

Altruism vs. Exchange in Intergenerational Transfers: New Evidence from Children's Health Care *

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Abstract

Altruism and exchange are competing hypothesis on the nature of intergenerational transfers. A better understanding of this issue is key to several topics in Public Economics. In this paper, we analyze the role of income as a determinant of parents' care for children. We show that this role is affected by which of the two paradigms on the nature of parent-to-child transfers is adopted. Then, we develop a test to discriminate between these alternatives. Unlike previous approaches, such a test focuses on measures of parents' effort on children care which are essentially non-monetary. Using data from the U.S., we find a negative relationship between family income and frequency of children emergency room utilization which cannot be explained by several alternative controlling factors. In our framework, this is interpreted as evidence against the null of prominently altruistic behavior. Similar results are found for the case of home-accident preventive care and for data on infant mortality rates.

Keywords: Intergenerational Transfers; Altruism and Exchange Motivations; Child Health.

JEL classification: D64, D91, I12, J13.

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1 Introduction

Understanding the determinants of the transfers between parents and children is an essential issue in several prominent fields of Economics. For instance, in some models of Public Economics these transfers have important consequences regarding the financial impact of taxes on Social Security systems because the determinants of savings by families cannot be fully understood without considering the economic links between them. In other topics such as economic growth, investment in human capital or income distribution, a better understanding of the nature of this relationship is essential.

There are two main paradigms regarding this intergenerational linkage and economists have not yet reached agreement as to which of them describes the behavior of families more accurately. If children's welfare enters directly into the preferences of their parents, (Barro, 1974; Becker, 1974,1991), intergenerational transfers in the form of *inter vivos* or *post mortem* compensatory transfers arise (Altonji, Hayashi and Kotlikoff 1997; Cox and Rank 1992). We will refer to this approach as the *altruistic model*¹ henceforth. On the other hand, if parents expect some type of return from their children when they are old, they have an incentive to make transfers and invest in the human capital of their children (see Bernheim, Shleifer and Summers, 1985 or Cox, 1987). We will refer to this approach as the *exchange model*.

These two paradigms generate different predictions concerning several issues in the household economy. For this reason, an important point of the research agenda in economics is to discriminate between the two paradigms on the basis of the observed behavior of families (Altonji et al., 1997). Some papers analyze monetary transfers such as bequests (Tomes, 1981) or gifts (Menchik, 1980) or investment in human capital such as education for children. Their results are however inconclusive because it is hard to distinguish which part of these transfers are a reaction to market imperfections rather than being motivated purely by altruistic behavior.

This paper follows a different approach: we focus on parental actions which are mostly non-monetary such as taking the child to the emergency room (ER, henceforth) when a sudden symptom of poor health is observed or the decision of adopting some simple and cheap home-accident preventive measures. If these actions are similarly costly for rich and poor, we show that

¹In the context of our paper, the "joy of giving" approach in, for example, Andreoni (1989) and Hurd (1989) is equivalent to the *altruistic approach* of Barro (1974) and Becker (1974,1991).

the relationship between the frequency of such actions and family income is affected by the prevailing assumption on the type of intergenerational linkage. Thus, if parents are altruistic, rich households take their children to the ER more often than poor ones, whereas the opposite could be observed if parents' actions are driven by exchange motivations. By focusing on non-monetary actions, we expect to reduce the distortion in parent-to-child transfers in education or bequests induced by the income effect.

Since we use frequency of child ER utilisation or home-accident preventive care, we can exploit information from data bases which have not been used for this purpose until now. Our main data source is the 1999 and 2000 National Health Interview Surveys (NHIS, henceforth). This survey provides a rich source of information on the socioeconomic and health conditions of a large number of US families. Exhaustive Information on socio-economic and health conditions of families is important since the robustness of our results is sensitive to an appropriate control of alternative explanatory factors, such as ex-ante health status or ease of access to care services. Then, we propose an ordered-choice in latent counts model of ER frequency utilization. Using the NHIS data, we find that poor parents use the ER services more often even after we control for as many alternative explanations as we can. Furthermore, the data is consistent with a theoretical prediction of the exchange model, namely, that the differences in the use of ER services between rich and poor should be smaller in economies with a low level of social mobility.

A secondary data source is used to cross-check the results above. We used data from the National Survey of Early Childhood Health (NSECH, henceforth), to compute the number of inexpensive actions that parents take in order to prevent accidents at home. The results show again that there is a negative relationship between the number of such actions taken by families and their income level.

Finally, we obtained infant mortality data from the 1988 Maternal and Infant Health Survey (MIHS henceforth) and we identified a number of serious diseases whose prevalence is well-known to be independent of income. One should expect that if our previous results in support of the exchange model are correct, infant mortality rates in these pathologies should be lower in poor families. The evidence shows that though this is the case, the low mortality caused by these pathologies among the U.S. infant population, makes the difference statistically non-significant.

As a conclusion, the evidence shows that the observed behavior of parents cannot be explained using the altruist model. However, we cannot reject the

exchange model as an explanation of parental attitudes. Needless to say, the reader should not interpret this claim as equivalent to saying that altruism is absent in the relationship between generations. On the contrary, a careful reading of our results leads to the conclusion that both altruism and exchange motivation are present in society, but the latter plays an essential role in explaining some of the actions taken by parent regarding their children's health.

The rest of the paper is structured as follows. In section 2 we propose a theoretical model which tries to explain the role of income as a determinant of parents' willingness to take an action. In section 3, we derive an empirical test of the null of altruism using data from child ER utilization by U.S. families. The main result is cross-tested in section 4 now using data from home-accident preventive care and infant mortality rates in U.S. Section 5 presents the main conclusions and future research agenda.

2 The Theoretical Model

We propose a simple theoretical model to explain the role of income and intergenerational linkages in children care. We consider families consisting of one parent and a single child.²

Individuals live for two periods. In the first period, the child is a minor and the parent is the only one who works and consumes. There is neither saving nor borrowing for the next period, so that the parent in the first period consumes their whole current income, y_p . During this first period the child might show symptoms potentially indicating a fatal illness. Let us write $r = 1$ if the child gets the disease and $r = 0$ if she does not. Parents do not observe r but rather an informative signal $s \in [0, 1]$. This signal can be thought of as fever or other general symptoms which do not clearly identify the pathology of the child. We denote the (subjective) probability that the child has the disease conditional on observing signal s as $P(r = 1|s) \equiv p(s)$, where the function $p(s)$ is increasing in s . Thus, the higher the fever, the more likely it is that the child has a serious health condition such as, for

²Note that this assumption is inherently implying that in the model, fertility is completely predetermined and equal to one child per adult. A model where fertility is endogenous and simultaneously determined with children care would make the analysis much more complex and would probably yield similar results.

example, meningitis³.

Having observed the signal s , the parent must decide whether or not to take the child to the ER. Taking the child to the ER requires an effort by the parents of magnitude e . This effort is assumed to be nonmonetary and equal for rich and poor families. The reader might claim that this assumption is unrealistic as rich and poor families should face a dissimilar value of e due to differences in ease of access to the health system or differences in the shadow price or opportunity cost of time. Since our main objective for this section is to obtain implications which can be tested with sample data, the first problem can be treated in the empirical part if the information in the sample allows to control for differences in ease of access, i.e., information on insurance benefits or distance to the nearest hospital. However, with respect to the differences in the shadow price of time the problem from the empirical point of view is that this variable is generally unobservable and therefore we cannot control for it. On the one hand, the shadow price of time for the rich is higher than for the poor and thus, the effort e is higher for rich families. On the other hand, rich people have access to baby sitters and often enjoy of more flexible job-schedules and day-care facilities and thus, rich families should use less of their (more valuable) time. Unfortunately, we are not aware of any evidence that help us to decide which of the two effects prevail. Since both can be present, we consider that income is not determinant for the cost e in principle.

In the second period, the child's health status is realized. If during childhood she had the disease but she was not treated, it is assumed that she becomes disabled in economic terms. This means that the child is unable to have an independent productive life and disappears as an economic agent. If, by contrast, she did not have the disease or if she did but was treated, the child grows and becomes a healthy adult. In this latter case, both the parent and the child work and consume during this second period. Children are endowed with an income y_d which is random with expected value \bar{y}_d . For the

³Pathologies like meningococcal infection, septicemia, meningitis, pneumonia, acute bronchitis and similar, normally appear associated to mild symptoms but they are often fatal if parents do not act soon enough. One can obtain crude estimates of $p(s)$, i.e., the probability of death after receiving a signal from one of these spells, using data from the National Vital Statistics Report, 2001, and from other sources in the National Center for Health Statistics. Using these data we find that the probability is around 1/1000 on average. The details of how this estimate was computed are available from the authors upon request.

sake of simplicity, it is assumed that this income takes the value $y_d^H = \varepsilon_H \bar{y}_d$ with probability $1 - \alpha$ and the value $y_d^L = \varepsilon_L \bar{y}_d$ with probability α , where $\varepsilon_L < 1 < \varepsilon_H$ and then $\bar{y}_d = (1 - \alpha)y_d^H + \alpha y_d^L$. It should be noted that all the results in the paper can also be obtained adopting a deterministic approach in which $\varepsilon_L = \varepsilon_H = 1$. Introducing a stochastic component, however, does not increase the complexity of the model substantially but does help to make the interpretation of the model more clear. Moreover, we assume that the expected income \bar{y}_d depends on the parents' income \bar{y}_p and is given by $\bar{y}_d = v(\bar{y}_p)$ where the function v is increasing and concave.⁴ Note that child's income in the second period is implicitly dependent on the child's condition and parental health expenditure during the first period, her income being exactly zero if she does not survive.

We also assume that the parents' income in the second period is deterministic and of the same magnitude as their income in the first period, i.e. y_p . This assumption is made without loss of generality and similar results could be obtained in a model with economic growth where the parent's income in the second period is stochastic. Also during this second period, monetary transfers are allowed between the parent and the child. To concentrate the analysis on the interesting cases, assume that $y_d^H > y_p$ and $y_d^L < y_p$.⁵

The only decision variable of parents is whether to take their child to the ER when they observe s or not. Such a decision is made on the basis of two possible alternative consequences of their action:

- *Pure altruism*: Parents love their children and care about their welfare, so they want them to reach adulthood in optimal health.
- *Exchange model*: Parents are selfish and they derive utility only from their own consumption. However, they know they may receive help from their children in the future.

Casual observation and introspection indicate that both motives are present in current societies. The question is whether one of the two factors dominates

⁴Mulligan (1997) provides a discussion on this assumption and a survey on the empirical estimation of the function v .

⁵This assumption together with the previous one on ε_L and ε_H implies that $\varepsilon_L \leq \frac{y_p}{v(y_p)} \leq \varepsilon_H$ for all y_p . It will be assumed that $v'' \leq 0$. In this case, the expression $\frac{y_p}{v(y_p)}$ is not upper bounded. This is not a problem for the existence of ε_H if there is a maximum income level of, say, 500,000, i.e., in principle, transfers between the parent and the child can go either way in the second period.

the other and whether the above model allows us to build an implementable test of this question.

2.1 The Altruistic Case

Altruistic parents, (Barro, 1974; Becker, 1974,1991), care about the (future) welfare of their child, so they may be willing to make effort e during the first period so that the child has a healthy life in the second period. Moreover, by raising a healthy descendent, the possible transfers that they might give to the child in the second period will increase the parent's own welfare. Let $b \geq 0$ be the monetary transfer given to the child in the second period.⁶ The budget constraint imposes that $b \leq y_p$. Parents care about their own consumption during the first and second period and their child's consumption in the second period. Let $u_p(\cdot)$ be the utility function of the parent in their second period of consumption, and $u_d(\cdot)$ be that of her child regarding the child's own consumption (also in the second period). These utility functions are assumed to have all the standard properties. Therefore, the parent evaluates the consumption of the child (say c_d) and her own consumption (say c_p) according to $U(c_p, c_d) = u_p(c_p) + \beta u_d(c_d)$ where β is the degree of altruism towards the child. Notice that we have dropped the first period consumption from the parent's decision problem because our model does not allow for saving, the child does not consume in the first period and cost e is non-monetary. The parents will give transfer $b > 0$ to the child if her income is y_d^L , and $b = 0$ if it is y_d^H . We assume that parents do not want to give transfers to their child when the child is richer, i.e., when the child has income $y_d^H > y_p$.⁷

Thus, with probability α the child gets income y_d^L and her consumption is $y_d^L + b$ in the second period while her parent's consumption is $y_p - b$. With probability $1 - \alpha$ the child gets income y_d^H and there are no transfers. Notice that our definition of altruism is one-sided. The case of two-sided altruism in which the child also cares about the utility of the parents is not

⁶In our model b is an *inter vivos* transfer. In a more general model this transfer could also be a bequest.

⁷This is assumed for the sake of simplicity. If the degree of altruism towards the child is very high, parents may want to transfer even when the adult child is rich. However, our main result concerns the decision of the parents in the first stage: parents have to decide whether to take their child to the ER or not. Since this decision is taken in the first stage and since (due to the decreasing marginal utility) the size of the bequest decreases with the adult child's income, the assumption does not alter our results.

considered here since it would yield a result (with respect to the parent's behavior) similar to the one provided in the exchange case considered in the next section.

If parents exert effort e , the child will be healthy in the second period and the maximum expected utility parents get is the solution to ⁸

$$\max_b \alpha U(y_p - b, y_d^L + b) + (1 - \alpha)U(y_p, y_d^H) - e. \quad (1)$$

An interior solution to (1) satisfies the first order conditions:

$$\beta = \frac{u'_p(y_p - b)}{u'_d(y_d^L + b)} \quad (2)$$

If parents decide not to take the child to the emergency room, then, with probability $[1 - p(s)]$ the child survives and the parent's expected utility is $\alpha U(y_p - b, y_d^L + b) + (1 - \alpha)U(y_p, y_d^H)$. Otherwise, with probability $p(s)$ the child dies and parents get utility $u_p(y_p)$. Thus, the maximum expected utility if parents do not take the child to the ER is the solution to,

$$\max_b (1 - p(s)) (\alpha U(y_p - b, y_d^L + b) + (1 - \alpha)U(y_p, y_d^H)) + p(s)u_p(y_p) \quad (3)$$

Note that the solution to (3) is also given by condition (2). Let b^* be the solution to (2). This solution b^* depends on the parameters y_p and y_d^L . However, the income of the child is given by $y_d^L = \varepsilon_L v(y_p)$ so that b^* is simply a function of y_p . We want to determine the values of the signal s for which parents will take the child to the ER. The level of s^* that renders parents indifferent between taking the child to the ER or not is obtained by solving the following equation:

$$\begin{aligned} & \alpha U(y_p - b^*, y_d^L + b^*) + (1 - \alpha)U(y_p, y_d^H) - e \\ & = (1 - p(s)) (\alpha U(y_p - b^*, y_d^L + b^*) + (1 - \alpha)U(y_p, y_d^H)) + p(s)u_p(y_p) \end{aligned} \quad (4)$$

⁸Apparently, there is time-inconsistency in the way we model parents' expected utility. The cost of taking the child to the ER, e , takes place in the first period and the utility $\alpha U(y_p - b, y_d^L + b) + (1 - \alpha)U(y_p, y_d^H)$ occurs in the second period. Nothing would change, however, if we adopt the correct specification of the expected utility function $\gamma [\alpha U(y_p - b, y_d^L + b) + (1 - \alpha)U(y_p, y_d^H)] - e$, where γ is the time discount factor. Notice also that in (1) the amount of the transfer b is decided in the first period. It is straightforward to see that this amount is also optimal in the second period, thus in fact, there is no time inconsistency.

The left-hand term in (4) represents the parents' utility when the child is taken to the ER and the right hand term the utility when the child is not taken to the ER. Since this value of s is a function of income y_p we write it as $s^*(y_p)$. Thus, the child is taken to the ER whenever $s \geq s^*(y_p)$.

Proposition 1 *The function $s^*(y_p)$ is decreasing. Thus, in the Altruistic model, the richer the parents are the more often they take their children to the ER.*

(The proof is provided in the Appendix).

The intuition is simple: the welfare of a child enters into the preferences of the parents as a normal good. Rich families will value more the chance of giving bequests to their children so they will be more ready to pay cost e . This cost is the same for rich and poor families so rich families will cross the hurdle more often and will make a more intensive use of ER services.

2.2 The Exchange Case

Apart from altruism as exposed in the previous section, there may be another motivation for parents to rush to the ER when observing a signal s . If her child becomes an able adult, the parent may receive resources from her in the second period. This will be the case if the welfare of the parents enters into the utility function of the child, but can also be the result of some social norm that obliges children to give resources to parents under certain circumstances. This is what we consider as *exchange* motivations. In models with uncertainty about lifespan it is often assumed that transfers from children to parents are part of a *quid pro quo* agreement between parents and children. Parents leave a bequest in exchange for receiving financial (or emotional) support until they die. See Kotlikoff and Spivak (1981), Cox (1987) or Bernheim et al. (1985). Our model differs in that parents do not make transfers or promises of transfer to their adult children. Moreover, they cannot control the probability of their children being rich or poor (i.e., the α) since this probability is exogenously given. This precludes the possibility that parents have an incentive to raise living but poor children whose time and dedication could be bought at a lower price.

Let us assume that in the second period parents receive the amount $h \geq 0$, if the income of the child is y_d^H and the amount $h = 0$ whenever the income of the child is y_d^L . Thus, parents expect to receive a transfer only when their

income is smaller than their child's income.⁹ It is natural to assume that, in principle, the magnitude of h depends on the parent's income, y_p , relative to their child's, y_d^H . Since $y_d^H = \varepsilon_H v(y_p)$ the amount h can be seen as a function of y_p , and we write it as $h = h(y_p)$. It is not difficult to realize that our results will depend on the assumptions adopted regarding the function $h(y_p)$.

Parents do not care about the consumption level of their child, and their preferences depend exclusively on their total consumption (which is their income y_p plus the amount h given by the child) and the possible effort of taking the child to the ER. Thus, the expected utility (computed at the first period) that parents get if they take the child to the ER is

$$(1 - \alpha)u_p(y_p + h(y_p)) + \alpha u_p(y_p) - e \quad (5)$$

If the child is not taken to the ER her probability of death is $p(s)$ and the parent will receive nothing. Thus, in this case parents' expected utility after receiving signal s is given by

$$(1 - p(s))((1 - \alpha)u_p(y_p + h(y_p)) + \alpha u_p(y_p)) + p(s)u_p(y_p) \quad (6)$$

Let \tilde{s} be the value of the signal that makes (5) equal to (6), i.e., such that

$$u_p(y_p + h(y_p)) - u_p(y_p) = \frac{e}{(1 - \alpha)p(\tilde{s})} \quad (7)$$

Since \tilde{s} in (7) depends on the income y_p we also write $\tilde{s}(y_p)$. Thus, parents are indifferent as to whether they take the child to the ER or not when the signal s takes the value $\tilde{s}(y_p)$, and they prefer to take the child to the ER whenever $s > \tilde{s}(y_p)$. We want to analyze the sign of $\tilde{s}'(y_p)$, the derivative of $\tilde{s}(y_p)$ with respect to the income y_p . It is clear from equation (7) that this sign depends on the specific function $h(y_p)$. Consider, for instance, the case in which the transfers from child to parents do not depend on the parents' income level so that $h(y_p) = \bar{h}$ for all y_p . In this case, it is straightforward to show that, by concavity of the utility function $u_p(\cdot)$, the expression $u_p(y_p + \bar{h}) - u_p(y_p)$ is decreasing in y_p and, since $p(\tilde{s})$ is increasing, equality (7)

⁹Thus, the analysis becomes relevant only if the income, or the wealth, of the parents is below the income of the child at a certain point in time not too close to their death. In the USA the average wealth at age 50 is higher than the average wealth for people over 65. See Budriá-Rodríguez, Díaz-Giménez, and Rull (2002).

implies that $\tilde{s}'(y_p) > 0$. The same result holds true for the case of decreasing transfers, i.e. when $h'(y_p) < 0$. Thus, we have a second result:

Proposition 2 *In the exchange case, if the transfers from children to parents are non-increasing in parent's income, i.e. if $h'(y_p) \leq 0$, we have $\tilde{s}'(y_p) > 0$. Thus, the richer parents are the less often they take their children to the ER.*

One might claim, however, that the most realistic case is the one with $h'(y_p) > 0$. This might happen if rich parents have a rich child and transfers from children to parents are given by an increasing function in the child's income. In this case, to obtain that $\tilde{s}'(y_p) > 0$ the term on the left-hand side in equation (7) must be decreasing on y_p , i.e. $u'_p(y_p + h(y_p))(1 + h'(y_p)) - u'_p(y_p) < 0$, and this inequality can be written as

$$1 + h'(y_p) < \frac{u'_p(y_p)}{u'_p(y_p + h(y_p))} \quad (8)$$

Inequality (8) may hold depending on the value of $h'(y_p)$. It is quite easy to provide (generic) examples of specific utility functions and specific functions $h(y_p)$ satisfying this inequality and, as a consequence, we can easily obtain examples with $\tilde{s}'(y_p) > 0$.

An important case is that in which the transfer from the child to the parents is endogenously determined as the solution to the maximization problem of the child.¹⁰ When the child gets income y_d^H she will choose the level of transfer to her parents that maximizes a weighted sum of her own utility and that of her parent's:

$$\begin{aligned} \max_h & : u_d(\varepsilon_H v(y_p) - h) + \delta u_p(y_p + h) \\ \text{s.t.} & : h \geq 0 \end{aligned} \quad (9)$$

where δ is the degree of altruism from the child to the parents. Consider the class of utility functions given by $u(x) = \frac{x^{1-\theta}}{1-\theta}$. It is not difficult to show that in this case the solution to the maximization problem (9) is given by

$$h = \text{Max}\left\{0, \frac{\varepsilon_H v(y_p) - \delta^{\frac{-1}{\theta}} y_p}{1 + \delta^{\frac{-1}{\theta}}}\right\}.$$

¹⁰See Boldrin and Jones (2002) for an explicit solution to this problem and Cox and Stark, (1994) for an explanation of the enforcement of this intergenerational agreement.

Let us assume that the solution to (9) is interior¹¹ so that

$$0 < \frac{\varepsilon_H v(y_p) - \delta^{\frac{-1}{\theta}} y_p}{1 + \delta^{\frac{-1}{\theta}}}.$$

Thus, condition (8) becomes

$$1 + \varepsilon_H v'(y_p) < (1 + z)^{1+\theta} \left(\frac{y_p}{\varepsilon_H v(y_p) + y_p} \right)^{-\theta} \quad (10)$$

Assume that the expected income of the child is given by an increasing, concave function on parents' income, namely $v(y_p) = ky_p^\gamma$ where $k > 0$ and $0 < \gamma < 1$. Thus, condition (10) becomes

$$0 < -1 - k\gamma y_p^{\gamma-1} + (1 + \delta^{\frac{-1}{\theta}})^{1+\theta} \left(\frac{y_p}{\varepsilon_H k y_p^\gamma + y_p} \right)^{-\theta} \quad (11)$$

Inequality (11) can hold or not depending on the values of the parameters. However, it is easy to provide robust examples satisfying such inequality. Consider an economy with the following realistic values of the parameters: the utility discount factor $\delta = 0.45$; the degree of relative risk aversion $\theta = 2$, and $k = 20$; $\varepsilon = 1.25$ and $\alpha = 0.5$. Thus, with probability 0.5 the child will end up with an income 25% higher than her expected income. Let us take the specific function $p(s) = s$. The transfer from the child to the parents is given by the solution to the maximization problem (9). We compute the critical value $\tilde{s}(y_p)$ for three different values¹² of the parameter $\gamma \in \{0.4, 0.5, 0.6\}$, and parent's income levels ranging from zero to $y_p = 40$. Figure 1 shows the results. In all three cases function $\tilde{s}(y_p)$ is increasing. We must emphasize that this example is quite robust to changes in all the parameters.

Thus, we conclude that when function $h(y_p)$ is not chosen *ad hoc* but is the result of the maximization problem of the children, the result provided in Proposition 2 holds for a (large) set of parameters. The intuition is also clear.

¹¹It might happen that the unrestricted solution to problem (9) is such that $h < 0$. This means that the child would like to get transfers from the parents. If we allowed for this possibility, or considered corner solutions with $h = 0$, it would reinforce our results. If function g is concave, as is often assumed, corner solutions may appear for rich families. The child of a rich family is, in relative terms, poorer than her parents so that she would like to get transfers from them. Thus, from the point of view of rich parents the child will not report any positive return in the future and, as a consequence, their incentives to invest in the health of the child are lower than for poor families.

¹²See, for example, Mulligan (1997) for the empirical estimations of this parameter.

Parameter γ can be seen as an index of social mobility. Most estimates of this parameter give a value always less than unity (Benabou, 2002), so that function $v(y_p)$ is concave. This implies that, in expected terms, the child of a rich family will become relatively less rich than the parent. Thus, investing in the child yields a higher return in poor families than in rich families. In other words, in an economy with social mobility where parents contemplate their offspring as an asset for the future, children are more valuable to poor families than to rich families. This discussion and the example in Figure 1 also suggest that in societies with a high level of social mobility (low values of γ) function $\tilde{s}(y_p)$ will be flatter. In the empirical section of the paper we will show some evidence supporting this possible relationship between social mobility and the slope of $\tilde{s}(y_p)$.

A key feature of this approach is the expectations that parents have about receiving help from their children. One might ask whether in reality these expectations are rational or not. In other words, do parents really get help from their children? Fortunately, there is some empirical evidence showing the nature and size of this type of transfer. McGarry and Schoeni (1995) analyze the 1992 Health and Retirement Study and show that 7 percent of the parents receive an average transfer of \$2.120. Rendall and Bahchieva (1998) argue that without transfers from children (and relatives and friends), the US elderly poverty rate would be double. Using data from the 1988 wave of the PSID Couch, Daly and Wolf (1999) show that transfers to parents decrease with parent's wealth. Thus, transfers from children to parents in the U.S. play an important role for a significant number of families. However, it is also true that transfers flow in the "downward" direction for most families in the sense that parents provide more money and time to their child than they receive later on in life, and this downward flow seems to be more common among rich parents. Indeed, our model predicts that parents in relatively rich families should not expect to receive transfers from their children, since the expected income of a child in a family with above mean income is lower than his parent's income. This feature is key to understand our main result. Under the exchange framework, richer parents do not expect much transfers or help from their kids. Poorer parents, on the contrary, expect their children to help them in the future. Thus, beside the common interest all parents have on the health of their children, poor parents have an additional incentive to invest in the health of their children, which explains why income and frequency of ER utilization is negatively related.

3 Empirical evidence from ER utilization

The main conclusion of the above section is that under the altruism hypothesis, mild symptoms will prompt rich parents to take action while poor parents will need to observe a stronger signal of illness. On the other hand, under exchange motivations, the opposite may be true, i.e., rich parents would need to observe a more severe signal than poorer ones. Thus, our purpose is to test the sign of the slope between the signal threshold $s(y_p)$ and family income. Notice that the exchange model may well support either a positive or negative slope depending on other factors, such as social mobility or, equivalently, the degree of concavity of the children-parents income function. Thus, our test contemplates the altruistic paradigm as the null, while the alternative is considered to contain the exchange model. Further testing of the null of the exchange model cannot rely exclusively on the sign of this slope and would require the development of new testable predictions.

Now we address the question whether such a procedure is empirically testable. In principle, the signal threshold that makes parents indifferent between taking action or not is not observable and we can not perform a test based on the slope of the function $s(y_p)$ with respect to income. Let us now imagine a world where the probability of falling sick or the ease of access to health care is not affected by income. Under this assumption, the sign of the slope of $s(y_p)$ should be the same as the one between the frequency of parents' actions and their income, since parents with a lower signal will be more often prompted to exert effort e and thus will take action more frequently.

It is important to stress that this action or effort that parents take is not only represented by ER utilization and may involve things such as ensuring adequate nutrition, paying visits to the doctor, making sure children put their seat belts on, and others (see for example Case-Paxson, 2000). In any case, these are all observable actions, and so an estimate of how they are affected by family income is achievable. In the next section we consider other alternative measures, but here we concentrate mainly on the action of taking the child to the ER, as presented in the theoretical model.

We think that this action represents most accurately the type of non-monetary effort and risk that we describe in the model: parents may face a fatal outcome if they do not take a decision quickly and the use of ER services for children is a non-monetary or at least, low cost option for insured families. Moreover, there exist excellent health surveys like the National Health Inter-

view Survey (NHIS) from the National Center for Health Statistics,¹³ which provide empirical data on the use of the ER and the socioeconomic characteristics of families. One important drawback is that our test is based on the assumption that the probability of falling sick or facing access barriers is not affected by family income. This assumption has proved to be unrealistic for the U.S. in many studies (Case, Lubotsky and Paxson, 2002, Currie and Reagan, 1998, Currie and Moretti, 2003). Our approach is then to control as much as possible for the distortion of these factors by introducing regressors in the model. Also, we must consider that there might be alternative actions, such as doctor's office visits and regular infant check-ups which could be substitutes for ER utilization particularly for some low-income groups which have not open access to these alternatives. And a minor technical difficulty is that the estimation of health demand often requires the use of non-linear models. How we deal with all these issues will be made clear in the following sections.

3.1 The NHIS sample data: an overview

The basic purpose of the National Health Interview Survey (NHIS) is to obtain information from U.S. families on the amount and distribution of illness, its effects in terms of disability and chronic impairments, and the kind of health services received. Data are collected on a yearly basis from a sample of households across the 50 states and structured into three layers of information requested at household, family and personal levels.¹⁴ From each household with non-adult members a sample child is selected and the family respondent is prompted to answer about the child's health status and disabilities.

A total of 13,500 families with children were interviewed in year 2000 and 12,500 in 1999. Central to our interests is the ER variable which contains recorded information on the frequency of emergency room visits by the sample

¹³Data available at website <http://www.cdc.gov/nchs>.

¹⁴The NHIS Basic core questionnaire was redesigned in 1997. The surveys are conducted by U.S. Census Bureau interviewers, who use a computer-assisted procedure instead of traditional paper-and-pencil forms. The sample design includes stratification, clustering and multistage sampling. No-one in the population covered has a zero probability of being sampled but Black and Hispanic households are slightly oversampled to increase the power of testing. For further details see the NHIS website <http://www.nhis.cdc.gov>.

child. The recoding changed from 1999 to 2000. In 2000, codes 1 to 9 corresponded to 0, 1, 2–3, 4–5, 6–7, 8–9, 10–12, 13–15 and more than 16 visits, while in the 1999 sample, codes 1 to 5 corresponded to 0, 1, 2–3, 4–9, 10–12 and more than 13 visits.

The information on income was also recoded in income intervals and the income/poverty level ratio. Measurement errors can be reduced by using recoding, but it makes elasticity harder to estimate. For this reason, we computed an estimate of family income in dollars using the original coded variables and additional information from the U.S Census Bureau for years 1999 and 2000. For each individual in the NHIS sample we compute the average income of families in the US Census Bureau data who match their income category, age, education and race. Qualitative results are not affected by the use of the original or the attributed income measures and the choice of the latter is solely for the purpose of obtaining an elasticity measure in dollars that can be more readily interpreted.

Table 1 constitutes a first approach to the data. We compute a cross-frequency matrix between ER and income for the year 2000. Of the 5,736 children that never went to the emergency room, 1,702 live in families earning more than USD \$75,000, 1,134 in families earning between 55,000 and 75,000, 1,334 in families earning between 35,000 and 55,000 and 1,566 in the category of less than USD \$35,000. Of the families in the top income category, 82.82% never visited the ER. This contrasts with the figure of 77.37% for the poorest. Moreover, if we consider those families that went at least once to the emergency room, the low-income ones tend to show longer tails of frequency counts: for instance, of the 49 children that went four or five times to the ER, 18 lived in families earning less than USD \$40,000 while only 11 fell in the category of more than USD \$75,000.

3.2 Choice of regressors and case selection.

The figures in Table 1 do not constitute a valid test of the altruistic hypothesis versus the alternative of the exchange model because we do not control for many factors that may affect the correlations. Some of them have already been mentioned. For instance, there are uninsured people in this sample who do not face a non-monetary cost when willing to use the ER. Also, poor children have worse health conditions than rich children (even ex-ante, see Case and Paxson, 2002), and thus they will use the ER more frequently. Rich children are likely to have options other than the emergency room and this

make less use of emergency services. Thus it is important to specify a model where we use the information available in the NHIS to control for as many of these factors as we can.

First we extract a sub-sample consisting of biparental families with at least one child between 0 and 5 years old, covered by private insurance. Thus we do not include those families who report that the sample child was not covered at the time of the interview or that was covered by Medicaid. In 2000, 12% of children were not covered at the time of the interview and about a quarter of those covered received assistance from Medicaid or other state programs. The uninsured and Medicaid enrollees have a reputation for abusing hospital emergency room services and not getting regular infant check-ups (see Sharma et al. 2000, Fosset and Thompson 1999, Grossman, Rich and Johnson 1998, Billings and Mijanovich 2000). Because Medicaid beneficiaries usually belong to the poorest layers of society, much of the potentially observed relation between ER and income could be just reflecting this evidence. We must however mention the work of Halfon et al. (1998) who found that health insurance status is not a significant predictor of ER use. In fact we find that in our sample less than 3% of individuals reported having the ER as a usual source of infant check-ups. In any case, **since we only include children covered by private insurance, the wider use of the ER by low-income groups cannot be held responsible for our result.**

After selection, we end up with a sample of 3,379 children. Then we specify the covariates for the analysis. In choosing regressors we wanted to select factors that explain the utilization of ER services simultaneously but that can be also correlated to income. First, we included dummies for sex, race and hispanic ethnicity of the children. Additionally, the following regressors were considered:

3.2.1 Health status

Health is a major determinant of the utilization of ER services and it has been found that health and income are related in the adults. Case, Lubotsky and Paxson (2002) find that such a relation also holds during childhood even in developed countries such as the U.S., so that poor parents with poor health conditions will have sickly children who in turn perform worse in the job market and will grow poor. Because poor health conditions are determinant for the use of ER services, we include several regressors to control for the

health status of the child. First, the risk and type of children illness varies with age. Second, we include two dummy variables controlling for having suffered from allergic (asthma, digestive allergies) or infectious conditions (otitis, urine infections). Finally, the sample includes a variable which recodes the health status of the children as reported by the parents.

In addition to diseases, the utilization of ER services also depends on the risk of injury. Unfortunately, the sample does not provide detailed information to control for such a risk (for instance, parents' addictive conducts, the use of appropriate safety measures in home and car, time spent in child monitoring etc. . . .). This omission could bias the results if the risk of injury was negatively correlated to parents' income. However, the literature¹⁵ is not concluding on how the risk of injury for middle and upper-class infants below five years in the U.S. is affected by parents' income.

3.2.2 Risk evaluation and family structure

Our model assumes that parents' ability to evaluate the seriousness of the child's symptoms does not depend on income. Such an ability may be in principle related to two main characteristics: the education level of parents and their experience. The existence of a link between education and income is well documented (see for instance Ashenfelter and Rouse, 2000), so that richer parents may use ER services less just because they are able to identify the seriousness of the symptoms with more accuracy than poor uneducated parents. Also, it may happen that richer mothers have healthier babies at birth just because they have better education than poorer ones (Currie and Moretti, 2003). Because controlling for the education level is essential, we include the parent's education level with range 1 (never attended school) to 11(PhD).

Having reared children previously is an important source of experience and the number of siblings is included as a regressor. Another source of experience in the detection and treatment of bad health episodes could be the presence of older people in the household (Weitzman, Byrd and Auinger, 1999; Ellen, Ott and Schwarz, 1995), or friends and relatives who are health

¹⁵Khoshnood, Lee and Concato (2005) recently found that Mexican-American infants have smaller odds of homicide or unintentional injury than whites, but Native-American (and blacks in a minor degree) have higher ones. Pickett et al. (2002) use data from an interview and find no relevant correlation between income and risk of injury in canadian adolescents.

professionals. The NHIS does not include detailed information in this respect. Nevertheless, our sample is composed of biparental families with their own biological or adopted children only (no more adults in the household), and although we find no evidence of it, rich parents may be more likely to have a health professional relative or friend, but we think that any distortion this may cause should be small once we control for education level.

Because parents may have different feelings with respect to their own and their adopted children, we include a dummy regressor indicating whether the father or mother is a step parent.

3.2.3 Other socio-economic factors

It has been shown that the proximity of health facilities could be correlated with family income (see Currie and Reagan, 1998) and thus, is a factor we should control for. We include dummy variables for the region of the household (North, West, Midwest and South) and to indicate whether the house is located in a metropolitan area.

Additionally, over the last decade, insurance companies have been progressively introducing health management organizations (HMO) in order to reduce the impact of agency problems such as induced demand, and thus the former fee-for-service schemes have become less frequent. These organizations control the access of families to ER services. We include a dummy which indicates whether family health insurance is managed by such an HMO.

3.3 A regression model for ordered choice in latent counts data

Although some or all of the above variables may be affecting ER utilization, our main interest is centered on income which, as mentioned above is measured as attributed total family income in 1999 dollars. But before proceeding we must solve a minor technical problem. The frequency of utilization of the ER is measured as a categoric variable where each category represents an interval of frequency counts of emergency room visits. Respondents must tick the category which contains the number of visits they made during the last year. Ordered choice models have been widely used in applications where an observable categoric variable y represents the re-scaling of a latent continuous variable y^* so that each category of y represents an interval of y^* . It is standard to assume normality of the latent variable. The

problem we face here is the analog where the latent y^* is not continuous but a discrete positive variable representing counts or frequencies of visit.

Hence, let $\{y_i, x_i\}_{i=1}^N$ be a random sample of an observable categorical variable y with support $\{1, \dots, J\}$ and a vector of covariates x . We will assume that y_i^* is a transformation $T(y_i^*)$ from a latent count variable y_i^* whose probability distribution is $G(\cdot | x_i, \theta_0)$ with support given by the natural numbers plus zero. Therefore, the conditional probability of category j in observation i is

$$P(y_i = j | x_i, \theta_0) = \sum_{y^* \in T^{-1}(j)} g(y^* | x_i, \theta_0), \quad (12)$$

and the conditional probability function f of y_i is given by

$$f(y_i | x_i, \theta_0) = \sum_{j=1}^J 1_{\{y_i=j\}} \sum_{y^* \in T^{-1}(j)} g(y^* | x_i, \theta_0). \quad (13)$$

A Maximum Likelihood Estimator is available up to specification of the probability function of latent counts $g(\cdot)$ by maximization in θ of the loglikelihood function. Notice that identification of (13) relies completely on identification of the model for the latent count. The literature on count data regression models starts with the basic Poisson linear exponential model where it is assumed that $y_i^* | x_i, \theta_0 \sim P(\lambda_i)$ with $\lambda_i = \exp(x_i' \theta_0)$. In our notation,

$$g(y_i^* | x_i, \theta_0) = \frac{\lambda_i^{y_i^*} \exp(-\lambda_i)}{y_i^*!}. \quad (14)$$

The basic Poisson model is well known¹⁶ for failing to capture some relevant features that often appear in applications, such as an excess of dispersion and/or zero counts not suited to a Poisson process. A popular alternative is the Negative Binomial distribution which is characterized by a mean parameter λ which is linear exponential and an additional parameter α controlling the variance. An interesting feature of the Negative Binomial model is that it can be interpreted as a Poisson process with unobservable Gamma-distributed heterogeneity affecting the mean. In our context, if $y_i^* | x_i, \theta_0$ follows a Negative Binomial law then

¹⁶See Cameron and Trivedi, 1998) for a general reference on count data regression models.

$$g(y_i^* | x_i, \theta_0) = \frac{\Gamma(\alpha + y_i^*)}{\Gamma(\alpha)\Gamma(y_i^* + 1)} \left(\frac{\alpha}{\alpha + \lambda_i}\right)^\alpha \left(\frac{\lambda_i}{\alpha + \lambda_i}\right)^{y_i^*}. \quad (15)$$

However, neither Poisson nor Negative Binomial seems an appropriate choice in those cases where the data shows an abnormal excess of zeros. As reported in table 1, zeros represent about 80% of the ER observations. The hurdle model can encompass both the Poisson and the Negative Binomial models by assuming that the observable counts are the result of the mixture of two different processes: one driving the zero/non-zero outcomes and another which specifies the frequency counts conditional on non-zero category. Let y_{1i}^* , y_{2i}^* be two count latent variables with distributions $g_1(y_{1i}^* | x_{1i}, \theta_{01})$ and $g_2(y_{2i}^* | x_{2i}, \theta_{02})$, the data generating process is defined as

$$y_i^* = \begin{cases} 0 & \text{if } y_{1i}^* = 0 \\ y_{2i}^* & \text{if } y_{1i}^* > 0, y_{2i}^* > 0. \end{cases}$$

Therefore,

$$g(y_i^* | x_i, \theta_0) = 1 \{y_i^* = 0\} g_1(0 | x_{1i}, \theta_{01}) + 1 \{y_i^* > 0\} \frac{g_2(y_{2i}^* | x_{2i}, \theta_{02})}{1 - g_2(0 | x_{2i}, \theta_{02})} (1 - g_1(0 | x_{1i}, \theta_{01})), \quad (16)$$

where a common shortcut is to assume that g_1 and/or g_2 are Poisson or Negative Binomial. The hurdle model roughly implies that the subpopulation of individuals who went at least once to the emergency room is allowed to differ in terms of its characteristics from the whole population. This model has often been applied in a health economics context where the above interpretation is particularly appealing for modelling some documented features of this market, such as induced demand (see Deb and Trivedi, 1997).

3.4 Results

Table 2 shows the estimates of the model using three alternative specifications for the conditional probability function $g(\cdot)$. Column 1 specifies a Poisson process for the latent count variable as in (14). The income parameter is negative and significant at the 1% level. Roughly, each 10,000 USD increment in family income reduces expected frequency of use of ER facilities by approximately 4%. Other than that, age and white race negatively affect ER

utilization frequency while the regressors that control for health condition show also a negative sign as expected. With respect to family structure, the number of siblings, the education of the father, and being a step father or working mother affect the ER utilization significantly.

The bottom of table 2 shows the frequencies of the observed data and the predictions using the model estimates. The Ordered Choice Poisson model fails to fit the frequencies of the observed counts. However, the NB model improves the fit significantly and is not rejected (see the Pearson's and Andrew's specification test coefficients). In this model, the coefficient on income is slightly smaller (3.5%) but still significant and negative.

It could be argued that individuals having a zero observation may include two different subpopulations: families where the child did not have a spell the previous year and those where she did but the parents did not take her to the ER. In any case, the income coefficient on the subpopulation of individuals who visited the ER at least once should include about only families who experienced at least one bad health episode and the income coefficient contains more information about the parents' decision which is what we are interested in. This coefficient is precisely what we can get with the hurdle model in (16). Once we do so, we still detect (see the last two columns of Table 2) the presence of a significant negative gradient between income and ER utilization both in the whole sample and in the subpopulation of individuals that went at least once to the ER. As a first conclusion then, the negative ER/income slope not only seems to be robust to the choice of $g()$, but its size also seems to be greater for the subpopulation of ER users.

Still we were worried about the possibility that these results could simply be reflecting differences in health care access for rich and poor families with private health insurance. Particularly, rich families could be enjoying better health insurance coverage and hence, they could be using regular care in doctors' offices to substitute their potential demand for ER services. For instance, in a recent article, Christakis, Mell, Koepsell, Zimmerman and Connell (2001) show that lower continuity of primary care implies a higher risk of ER utilization for children, while Billings and Mijanovich (2000) say that economic constraints cause many of the uninsured to delay seeking treatment until their medical condition has seriously worsened. We estimate another model where the dependent variable is the frequency of visits to a doctor's office. The results are shown in Table 3. The estimated coefficient on income using a Negative Binomial or a Poisson as the latent distribution is around 0.1% positive but non significant. Using a hurdle Negative Binomial

distribution, coefficients showed opposite signs in the PROBIT and COUNT part. The overall elasticity of income was smaller than 0.4% very far from the 3.8% negative elasticity in the case of ER utilization (see Table 2). One of the reasons why the income–elasticity of doctors’ office visits is so small is that we do not consider MEDICAID and uninsured families in our sample. Thus, we find that for our sample the negative income–elasticity of ER utilization cannot be explained by poor families using emergency services as a substitute for regular visits and baby check-ups.

4 Further results

4.1 Permanent income and social mobility

Up to now, no distinction has been made between permanent and current income. It is sensible, however, to think that individuals make long run decisions on the basis of permanent income and not using their current income profile. For instance, individuals with a low current wage (say, doctoral students) have a higher permanent or expected income. These people are being considered as poor in the sample, while their decisions are driven by the prospect of higher wages in the future. If there is some unobservable factor that makes these individuals particularly prone to using emergency room services, then an incorrect measurement of income could be responsible for the large gradient found in the previous subsection. Measuring permanent income is problematic due to its non observability. However the gap between permanent and current income is expected to shrink as the individual approaches retirement age. Hence, if the dichotomy between permanent and current income has a role, the estimated ER/income gradient may also be expected to differ for those individuals whose permanent income is not actually far from their current income. To capture the effect of permanent income in our model, we include the cross-product of income using a dummy that indicates whether the head of the family is older than 40.

There is another topic that we were interested in pursuing. In the exchange model, a negative income–elasticity of ER utilization arises when the intergenerational income transition function is concave. The curvature of this function defines the level of intergenerational social mobility of the economy, and in those economies where social mobility is higher the elasticity of ER utilization should also be higher. Thus, we will include cross-products of

income and the US region.

Table 4 shows that including these regressors does not alter the income gradient for the Poisson and Negative Binomial. However, the hurdle model detects that the elasticity in the count part is significantly greater for people under 40, precisely where one would expect to find the greatest differences between current and permanent income. Also, we detect that elasticity differs significantly for different US regions and more specifically for the southern states. Figure 2 depicts a plot of the relationship between income and emergency room utilization. Notice that in the states of the South, where social mobility is lower (see Levine, 1999), this relationship is much flatter. In conclusion, the above results show that the evidence does not reject the presence of implications of the exchange model in terms of social mobility and permanent income.

4.2 Home-accident preventive care

Altogether, the above evidence suggests that when discussing parent-children health-care decisions, the theoretical altruistic model proposed and its predictions do not match the observed data, whereas a model where parents see their children as an investment good fits the observed evidence better. Still, a test of the theoretical model in section 2 using data on ER shows several potential weak points. The main objection is that, despite our efforts, we may not have been able to control properly for market distortions and unobservable factors other than parents' attitudes towards children that may be affecting the estimated income-elasticity. For this reason we devised a cross-test of the above results using a different approach.

We collected data from the National Survey of Early Childhood Health (NSECH, available by anonymous ftp at <ftp.cdc.gov>) which contains information on the actions that parents take in order to prevent home accidents, which include putting up baby gates, locking cabinets containing cleaning agents, padding sharp edges, putting stoppers in electrical outlets, lowering hot water setting on the thermostat or having syrup of ipecac at home. All these investment measures imply minimal financial cost and, in that sense, are consistent with the assumption of the model. In addition, the survey includes some socioeconomic and demographic information on the families (age, race, ethnicity, education level, region) including family income measured in income intervals, family composition and structure (marital status, number of children, etc.). The survey was run during the first semester of

year 2000 through computer-assisted telephonic interviews of 2,068 families with children aged between 4 and 35 months. Table 5 contains the results of the estimation of an ordinal Probit model¹⁷ where the dependent variable is the number of preventive measures that parents report having taken out of those listed in the interview. A significant and negative effect of family income confirms our previous findings on ER utilization frequency.

We compare our results with the work of Case and Paxson (2000) where the authors use information from the 1988 National Health Interview Survey Child Health Supplement to analyze the use of seat belts. In contrast with our results, these authors find a positive relation between family income and children's seat belt use. It must be noted that these authors make a different selection of the covariates and our results are necessarily sensitive to the model specification because we want to pick up the effect of income on parental care net of the impact of a group of factors that may affect this relationship. There are though, some points of agreement. In their work, Case and Paxson (2000) find that there is a negative link between the use of the seat belt and the number of children. This seems to be more in accordance with an exchange approach since having more children implies a less risky asset and therefore less effort will be exerted on the care of each child. Also, it is interesting to notice that in our Table 5, married or widowed mothers seem to be more careful in home accident prevention than non-married or divorced ones. Case and Paxson (2000) found that biological mothers tended to be use seat-belt for their children more regularly than non-biological. Note that their result is consistent with both the altruistic and the exchange models.

In conclusion, our results with data on accident prevention still reject the null of altruism. A potential criticism is that using the answers to this type of surveys could be misleading: parents may want to over-report their actions in order to be considered as good parents and there is no way to control for the size of this potential bias. For this reason, we sought a third source of

¹⁷An ordinal Probit specifies that there exists an unobservable variable y_i^* which follows a linear regression model $y_i^* = x_i'\beta + u_i$ such that the observable variable y_i is a non-linear transformation of y_i^* on the set of integers $\{0, 1, \dots, k\}$. This transformation is ordinal in the sense that there exist levels $\{\mu_0, \mu_1, \dots, \mu_k\}$ such that

$$\begin{aligned} y_i = 0 & \quad \text{if } y_i^* \leq \mu_0 \\ y_i = 1 & \quad \text{if } \mu_0 < y_i^* \leq \mu_1 \\ \dots & \quad \dots \\ & \quad \text{if } \mu_{k-1} < y_i^* \leq \mu_k \end{aligned}$$

data: records on infant mortality.

4.3 Infant Mortality Data

If rich parents show a more relaxed attitude towards their children's care then it would be sensible to think that mortality rates should be greater among rich families than among poor ones. In principle, this affirmation is against-evidence.¹⁸ However, we think that this may be due to the fact that higher rates of infant mortality among poor children may reflect differences in cost of access to the health system, education or feeding. We would need then to focus on the rates of mortality caused by diseases which are not related to any income-related factor.

We identify a group of diseases which meet three conditions: first, there is no evidence that they affect the children of rich and poor families differently; second, they are acute and are considered dangerous if not treated in the first 24 hours and third, they course with symptoms which cannot be easily identified except by a professional (i.e., symptoms that can be misinterpreted, for instance, as a simple cold). These diseases correspond to approximately 85 ICD (International Classification of Diseases) codes, and meningitis, septicemia and pneumonia are the most prevalent ones among children aged one year old or less.

We use data from the National Maternal and Infant Health Survey in 1988. This survey samples 13,417 live births from 1988 U.S. birth certificates and 8,166 infant deaths (below one year old) from death certificates. The survey includes not only information on the ICD code of the cause of death but also the income of the family. We find that for any cause of death, death rates are higher among poor people (Mann-Whitney test, p-value 0.01). Next we select those diseases which match our criteria. Less than 3.7% of these infant death are caused by one of these diseases which leaves about 298 observations. Mean income for this group is of 28,701 USD, 6.8% higher than the mean income of the infant death sample and 3.7% higher than that of the live births sample. The differences between these two groups may be due to the observed higher rate of mortality among poor children. However, the Mann-Whitney tests conclude that the differences are not significant in

¹⁸In 1998, children of women with household incomes below the poverty level displayed an infant mortality rate that was 60% higher and a post-neonatal mortality rate twice as high as those for women living above the poverty level. Figures are extracted from the *Morbidity and Mortality Weekly Report*, December 15, 1995.

any case with p-values of 0.211 and 0.879 respectively. Summarizing, we find that the income of those families where a child died of one of these diseases is higher when compared to the whole population of live births or the population of infant deaths. Nevertheless, we cannot reject the argument that this may be due to the small sample size used.

5 Final Comments

We propose a two-period theoretical model where parents have to decide whether to take their children to the emergency room or not. Their decision is analyzed under two competing frameworks: either parents are motivated by altruism or their decisions are based on contemplating children as an investment. Under generic altruism, rich parents should *ceteris paribus* take their children more often to the emergency room when faced with a given sign of illness. We find that this testable prediction is not verified in an ordered latent count model where the frequency of emergency room utilization is regressed on a set of covariates which include family income. We also find that explanations other than those predicted by an exchange model do not affect this main result. First, although rich families could have better access to preventive care and hence replace the need for emergency room utilization by more continued well-baby check-ups, this substitution effect is not enough to explain the magnitude of the gradient observed. Second, a similar result follows when we include controls for the differences between permanent and current income. And third, we find that the predictions of the exchange model in terms of the relation between income gradient and social mobility are not rejected by the evidence at hand. Finally, we find that alternative measures of parental effort regarding children's health, such as home accident prevention, are also negatively correlated with income as in the case of emergency room utilization.

The evidence presented here suggests that children might still play an important role as assets for parents' old age in developed economies. Integrating parents' health investment in children with fertility decisions will be part of further research on this issue. There are economic measures other than the health investment decision analyzed here and the ones already considered in the relevant literature that should also be studied. For instance, if our analysis is correct and children can be seen as an investment, parents might invest less in pension funds than adults with no children. This and

other similar empirical questions will also be analyzed in future work.

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Appendix A. Proof of Proposition 1

The value of s that renders parents indifferent between taking the child to the emergency room and staying at home is the solution to equality (4), that we write here again:

$$\begin{aligned} & \alpha U(y_p - b^*, y_d^L + b^*) + (1 - \alpha)U(y_p, y_d^H) - e \\ &= (1 - p(s)) [\alpha U(y_p - b^*, y_d^L + b^*) + (1 - \alpha)U(y_p, y_d^H)] + u_p(y_p)p(s) \end{aligned}$$

Let $s^*(y_p)$ be the solution to the above equation. We want to show that $s^*(y_p)$ is decreasing in y_p . Simplifying terms (4) can be written as

$$\alpha(u_p(y_p - b^*) + \beta u_c(y_d^L + b^*) - u_p(y_p)) + (1 - \alpha)\beta u_c(y_d^H) = \frac{e}{p(s)} \quad (\text{a})$$

Since function $p(s)$ is increasing in s and $u_c(y_d^H)$ is increasing in y_p , it is enough to show that $u_p(y_p - b^*) + \beta u_c(y_d^L + b^*) - u_p(y_p)$ is increasing in y_p . And that is equivalent to showing that

$$u_p(y_p - b^*) + \beta u_c(\varepsilon_L v(y_p) + b^*) - u_p(y_p) \quad (\text{b})$$

is increasing in y_p . Notice that b^* is the solution to (2) and therefore it depends on y_p . Thus, (b) is increasing whenever the following inequality holds

$$u'_p(y_p - b^*)(1 - b'^*) + \beta u'_c(\varepsilon_L v(y_p) + b^*)(\varepsilon_L v'(y_p) + b'^*) - u'_p(y_p) \geq 0 \quad (\text{c})$$

where b'^* and $v'(y_p)$ stand for the derivative of b^* and the derivative of $v(y_p)$ with respect to y_p . And inequality c is equivalent to

$$\beta u'_c(\varepsilon_L v(y_p) + b^*)(\varepsilon_L v'(y_p) + b'^*) \geq u'_p(y_p) - u'_p(y_p - b^*)(1 - b'^*) \quad (\text{d})$$

and from equality (2) we have $\beta = \frac{u'_p(y_p - b^*)}{u'_c(y_d^L + b^*)}$. It follows that inequality (d) is equivalent to

$$u'_p(y_p - b^*)(\varepsilon_L v'(y_p) + b'^*) \geq u'_p(y_p) - u'_p(y_p - b^*)(1 - b'^*) \quad (\text{e})$$

And inequality (e) can be written as

$$u'_p(y_p - b^*)(1 + \varepsilon_L v'(y_p)) \geq u'_p(y_p) \quad (\text{f})$$

By concavity of u_p , and since $b^* \geq 0$ and $v'(y_p) \geq 0$, it is easy to see that inequality (f) holds. It follows that inequality (a) also holds and this proves that $s^*(y_p)$ is decreasing.

Appendix B. Figures and Tables

Table 1

ER freq.	Family income (in thousands of USD)				TOTAL
	≤35	35-55	55-75	≥75	
0	1566 (77.37%)	1334 (79.40%)	1134 (82.77%)	1702 (82.82%)	5736 (80.46%)
1	280 (13.83%)	235 (13.99%)	170 (12.41%)	266 (12.94%)	951 (13.34%)
2-3	148 (7.31%)	96 (5.71%)	54 (3.94%)	76 (3.70%)	374 (5.25%)
4-5	18 (0.89%)	10 (0.60%)	10 (0.73%)	11 (0.54%)	49 (0.69%)
6-7	5 (0.25%)	1 (0.06%)			6 (0.08%)
8-9	5 (0.25%)		2 (0.15%)		7 (0.10%)
10-12	1 (0.05%)	3 (0.18%)			4 (0.06%)
13-15		1 (0.06%)			1 (0.01%)
16+	1 (0.05%)				1 (0.01%)
TOTAL	2024 (100%)	1680 (100%)	1370 (100%)	2055 (100%)	7129 ⁽¹⁾ (100%)

NOTES:

- (1) Number of valid observations after listwise deletion of missing values.
- (2) Figures in parenthesis show row percentages

Table 2.

Parameters	EMERGENCY ROOM UTILIZATION			
	OC-Poisson	OC-NB	OC-Hurdle-NB	
			Probit part	Count part
Constant	(***)-0.50627	(***)-0.46252	(***)-0.95116	(*)0.42543
Sex	0.00720	0.02476	(*)0.12617	(***)-0.23746
Age	(***)-0.06936	(***)-0.06464	(**)-0.04697	(***)-0.07892
White	(***)-0.28795	(***)-0.29059	(*)-0.16464	(***)-0.39091
Hispano	-0.06786	-0.07249	(*)-0.20543	(***)0.32016
Mother's education	0.00386	-0.00281	-0.01113	0.02955
Father's education	(***)-0.04171	(**)-0.04296	-0.03090	(*)-0.04904
Step Mother	-0.40305	-0.29702	-0.48814	0.07160
Step father	(***)0.81212	(*)0.71401	0.70336	0.53276
Mother works FT	(**)0.10406	0.09628	0.06000	0.13741
Number of Sibling	(***)-0.10969	(***)-0.10186	-0.06975	(***)-0.14788
Infectious spell/illness	(***)0.42188	(***)0.39809	(***)0.38324	(**)0.18120
Alergic spell/illness	(***)0.40880	(***)0.42580	(***)0.33182	(***)0.28241
Health status	(***)0.19649	(***)0.18333	(**)0.13464	(***)0.21682
Health insurance is HMO	(*)-0.09635	-0.06898	-0.02125	-0.14346
Urban	(***)-0.33289	(***)-0.34199	(***)-0.30307	(**)-0.20136
Midwest	0.01574	-0.02605	-0.12716	(**)0.31616
Northeast	(**)-0.19020	(**)-0.21704	-0.18251	-0.15980
South	0.03807	0.02542	0.02497	0.05482
<i>Income</i>	(***)-0.04161	(***)-0.03565	(*)-0.02675	(***)-0.04995
NB Variance constant		0.75702		-2.00149
Goodness of fit and specification tests				
Average Loglikelihood	-0.4056	0.2319		0.5728
Sample Size ⁽¹⁾	3379	3379	3379	724
LK ratio test		⁽²⁾ 0.0000	⁽²⁾ 0.0000	⁽³⁾ 0.0000
Count	⁽⁴⁾ Observed			
0	78.57	73.55	78.87	78.55
1	15.12	21.71	14.15	13.96
2, 3	5.38	4.62	5.81	6.70
4+	0.91	0.10	1.16	0.76
Pearson's test		21.43	0.44	0.97

NOTES:

- (1) Number of valid observations after case selection and deletion of missing values.
- (2) P-Value of the null of OC-Poisson model.
- (3) P-Value of the null of OC-Negative Binomial model.
- (4) Figures in percentage points.

Table 3.

Parameters	DOCTOR OFFICE VISITS			
	OC-Poisson	OC-NB	OC Hurdle NB	
			Probit part	Count part
Constant	(***)1.18045	(***)1.20713	(***)0.79926	(***)1.23884
Sex	0.00078	0.00654	-0.03488	0.00976
Age	(***)-0.12528	(***)-0.12370	(***)-0.05704	(***)-0.12951
White	(***)0.12189	(***)0.11706	-0.00254	(***)0.13376
Hispano	-0.01410	-0.01578	0.03552	-0.02322
Mother's education	(***)0.01827	(***)0.01821	0.03078	(***)0.01591
Father's education	(***)0.01969	(***)0.01814	-0.01015	(***)0.02176
Step Mother	-0.03325	-0.02401	-0.34991	-0.01121
Step father	0.09573	0.10938	0.24792	0.11095
Mother works FT	(***)-0.04798	(***)-0.05103	-0.07222	(**)-0.04734
Number of Sibling	(***)-0.05367	(***)-0.05227	-0.02814	(***)-0.05399
Infectious spell/illness	(***)0.27626	(***)0.26592	(***)0.16351	(***)0.27178
Alergic spell/illness	(***)0.28584	(***)0.28514	(*)0.14170	(***)0.29309
Health status	(***)0.12101	(***)0.11625	(*)0.08214	(***)0.11644
Health insurance is HMO	0.00497	0.00447	0.02813	0.00258
Urban	(**)0.03111	(*)0.03516	0.01781	(*)0.03728
Midwest	0.00693	0.01021	0.08625	0.00117
Northeast	(***)0.08686	(***)0.08919	(*)0.16505	(***)0.07844
South	(***)0.04402	(**)0.04875	0.07997	(*)0.04384
<i>Income</i>	<i>0.00153</i>	<i>0.00119</i>	<i>(***)0.03832</i>	<i>-0.00374</i>
NB Variance constant		(***)-1.44047		(***)-1.68182
Goodness of fit and specification tests				
Average Loglikelihood	3.16284	2.8818	2.8220	
Sample Size ⁽¹⁾	3379	3379	3379	3254
LK ratio test		(2)0.0000	(2)0.0000	(3)0.0000
Count	Observed ⁽⁴⁾			
0	3.69	2.08	5.54	3.69
1	11.42	6.98	10.99	10.42
2,3	32.49	28.37	27.75	28.28
4+	52.38	62.55	55.70	57.60
Pearson's test	(***)48.3237	(***)13.2006	15.63	

NOTES:

- (1) Number of valid observations after case selection and deletion of missing values.
- (2) P-Value of the null of OC-Poisson model.
- (3) P-Value of the null of OC-Negative Binomial model.
- (4) Figures in percentage points.

Table 4

Parameters	MODEL			
	OC-Poisson	OC-NB	OC Hurdle NB	
			Probit part	Count part
Constant	(***)-0.50034	(**)-0.42680	(***)-1.06180	(***)0.77885
Income	(***)-0.04107	(**)-0.03928	-0.00800	(***)-0.11585
Income x Age _j 40	-0.00394	-0.00372	-0.02024	(***)0.05107
Midwest	0.12203	0.00924	-0.22325	(**)0.56974
Northeast	0.03908	-0.00480	0.26793	(*)-0.54946
South	-0.12343	-0.16388	0.11358	(***)-0.71433
Midwest x Income	-0.01770	-0.00592	0.01420	-0.05201
Northeast x Income	-0.03601	-0.03232	(*)-0.07027	0.06953
South x Income	0.02912	0.03202	-0.01475	(***)0.14455
Goodness of fit and specification tests				
Average Loglikelihood	-0.4017	0.2310	0.5649	
Sample Size ⁽¹⁾	3379	3379	3379	724
LK ratio test		(2)0.0000	(2)0.0000	(3)0.0000
Count	(4)Observed			
0	78.57	73.56	78.87	78.55
1	15.12	21.68	14.15	14.08
2,3	5.38	4.64	5.81	6.55
4+	0.91	0.10	1.16	0.80
Pearson's test	(***)21.32	0.44	0.77	

Table 5.

Parameter	ACCIDENT PREVENTIVE CARE		
	Estimate	Std.Dev.	P-Value
Constant - Levels for number of preventive measures			
Parents take 0 measures	-2.614	0.3805	0.000
" " 1 measure	-1.299	0.3518	0.000
" " 2 measures	-0.212	0.3452	0.538
" " 3 " "	1.048	0.3456	0.002
" " 4 " "	2.471	0.3514	0.000
Slope			
Male	0.1113	0.0973	0.252
White	0.1994	0.1062	0.060
Age in months	0.1912	0.0557	0.000
Hispano	0.1375	0.1117	0.218
Number of Siblings	0.0601	0.0529	0.248
Number of Adults in Family	0.1476	0.0626	0.018
Mother works full-time	0.0785	0.1014	0.437
Education of mother	-0.0623	0.0779	0.416
Mother widowed	0.1968	0.2323	0.399
Mother married	0.3942	0.1332	0.003
Age of mother	0.0069	0.0108	0.520
Northeast	0.3712	0.1498	0.013
Midwest	0.1874	0.1475	0.877
South	0.0195	0.1286	0.204
<i>Income</i>	-0.0693	0.0296	0.019
Goodness of fit and specification tests			
Sample Size			1382
LK ratio test			0.000
Pearson's test P-value			0.547

Figure 1: Signal threshold \tilde{s} as a function of family income for different levels of social mobility (γ).

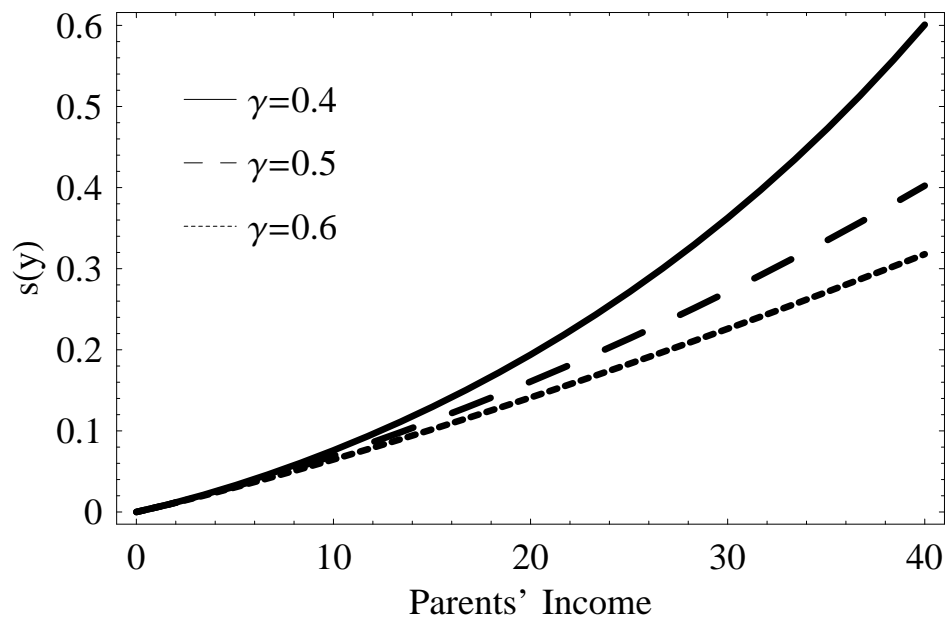


Figure 2: Estimated slope of ER utilization with respect to income in four regions of the U.S.

