identified. Using evidence from development psychology, I argue that this is indeed the case. Finally, I show that peer (and parental) influences have long-lasting effects on the behavior of teenagers.

This paper is organized as follows. The next section develops a model of endogenous parental and peer effects, describes its main properties and explores the comparative static results that will be used to answer the empirical questions. In the third section I discuss the empirical implementation and estimate peer and parental effects for different ethnic groups and dependent variables, discuss the stability of the effects, and test the main predictions coming from the comparative static analysis of the problems. The final section concludes.

2 The Model

Consider a stationary population of N (asexual) adults and their corresponding children. For ease of exposition, I will assume that at time zero, the adult population is partitioned into two groups with population shares $\omega_j = n_j/N$ for $j = 1, 2$; individuals within each group are identical. I will make the necessary assumptions to ensure that these population shares remain constant across time, so in practice I will be describing the transmission process of two different dynasties.

I am interested in studying the transmission of preference $e \in [0, 1]$. Notably, this class of preferences has an intensity interpretation, where, e.g. $e = 0$ ($e = 1$) is the lowest (highest) preference intensity.

The game played at each time t has two stages: in the first stage parents get to choose actions that affect the socialization outcomes of their children. Given these strategic choices, in stage two children play a conformity game where the value of their preferences is chosen. Figure (1) depicts the timing of decisions.

2.1 Children's Game

The distinguishing characteristic of the childhood stage in the model is that children have not yet formed their preferences. I assume that the driving force of the process of identity formation is the desire to be accepted, leading them to attempt to conform to the people they interact with,

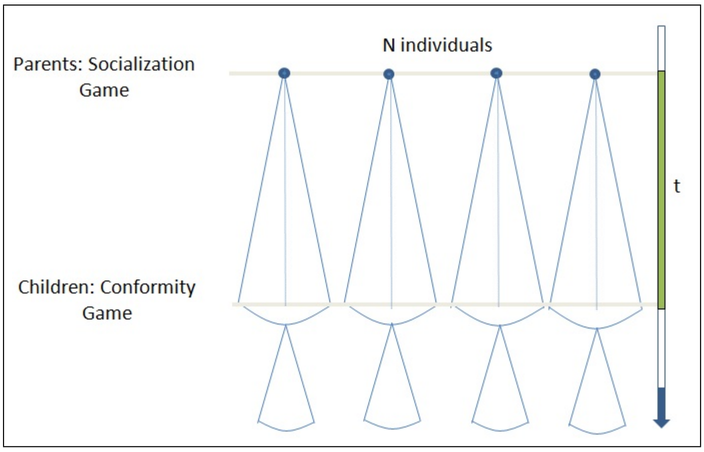

Figure 1: Timing of Decisions

i.e. their parents and peers. This is done by playing a *conformity game*. At each time t, each child $i = 1, \cdots, N$ solves the following problem

$$[\mathrm{C}] : \min_{e_{i,t+1} \in [0,1]} \alpha_{i,t+1} (e_{i,t+1} - e_{i,t})^2 + (1 - \alpha_{i,t+1}) (e_{i,t+1} - \bar{e}_{t+1})^2$$

where $\bar{e}_{t+1} = (1/N) \sum_{j=1}^{N} e_{j,t+1}$. Since I consider only symmetric equilibria, at each time t, children from the same group have the same parental preferences e_t and parameters α. In this section I will abuse notation by letting individual subscripts i denote groups, i.e. $i \neq j \in \{1, 2\}$.[14]

Problem $[C]$ says that children decide between conforming to their parents or to their peers. Contrary to other approaches where this desire to conform arises in equilibrium,[15] here I assume that it is part of the individual preferences *during the childhood stage*. Whenever $\alpha_i = 0$ the game becomes a *beauty contest* which not only appears to be an appropriate approximation of many games played by children and teenagers, but most importantly, is well known to have multiple equilibria.

Proposition 1 (Existence and Uniqueness of Symmetric Nash Equilibrium)**.** A necessary and sufficient condition for the existence of a unique symmetric Nash Equilibrium of the conformity game for any time $t > 0$, is that $\alpha_i > 0$ for at least one of the groups. □

Proofs of all propositions can be found in the Appendix. In general, whenever both groups have $\alpha_j = 0$ there is a continuum of equilibria where all children choose the same $e \in [0, 1]$.[16] If $\alpha_i = 0$ and $\alpha_j \in (0, 1]$ the unique symmetric Nash equilibrium is $e_{i,t+1} = e_{j,t+1} = e_{j,t}$.

[14] In the empirical section I will treat the problem with all generality.

[15] As in Bernheim (1994) for example.

[16] In the empirical section it will be argued that this is not just an intellectual curiosity: in fact, alcohol consumption patterns in high school appear to have this property.

In general, Nash equilibrium choices generate a system of first-order linear difference equations:

$$e^*_{i,t} \;=\; \gamma_i e_{i,t-1} + (1-\gamma_i)e_{j,t-1} \tag{1}$$

where $\gamma_i = A_i/(A_i + A_j(1 - A_i))$, and $A_i = \alpha_i/(\alpha_i + (1 - \alpha_i)(1 - \omega_i)^2)$ for $i \neq j \in \{1, 2\}$. It is evident from Equations (1) that whenever $\gamma_i \in (0, 1)$, the process of preference transmission converges to a blending-type steady state, i.e. one where *both* groups assimilate to each other. I now pursue a stronger characterization of the steady state. Without loss of generality, assume that initial preferences for each group are $\mathbf{e_0} = [e_{10}, e_{20}] = [0, 1]$.

Proposition 2 (Blending-type Steady State)**.** Assume that $\alpha_i \in (0, 1)$, $i = 1, 2$. Given initial conditions $\mathbf{e_0}$, there exists a unique interior stable steady state equilibrium $\mathbf{e}^* = (e, e) \in (0, 1)^2$. Furthermore the equilibrium will be unbiased, i.e. $(1/2, 1/2)$, whenever

$$(1-\alpha_1)(1-\omega_1)/\alpha_1 = (1-\alpha_2)(1-\omega_2)/\alpha_2 \tag{2}$$

biased towards type 1's ethnic trait whenever $(1 - \alpha_1)(1 - \omega_1)/\alpha_1 < (1 - \alpha_2)(1 - \omega_2)/\alpha_2$ and biased towards type 2's ethnic trait when the inequality is reversed. □

The proof of the proposition can be found in the Appendix, but it is instructive to see the role played by Equation (2). From Equation (1) it is straightforward to check that

$$(e_{1,t+1} - e_{2,t+1}) \;=\; (\gamma_1 + \gamma_2 - 1)(e_{1,t} - e_{2,t}) \tag{3}$$

$$(e_{1,t+1} - e_{1,t}) \;=\; (1 - \gamma_1)(e_{2,t} - e_{1,t}) \tag{4}$$

In the Appendix it is shown that under the assumptions of the proposition $0 < \gamma_1+\gamma_2-1 < 1$, so from Equation (3) it follows that there is horizontal or intracohort convergence. Since $\gamma_i \in (0, 1)$ it follows then that there is also vertical or intergenerational convergence. Using Equation (4) for each time t one can also verify that

$$\begin{aligned}\left|e_{1,t+1} - e_{1,t}\right| > \left|e_{2,t+1} - e_{2,t}\right| \;&\Leftrightarrow\; \frac{1-\gamma_1}{1-\gamma_2} > 1 \Leftrightarrow A_2 > A_1 \\ &\Leftrightarrow\; \frac{(1-\alpha_1)(1-\omega_1)}{\alpha_1} > \frac{(1-\alpha_2)(1-\omega_2)}{\alpha_2}\end{aligned}$$

from where the qualitative properties of the steady-state discussed Proposition (2) follow: other things equal, in the steady-state, the position of the relatively larger ethnic group is relatively less distant from their initial preferences. An analogous condition holds for groups that put relatively more weight on their parents. Graphically, these conditions are shown in Figure (2):

in the right panel, a symmetric steady state where both groups have the same population weights and parameters α is shown. The left panel shows the case of groups with equal parameters α but where one has a considerably larger population share. While groups blend with each other ("the melting pot"), the final mixture looks more like the original majority group.[17]

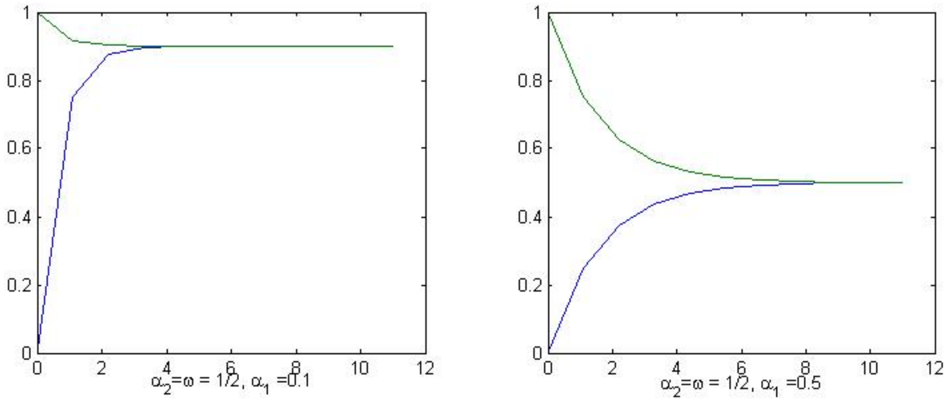

Figure 2: Equilibrium steady state and Transition

Having derived the properties of the Conformity Game in isolation, I proceed to study the general game, that includes endogenous parental socialization.

2.2 General Preference Formation Game

I solve for the symmetric Nash equilibrium by backward induction (Figure 1). In the previous section I studied the properties of the second-stage conformity game, so I proceed now to solve the first-stage socialization game. Parents are assumed to prefer having children with preferences that are similar to their own, and that they can purposefully affect their socialization process and outcomes. Specifically, I assume that parents can choose parental weights α, interpreted as exerting a socialization effort that maps monotonically to these metapreferences α.[18]

Given children's optimal strategies, the parental problem is:

$$[\mathrm{P}] : \max_{\alpha_{i,t+1} \in [0,1]} -\kappa(e_{i,t} - e^*_{i,t+1}(\alpha_{i,t+1}))^2 - c(\alpha_{i,t+1})$$

I require that the cost function satisfies the following:

[17]Notably, the proposition says that there is a *local Melting Pot*, i.e. children in each peer group converges to each other, a condition that is exploited later to identify and estimate peer effects.

[18]This makes the first-stage problem in the general preference formation game very similar to the class of games studied by Bisin and Verdier (2000).

Assumption A. 1. The cost function $c : [0, 1] \to \mathbb{R}$ is of the class C^3, strictly convex on $[0, 1]$, increasing and satisfying $c(0) = 0$.

Now that each cohort's game has been defined I am are ready to define an equilibrium for the class of games studied here.

Definition 1 (Equilibrium)**.** For each time $t \geq 0$, an *equilibrium* is a profile $(\alpha^*_{1,t+1}, \alpha^*_{2,t+1}, e^*_{1,t+1}, e^*_{2,t+1})$, that (1) arises as a subgame perfect equilibrium to the intergenerational problem, and (2) is an equilibrium for the intracohort games played by parents and children.

A first observation is that $(\alpha^*_{1,t+1}, \alpha^*_{2,t+1}, e^*_{1,t+1}, e^*_{2,t+1}) = (0, 0, e, e)$ can only arise as an equilibrium when parents have already blended with each other. In fact, this is the unique equilibrium when parents have completely converged, i.e. $e_{1,t} = e_{2,t} = e$. The first claim follows by noticing that given $\alpha_j = 0$, parents of group i will only choose $\alpha_i = 0$ if they believe that all children will choose $e_{i,t+1} = e_{j,t+1} = e_{i,t}$ in the beauty contest. But for this to be an equilibrium, it must be that parents of group j also believe that $e_{j,t+1} = e_{i,t+1} = e_{j,t}$. These beliefs are inconsistent with each other whenever $e_{i,t} \neq e_{j,t}$ so it cannot be an equilibrium when parents have not converged. To see that it is the unique equilibrium, recall that whenever $\alpha_j > 0$, and $\alpha_i = 0$, all children will choose to be like type j parents, i.e. $e_{i,t+1} = e_{j,t+1} = e_{j,t}$. Since parents have already converged, type i parents have no incentive to deviate, and because of the monotonicity of the cost function, parents of type j will choose any smaller socialization effort α_j. In the limit, they will choose $\alpha_j = 0$ too, since $(0, 0, x, x)$ with $x \neq e$ cannot be an equilibrium, since parents of any type can unilaterally deviate by choosing α_i small enough.

This observation allow us to concentrate only on the case where $\alpha_j > 0$ for parents of both types, and substitute children's optimal choices to obtain the following version of the parental problem:

$$\max_{\alpha_{i,t+1} \in [0,1]} -\Delta_t (1 - \gamma_{i,t+1}(\alpha_{i,t+1}, \alpha_{j,t+1}))^2 - c(\alpha_{i,t+1})$$

where $\Delta_t = \kappa(e_{i,t} - e_{j,t})^2$, and $i \neq j \in \{1, 2\}$. Dropping the time subscript to simplify notation, type i parents' first-order conditions are given by

$$2\Delta(1 - \gamma_i)\frac{\partial \gamma_i}{\partial \alpha_i} - c'(\alpha_i) = 2\Delta \left[\frac{(1 - \alpha_i)k_i^2}{(k_i + \alpha_i(1 - k_i))^3} \right] - c'(\alpha_i) \quad = \quad 0 \tag{5}$$

where $k_i = A_j(1-\omega_i)\psi_N$. Using Assumption (1) and the first-order condition it is straightforward to verify that for any $\alpha_j \in (0, 1]$ a unique interior solution $\alpha_i \in (0, 1)$ always exists.

Second-order conditions are given by

$$
\begin{aligned}
& -2\Delta\left[\left(\frac{\partial\gamma_i}{\partial\alpha_i}\right)^2-(1-\gamma_i)\frac{\partial^2\gamma_i}{\partial\alpha_i^2}\right]-c''(\alpha_i) \\
= & -\frac{2\Delta k_i^2[1+2(1-\alpha_i)(1-k_i)]}{(k_i+\alpha_i(1-k_i))^4}-c''(\alpha_i)<0
\end{aligned}
$$

satisfied for all $(\alpha_1,\alpha_2)\in(0,1]^2$, since $k_i\in(0,1)$ for all $\omega_1\in(0,1)$. It now follows from the Implicit Function theorem that best-reply functions are well defined on $(0,1]$.[19] In the Appendix it is shown that by carefully restricting the action space, a standard fixed-point theorem can be used to prove existence of a Nash Equilibrium for the socialization problem.

Proposition 3 (Existence of an Equilibrium of the Parental Socialization Game)**.** For any time t such that $\Delta_t>0$, under Assumption (1), the first-stage parental socialization game has at least one symmetric Nash Equilibrium. □

Solving the model numerically one can also verify that at least for class of quadratic cost functions the equilibrium is unique.[20] This discussion, along with Propositions (1)-(3) show that at least for the class of quadratic cost functions and under Assumption (1) the general preference formation game has a unique interior equilibrium.

I end this discussion by noting that under these assumptions there is a unique blending-type steady state. The intuition for this result is straightforward: if groups have not converged parents will always choose $\alpha\in(0,1)$. Equations (3) and (4) then show that intracohort $(e_{1,t+1}-e_{2,t+1})$ and intergenerational differences $(e_{1,t+1}-e_{1,t})$ are decreasing. Once convergence is achieved the unique Nash equilibrium sustains the blending-type steady state indefinitely. However, endogenizing parental effects affects the speed of convergence: intuitively, parents tend to retard the convergence process at the beginning, but it is easy to show that $\partial\alpha_{i,t+1}/\partial\Delta_t>0$, so that parental incentives to socialize their children decrease as parents converge to each other, thus speeding up the process.

Proposition 4 (Blending-type steady state for the General Preference Formation Game)**.** Assume that for any time t, the cost function is of the type $c(\alpha)=k\alpha^2$, $k>0$. The unique steady state equilibrium is of the blending-type. Moreover, when both groups have equal population shares, the steady state is unbiased.

[19] As noted above, when $\Delta_t>0$ the best-reply function is not defined at zero. This follows from the fact that when type j parents choose $\alpha_j=0$ any small enough α_i guarantees that all children have $e_{i,t+1}=e_{j,t+1}=e_{i,t}$, and by continuity and monotonicity, the cost can be made as small as desired.

[20] The general class includes quadratic cost functions $c(\alpha)=k\alpha^2$ and exponential cost functions.

2.3 Comparative Statics

I now collect a series of results that will be useful in the empirical section of the paper. Since the relevant parameters for the parental socialization game are population weights ω and parental differences $\Delta_t = \kappa(e_{j,t} - e_{i,t})^2$, rewrite children Nash equilibrium strategies as in Equation (4).

Start by noting that:

$$\frac{\partial(e_{i,t+1} - e_{i,t})}{\partial(e_{j,t} - e_{i,t})} = (1 - \gamma_i) - (e_{j,t} - e_{i,t})\frac{\partial \gamma_i}{\partial(e_{j,t} - e_{i,t})}$$

In the absence of endogenous parental effects $\frac{\partial \gamma_i}{\partial(e_{j,t}-e_{i,t})} = 0$ so the effect is bounded to the unit interval, as $1 - \gamma \in (0, 1)$. After noting that $\partial\gamma_i/\partial\alpha_i > 0$ and $\partial\alpha/\partial\Delta > 0$ one can verify that if parental effects are endogenous the sign is still positive. To get a sense of the relative magnitudes, Figures (12)-(13) plot corresponding marginal effects when $(e_{j,t} - e_{i,t}) \gtreqless 0$ for alternative parametrizations of the model.

A stronger test of the endogeneity of parental effects is obtained by taking the second partial derivative. If parental effects are exogenous this term is zero, otherwise these are

$$\frac{\partial^2(e_{i,t+1} - e_{i,t})}{\partial(e_{j,t} - e_{i,t})^2} = -\frac{\partial \gamma_i}{\partial(e_{j,t} - e_{i,t})} - (e_{j,t} - e_{i,t})\frac{\partial^2 \gamma_i}{\partial(e_{j,t} - e_{i,t})^2}$$

Using alternative parameterizations, one can check numerically that the sign depends on the sign of parental differences $(e_{j,t} - e_{i,t})$. Figures (14)-(15) show that when $(e_{j,t} - e_{i,t}) > 0$ the sign is negative in general; otherwise for small enough parental differences, and depending on population weight ω_i, the term can be positive.

Turning now to the effects of population weights, from the children's conformity game (see the discussion of Proposition 2) it can be readily seen that if γ_i does not depend on population weight ω_i the partial derivative $\partial(e_{i,t+1} - e_{i,t})/\partial\omega_i = 0$. Alternatively, the expression depends on the sign of parental differences $(e_{j,t} - e_{i,t})$ since

$$\frac{\partial(e_{i,t+1} - e_{i,t})}{\partial\omega_i} = -(e_{j,t} - e_{i,t})\left(\underbrace{\frac{\partial\gamma_i}{\partial\omega_i}}_{Exo.Effects(+)} + \underbrace{\frac{\partial\gamma_i}{\partial\alpha_i}\frac{\partial\alpha_i}{\partial\omega_i} + \frac{\partial\gamma_i}{\partial\alpha_j}\frac{\partial\alpha_j}{\partial\omega_i}}_{End.Effects(+|-)} \right) \tag{6}$$

The first term inside the brackets captures the direct effect of ω_i on children's Nash equilibrium strategies. The second term captures the endogeneity of parental effects. If these are absent, this term is zero, and since $\partial\gamma_i/\partial\omega_i > 0$— an increase in a child's group share reduces the child-parental differences as children interact more with children of parents of the same type— in general

$$\text{sgn}\left(\frac{\partial(e_{i,t+1} - e_{i,t})}{\partial\omega_i}\right) = -\text{sgn}(e_{j,t} - e_{i,t})$$

If parental effects are endogenous, one needs to find the sign of $\partial\alpha_i/\omega_i$. In the Appendix it is shown that this sign can be positive or negative depending on the sign of $\alpha_i - k_i/(2 + k_i)$, which itself depends on the shape of cost function.

Proposition 5. $\partial\alpha_i/\partial\omega_i < 0$ if and only if $\alpha_i > k_i/(2 + k_i)$. □

Figure (3) depicts reaction curves for the parental socialization game and the effect that an increase in ω_1 has on the Nash equilibrium strategies for parents.

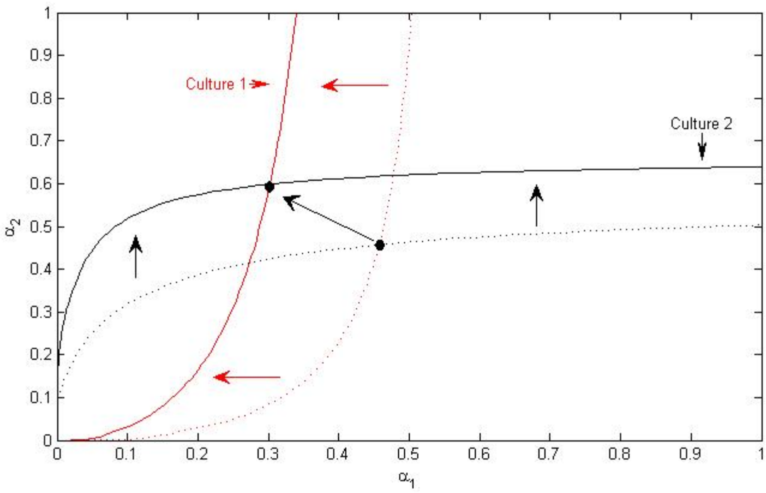

Figure 3: Reaction Curves for the Socialization Game and An Increase in ω_1

It follows that the second term inside the brackets in Equation (6) can be positive or negative. If positive ($\partial\alpha_i/\partial\omega_i > 0$) the same condition as in the case of exogenous parental effects applies, otherwise the sign can be positive, negative or zero.

3 Empirical Exercise

As discussed in the Introduction, this paper has an empirical motivation and the model was tailor-made to serve such purpose: the conformity game maps clearly to a class of recent econometric methods used to identify peer effects. The socialization game generates predictions that allows us to test for the endogeneity of parental effects.

3.1 Data

The National Longitudinal Study of Adolescent Health (Add Health) consists of a random sample of US high schools, with students from grades 7 to 12 interviewed in school and at home in several waves, starting in 1994, with follow ups in 1996, 2001 and 2008.[21] In this paper I use the public-use data that includes only the first three waves of interviews and a smaller sample size.

I will consider four ethnic groups including Hispanics, non-Hispanic Whites, Blacks and Asians.[22] and three dependent variables: religious importance (*How important is religion for you?*), religious activity (*How often do you pray?*), and alcohol consumption (*During the past 12 months, how often did you get drunk?*). The criteria for selection is simple: answers should have the continuous, linearly ordered intensity property used in the model, and exactly the same question should be asked to parents and children. To study the stability of the effects I use information on the first three waves of interviews. The median ages for each of these waves are: 15, 16 and 22 years old, but since all children in grades 7 to 12 were interviewed the age range is larger. Table (1) presents descriptive statistics for all dependent variables across all waves information.

Religious importance (relimpo) takes values from 1 to 4, 1 being *Very Important* and 4 *Not Important*. Religious activity or praying frequency (pray) and alcohol consumption were recoded to measure the fraction of days per month and year, respectively.

Corresponding parental questions were asked only in Wave 1, so these remain fixed in the subsequent analysis. Figure (4) summarizes the information on intergenerational differences across ethnic groups and waves of information.

Finally, to get a sense of school average intergenerational differences, Figure (5) plots average children outcomes against corresponding parental outcomes in Wave 1, along with the 45 degrees line. The first two scatter plots show that the children's cohort has become less religious than the parental cohort, while no clear pattern emerges for alcohol consumption.

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[21] A thorough description of the survey can be found online at http://www.cpc.unc.edu/projects/addhealth.

[22] Native Americans were dropped from our samples due to the small sample sizes.

Table 1: **Descriptive Statistics for Dependent Variables Across Waves of Information**

	N	Mean	Std	Min	Max	q25	q50	q75	q99
Religious Importance									
Wave 1	5614	1.64	0.76	1	4	1	1	2	4
Wave 2	4124	1.67	0.79	1	4	1	2	2	4
Wave 3	4829	2.51	0.86	1	4	2	2	3	4
Praying									
Wave 1	5614	0.45	0.37	0	0.83	0.07	0.17	0.83	0.83
Wave 2	4128	0.44	0.37	0	0.83	0.07	0.17	0.83	0.83
Wave 3	4836	0.54	0.61	0	1.67	0.02	0.33	1.00	1.67
Alcohol Consumption									
Wave 1	4480	0.05	0.16	0	1	0	0.004	0.03	1
Wave 2	4782	0.05	0.14	0	1	0	0	0.03	0.57
Wave 3	3704	0.16	0.21	0	1	0.03	0.08	0.21	1

Notes: Table shows descriptive statistics for each dependent variable and wave of information. Last four columns correspond are the corresponding percentiles.

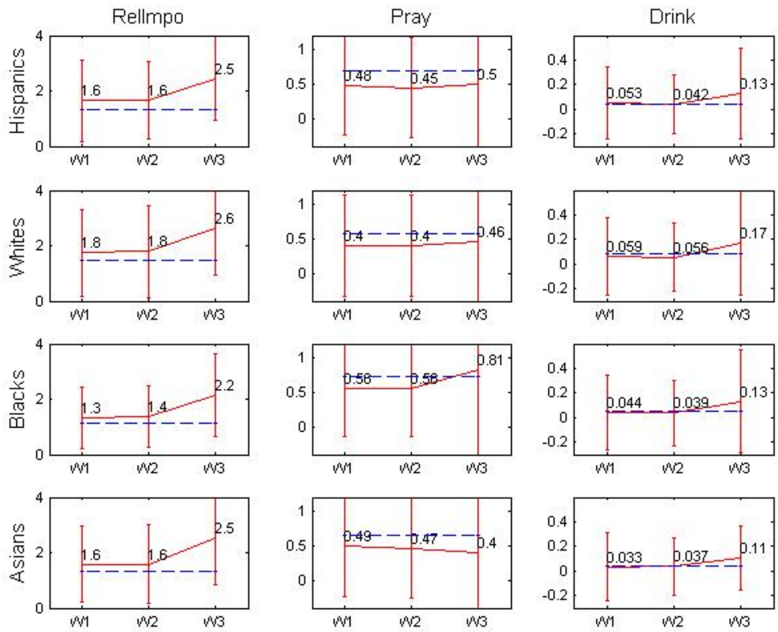

Figure 4: **Intergenerational Ethnic Differences**: For each ethnic group (rows) and each dependent variable (columns), the graph displays average children outcomes along with 95% confidence intervals (continuous lines) and corresponding parental outcomes (dotted line). Parental outcomes were only asked in Wave 1 and remain fixed across all waves of information.

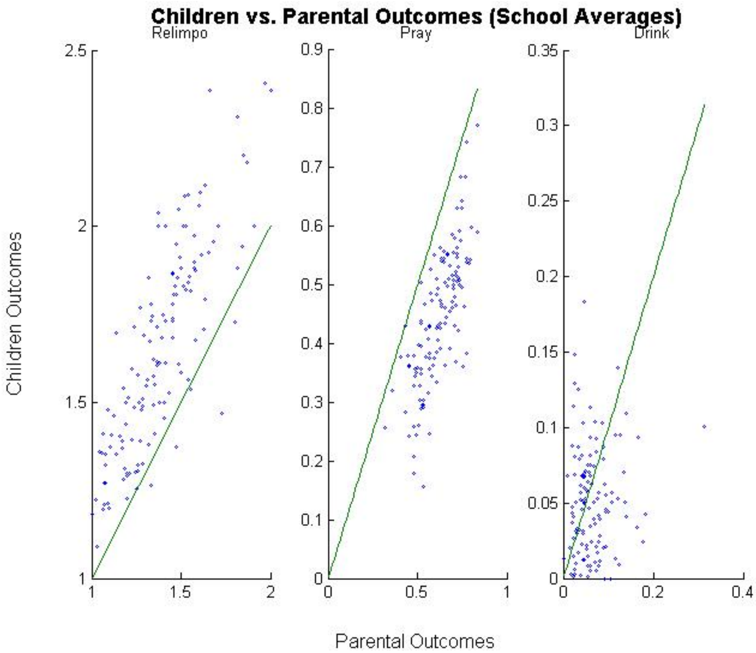

Figure 5: **School Average Children and Parental Outcomes**: Figure plots school averages of children outcomes against corresponding average parental outcomes in Wave 1, along with the 45 degrees line.

3.2 Estimating Parental and Peer Effects

To achieve full generality and make the model estimable, I introduce a source of uncertainty by assuming that each child i in school $s(i)$ receives a private signal $\epsilon_{i,t} \overset{\text{iid}}{\sim} N(0, \sigma^2)$, and let $\nu_{i,t} = X'_{i,t}\tilde{\beta} + Y'_{s(i),t}\tilde{\gamma} + \epsilon_{i,t}$, where , $X_{i,t}$ and $Y_{s(i),t}$ denote vectors of child-specific and school-specific controls, and $\tilde{\beta}$ and $\tilde{\gamma}$ are the corresponding parameter vectors. Formally, I have gone from the complete information, homogenous setting in Section 2, to a general setting that allows for individual heterogeneity and incomplete information.[23]

The problem for each child is then[24]

$$\min_{e_{i,t+1}\in[0,1]} \alpha_i(e_{i,t+1} - (e_{i,t} + \nu_{i,t+1}))^2 + (1-\alpha_i)\left(\frac{N-1}{N}\right)^2 \int \cdots \int (e_{i,t+1} - \bar{e}_{-i,t+1}(\boldsymbol{\epsilon}_{-\mathbf{i,t}}))^2 \, dF(\boldsymbol{\epsilon}_{-\mathbf{i,t}})$$

where $\bar{e}_{-i,t+1} = (1/(N-1)) \sum_{j\neq i} e_{j,t+1}$ denotes the sample average across all children different from child i, $\boldsymbol{\epsilon}_{-\mathbf{i,t+1}} = (\epsilon_{1,t+1}, \cdots, \epsilon_{i-1,t+1}, \epsilon_{i+1,t+1}, \cdots, \epsilon_{N,t+1})$ is a vector of idiosyncratic shocks for all other children $j \neq i$ and $F(\boldsymbol{\epsilon}_{-\mathbf{i,t}}) = \prod_{j\neq i} F(\epsilon_{j,t})$ is the joint distribution function of the shocks of all other children, where the equality follows from the iid assumption.

Using Leibniz's rule for integration and the independence of the shocks, optimal choices for the children become:

$$e_{i,t+1} = A_i e_{i,t} + \frac{(1-A_i)}{N-1}\sum_{j\neq i} \mathbb{E}(e_{j,t+1}|s(i)) + A_i(X'_{i,t}\tilde{\beta} + Y'_{s(i),t}\tilde{\gamma}) + A_i\epsilon_{i,t+1}$$

where the expectation is taken conditional on being in school $s(i)$. This first-order condition corresponds to the standard linear-in-means regression used to estimate peer effects and can be conveniently expressed as[25]

$$e_{i,t+1} = \alpha_{s(i)} + \alpha_p e_{i,t} + X'_{i,t+1}\beta + Y'_{s(i),t+1}\gamma + \alpha_g \mathbb{E}(\bar{e}_{-i,t+1}|s(i)) + \zeta_{i,t+1} \quad (7)$$

Here α_p denotes the direct parental effect, and α_g denotes the endogenous peer effect, $\beta = A\tilde{\beta}$

[23] Vaughan (2011a) studies the theoretical properties of the more general model. Notably the existence and uniqueness results are maintained, as well as the convergence to a unique steady state, where convergence is now defined as convergence in expectations. To focus on the empirical implementation and not on the technical details I refer the reader to that paper.

[24] Needless to say, one can introduce uncertainty using other channels, e.g. through preference heterogeneity. Our choice not only simplifies the analysis (since parameters are independent of controls), but allows us to map the class of dynamic systems studied here, to those in Cavalli-Sforza and Feldman (1973).

[25] The linear-in-means peer effects model has been extensively studied, especially since the seminal work of Manski (1993) was published. Conditions for (non)identification under this model have been further described and extended in Manski (1995), Manski (2000), Brock and Durlauf (2001), Glaeser and Scheinkman (2003), Moffitt (2001) and Graham and Hahn (2005). See also Graham (2008).

and $\gamma = A\tilde{\gamma}$. As observed by Manski (1993), one must control for exogenous (contextual) effects ($Y_{s(i),t}$), and unobserved correlated effects common to all children in each school $\alpha_{s(i)}$ in order to estimate endogenous social-interaction effects ($\mathbb{E}(\overline{e}_{-i,t}|s(i))$). I describe now the identification strategy.

3.2.1 Identification Strategy

I use the identification strategy proposed by Graham and Hahn (2005). Intuitively speaking, whenever there are positive interaction effects, the variation between groups should be in excess of the within variation, in a process modulated by the *social-multiplier*.[26] Graham and Hahn's (GH, thereafter) identification strategy consists of estimating a within-school regression using the first-order condition of the children's problem, and a between-school regression of the reduced-form equation, and use the multiplier effect as the extra source of information to credibly identify the endogenous and exogenous interaction effects. In order to do this one must view the data as a quasi-panel, where the cross-sectional dimension corresponds to groups— schools in our application— and the time dimension corresponds to children in each school.

As a first step, it is convenient to solve for equilibrium conditional expected actions:

$$\mathbb{E}(e_{i,t+1}|s(i)) = \frac{\alpha_p \mathbb{E}(e_{i,t}|s(i)) + \mathbb{E}(X_{i,t+1}|s(i))'\beta + Y'_{s(i),t+1}\gamma + \alpha_{s(i)}}{1-\alpha_g} \tag{8}$$

from where it follows that whenever $\alpha_g \in (0, 1)$ there is a *social multiplier* effect derived from the fact that children are interacting with each other. Substituting this expression in (7), and assuming that variables Y correspond exactly to the expected child characteristics at the school level (i.e. $Y_{s(i),t+1} = \mathbb{E}(X_{i,t+1}|s(i))$),[27] one derives the reduced-form equation

$$e_{i,t+1} = \alpha_p e_{i,t} + X'_{i,t+1}\beta + \frac{\alpha_p \alpha_g}{1-\alpha_g}\mathbb{E}(e_{i,t}|s(i)) + \mathbb{E}(X_{i,t+1}|s(i))'\frac{\gamma + \beta\alpha_g}{1-\alpha_g} + \frac{\alpha_{s(i)}}{1-\alpha_g} + \epsilon_{i,t+1} \tag{9}$$

Using the first-order condition (7) parental effects can be estimated consistently from the within-schools regression:

$$\tilde{e}_{i,t+1} = \alpha_p \tilde{e}_{i,t} + \tilde{X}'_{i,t+1}\beta + \tilde{\epsilon}_{i,t+1} \tag{10}$$

where for any variable $z_{i,t}$, $\tilde{z}_{i,t} := z_{i,t} - \bar{z}_{s(i),t}$, denotes the deviation from the school sample mean.

[26] On the social multiplier, see Becker and Murphy (2000) or Glaeser and Scheinkman (2003).

[27] Brock and Durlauf (2001) assume that there is at least one child-specific characteristic that does not enter as a school-specific variable, and rely on this assumption to derive necessary conditions for the identification of interaction effects. Similarly, Graham and Hahn (2005) assume the existence of such variables in order to achieve identification.

Using the reduced-form equation, and replacing unobservable conditional expectations in terms of observable sample means, the between-schools representation becomes

$$\overline{e}_{s(i),t+1} = \frac{\alpha_p}{1-\alpha_g}\overline{e}_{s(i),t} + \overline{X}'_{s(i),t+1}\frac{\beta+\gamma}{1-\alpha_g} + \nu_{s(i),t+1} \quad (11)$$

where

$$\nu_{s(i),t+1} = \frac{\alpha_p\alpha_g}{1-\alpha_g}(\mathbb{E}(e_{i,t}|s(i)) - \overline{e}_{s(i),t}) + (\mathbb{E}(X_{i,t+1}|s(i))' - \overline{X}_{s(i),t+1})\frac{\gamma+\beta\alpha_g}{1-\alpha_g} + \frac{\alpha_{s(i)}}{1-\alpha_g} + \bar{\epsilon}_{s(i),t+1}$$

As GH remark, writing the reduced-form equation in terms of observables creates an error-in-variables problem that depends crucially on the deviation between the sample and conditional expectations of the child-specific variables; however, this deviation depends on the behavioral assumptions made by the econometrician. It is shown later that a Hausman test allows us to test the hypothesis of complete versus incomplete information.

The social multiplier $(1/(1-\alpha_g))$ provides the extra source of information needed to identify both the endogenous and exogenous interaction effects, as seen by comparing Equations (10) and (11). I rely on the following identification assumption:

Assumption A. 2 (Identification Assumption)**.** Parental variables $e_{i,t}$ are excluded from the set of child-specific variables that have school effects, $X_{i,t+1}$.

Two comments are in place. First, the assumption does not rule out that children may interact occasionally with the parents of their peers, but merely they do not wish to conform to them. Second, while the identification assumption appears to be rather extreme, there is a growing literature in sociology and development psychology on *non-parental adults*, or “adults who have had a significant influence on the adolescent and on whom the adolescent can rely for support” (Chen, Greenberger, Farrugia, Bush, and Dong, 2003, p.35). Galbo and Demetrulias (1996) show that for a sample of 285 college students in the United States, only 4.6% of the subjects report a friend’s parent being a significant adult, while 56.3% declared parents being such. Of the reported nonrelated significant adults, teachers, coaches and counselors are the most widely identified by the students (59.8%). In their survey of the existing literature, they report a study by Garbarino, Burston, Raber, Russell, and Crouter (1978) where 60% of suburban children do not report any significant nonparental adult. They also report a study by Blyth, Hill, and Thiel (1982) where they find that out of 2800 public school students, only 10% report having nonrelated significant adults. A more recent paper by Chen, Greenberger, Farrugia, Bush, and Dong (2003) studies cross-cultural differences in the roles played by non-parental adults, for the specific case of China and the United States. Out of 201 American students, only 8 report a friend’s parent as a significant adult; of 502 Chinese students, only 2 report having such a significant adult. Overall, this suggests that the identification assumption is likely to be valid.[28]

3.2.2 Control Variables

The Add Health Study includes a rich battery of children, family and school questions that could potentially be used as exogenous controls. In order to avoid running out of degrees of freedom in the ethnic-group regressions reported below, I restricted the set of available controls using the following approach: I first run a pooled regression with all ethnic groups and all control variables listed in Table (4) from where I selected only those that achieve a minimum significance level, arbitrarily set at 20%. All other potential controls are excluded from subsequent ethnic-group regressions. The subset of controls that classify are presented in Table (6), along with those that remain significant in each ethnic-group regression.

3.2.3 Result 1: Parental and Peer Effects Sum to One

I first estimate parental and peer effects using the GH method under the assumption of complete information— i.e. no measurement error of population expectations— for each ethnic group, each dependent variable and wave of information. A total of $4 \times 3 \times 3 = 36$ sets of coefficients (α_p, α_g) are plotted in each panel of Figure (6)— left (right) panel corresponds to a specification without (with) controls — and the corresponding table of results can be found in Table (5) in the Appendix. In the Figure, for each variable v, ethnic group g and wave w, ordered couples from each regression are denoted by v_w^g.

It is noteworthy that estimates are on average very close to the theoretical prediction that both effects add up to one.[29] This is most clear with estimates for both religious variables across all waves of information, while estimates for alcohol consumption peer effects display large variation. Since parental effects are estimated by $\alpha_p = 1 - \theta/\alpha_g$, where θ is the coefficient for parental averages in the between-school regression (Equation 11), the variation in α_p is a direct result from the small estimated parental effect. One could question the validity of the identification assumption when parents have no effect, but as reported in Table (5), in four out of 12 regressions for alcohol consumption (Whites and Blacks in Wave 2, and Whites and Asians in Wave 3) parental effects are statistically significant.[30] These results show that at least for alcohol consumption, teenagers appear to be in the "beauty-contest case" where

[28]The same identifying assumption is used by Gaviria and Raphael (2001). They argue that, contrary to identification of neighborhood effects where children interact with both peers and their parents, at the school level the only source of interaction is through their peers.

[29]For expository reasons, the figure includes only the confidence intervals corresponding to peer effects— on the vertical axis. Theoretically, one should plot confidence ellipses or rectangular regions, depending on the correlation of parental and peer effect estimates.

[30]As discussed in the previous section, identification of peer effects relies on the explicit assumption that parental effects have no indirect group level effects, but that they *do have* a direct effect, i.e. $\alpha_p \neq 0$.

parental effects are negligible and peer effects dominate completely. As mentioned before, one implication is that observed behavior is one along a continuum of equilibria where all children coordinate, an interpretation that, at least for the case of alcohol consumption, does not seem to be inappropriate at all.

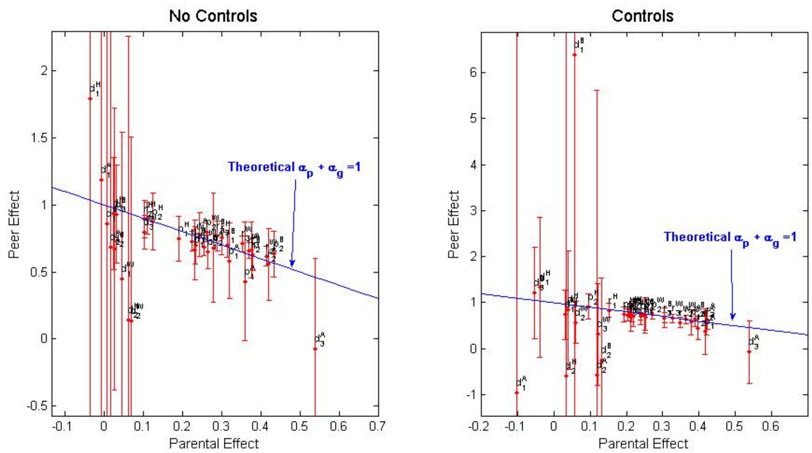

Figure 6: **Peer Effects vs. Parental Effects**: Each panel plots parental and peer effect estimates (α_p, α_g) obtained from ethnic-specific regressions (Table 5). Left (right) panel shows estimates from a specification without (with) exogenous controls. Each ordered couple denotes results from a regression for each ethnic group g, each variable v and each wave w, and are denoted as v_w^g (eg. d_1^A denotes the estimates for the Asian subgroup, using alcohol consumption (drink) for wave 1). Straight line corresponds to the theoretical $\alpha_p + \alpha_g = 1$. 95% cluster-robust confidence intervals for peer effects are also plotted.

Theoretically, the result that $\alpha_p + \alpha_g = 1$ follows from the functional assumptions made for the children's problem. In particular, I posed that loss functions are (i) weighted quadratic functions, and (ii) children care only about deviations from their parents and peers. To see how remarkable the empirical result is, consider the following utility functions where either assumption is not satisfied:

$$u(e_{t+1}) = -\alpha(e_{t+1} - e_t)^2 - \beta(e_{t+1} - \overline{e}_{t+1})^2 - \gamma(e_{t+1} - \overline{e}_t)^2 \quad (12)$$

$$u(e_{t+1}) = -\alpha(e_{t+1} - e_t)^2 - \beta(e_{t+1} - \overline{e}_{t+1})^2 - \gamma(e_{t+1} - e_{g,t+1})^2 \quad (13)$$

$$u(e_{t+1}) = -\alpha(e_{t+1} - e_t)^2 - \beta(e_{t+1} - \overline{e}_{t+1})^2 + V(e_{t+1}) \quad (14)$$

$$u(e_{t+1}) = V(e_{t+1}; e_t, \overline{e}_{t+1}) \quad (15)$$

Equation (12) captures a conformity model where children dislike deviating from parents (vertical effect), peers (horizontal effect) and other adults (oblique effect). Our identification assumption forbids that peers' parents have an oblique effect. Equation (13) captures the idea that children dislike deviating from parents and peers, but also from what their genes dictate ($e_{g,t+1}$). Equation (14) captures the idea that children are myopic (only concerned about fitting in at the current time), but also possibly forward looking since their preferences have an intrinsic value captured by V. Equation (15) takes a general functional form; it is straightforward to see that both marginal effects add up to one whenever $\frac{-(V_{e_{t+1}\bar{e}_{t+1}}+V_{e_{t+1}e_t})}{V_{e_{t+1}e_{t+1}}} = 1$, where subindexes denote partial derivatives.

Notice that if parental, peer and genetic effects are present (Equation 13), the sum of parental and peer effects *must* add up to less than one. This follows from the fact that the first and third terms can never be the same— even when one is willing to make the assumption that $e_{g,t} = e_{g,t+1}$—, since parental preferences will themselves be a weighted average of their own parents', peers' and genetic effects, i.e. $e_t \neq e_{g,t+1}$. This suggests that if present, genetic effects play only a minor role for this particular class of outcomes. However, with this data we cannot ascertain that this is indeed the case.

An example where at least one of these assumptions is violated is number of years of education, since genes (unobserved ability) and forward-looking behavior could both be present. Figure (7), taken from Vaughan (2011d) shows that parental and peer effects in education do not add up to one. Similarly, Vaughan (2011b) uses longitudinal data and a wide array of political values and finds that both effects add up to one for some variables, but by no means for all of them.

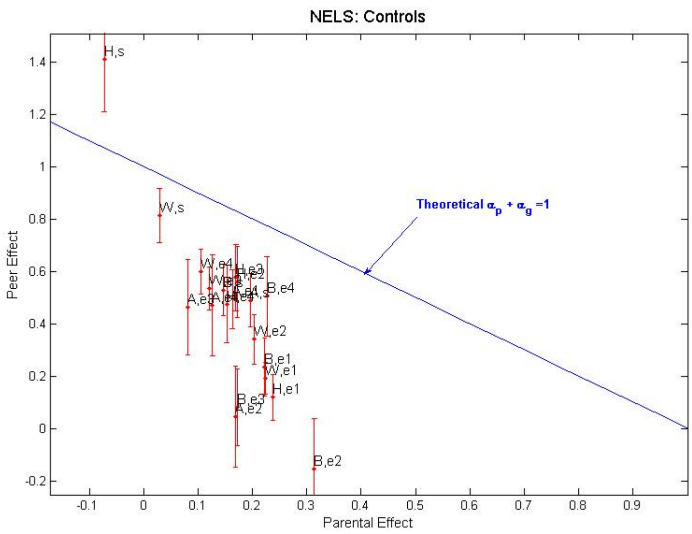

Figure 7: **Parental vs Peer Effects:** *Each point corresponds to estimates* $(\hat{\alpha}_p, \hat{\alpha}_g)$ *from a regression using a different dependent variable and subsample (ethnic group) using the following notation: Schooling (s), Expectations Follow-up study 1,2,3,4 (e1,e2,e3,e4). Hispanics (h), Whites (w), Blacks (b), Asians (a). The straight lines denote the theoretical* $\alpha_p + \alpha_g = 1$. *See Vaughan (2011d) for details.*

Figures (8-9) present the same results in such a way as to facilitate the comparison of estimates across ethnic groups. In general, magnitudes for parental and peer effects differ between groups, but the differences are not statistically significant. There are two reasons why these could vary across groups: first, the comparative statics results for the parental socialization problem show that, other things equal, parents from a minority may exert more socialization effort, making their children relatively more parent-oriented.[31] If this is true one should observe that children from minorities are relatively more vertical-oriented than White children. Also, parents from different ethnic groups that have already blended enough should exert the same parental efforts.[32] Second, there is a literature that examines differences across ethnic groups in personality traits such as familialism, individualism and collectivism. While this literature comes mainly from developmental psychology and sociology,[33] Alesina and Giuliano (2010) examine data from the World Values Survey, and rank countries according to an index of *strength of family values*. If these values are themselves transmitted through the social environment, one would expect these to affect the relative weights given to both effects. However, with the exception of Wave 3 parental effects on drinking behavior for Asians, most estimates are not statistically different. Because of the one-to-one negative relationship between both effects, it does not come as a surprise that the same conclusion is observed for peer effects across ethnic groups.

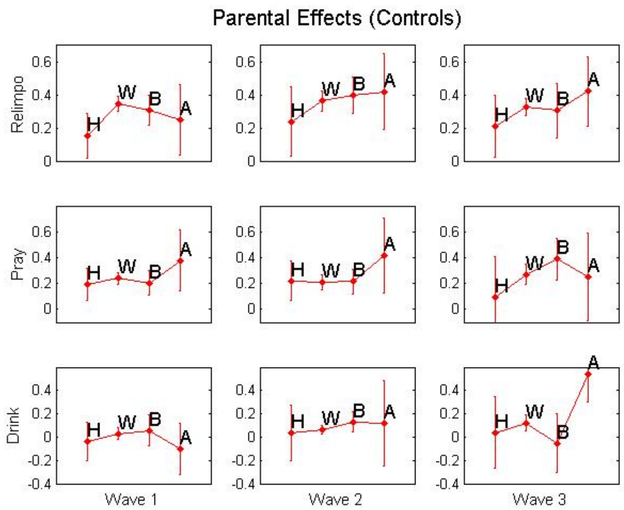

Figure 8: **Comparison of Parental Effects Across Ethnic Groups**: Each panel plots estimated parental effects across ethnic groups for each variable (rows) and wave (column). Dotted line corresponds to the case where estimated effect is equal to zero. 95% robust confidence intervals are included. Specification includes controls (Table 5).

[31] Theoretically, the opposite effect could also be true.

[32] It was shown that parents will not exert any socialization effort once all of them have already blended with each other. Recall however that this result was derived for the case of identical agents within each group. In the more general case with heterogeneity only convergence in expectations is achieved, so parental efforts will never be zero.

[33] See Dikstra and Fokkema (2010), for example.

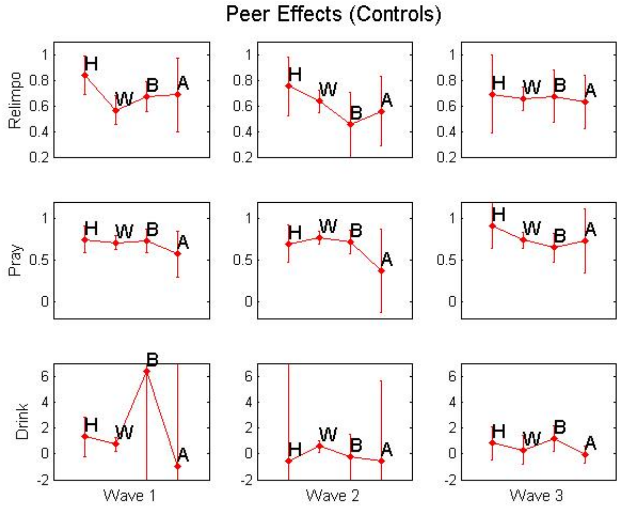

Figure 9: **Comparison of Peer Effects Across Ethnic Groups**: Each panel plots estimated peer effects across ethnic groups for each variable (rows) and wave (column). Dotted line corresponds to the case where estimated effect is equal to zero. 95% robust confidence intervals are included. Specification includes controls (Table 5).

3.2.4 Result 2: Stability of Parental and Peer Effects

As described above, median age in Waves 1 and 3 were 15 and 22 years old, respectively. I will now show that both peer and parental effects have enduring effects during the life-cycle of teenagers in our sample. This is important, since the model proposed is one of preference transmission, and not just a model of temporary changes in behavior due to peer or parental pressure. While one cannot extrapolate these effects, and claim that by the age of 22 young adults preferences are fixed and invariant, a period of 7 years is long enough for us to assess whether peers and parents during adolescence have an enduring effect. It is important to remember that the peer group is fixed in this analysis, i.e. I do not update the peer or reference group with each wave of information.[34]

Figure (10) rearranges graphically the parental effects in Table 5 to facilitate comparison across time. Parental effects are increasing for the cases of religious importance in Asians, frequency of praying in Blacks, and alcohol consumption for Whites, but most notably Asians. In fact, only for the latter case the difference between first and third waves estimates is significant. Similar patterns emerge for peer effects, which are not shown here. The stability of parental and peer estimates is evidence of an enduring preference transmission mechanism, and not of a temporary peer pressure effect.

[34]One can conjecture that this is indeed desirable, since once preferences are formed, selection effects— e.g. choosing your friends inc college—, should bias the estimates.

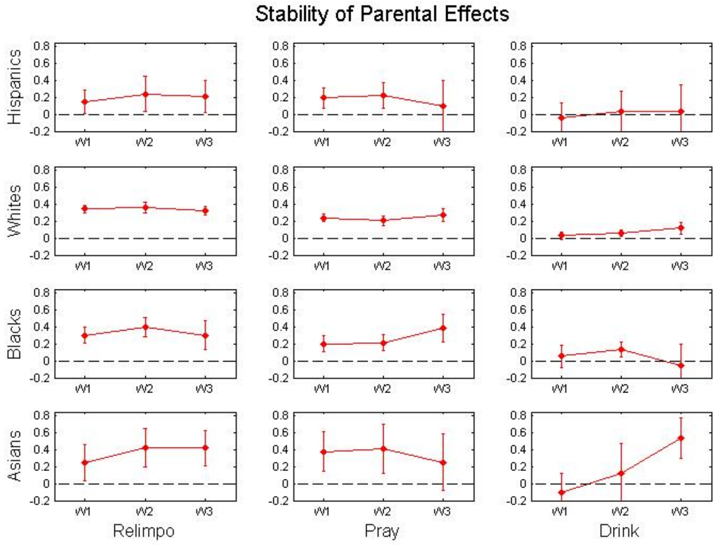

Figure 10: **Stability of Parental Effects**: Each panel plots estimated parental effects across waves of interviewing for each ethnic group (rows) and each variable (column). Dotted line corresponds to the case where estimated effect is equal to zero. 95% robust confidence intervals are included. Specification includes controls (Table 5).

3.2.5 Result 3: Robustness to Measurement Error

As discussed in the previous section, while GH permits credible estimation of parental and peer effects under identification assumption (2), replacing school-level population expectations with observable sample means creates an error-in-variables bias whenever the environment is one of incomplete information. This can be tested by noting that the measurement error caused by replacing population moments with the observable sample counterparts operates only at the school level, so a Hausman test of fixed versus random effects using the reduced-form equation (9) can be used. To implement it, replace unobservable expectations with corresponding sample means and estimate the parameters using two different estimators in the spirit of panel data fixed vs. random effects tests. If both estimator systematically deviate from each other, the measurement error is biasing the random effects estimates. Failure to reject the hypothesis that both estimates are equal is evidence that the complete information assumption is not a likely source of concern.

Table 2 reports F statistics and robust p-values corresponding to the Hausman test for each ethnic group regression using all waves of information.[35] Out of the 36 regression estimates, only in four cases the Hausman test allow us to reject the hypothesis that both sets of estimates

[35]Covariance matrices for the chi-squared Hausman tests using vector of contrasts are generally negative definite, yielding negative test statistics for all specifications. As argued by Greene (2008) this could be interpreted as evidence of no systematic difference between the two estimators, or in the particular case under study, that the complete information assumption does not bias the estimates. As a check, I ran augmented regressions that yield asymptotically equivalent F statistics reported in Table 2.

are equal: religious importance (Waves 2 and 3) and praying frequency (Waves 1 and 3) for Whites. In all other cases I can conclude that no relevant school-level variables are being omitted, and in particular, that the complete information assumption is not biasing the estimates.

Table 2: **Hausman Test**

	RelImpo			Pray			Drink		
	Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3
Hispanics	0.9997	1.1229	0.8641	1.7256	1.6882	1.2639	0.7565	1.3666	1.5309
	(0.425)	(0.408)	(0.648)	(0.316)	(0.273)	(0.399)	(0.641)	(0.559)	(0.442)
Whites	2.9571	4.8854	8.6934	4.1243	2.086	4.1318	1.2894	0.5423	1.6798
	(0.12)	(0.019)	(0.007)	(0.026)	(0.187)	(0.068)	(0.258)	(0.62)	(0.114)
Blacks	2.3863	1.3819	2.1117	1.3373	1.0771	0.9234	0.5298	1.3467	1.1052
	(0.223)	(0.376)	(0.134)	(0.351)	(0.412)	(0.417)	(0.754)	(0.259)	(0.32)
Asians	0.6513	0.1061	1.1053	1.2558	1.1626	0.8388	1.4485	0.2412	0.5394
	(0.608)	(0.667)	(0.301)	(0.314)	(0.371)	(0.482)	(0.557)	(0.805)	(0.411)

Notes: The table shows the Hausman test statistic and and associated robust p-value in parenthesis for each regression per ethnic group and dependent variable. P-values were bootstrapped with 2000 bootstrap samples. The null hypothesis is that fixed and random school effects in the reduced-form regression (9) are statistically the same. Under the null, both the FGLS and within-school estimators are consistent, but only FGLS is efficient. Under the alternative, FGLS is inconsistent.

The previous results give us some confidence that estimates are not biased, but the results of the test for Whites may be a cause of concern. Since this is a standard measurement error problem, I now use independent samples to compute corrected estimates.[36] Writing the between-schools regression (11) in vector form:

$$\begin{aligned} y &= X^{*}\beta + u \\ X &= X^{*} + V \end{aligned}$$

where X^{*} is a matrix with the true unobserved conditional expectations of parental and control variables, and X denotes the corresponding matrix with observed sample means. A standard result is that the OLS estimator of the parameters β is inconsistent, but that the adjusted estimator

$$\hat{\beta}^{a} = (X'X - \hat{\Sigma}_{VV})^{-1}X'y$$

is consistent, where $\hat{\Sigma}_{VV}$ is an estimator of the covariance matrix of the measurement error. Under the assumption that measurement error for any two variables are independent (implying that $\Sigma_{VV} = diag(\sigma_1^2, \cdots, \sigma_K^2)$), given two independent measurements of the sample means for

[36] I follow the approach in Cameron and Trivedi (2005) which is somewhat standard. Graham and Hahn (2003), in the unpublished, working paper version of the paper cited above, suggest a similar procedure to find suitable instruments for the error-in-variables. See also Arellano (2003), who discusses the effect of measurement error and unobserved heterogeneity in panel data.

each variable X_{k1}, X_{k2}, the variance of each measurement error can be estimated by

$$\hat{\sigma}_k^2 \;=\; \hat{\sigma}_{X_k}^2 - \;\hat{\text{Cov}}\;(X_{k1}, X_{k2})$$

I estimate each sample mean for $\overline{e}$ and $\overline{X}$ using two randomly drawn subsamples of the students in each school, using the *pooled data*, i.e. using all the information, regardless of the ethnic identification of children within each school, and estimate the corresponding covariance matrix $\hat{\Sigma}_{VV}$. This covariance matrix is used to adjust the estimates in the between-school regression. Figure (11) depicts the results. In the left panel, corrected peer effects against parental effects are plotted. The right panel plots the original peer effect estimate $\hat{\alpha_g}$ on the vertical axis, and the corresponding adjusted estimates on the horizontal axis, along with the 45° line. Under the null hypothesis of no measurement error (i.e. the complete information assumption), both estimates should be the same, and therefore, should be very close to the diagonal. As the figure shows, this is indeed the case for most estimates.

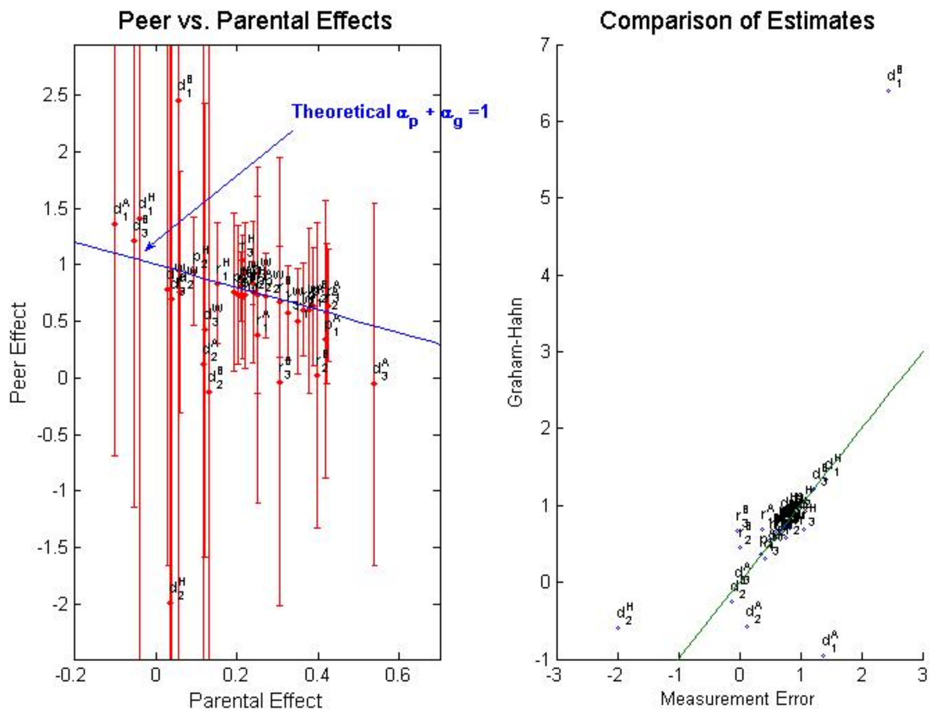

Figure 11: **Measurement Error Correction**: Left panel plots estimate peer effects against parental effects correcting for measurement errors along with theoretical prediction $\alpha_g + \alpha_p = 1$ (straight line) and 95% cluster-robust confidence intervals for peer effects. Right panel plots parental and peer effects using Graham and Hahn method without correction against corresponding estimates correcting for measurement errors.

3.3 Result 4: Comparative Statics

I now summarize the findings presented in Section (2.3)

$$\frac{\partial(e_{i,t+1}-e_{i,t})}{\partial(e_{j,t}-e_{i,t})} = \begin{cases}(1-\gamma_i)\in(0,1) & \text{absence of endogenous parental effects (NPE)}\\ (1-\gamma_i)-(e_{j,t}-e_{i,t})\frac{\partial\gamma_i}{\partial(e_{j,t}-e_{i,t})} & \text{presence of endogenous effects (PE)}\end{cases} \quad (16)$$

$$\frac{\partial^2(e_{i,t+1}-e_{i,t})}{\partial(e_{j,t}-e_{i,t})^2} = \begin{cases}0 & \text{(NPE)}\\ -\frac{\partial\gamma_i}{\partial(e_{j,t}-e_{i,t})}-(e_{j,t}-e_{i,t})\frac{\partial^2\gamma_i}{\partial(e_{j,t}-e_{i,t})^2} & \text{(PE)}\end{cases} \quad (17)$$

$$\frac{\partial(e_{i,t+1}-e_{i,t})}{\partial\omega_i} = \begin{cases}0 & \text{if } \gamma \text{ is independent of } \omega\\ -(e_{j,t}-e_{i,t})\left(\underbrace{\frac{\partial\gamma_i}{\partial\omega_i}}_{Exo.Effects(+)}+\underbrace{\frac{\partial\gamma_i}{\partial\alpha_i}\frac{\partial\alpha_i}{\partial\omega_i}+\frac{\partial\gamma_i}{\partial\alpha_j}\frac{\partial\alpha_j}{\partial\omega_i}}_{End.Effects(+|-)}\right) & \text{if } \gamma \text{ depends on } \omega\end{cases} \quad (18)$$

For the case of complete heterogeneity (equivalently, N groups), Vaughan (2011a) shows that Nash equilibrium strategies in the conformity game can be written as

$$e_{i,t+1} = \gamma_{ii}e_{i,t}+\sum_{j\neq i}\gamma_{ij}e_{j,t}$$

with $\gamma_{kl}\in(0,1)$ for all $k,l=1,\cdots,N$ and $\sum_j\gamma_{kj}=1$ for any child k. It now follows that

$$e_{i,t+1}-e_{i,t} = (1-\gamma_{ii})(\tilde{e}_{i,t}-e_{i,t})$$

where $\tilde{e}_{i,t}=\sum_{j\neq i}\tilde{\gamma}_{ij}e_{j,t}$ with $\tilde{\gamma}_{ij}=\gamma_{ij}/(1-\gamma_{ii})$ for all $j\neq i$, is a weighted average of all other parents preferences. Since child-specific weighted averages $\tilde{e}_{i,t}$ are not observed, I use the corresponding sample average $\overline{e}_{-i,t}=\sum_{j\neq i}e_{i,t}$.[37] I now estimate the following child-specific regression pooling across all ethnic groups:[38]

$$e_{i,t+1}-e_{i,t} = \beta_0+\beta_1(\overline{e}_{-i,t}-e_{i,t})+\beta_2(\overline{e}_{-i,t}-e_{i,t})^2+\beta_3\omega_{s(i)}+\beta_4\omega^2_{s(i)}+X_i'\eta+\epsilon_{i,t+1} \quad (19)$$

where $\omega_{s(i)}$ denotes the share of child i's ethnic group in school $s(i)$.

Results are presented in Table (3) where, for each Wave 1 dependent variable three alternative specifications are reported. Columns (1) show OLS estimates for $\beta_0-\beta_4$ in Equation (19)

[37]While this creates a measurement error, I am only interested in observing the sign of the estimates. Also, notice that a similar procedure as the used above for school averages cannot be used here, since the measurement error is at the individual level and we have only one observation per individual (i.e. no independent measurements can be obtained without a panel structure with repeated observations for each individual).

[38]Including further polynomial terms do not affect the results shown.

without additional controls ($\eta = 0$). Columns (2) include child-specific controls. Columns (3) show results of a specification where each individual's ethnic group share is replaced by shares for all ethnic groups excluding Asians and the corresponding quadratic terms. In a setting with more than two ethnic groups the latter is more appropriate, but interpretation of the results is not as straightforward as in the former case.

A first result is that across all specifications $\hat{\beta}_1 \in (0, 1)$. In the absence of parental effects— (NPE) in Equation (16)— this value is an estimate of $1 - \gamma_{ii}$. Estimates for the quadratic effect of parental differences β_1 are negative in general, as the theory predicts (see Figures (14-15) for a two-groups case), and significant for all specifications excluding those when the dependent variable is frequency of praying. As Equation (17) shows, the sign should be zero in the absence of parental effects, so at least for religious importance and alcohol consumption the hypothesis that parents endogenously affect their children's relative preference to conform to parents and children cannot be rejected. Moreover, this also suggests that the estimate $\beta_1 \neq 1 - \gamma_{ii}$.

A group's own ethnic share in the school is significant only for praying frequency. Moreover, quadratic effects are not significant either. This, however is the weakest test of the theory— see Equation (18)— since a zero marginal effect could be either a sign of the children's problem being independent of ω, or a sign of presence of endogenous effects. When all ethnic groups' shares are included— specification (3)— these are negative and significant for religious importance only, and there is no evidence that quadratic effects matter.

At this point it is worth discussing the role of ethnic weights in a heterogenous agents model. The interpretation put forward in Vaughan (2011a) is that at time zero, a population of parents is drawn from M distributions. An ethnic group is defined by the distribution from which the original ancestors were drawn. Since population is stationary, the size of each ethnic group remains fixed across time, as well as population shares ω_m ($m = 1, \cdots, M$). In this context, the concept of convergence proposed by Vaughan (2011a) is that of convergence in expectations, that holds in this more general case whenever $\alpha_i \in (0, 1)$ for all agents.

Table 3: **Comparative Statics - Individual Level Regressions**

	RelImpo1			Pray1			Drink1		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Cons (β_0)	0.290	-0.060	1.361	-0.127	0.061	0.277	-0.007	-0.134	-0.117
	(0.036)	(0.196)	(0.651)	(0.019)	(0.103)	(0.313)	(0.009)	(0.034)	(0.075)
$ParDiff$ (β_1)	0.611	0.592	0.575	0.730	0.812	0.811	0.753	0.746	0.792
	(0.027)	(0.039)	(0.039)	(0.024)	(0.034)	(0.035)	(0.041)	(0.05)	(0.049)
$ParDiff^2$ (β_2)	-0.050	-0.073	-0.089	0.004	-0.130	-0.136	-0.319	-0.335	-0.268
	(0.023)	(0.035)	(0.034)	(0.07)	(0.104)	(0.107)	(0.067)	(0.084)	(0.083)
$EthShare$ (β_3)	-0.024	0.007		-0.145	-0.204		-0.003	0.085	
	(0.138)	(0.22)		(0.07)	(0.12)		(0.037)	(0.051)	
$EthShare^2$ (β_4)	0.059	0.089		0.101	0.122		0.006	-0.077	
	(0.12)	(0.184)		(0.062)	(0.102)		(0.032)	(0.045)	
$Share_H$			-1.681			-0.485			0.118
			(0.739)			(0.372)			(0.131)
$Share_W$			-1.710			0.010			0.031
			(0.73)			(0.345)			(0.103)
$Share_B$			-1.537			-0.389			-0.033
			(0.669)			(0.315)			(0.096)
$Share_H^2$			0.318			0.224			-0.001
			(0.522)			(0.269)			(0.139)
$Share_W^2$			0.361			-0.290			-0.053
			(0.299)			(0.155)			(0.076)
$Share_B^2$			0.084			0.109			0.038
			(0.297)			(0.156)			(0.08)
$\overline{R}_2$	0.218	0.262	0.266	0.300	0.371	0.370	0.400	0.444	0.452
Nobs	4729	2033	2033	4724	1934	1934	3912	2071	2071
Controls	N	Y	Y	N	Y	Y	N	Y	Y

Notes: Table presents results from estimating Equation (19) for each dependent variable using only the first wave of information. Columns (1) do not include controls, (2) include controls and own ethnic group's school population share, and (3) include controls, all ethnic groups' shares (excluding Asians) and quadratic terms of these. Cluster-robust standard errors in parenthesis.

4 Conclusions

In her book, *The Nurture Assumption*, Harris (1999) forcefully argues that endogenous parental effects— as opposed to those of genetic origin— have no enduring consequences on children's behavior. Since behavioral genetic studies usually find that around 50% of the variance of most behavior can be accounted by genetic factors, she claims that researchers that fail to control for these, overstate the importance of parental nurturing practices. In summary, she argues that genes, but most importantly peers, are responsible for how "children turn out the way they do". Emphasizing the genetic and peer transmission channels, this subject has been increasingly studied in recent years by economists, who are mostly interested in understanding the process of preference transmission.

In this paper I develop a model that allows me to test both of Harris' claims using a data set that lacks the information needed to control for genetic differences. The model has two components, each designed to attain my empirical objectives: first, in order to estimate peer effects using a relatively novel econometric technique proposed by Graham and Hahn (2005), I assume that children interact strategically and choose their preferences with the only desire to fit in. Specifically, I assume that the main tradeoff they face is being like their parents or like their peers. Second, I assume that parents purposefully socialize their children in order to reduce any significant deviation from their own preferences. This second component allows me to derive testable predictions from the static comparative analysis of the game, necessary to separate between exogenous, role-model effects and endogenous parental nurturing choices.

Empirically, I find that for two religious variables and teenage alcohol consumption both of Harris' claims are not substantiated. First, I show that parental and peer effects are important. While parental effects are relatively small for alcohol consumption, these are non-negligible for the importance that children ascribe to religion and explaining the frequency of praying. Second, I show that at least for the seven years covered by the data, both of these effects are enduring. Specifically, I show that high school peers and parental attitudes during the first wave of interviewing affect attitudes that are measured repeatedly across the three waves of interviewing under study, with no signs of "fading out". While I cannot extrapolate these results to later stages in life, the period of seven years is long enough to argue that parental and peer effects are not merely temporary deviations from another more fundamental source.

Nonetheless, taken in isolation, these findings are consistent with the view that genes and peer effects dominate, but the next two results allow me to question the *nature hypothesis*. First, I find that on average, parental and peer marginal effects on their children outcomes add up to one, implying that children's attitudes are a weighted average of the corresponding parental and peer attitudes, conditional on other exogenous controls. As Equations (12)-(15) show, this result depends crucially on the functional assumptions made on children's payoff functions, and in general, one should expect the sum of both effects to be less than one. To see how remarkable this empirical finding is, I also present results from one of two related papers on the transmission of schooling outcomes and political preferences: Figure (7)— taken from Vaughan (2011d)— shows that parental and peer effects in years of schooling (estimated with the same exact econometric method as the one used here) in general add up to less than one, as expected if genetic (eg. ability) effects are present, if children have nonparental adult mentors (oblique effects), or if they are forward-looking and education has an intrinsic value (increased lifetime consumption). The conclusion is that as long as children view their parents and peers as role models, if genetic effects are also present the sum of parental and peer effects will be *less* than one. The outcomes under study here— religious practices and beliefs and alcohol consumption— are such that dismissing the role model effect in favor of the genetic explanation is at odds with common intuition, thereby suggesting that genetic effects are absent.

However, since Harris' critique of the "Nurture Assumption" attacks precisely this type of intuition-based arguments, I perform some formal testing using the comparative statics analysis of the parental socialization problem. By running reduced-form regressions, I find evidence consistent with the endogenous socialization hypothesis that would be hard to defend if genes, and not parenting practices, were responsible for children's behavior. Specifically, I show that other things equal, intrafamily parental-child differences $e_{i,t+1} - e_{i,t}$ are concave with respect to intracohort parental differences $\overline{e}_{-i,t} - e_{i,t}$, consistent with the endogeneity of parental practices in the model.

It is important to emphasize that these results *do not* show that genes play no role, but only that conformity is an important driving force in the transmission of preferences. While the results suggest that genes play a minor role if any, the data used does not allow to identify these effects.

I now discuss the validity of the econometric method used to estimate peer effects. Graham and Hahn (2005) method depends crucially on the existence of at least one child-specific variable that has no school-level effects, in order to circumvent Manski's reflection problem.[39] My identification assumption is that the corresponding parental outcome serves that specific role, i.e. that school-level parental averages do not have a direct effect on children's outcomes. An example will help clarify this: suppose that there are only two children, with their two corresponding parents. In general, one can pose that children's outcomes are generated from the

[39] Brock and Durlauf (2001) emphasize that in linear models this is indeed a general necessary condition for identification of peer effects.

following first-order condition:

$$e_{1,t+1} = \alpha_0 + \alpha_1 e_{1,t} + \alpha_2 e_{2,t} + \alpha_3 e_{2,t+1} + \epsilon_{1,t+1}$$
$$e_{2,t+1} = \alpha_0 + \alpha_1 e_{2,t} + \alpha_2 e_{1,t} + \alpha_3 e_{1,t+1} + \epsilon_{2,t+1}$$

Here α_1 corresponds to each child's own parental effect and α_3 denotes to the peer effect. My identification assumption corresponds to the exclusion restriction that $\alpha_2 = 0$ i.e. that parents of a child's peers do not have a direct effect on her outcomes. In terms of the model, this amounts to assuming that peers' parents are not role models for the children. I argue that since interactions with peers take place mostly within the school— that is the definition of the peer group used in this paper— other parents only have an indirect effect through the direct effect they have on their own children. I also show evidence coming mainly from developmental psychology that shows that while nonparental adults may act as role models for children and teenagers, it is mostly through school-specific actors, such as teachers and councelors and not through friends' parents.

I further perform two robustness checks: first, I test that replacing observable school-level sample means for unobservable expectations is not creating an error-in-variables problem, or in behavioral terms, that the conformity game is not one with incomplete information. Graham and Hahn (2005) show that the econometric method they design to estimate peer effects is sensitive to this specific type of problem, so I use a fixed-versus-random effects Hausman test using the reduced-form equation of the children's problem. I am not able to reject the hypothesis that the complete information assumption is systematically biasing the results for the majority of my estimates, and for the remaining I use a standard method to adjust OLS estimates in the presence of measurement error.

Second, while I do not report these results here, I have also checked the robustness of the choice of peer group.[40] Results shown in this paper take the school to be the group, but I have also checked that using each grade does not alter my main results. While it could argued that it is better to use the restricted networks reported by each student in the private-use data,[41] there are two sources of concern with such approach. First, children select their friends. Second, the restricted nature of this information — up to six friends are reported— may itself bias the results. In a Monte Carlo study, Vaughan (2011c) shows that using the more aggregated school-level peer group is not a source of concern as long as the complete network is connected, that is, whenever for any two respondents, there is a path of friends connecting them. Needless to say,

[40] Results available from the author upon request.

[41] The restricted-use Add Health data includes information for up to 6 of self-reported friends in school for each child.

when schools are segregated by ethnic groups, for example, in which case the full network has several unconnected components, the more aggregate choice will most likely bias the estimates.

Finally, it is worth commenting on a result that follows naturally in a model of peer and parental effects without genetic effects. As long as children put positive weight on both parents and peers, and these effects add up to one, a *Local Melting Pot* will take place, i.e. within a school, children from different ethnic groups will converge to each other.[42] Importantly, a *Global Melting Pot* where immigrants and natives blend with each other, will not necessarily follow, a view consistent with the type of segmented assimilation proposed by Portes and Zhou (1993).[43]

The results in the paper suggest a future research agenda that is worth discussing. From an empirical point of view, verifying these results with twin data is necessary to ascertain if genes play such a minor role as the results suggest. Moreover, to assess the stability of peer and parental effects along the life cycle one should use a data set that goes beyond the seven years spanned in the present study. From a theoretical point of view, this paper has shown that economics can help improving the methods used in behavioral genetics. Specifically, behavioral genetics assumes that agents— children and parents— play no active role in the transmission process— other than assortative mating. It follows that the tools used in economics can provide testable predictions that are not currently present. For example, in this paper I have shown that, contrary to standard practice in behavioral genetics, parental effects can enter through two different environmental channels. Moreover, these enter multiplicatively, and provide a rather convoluted testable prediction.

[42] The condition that effects add up to one is by no means necessary for convergence.

[43] A limited list of sufficient conditions is provided by Vaughan (2011a). Clearly, a connected network of of schools will suffice, but other conditions are that schools are not ethnically segregated, or that there is intergenerational spatial mobility for all ethnic groups.

Appendix: Proofs

In this Appendix we proof all propositions for the case of $M = 2$ groups. Proofs of the general case $M = N$ can be found in Vaughan (2011a).

Proposition 1: Existence and Uniqueness of a Nash Equilibrium for the Conformity Game
A necessary and sufficient condition for the existence of a unique symmetric Nash Equilibrium of the conformity game for any time $t > 0$*, is that* $\alpha_i \neq 0$ *for at least one of the groups.*

Proof. We will show that the statement is true at time $t = 0$; an analogous argument will show that it also holds for any finite time $t > 0$. Since the objective functions are quadratic, using the second-order conditions, after some algebra it can be seen that the problem is strictly convex whenever $\alpha_j > -\frac{(N-1)^2}{2N-1}$, satisfied under our assumptions. Since the problem is quadratic, from the first-order conditions and remembering that we are restricted to the set of symmetric equilibria, we get reaction functions that are linear in the parents' and other group's preference:

$$e^*_{i,1} = A_i e_{i,0} + (1 - A_i) e^*_{j,1} \tag{20}$$

where $A_i = \alpha_i/(\alpha_i + (1-\alpha_i)\psi_N(1-\omega_i))$, $\psi_N := (N-1)/N$, for $i \neq j = 1, 2$. The reaction curves (20) constitute a system of two linear equations

$$\begin{pmatrix} 1 & -(1-A_1) \\ -(1-A_2) & 1 \end{pmatrix} \begin{pmatrix} e^*_{1,1} \\ e^*_{2,1} \end{pmatrix} = \begin{pmatrix} A_1 e_{1,0} \\ A_2 e_{2,0} \end{pmatrix}$$

A necessary and sufficient condition for existence and uniqueness of a Nash Equilibrium is that the matrix in the left-hand side is invertible. The determinant of this matrix is $A_i + A_j(1 - A_i)$. After some algebra, it is easy to see that:

$$A_i + A_j(1 - A_i) = \frac{\alpha_i\alpha_j(1-\psi_N) + \psi_N(\alpha_i\omega_i + \alpha_j\omega_j)}{(\alpha_i + (1-\alpha_i)\psi_N(1-\omega_i))(\alpha_j + (1-\alpha_j)\psi_N(1-\omega_j))}$$

Since we are restricting α to be in the closed unit interval this term is always well defined, and it is non-zero if and only if $\alpha_i \neq 0$ for at least one of the groups. □

Proposition 2: Existence and Uniqueness of a Blending-Type Steady State
Assume that $\alpha_i \in (0, 1)$*,* $i = 1, 2$*. Given initial conditions* $\mathbf{e_0}$*, there exists a unique interior stable steady state equilibrium* $\mathbf{e}^* = (e, e) \in (0, 1)^2$.

Proof. It is straightforward to verify that $\alpha_i \in (0, 1)$ implies $A_i, \gamma_i \in (0, 1)$ and $\gamma_1 + \gamma_2 > 1$,

$i = 1, 2$. Nash Equilibrium strategies generate a system of linear difference equations:

$$\begin{pmatrix} e_{1,t+1} \\ e_{1,t+1} \end{pmatrix} = \begin{pmatrix} \gamma_1 & 1-\gamma_1 \\ 1-\gamma_2 & \gamma_2 \end{pmatrix} \begin{pmatrix} e_{1,t} \\ e_{1,t} \end{pmatrix}$$

for which a general solution is $\mathbf{e_t} = \lambda_1 c_1 \mathbf{v}_1 + \lambda_2 c_2 \mathbf{v}_2$, where $\lambda_i, \mathbf{v}_i$, $i = 1, 2$ are the eigenvalues and eigenvectors of the matrix $\Gamma = [\gamma_{i,j}]$ and c_1, c_2 are constants determined by the initial conditions. Since Γ is a stochastic matrix, it follows from the Perron-Frobenius theorem that

$$\lim_{t\to\infty} \mathbf{e}_t = c_1 \mathbf{v}_1$$

where $\mathbf{v}_1$ is the eigenvector corresponding to the unit vector, showing that a steady state exists. To see that it is interior, notice that since $e_t = \Gamma^t e_0$ and Γ^t is a stochastic matrix for any t, at each time t $e_{i,t} \in (e_{i,t-1} \wedge e_{j,t-1}, e_{i,t-1} \vee e_{j,t-1})$. □

Proposition 4: Existence of a Nash Equilibrium: Socialization Game
For any time $t \geq 0$ such that $A_t > 0$, under Assumption (1), the first-stage parental socialization game has at least one symmetric Nash Equilibrium.

Proof. Our strategy will be to choose a small enough $\epsilon > 0$ such that the restriction $G_\epsilon : [\epsilon, 1]^2 \to \mathbb{R}^2$ is a continuous self-map on $[\epsilon, 1]^2$, satisfying the conditions of Brouwer's fixed-point theorem.

The slope of the reaction function for a type i parent is given by:

$$\frac{\partial g_i}{\partial \alpha_j^*} = \frac{2A(1-\alpha_i^*)k_i(\partial k_i/\partial \alpha_j^*)(\alpha_i^*(2+k_i)-k_i)}{2Ak_i^2[1+2(1-\alpha_i^*)(1-k_i)] + D_i c''(\alpha_i^*)}$$

where $D_i = (k_i + \alpha_i(1-k_i))^4$. Since $\lim_{\alpha_j \to 0} g_i(\alpha_j) = 0$, both the numerator and denominator go to zero as $\alpha_j \to 0$, but it is straightforward to check that the denominator is a polynomial of higher order in α_j than the numerator from which it follows that as long as $c''(\alpha_i) > 0$, the slope of the best-reply function is unbounded (from above) in a sufficiently small neighborhood of zero. For each player of type i, we can therefore choose $\epsilon_1^i > 0$ small enough such that $\partial g_i(\alpha_i)/\partial \alpha_j^* > 1$ for all $\alpha_i \in (0, \epsilon_1^i)$. This condition guarantees that $g_i(\epsilon_1^i) > \epsilon_1^i$.

The Implicit Function theorem guarantees that $g_i(\alpha_j)$ is continuous on $(0, 1]$ so, in particular, the restriction on $[\epsilon_1, 1]$ is also continuous and has a minimum; as we already saw, this minimum is strictly positive. Denote by $\alpha^{m_i} = \arg\min_{\alpha_j \in [\epsilon_1, 1]} g_i(\alpha_j) \in (0, 1]$. Let $\epsilon_i = \min\{\epsilon_1^i, g_i(\alpha^{m_i})\}$, and $\epsilon = \min\{\epsilon_i, \epsilon_j\}$.[44] From the above discussion, it follows that the restriction $G_\epsilon((\epsilon, 1]^2) \subseteq (\epsilon, 1]^2$

[44]Clearly, $\epsilon_i = \epsilon_1^i$ whenever the best-reply function $g_i(\alpha_j)$ is increasing. However, Proposition (**??**) shows that g_i could be decreasing on a subset of the domain, when the condition $\alpha_i(2 + k_i) < 0$ is met. For this reason we need

is a continuous selfmap, and therefore has a fixed point. This guarantees that the parental socialization game has a symmetric Nash Equilibrium. □

Monotonicity of Best-Reply Functions in the Socialization Game

Under Assumption (1)

$$\frac{\partial \alpha_i^*}{\partial \alpha_j^*} > 0 \Longleftrightarrow \alpha_i^* > k_i/(2+k_i) \text{ for } i \neq j \in \{1,2\}$$

Proof. After total differentiation of the first-order condition, it is straightforward to show that

$$\frac{d\alpha_i^*}{d\alpha_j^*} = \frac{2A\left[(1-\gamma_i)\frac{\partial^2 \gamma_i}{\partial \alpha_i \partial \alpha_j^*} - \frac{\partial \gamma_i}{\partial \alpha_j^*}\frac{\partial \gamma_i}{\partial \alpha_j^*}\right]}{2A\left[\left(\frac{\partial \gamma_i}{\partial \alpha_j^*}\right)^2 - (1-\gamma_i)\frac{\partial^2 \gamma_i}{\partial \alpha_i^2}\right] + c''(\alpha_i)}$$

From the second-order conditions, we know that the denominator is well-defined and positive for $\alpha_k \in (0,1]$, $k = 1,2$, so we need only check the sign of the numerator. After some algebra, it can be shown to be

$$\frac{2A}{D_i}(1-\alpha_i^*)k_i\left(\partial k_i/\partial \alpha_j^*\right)(2\alpha_i^* - k_i(1-\alpha_i^*))$$

where $D_i = (k_i + \alpha_i^*(1-k_i))^4$ and $\frac{\partial k_i}{\partial \alpha_j^*} = \psi_N(1-\omega_i)\frac{\partial A_j}{\partial \alpha_j^*} > 0$, yielding the desired condition. □

Proposition 5: Comparative Statics

$\partial \alpha_i/\partial \omega_i < 0$ if and only if $2\alpha_i - k_i(1-\alpha_i) > 0$.

Proof. Totally differentiating the first-order conditions for both players we get

$$\frac{\partial \alpha_i}{\partial \omega_i} = \frac{2A\left[(1-\gamma_i)\frac{\partial^2 \gamma_i}{\partial \alpha_i \partial \omega_i} - \frac{\partial \gamma_i}{\partial \alpha_i}\frac{\partial \gamma_i}{\partial \omega_i}\right]}{2A\left[\left(\frac{\partial \gamma_i}{\partial \alpha_i}\right)^2 - (1-\gamma_i)\frac{\partial^2 \gamma_i}{\partial \alpha_i^2}\right] + c''(\omega_i)}$$

Since the denominator is positive (from the second-order condition), the sign of the partial

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to allow for the possibility that $0 < g_i(1) < \epsilon_1$, in order to guarantee that the restriction is indeed a selfmap.

derivative depends only on the sign of the numerator. After some algebra we can verify that

$$\begin{aligned}
\frac{\partial^2 \gamma_i}{\partial \alpha_i \partial \omega_i} &= (1/D_1)\,\frac{\partial k_i}{\partial \omega_i}\,(\alpha_i - k_i(1-\alpha_i)) \\
\frac{\partial k_i}{\partial \omega_i} &= -(1/D_k)\alpha_j \psi_N(\alpha_j + (1-\alpha_j)\psi_N) < 0 \\
\frac{\partial \gamma_i}{\partial \alpha_i} &= \frac{k_i}{(k_i + \alpha_i(1-k_i))^2} \\
\frac{\partial \gamma_i}{\partial \omega_i} &= \frac{-\alpha_i(1-\alpha_i)\frac{\partial k_i}{\partial \omega_i}}{(k_i + \alpha_i(1-k_i))^2}
\end{aligned}$$

where $D_1 = (k_i + \alpha_i(1-k_i))^3$, $D_k = (\alpha_j + (1-\alpha_j)\psi_N \omega_i)^2$. With these it is straightforward to check that the sign of the numerator depends on the sign of

$$(1-\alpha_i)k_i \frac{\partial k_i}{\partial \omega_i}(2\alpha_i - k_i(1-\alpha_i))$$

so that the property in the proposition holds whenever best-reply functions are increasing:

$$2\alpha_i - k_i(1-\alpha_i) > 0 \Longleftrightarrow \frac{\partial \alpha_i^*}{\partial \omega_i} < 0 \tag{21}$$

for $i = 1, 2$. These conditions correspond to the ones derived for the monotonicity of the best-reply functions. □

Data Appendix

Table 4: **Description of Control Variables**

Variables	Description	Min	Max	Mean	Median	Nobs
age	Age	12	21	16.04	16	6501
female_w1	Female Dummy	0	1	0.52	1	6503
attract_w1	Interviewer subjective assessment: Attractive	1	5	3.58	4	6494
persona_w1	Interviewer subjective assessment: Personality	1	5	3.59	4	6499
physmat_w1	Interviewer subjective assessment: Physically Mature	1	5	3.38	3	6496
build1	Type of dwelling: detached single-family house	0	1	0.75	1	6504
build2	Type of dwelling: Mobile home-trailer	0	1	0.07	0	6504
build3	Type of dwelling: Single-family row-town house	0	1	0.05	0	6504
street_w1	How well kept is the building where R lives	1	4	1.62	1	6413
street2_w1	Description of immediate area or street	1	6	2.14	2	6432
smokehh_w1	Were there signs of smoking at home?	0	1	0.21	0	6435
drinkhh_w1	Signs of drinking at home	0	1	0.03	0	6435
feel_appe	(How often, in the last week) Didn't feel like eating	0	3	0.46	0	6487
feel_mind	(How often, in the last week) You had trouble keeping your mind on what you were doing	0	3	0.81	1	6485
feel_hope	(How often, in the last week) You felt hopeful about the future	0	3	1.84	2	6475
catholic	Dummy variable for catholic denomination	0	1	0.51	1	6365
protestant	Dummy variable for protestant denomination	0	1	0.23	0	6365
none	Dummy variable for atheist/agnostic denomination	0	1	0.12	0	6365
phys_limit	Dummy for physical limitations	0	1	0.02	0	6493
work_hrs	Hours a week R works.	0	140	7.66	2	6435
adopted	Dummy variable for adopted respondent.	0	1	0.03	0	4610
tvhours	Hours a week watching TV.	0	4	2.33	2	4558
siblings_no	Number of Siblings	1	14	2.55	2	6457
work_tp_m	What kind of work does she do?	1	16	8.17	6	6101
work_mom	Does she work for pay?	0	1	0.90	1	5238
home_mom	How often is she at home when you return from school?	0	5	2.66	2	6120
warm_mom	Most of the time, your mother is warm and loving toward you	1	5	1.63	1	6119
warm_dad	Most of the time, your father is warm and loving toward you.	1	5	1.86	2	4541
indep_mom	Your mother encourages you to be independent	1	5	1.79	2	6118
talk_mom	When you do something wrong that is important, your mother talks about it	1	5	1.88	2	6120
number_chi	Which child are youthe first, the second, or what?	1	14	2.03	2	5083
quality_chi	You have a lot of good qualities	1	8	1.74	2	6504
income_par	About how much total income, before taxes did your family receive in 1994?	0	999	47.70	40	4929
bills_par	Do you have enough money to pay your bills?	0	1	0.82	1	5505
welfare_par	Last month, did you or any member of your household receive (SS,SSI,AFDC,Food Stamps,Unemployment Compensations)	0	6	0.44	0	5528

		Wave 1				Wave 2				Wave 3			
		H	W	B	A	H	W	B	A	H	W	B	A
RelImpo	Parents	0.152	0.349	0.305	0.252	0.239	0.365	0.398	0.42	0.212	0.326	0.305	0.424
		(0.07)	(0.023)	(0.046)	(0.109)	(0.107)	(0.032)	(0.056)	(0.116)	(0.096)	(0.026)	(0.084)	(0.107)
	Peers	0.836	0.564	0.673	0.686	0.75	0.635	0.451	0.558	0.691	0.656	0.674	0.626
		(0.077)	(0.057)	(0.059)	(0.146)	(0.115)	(0.046)	(0.13)	(0.137)	(0.155)	(0.048)	(0.104)	(0.106)
	Nwith	349	2658	955	93	169	1542	644	99	179	2295	640	113
	Nbet	89	124	96	55	83	116	96	58	89	124	96	58
Pray	Parents	0.192	0.239	0.203	0.378	0.219	0.208	0.215	0.417	0.094	0.271	0.389	0.251
		(0.062)	(0.022)	(0.049)	(0.119)	(0.078)	(0.029)	(0.048)	(0.148)	(0.159)	(0.039)	(0.083)	(0.171)
	Peers	0.75	0.711	0.733	0.576	0.698	0.775	0.722	0.371	0.916	0.74	0.65	0.727
		(0.084)	(0.042)	(0.071)	(0.141)	(0.114)	(0.039)	(0.073)	(0.257)	(0.143)	(0.05)	(0.089)	(0.197)
	Nwith	445	1967	761	107	292	1234	749	72	147	1671	881	113
	Nbet	89	116	96	58	89	116	96	55	83	116	96	58
Drink	Parents	-0.039	0.03	0.056	-0.102	0.035	0.061	0.131	0.118	0.039	0.12	-0.053	0.539
		(0.086)	(0.024)	(0.069)	(0.112)	(0.122)	(0.018)	(0.046)	(0.185)	(0.157)	(0.035)	(0.129)	(0.123)
	Peers	1.331	0.744	6.386	-0.957	-0.589	0.571	-0.25	-0.582	0.839	0.309	1.207	-0.073
		(0.778)	(0.274)	(43.653)	(4.74)	(8.026)	(0.229)	(0.909)	(3.16)	(0.657)	(0.561)	(0.509)	(0.344)
	Nwith	254	1813	455	115	142	2133	377	68	122	1400	355	96
	Nbet	83	116	92	55	83	124	96	55	83	115	95	58

Notes: Robust standard errors in parenthesis. Each column displays estimated parental and peer effects (α_p, α_g) for separate ethnic group-specific regressions with the following notation: Hispanics (H), Whites (W), Blacks (B), Asians (A). Samples sizes for within (Nwith) and between (Nbet) regressions are also included.

Table 5: Parental and Peer Effects Estimates

Table 6: **Significant Regressors in Peer Effect Regressions**

	Hispanic			White			Black			Asian		
	R	P	D	R	P	D	R	P	D	R	P	D
age				Y	Y							
female_w1	Y	Y	Y	Y	Y	Y		Y				
attract_w1	Y					Y		Y				
persona_w1			Y	Y				Y				
physmat_w1	Y	Y		Y					Y			Y
build1				Y		Y	Y	Y				
build2						Y	Y	Y				
build3			Y	Y	Y							
street_w1	Y		Y			Y				Y		
street2_w1									Y			Y
smokehh_w1			Y	Y	Y	Y		Y	Y	Y		Y
drinkhh_w1				Y								Y
feel_appe						Y						
feel_mind	Y						Y				Y	
feel_hope	Y			Y	Y	Y	Y	Y	Y			
catholic	Y								Y	Y		
protestant				Y				Y				
none			Y	Y	Y							
phys_limit			Y									
work_hrs			Y			Y						
adopted						Y						
tvhours					Y					Y		
siblings_no				Y			Y	Y			Y	
work_tp_m	Y		Y		Y							Y
work_mom												
home_mom						Y		Y		Y		
warm_mom			Y			Y					Y	
warm_dad	Y								Y		Y	
indep_mom									Y			
talk_mom				Y	Y							
number_chi						Y		Y				
quality_chi	Y		Y	Y			Y		Y			
income_par							Y					
bills_par				Y	Y				Y			
welfare_par			Y								Y	Y

Comparative Statics: Simulation Results

In this Appendix we solve the model numerically for different parametrizations to show several comparative static results that are difficult to get analytically. Our first result is related to the following partial derivative

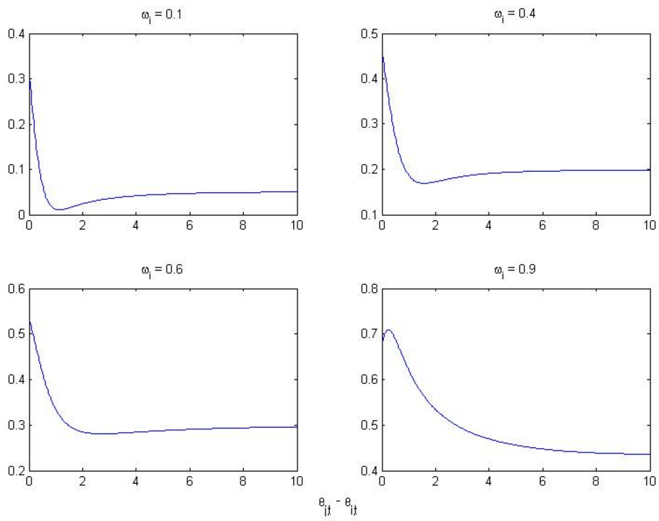
$$\frac{\partial e_{i,t+1} - e_{i,t}}{\partial(\tilde{e}_{-i,t} - e_{i,t})} \quad = \quad (1 - \gamma_{ii,t+1}) - (\tilde{e}_{-i,t} - e_{i,t})\frac{\partial \gamma_{ii,t+1}}{\partial(\tilde{e}_{-i,t} - e_{i,t})} \tag{22}$$

In Figures (12) and (13) we plot numerical partial derivatives as function of the parental differences $e_{-i,t} - e_{i,t}$ for four different plausible population shares. In order to do so we solve numerically the parental socialization problem

$$\max_{\alpha_{i,t+1}\in[0,1]} -\kappa(e_{i,t} - e^{*}_{i,t+1}(\alpha_{i,t+1}))^2 - c(\alpha_{i,t+1})$$

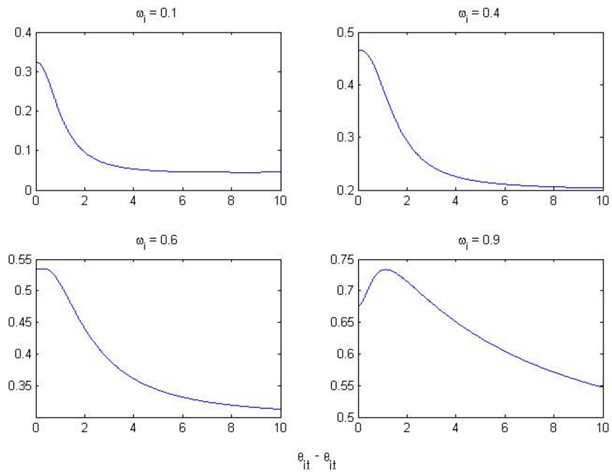
assuming $\kappa = 1$ and assuming $c(\alpha) = 0.5k\alpha^2$, with $k = 1$. Recall that for fixed $A_t = \kappa(\tilde{e}_{-i,t} - e_{i,t})^2$ smaller values of k make the marginal cost of exerting a larger socialization effort relatively smaller, which itself implies that parental best-reply functions will be monotonic increasing. By assuming a larger value of k we are in effect assuming a larger deviation from the pure-selfishness assumption used for parents.

Figure 12: $\frac{\partial(e_{i,t+1}-e_{i,t})}{\partial(e_{i,t}-e_{j,t})}$: case $(e_{i,t} - e_{j,t}) > 0$



Figures (14) and (15) plot estimated second partial derivatives making the same parametric assumptions, but considering a different set of population shares. Our selection is motivated by the fact that these are better approximations of actual population shares in our data, and these

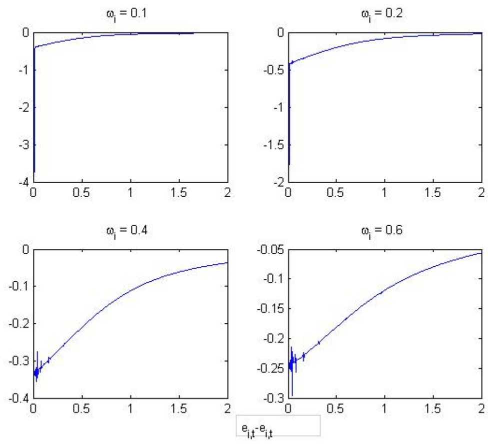
Figure 13: $\frac{\partial(e_{i,t+1}-e_{i,t})}{\partial(e_{i,t}-e_{j,t})}$: case $(e_{i,t}-e_{j,t})<0$



have an important effect on the sign of the effect. Importantly, the signs of these and the previous simulations do not depend crucially on the parameter values assumed for the cost function.[45]

$$\frac{\partial^2(e_{i,t+1}-e_{i,t})}{\partial(\tilde{e}_{-i,t}-e_{i,t})^2} = -2\frac{\partial\gamma_{ii,t+1}}{\partial(\tilde{e}_{-i,t}-e_{i,t})}-(\tilde{e}_{-i,t}-e_{i,t})\frac{\partial^2\gamma_{ii,t+1}}{\partial(\tilde{e}_{-i,t}-e_{i,t})^2}$$

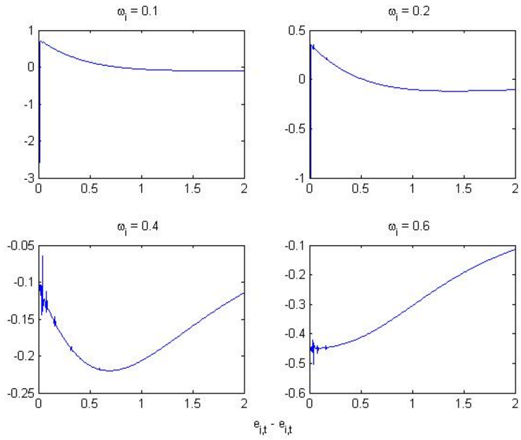
Figure 14: $\frac{\partial^2(e_{i,t+1}-e_{i,t})}{\partial(e_{i,t}-e_{j,t})^2}$: case $(e_{i,t}-e_{j,t})>0$



We now turn to the effects that the own ethnic group's population share ω_i has on the parental-child deviations. In Figures (16)-(17) the second partial derivative of parental-child differences with respect to the population shares, for different parameter values of k in the cost

[45]Matlab programs available upon request.

Figure 15: $\frac{\partial^2 (e_{i,t+1} - e_{i,t})}{\partial (e_{i,t} - e_{j,t})^2}$: case $(e_{i,t} - e_{j,t}) < 0$



function, for the the cases where $(e_{j,t} - e_{i,t})$ is positive and negative, respectively. Analytically, this can be found by differentiating the following equation with respect to group i's population share:

$$\frac{d(e_{i,t+1} - e_{i,t})}{d\omega_i} = -(e_{j,t} - e_{i,t}) \left(\frac{\partial \gamma_{i,t+1}}{\partial \omega_i} + \frac{\partial \gamma_{i,t+1}}{\partial \alpha_i} \frac{\partial \alpha_i}{\partial \omega_i} + \frac{\partial \gamma_{i,t+1}}{\partial \alpha_j} \frac{\partial \alpha_j}{\partial \omega_i} \right)$$

As both figures show, departures from the pure-selfishness assumption (larger k's) generate a wider variation in the sign of the second partial derivative. In particular, a unique sign is consistent only with a small k, and the larger the deviation the wider the range over the population shares where there is a change in sign. Also important is the fact that for a large subset of possible population shares, the second partial derivative is close to zero.

Figure 16: $\frac{\partial^2 (e_{i,t+1} - e_{i,t})}{\partial \omega_i^2}$: case $(e_{j,t} - e_{i,t}) > 0$

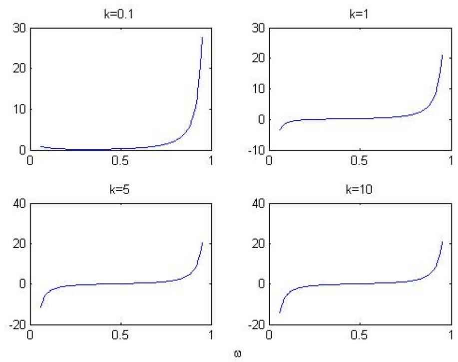
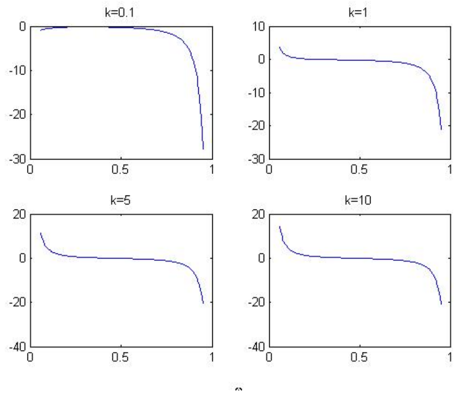


Figure 17: $\frac{\partial^2(e_{i,t+1}-e_{i,t})}{\partial\omega_i^2}$: case $(e_{j,t}-e_{i,t})<0$



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