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Antoni Calvó-Armengol and Matthew O. Jackson

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Antoni Calvó-Armengol*and Matthew O. Jackson†

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Abstract

We build a model where investments in human capital depend on the state of an individual's social network. We show that correlation patterns between parents' and children's human capital investment and income depend on the structure of their social network. Heavier reliance on the social network increases the correlation of human capital investments and income across generations and decreases the efficiency of their investment decisions.

Keywords: Social Mobility, Networks, Labor Markets, Human Capital.

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*ICREA, Universitat Autònoma de Barcelona and Université de Toulouse. Email: antoni.calvo@uab.es, http://selene.uab.es/acalvo. Support from the Fundación Ramón Areces, the Spanish Ministry of Education through grant BEC2002-02130, and the Barcelona Economics Program CREA is gratefully acknowledged.

†Division of Humanities and Social Sciences 228-77, California Institute of Technology, Pasadena, California 91125, USA. Email: jacksonm@hss.caltech.edu, http://www.hss.caltech.edu/∼jacksonm/Jackson.html Support of the Lee Center for Advanced Networking and the NSF under grant SES-0316493 is gratefully acknowledged.

1 Introduction

Wages and social class are strongly correlated across parents and their children. Moreover, such intergenerational mobility patterns are similar across countries and persistent over time. Economists' evidence for this is based on parent-child correlation of (log) earnings or income. For instance, recent estimates of the intergenerational correlation of long-run log earnings lie in the range [.4, .6] for the U.S. and the U.K., and [.2, .4] for Germany and Sweden.[1] Sociologists' analyses of this focus on mobility tables. Given a hierarchy of occupational classes, mobility tables relate the children-class destination to the parents-class origin. Odds ratios then compute the relative likelihood of identical versus different parent-child class, for any pair of classes in the mobility table. Odds-ratios vary from 1 and 15 depending on the occupational class and have been studied for a large set of countries.[2] It is also important to note that the strong similarities in mobility patterns are observed for countries that differ drastically in their labor market regulations, development, education policies, and other characteristics.[3] This suggests that the dynastic correlation of earnings does not fully stem from national idiosyncrasies.

In this paper, we propose a simple model based on social structure that exhibits strong persistence of family investment in human capital and in resulting earnings across generations.[4] In our model, skills are agent-specific, and the intergenerational correlation in human capital levels is solely governed by the influence of the social setting. In particular, we suppose that the marginal returns from higher educational achievements increase with the human capital composition of any given agent's social network. Economists and sociologists propose different channels for this social externality, among which are role-model theories, peer-pressure for conformism, and heredity of cultural traits or skills. Social networks, which are pervasively used in most labor markets to disseminate job information, also lead to complementarities in human capital investment decisions.[5] We show that this social externality correlates human capital investments across generations, which

[1]See Björklund and Jännti (1999), Solon (2002), Piketty (2000) and references therein, in particular, Solon (1992), Zimmerman (1992), Björklund and Jännti (1997), Dearden *et al.* (1997), and Mulligan (1997). Note that the data sets used for the different national studies differ in some important statistics (such as the average age of children and parents, etc.) that may introduce some national biases in the estimates. The income correlation is even higher and lies in the [.7, .8] range for the U.S. (Mulligan 1997). Also, most of the data analysed concerns only fathers and sons, which introduces some (gender) bias in the estimates. In particular, when daughters are included in the data set, the observed intergenerational correlation of income is higher.

[2]See Gazenboom and Treiman (1989) and Erikson and Goldthorpe (1992, 2002). Björklund and Jännti (1999) describe an alternative measure of social mobilit based on the intergenerational correlation of an index of occupational status.

[3]The time-series persistence also suggests some resilience of mobility patterns to school reforms and labor market policies.

[4]Parent-offspring correlation in labor earnings explains much of the income correlation: "the main component (at least 70%) of the intergenerational correlation of welfare is due to the persistent inequality of labor earnings" Piketty (2000), p. 446.

[5]See Calvó-Armengol and Jackson (2004a,b) for detailed analyses.

further translates into correlation of parent-child earnings. We also establish a monotonicity of the intergenerational persistence as a function of the strength of the social externality. Higher sensitivity of investment decisions to social circumstance leads to high correlation across generations. Lastly, we show that higher sensitivity of investment decisions to social circumstance leads to less efficient investment decisions.

Of course, there are several other well-studied theories of social immobility. Ours is complementary to those theories. In particular, standard economic theories of social mobility resort to the family transmission of economically relevant traits, to capital market imperfections, or to community-wide effects. First, wealth transfers in the form of bequests by altruistic parents are a clear source of dynastic correlation of income, while the genetic inheritance of productive abilities correlates human capital levels and labor earnings across generations (Becker and Tomes 1979). Second, imperfect credit markets impose borrowing constraints at the bottom of the earnings distributions. As a result, able children of poor parents under-invest in human capital, and initial inequalities persist across generations (Loury 1981). Finally, segregation of individuals into homogeneous communities spurs local public good externalities (e.g., peer effects in education and other local public goods) that homogeneize economic outcomes across community members and generations (Bénabou 1993, 1996 and Durlauf 1996).

Empirically, the family transmission of innate abilities has been estimated to account for around 1/4 of the observed persistence in intergenerational earnings (Bowles and Gintis 2002). Also, borrowing constraints do not seem to explain more than 8% of the observed differences in returns to human capital investment for otherwise identical agents, and more generally, non-cognitive skills play a prominent role in explaining labor outcomes (Carneiro and Heckman 2002, Heckman and Krueger 2004). Altogether, the available empirical evidence does not identify credit market imperfections nor genetic inheritance as powerful enough mechanisms to explain adequately the observed mobility patterns. In contrast, parental community traits and, more generally, social background characteristics, seem to have a higher incidence on children individual economic success. For instance, Borjas (1992) finds that the correlation between the average skill in parents' cohort and skills of a given family's children is twice as big as the purely dynastic parents-children correlation. Besides these disparities in human capital investment levels, the parental social background also affects short and long-run labor market outcomes of the children. In France, for identical educational achievements, higher social origin leads to better paid jobs when entering the job market, and the difference widens along the professional career (Goux and Maurin, 1997). In the U.S., the convergence of the college enrollment rates per race, together with the persistence in the white-black wage differential, provides indirect evidence of the (long-standing) labor market value of the social background.[6] More generally, Cooper *et al.* (1994) find that the strength of the parents-children

[6]See Kane (1994), who documents the role of family background for the rise of black's college enrollment rates since the 1980's, and Card and Krueger (1992), Chandra (2000) and Heckman *et al.* (2000) for evidence on the white-black wage gap.

income relationship varies non-linearly with the parental neighborhood income levels, with a higher persistence at the two tails of the distribution (that is, affluent and poor areas).[7]

Our model highlights the role of the social environment as a driver for social immobility, and relates the sensitivity of investment decisions to social circumstances to the level of intergenerational correlation, thus providing a different mechanism for intergenerational correlation.

We should emphasize that the social interaction that we describe is consistent with different social influences on investment decisions. We can crudely distinguish between three types of social processes. First, offspring from can *passively inherit* preferences as a function of their social surroundings. For instance, Boudon (1973) argues that low-class children display a much shorter time-horizon than others,[8] whereas Bourdieu and Passeron (1964) claim that high-class children inherit better suited attitudes and aptitudes for culture and education.[9] Second, the social background can influence educational outcomes through the *reaction* of the offspring to the behavior of those in their social network. For instance, children may learn how to behave by observing the adults in their social network;[10] norm-enforcing mechanisms can also induce conformism among peers.[11] Finally, the influence of the social setting can also result from the combination of passive inheritance and active reaction. For instance, the inherited social connections affect employment outcomes which, in turn, influence human capital acquisition.[12]

2 The model

2.1 Dynasties and (Random) Over-lapping Generations

There are n dynasties indexed by $i = 1, ..., n$. Time evolves in discrete periods indexed by $t = 1, 2, \ldots$. Each generation of a given dynasty consists of only one member. When there is no

[7] See also Datcher (1982), and Bjerve and Doksum (1993) for a description of correlation curves, best fitted to the analysis of non-linear relationships. Wilson (1987) popularizes the concept of underclass to identify the chronically poor, both socially and spatially isolated in urban ghettos.

[8] Given that they discount future payoffs more than children from wealthier parents, they invest less in human capital.

[9] Bourdieu and Passeron refer to this stock of attitudes and aptitudes for cultural activities as cultural capital. Cultural capital reduces the cost of acquisition of human capital. Sobel (XXX) offers an exhaustive and critical survey of the economic value of social capital.

[10] In this case, adults act as role models for children. See, for instance, Jencks and Mayer (1990) for a description of this theory.

[11] See Coleman (1990). Crane (1991) and Harding (2003) provide empirical evidence consistent both with role models and peer-pressure mechanisms.

[12] See Calvó-Armengol and Jackson (2004ab) for a dynamic model of labor market networks. That model also provides a rationale for conformity effects on school drop-outs within social groups. There, preferences from conformity arise endogenously from the use of social connections in the labor market, which correlate individual outcomes both within groups and across periods. Using census track data from Chicago, Topa (2001) shows that the impact on the individual employment probability of a one-standard deviation change in the average unemployment of neighbors is 1.5 times higher than a one-standard deviation on human capital (1.2% versus 0.8%).

confusion, we identify current generation members by their dynasty index.

At the beginning of each period, one dynasty is randomly chosen and its member replaced by his or her offspring. This happens with equal probability across dynasties.[13]

2.2 Social Networks and Human Capital Investment

When they are born, offspring invest in human capital. This is a once-and-for-all decision.

For simplicity we assume that human capital can only take two values, high and low (and the analysis has an obvious extension to any finite set of values). Letting h_i^t denote the human capital of the agent in dynasty i at time t, we set $h_i^t = 1$ for the high level, and $h_i^t = 0$ for the low level.

Let $w_i(h)$ denote i's expected discounted stream of wages conditional on the vector of current human capital levels being h.[14]

We normalize $w_i(0, h_{-i}) = 0$ for all h_{-i}, so that if i does not invest in human capital then his or her wage is 0. We let $w_i(1, h_{-i}) > 0$ for all h_{-i} so that high human capital leads to higher wages than low human capital. More importantly, we assume that $w_i(1, h_{-i})$ is non-decreasing in h_j for all $j \neq i$. As we argue below, this monotonicity arises endogenously when social contacts convey job information, a fact largely documented in many labor markets.[15]

Agents are also born with a randomly drawn cost c of investing in the high human capital level, which is described by a cumulative distribution function $F(c)$. We assume that at birth each agent gets an individual draw from F. An agent's human capital level is 0 unless the agent decides to invest.

This cost encompasses innate skills and abilities, as well as direct costs of education. Note that we completely abstract from any correlation in costs of education across generations. *We do not do this because we believe that costs are independent across generations, but rather because we wish to isolate the social setting as a driver of social immobility.*[16]

Thus, agent i can be completely characterized by a function $p_i(h_{-i}) = \Pr\{c_i < w_i(1, h_{-i})\}$ which gives the probability that he invests in a high human capital level when the human capital level of others is h_{-i}.

If c_i has a full support on the range from $w_i(1, 0_{-i})$ to $w_i(1, 1_{-i})$ this implies that $p_i(h_{-i})$ is also non-decreasing in h_{-i}. In words, the human capital composition of the social setting positively affects individual human capital investment decisions, as it increases the marginal returns from education.

[13]Therefore, the expected life span of any generation in dynasty i is: $\sum_{\tau=1}^{+\infty} \tau \frac{1}{n}(1 - \frac{1}{n})^{\tau} = n - 1$.

[14]Given the stationary random way that offspring are born, this is the same in any period, conditional on h.

[15]See, for instance, the recent evidence reported in Santamaría-García (2003), as well as the discussion and references in Calvo-Armengol and Jackson (2004a).

[16]In fact, intergenerational correlation in costs of education has been extensively studied as a driver of social immobility, both theoretically and empirically. See Bowles and Gintis (2002) and references therein.

Economists and sociologists propose different channels for this social positive externality, including role-model theory, peer-pressure for conformism, heredity of cultural traits or skills, some of which receive empirical support. When the monotonicity of $p_i(h_{-i})$ in h_{-i} is formulated as an assumption, our model encompasses all of them. Our model is also compatible with the prevalent use of social networks in many labor markets, and its effect on the individual and aggregate dynamics of labor market outcomes. In this case, the monotonicity of $p_i(h_{-i})$ in h_{-i} arises endogenously, and derives from the (endogenous) monotonicity of the wage function $w_i(1, h_{-i})$ in h_{-i}.

While our results extend to this general setting, we specialize the exposition to the case where agents have the same investment function, $p_i(\cdot) = p(\cdot)$ for all i, and where $p(\cdot)$ can be written as a function of $\sum_{j \neq i} h_j$.

We let $k^t = \sum_i h_i^t$ and $k_{-i}^t = \sum_{j \neq i} h_j^t$.

2.3 An Example: Labor Market Networks

The critical assumption for our results is that $p(\cdot)$ is a non-decreasing function.

We show that one (among many) justifications for this assumption is having social connections diffuse job information. Such a formal model is fully developed in Calvó-Armengol and Jackson (2004a,b), so we simply describe the results informally, and refer the reader to that work for the details.

Assume that individuals are connected by a social network, where network links represent direct communication channels between pairs of agents that know each other. The labor market is subject to a turnover, with some agents losing their job and others hearing of available job slots at every time period. When a currently employed worker cannot obtain a wage raise with one of these outside offers, he or she relays this information to his or her friends or acquaintances in the social network. When information about job opportunities is disseminated in this way, wages and employment are positively correlated across agents in both the short and long run.[17]

Let individual payoffs be the expected discounted stream of wages conditional on a given network. The correlation in wages implies that individual payoffs depend positively on the whole network status. Therefore, the payoff to every agent in the market is non-decreasing in the human capital level of every other agent. Formally, $w_i(1, h_{-i})$ is non-decreasing in h_j for all $j \neq i$. In such a model, w_i is strictly increasing in h_j whenever agents i and j are path-connected. Here, the assumption that $p_i(\cdot) = p_j(\cdot)$ for all i, j, is equivalent to all dynasties holding interchangeable locations in the social network.

For the purpose of illustration, let us explore a simple example. Suppose that n agents are

[17] See Propositions 1 and 2 in Calvó-Armengol and Jackson (2004a) for the case of constant wages, a fixed network and uniform information transmission to direct connections, and Propositions 1 and 2 in Calvó-Armengol and Jackson (2004b) for the general case with heterogeneous wages, general networks (random, weighted, directed, etc.) and general information diffusion (relayed information, preferential passing, etc.).

connected through a complete network (they all know each other directly). In each period, a currently employed worker loses his or her job with a probability $b = .015$, and all workers (both employed an unemployed) independently hear of a new job opportunity with probability $a = .100$. If a worker is currently at the highest wage level, the worker passes any job information on to an unemployed neighbor. If the worker is not currently at the highest wage level, then he or she keeps the information. A low human capital level $h = 0$ pays $w = 0$. A high human capital level $h = 1$ pays either $w = 1$ when the agent has heard of one job offer since their last unemployment spell, and $w = 2$ when the agent has heard about more than one job opportunity since their last unemployment spell.[18]

Number of agents	$n = 1$	$n = 2$	$n = 4$	$n = 8$	$n = 16$	$n = 32$	$n \to \infty$
$E_t[w_i^t]$	0.10	0.19	0.38	0.73	1.26	1.77	1.97
$\Pr\{w = 2\}/\Pr\{w = 1\}$	0	.05	.17	.47	1.4	6.6	∞

This table simply indicates how a given agent's wage prospects improve in a given period as the number of neighbors is increased. This calculation presumes all other agents are employed at the high wage level, and that the given agent starts unemployed. One can also easily do steady-state calculations, and for various network configurations, as reported in Calvo-Armengol and Jackson (2004ab).

2.4 A Markov Process

The random overlapping generations model, together with the human capital investment decision with idiosyncratic costs generates a Markov process. The state is the number of agents k^t at the high human capital level at the end of a period t, and transitions probabilities depend on the social setting according to the function $p(\cdot)$. We denote this Markov process by $\mathcal{M}(p)$.

This is a finite-state irreducible and aperiodic Markov process on dynastic human capital statuses. We characterize the long-run steady-state distribution of this process.[19] Given the symmetry in the model, we need only to keep track of how many agents are of the high type in any period. Thus, the steady-state of the Markov process can be described by $\mu = (\mu_0, ..., \mu_n)$, where μ_k is the probability that k agents are of the high type.

We also use the notation μ_k^{-i} to denote the probability that k agents other than i are of the high type.

We examine the parent-offspring correlation in human capital levels under this steady-state distribution.

[18]The higher wage could represent an expected improved match, or improved bargaining power during the wage-setting negotiation.

[19]For such a Markov process, the steady-state distribution has several nice features. First, it represents the relative frequencies spent in each state over long time horizons, second, starting with a random draw from that distribution, the distribution over next period states is governed by the same distribution, and third, starting from any state, given a long enough horizon, the probability that one will end up in any give state is given by that distribution.

3 Correlation in Parent-Child Human Capital and Earnings

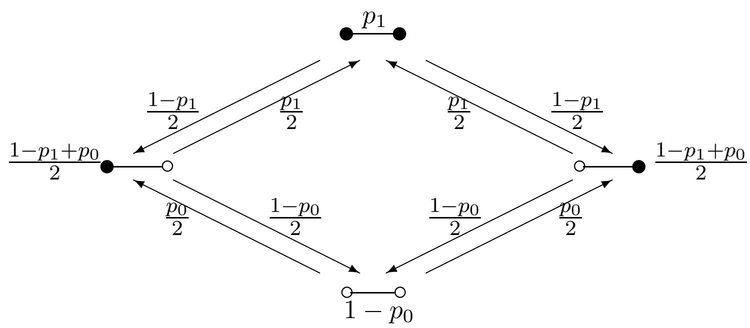
Given the structure of the setting, correlation in parent-child earnings are largely due to the correlation in human capital decisions. We focus our attention on the human capital decisions.

Dynastic correlation in earnings, though, goes beyond correlation in human capital decisions. We know that wages of networked agents are correlated both within and across periods. High parental wages thus lead to higher wages for the offspring network neighbors (recall that only one dynasty member is replaced every period) which, in turn, feeds back into higher wages for the offspring.

3.1 An Example with Dyads

Consider a simple case where $n = 2$ and the two agents are connected with each other and form a dyad. Let $p_0 = p(0)$ and $p_1 = p(1)$, where $p_1 \geq p_0$. We analyze the Markov process $\mathcal{M}(p_0, p_1)$.

The following figure summarizes the transition probabilities between the states of the dyad. A darkened node represents an agent with high human capital, while agents with low human capital are represented by empty nodes. The line between two nodes indicates the social interaction between agents. Arrows represent state transitions with their corresponding probabilities. The probability with which the dyad state does not change is indicated by the expression near the dyad.



The spread $p_1 - p_0$ is a measure of the sensitivity of human capital decisions to the social network. If p_0 is close to p_1, then one agent's wages and human capital investment decisions are largely independent of the status of the other agent.

Let $\mu = (\mu_0, \mu_1, \mu_2)$ be the steady-state distribution of $\mathcal{M}(p_0, p_1)$, where μ_k is the probability that k agents have high human capital level. It follows that

$$\begin{bmatrix} \mu_2 \\ \mu_1 \\ \mu_0 \end{bmatrix} = \frac{1}{1 + p_0 - p_1} \begin{bmatrix} p_0 p_1 \\ 2p_0(1 - p_1) \\ (1 - p_0)(1 - p_1) \end{bmatrix}.$$

In particular, both dyad members invest in the high human capital level with a long-run probability μ_2 that increases in both p_0 and p_1. In contrast, the probability of the joint low investment μ_0

decreases in both p_0 and p_1. Finally, the probability that dyad members display different human capital levels μ_1 increases in p_0 but decreases in p_1.

We can easily compute the parent-offspring correlation in human capital levels under the steady-state distribution μ, denoted ρ. It follows that[20]

$$\rho = (p_1 - p_0)^2.$$

This correlation increases with the square of the sensitivity, $p_1 - p_0$, of the human capital investment decision to the state of the other agent's status.[21] The more important the network influence on one's decisions, the larger the correlation in human capital decisions across generations of a same family.

3.2 A Simple Monotonicity Lemma

We begin with an obvious result that establishes monotonicity of the steady-state distribution of human capital decisions (in the sense of first-order stochastic dominance) with respect to the investment probability function $p(\cdot)$.

We write $p' \geq p$ if $p'(k) \geq p(k)$, for all k, and $p' > p$ if $p'(k) > p(k)$, for all k. This could represent an increase in wages, a decrease in the cost distributions, or some other reason for increased investment as a function of the state of the network.

LEMMA 1 *Let μ and μ' denote the steady-state distribution of $\mathcal{M}(p)$ and $\mathcal{M}(p')$, respectively. If $p' \geq p$, then μ' first-order stochastically dominates μ. When $p' > p$, the first-order stochastic dominance is strict.*

3.3 Correlation in Parent-Child Human Capital

We now explore the relationship between the social structure, as captured through $p(\cdot)$, and the intergenerational correlation in human capital decision.

Let $\overline{p}(p)$ be the average steady-state probability that any given agent is of a high type. Thus,

$$\overline{p}(p) = \sum_{k=1}^{n} \mu_k \frac{k}{n}.$$

Let $\widehat{p}_k = p_k - \overline{p}$ be the deviation of the investment probability from the mean.

We say that p' is *more sensitive* than p if

[20]The joint probability with which two consecutive generation members of the same dynasty have high human capital level is $\eta_{11} = p_1\mu_2 + \frac{1}{2}p_0\mu_1$. The expression follows from simple algebra.

[21]It is important to note that the correct measure of sensitivity is the difference between p_1 and p_0. If we simply have high levels of both p_1 and p_0, then the state of the network has no influence and the correlation disappears.

(i) there exists K such that $p'_k \leq p_k$ for all $k \leq K$ and $p'_k \geq p_k$ for all $k > K$, and[22]

$$\sum_{k \geq 0} \mu_k^{-i} \left(p'_k - p_k\right) \geq 0, \tag{1}$$

(ii)

$$\sum_{k \geq K} \mu_k^{\prime,-i} \widehat{p}'_k \geq \sum_{k \geq K} \mu_k^{-i} \widehat{p}_k \tag{2}$$

for all K, with strict inequality for some K.

The first part of condition (i) is straightforward: if p' is more sensitive than p, then the probability of investment is higher for in high social states and lower for low social states. The second part of (i) is a condition that makes sure that ensures that the overall mean investment has not dropped too much. As for (ii), note that (2) is equivalent to requiring that

$$\sum_{k \leq K} \mu_k^{\prime,-i} \widehat{p}'_k \leq \sum_{k \leq K} \mu_k^{-i} \widehat{p}_k$$

for all K, with strict inequality for some K. Thus, part (ii) is similar to a stochastic dominance condition. Noting that $Prob_p(k_{-i}^t = k \mid i \text{ invests at time } t) = \mu_k^{-i} \frac{p_k}{\overline{p}}$, (ii) is a non- normalized version of stochastic dominance regarding the distribution of the state conditional on having invested. Thus, the individual investment decision is more closely tied to state of the social network (the status of i's connections) under p' than under p.

As we saw in the dyad case, when p' is more sensitive than p, the parent-offspring correlation in human capital is equal to the square of this sensitivity. Therefore, in the dyad case, the intergenerational correlation of human capital decisions is greater under p' than under p. Theorem 1 generalizes this result.

Theorem **1** *If p' is more sensitive than p, then the intergenerational correlation in human capital investments in any dynasty under the steady state is higher under p' than under p.*

Note that Theorem 1 also implies that any p' that is more sensitive than a completely constant p must have positive intergenerational correlation.

The intuition behind Theorem 1 is that as the correlation of the human capital investment with the state of the network increases, this leads to increased intergenerational correlation due to the fact that there is likely to be some overlap in the state of the rest of the network between the parent and the child. The challenge in the proof is due to the fact that a change from p to p' has both a direct and an indirect effect. It directly increases correlation between decisions and the state of the network. However, it also changes the steady state distribution, which has indirect effects. The change in the steady state distribution is not necessarily a uniform one, some states get increased

[22] Inequality (1) can also be stated with $\mu_k^{\prime,-i}$ in place of μ_k^{-i}.

probability while others get lower probability, and not in some well-ordered manner. We need to show that the combination of these effects on the correlation is always positive. Part (ii) of the condition handles the indirect effect, while part (i) deals with the direct effect.

So far, we have assumed that the offspring social background is the same as that of his parent when the parent dies. Suppose, instead, that this inheritance is only partial. The child's social universe is now mixed. He evolves in the same social universe as his parent with probability q, but belongs to a completely different social circle with probability $1-q$. More precisely, the child accesses the same network as his or her parent with probability q, and otherwise gets an entirely new network (with k_{-i}^t determined by a fresh draw from the steady state distribution). We model this process as if with probability q the child's investment decision is governed by p_k, and with probability $(1-q)$ it is given by $\overline{p}$. The influence of the social setting now depends on q, and we denote by p^q the resulting function. A variation on the proof of Theorem 1 provides the following result.

Corollary 1 *The steady-state intergenerational correlation in human capital investments increases with q.*

To the extent that the overlap of the social universe across generations is higher for the two-tails of the income distribution, this finding is consistent with the $U-$shaped intergenerational income correlation curve as a function of income levels documented by Cooper *et al.* (1994).[23]

3.4 Wage Correlation

The relation between sensitivity and intergenerational correlation in human capital investment suggests that we ought to see a similar relationship between social sensitivity and intergenerational correlation in wages. There are some situations where results for wages follow along similar lines as Theorem 1.

Proposition 1 *If expected wages conditional on investment are linear in p_k or linear in k, then the steady-state intergenerational correlation under p' is larger than under p whenever p' is more sensitive than p.*

More generally, additional nonlinearities in the wage function require conditions similar to being more sensitive applying directly to expected wages (conditional on investment) rather than probability of investment. Another situation where we can deduce results for wages is in the p^q model.

[23] See Wright Mills (1945) for a seminal analysis of the social endogamy of the business elite in the U.S. and Wilson (1987) and Jencks and Mayer (1990) for an analysis of the social and economic consequences of living in the inner city in the U.S. Santamaría-García (2003) provides a model predicting a more extensive use of social contacts for job search among less-educated workers, consistent with empirical findings in many European countries and reported in the paper.

PROPOSITION **2** *If expected wages conditional on investment are increasing in k, then the steady-state intergenerational correlation in wages increases with q.*

3.5 Cost Efficiency

Let us now explore what we can conclude regarding efficiency. Given that p encompasses many things, we focus on the one aspect of efficiency that we can still draw conclusions regarding: costs of investment. That is, suppose that one agent invests in human capital with a high cost due to the fact that his or her social network is in good shape, while another agent does not invest despite a much lower cost due to the fact that his or her network is in bad shape. If we could exchange these two agents (and perhaps make some transfers) we would have an improvement. In particular, for two processes p and p' that have the same overall percentage of investment ($\overline{p}$), we expect that the one with the higher spread will have a higher overall cost associated with it, and thus is less efficient in terms of the costs of investment for the same average level of investment. We formalize this as follows.

Define

$$Spread(p) = \sum_{k=0}^{n-1} \mu_k^{-i} \left| p_k - \overline{p} \right|$$

This is not quite a direct measure of cost inefficiency because it is not weighted by the sizes of the inefficiencies. For some circumstances (that we explore below) this spread is directly related to cost efficiency.

THEOREM **2** *If p' is more sensitive than p, then $Spread(p') > Spread(p)$.*

Let $Cost(p)$ be the average cost per capita of those investing in high human capital. Under a uniform distribution on costs, from $[0, C]$, this can be written as

$$Cost(p) = \sum_{k=0}^{n-1} \frac{\mu_k^{-i} p_k}{\overline{p}} \frac{C}{2} p_k,$$

where $\mu_k^{-i} p_k / \overline{p}$ is the conditional probability that there were k other agents with high human capital at the time that i invested, conditional on i investing; and $Cp_k/2$ is expected cost given that i invested when there were k other agents with high human capital.

THEOREM **3** *If p' is more sensitive than p, $\overline{p}(p') = \overline{p}(p)$, and costs are uniformly distributed on $[0, C]$, then $Cost(p') > Cost(p)$.*

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Appendix

We can relate states according to,[24]

$$\mu_k^{-i} = \frac{k+1}{n}\mu_{k+1} + \frac{n-k}{n}\mu_k. \tag{3}$$

The following lemma is useful.

LEMMA **2** *For all* $0 \leq k \leq n-1$, $\mu_{k+1} = a_k \mu_k$, *where*

$$a_k = \frac{n-k}{k+1}\frac{p_k}{1-p_k},$$

and thus $\mu_k = a_j a_{j+1} \cdots a_{k-1}\mu_j$ *for all* $k > j$.

Proof of Lemma 2: Consider a state where exactly k agents are of high type. At steady-state, the inflow to and the outflow from this state exactly balance each other. This is written as

$$\begin{aligned}
\mu_0 p_0 &= \mu_1 \frac{1}{n}(1-p_0), \text{ for } k=0 \\
\mu_{k-1}\frac{n-(k-1)}{n}p_{k-1} + \mu_{k+1}\frac{k+1}{n}(1-p_k) &= \mu_k \frac{k}{n}(1-p_{k-1}) + \mu_k \frac{n-k}{n}p_k, \text{ for } 1 \leq k \leq n-1 \\
\mu_{n-1}\frac{1}{n}p_{n-1} &= \mu_n(1-p_{n-1}), \text{ for } k=n,
\end{aligned}$$

and the result follows. ■

Proof of Lemma 1: By Lemma 2, whenever $i > j$ we can write

$$\mu_i/\mu_j = a_j a_{j+1} \cdots a_{i-1}.$$

Noting that $p'_k \geq p_k$ implies $a'_k \geq a_k$ (with corresponding strict inequalities), it follows that

$$\mu'_i/\mu'_j \geq \mu_i/\mu_j$$

for all $i > j$, with strict inequality for some pairs when $p' \neq p$. Given that $\sum_{k=0}^n \mu'_k = 1 = \sum_{k=0}^n \mu_k$, the result follows directly. ■

Proof of Theorem 1: For a given dynasty i, we can write the covariance as

$$Cov(p) = \sum_{k=0}^{n-1} \mu_{k+1}\frac{k+1}{n}(p_k - \overline{p}) = \sum_{k=0}^{n-1} \mu_{k+1}\frac{k+1}{n}\widehat{p}_k, \tag{4}$$

[24] The number of states with k high types, not counting i, is $\binom{n-1}{k}$. There are exactly $\binom{n}{k+1}$ states with $k+1$ high types. Therefore, the fraction of such states for which i is of high type is $\binom{n-1}{k}/\binom{n}{k+1} = (k+1)/n$. Also, there are $\binom{n}{k}$ states with k high types, and the fraction of such states for which i is of low type is $\binom{n-1}{k}/\binom{n}{k} = (n-k)/n$.

noting that $\mu_{k+1}\frac{k+1}{n}$ is the probability that the parent is high human capital and there are k others of high human capital. We need to show that if p' is more sensitive than p, then $Cov(p') > Cov(p)$. First note that by Lemma 2

$$\sum_{k\geq K} \mu_{k+1}\frac{k+1}{n}\widehat{p}_k = \sum_{k\geq K} \mu_{k+1}\frac{k+1}{n}\left(1+\frac{1-p_k}{p_k}\right)p_k\widehat{p}_k \tag{5}$$

$$= \sum_{k\geq K} \mu_{k+1}\frac{k+1}{n}\left(1+\frac{\mu_k}{\mu_{k+1}}\frac{n-k}{k+1}\right)p_k\widehat{p}_k \tag{6}$$

$$= \sum_{k\geq K} \left(\mu_{k+1}\frac{k+1}{n}+\mu_k\frac{n-k}{n}\right)p_k\widehat{p}_k = \sum_{k\geq K} \mu_k^{-i}\widehat{p}_k p_k, \tag{7}$$

for all $0 \leq K \leq n-1$. Thus, by (5), we write

$$Cov(p') = \sum_{k\geq 0} \mu_k^{-i,\prime}\widehat{p}_k p_0' + \sum_{k\geq 1} \mu_k^{-i,\prime}\widehat{p}_k(p_1'-p_0') + \sum_{k\geq 2} \mu_k^{-i,\prime}\widehat{p}_k(p_2'-p_1') + \ldots$$

By (2) than we know that this is greater than

$$\sum_{k\geq 0} \mu_k^{-i}\widehat{p}_k p_0' + \sum_{k\geq 1} \mu_k^{-i}\widehat{p}_k(p_1'-p_0') + \sum_{k\geq 2} \mu_k^{-i}\widehat{p}_k(p_2'-p_1') + \ldots,$$

with the strict inequality following from the fact that p_k' is nondecreasing and not constant in k. Thus,

$$Cov(p')-Cov(p) > \sum_{k\geq 0} \mu_k^{-i}\widehat{p}_k(p_0'-p_0)+\sum_{k\geq 1} \mu_k^{-i}\widehat{p}_k(p_1'-p_0'-p_1+p_0)+\sum_{k\geq 2} \mu_k^{-i}\widehat{p}_k(p_2'-p_1'-p_2-p_1)+\ldots$$

or

$$Cov(p') - Cov(p) > \sum_{k} \mu_k^{-i}\widehat{p}_k(p_k'-p_k).$$

We can then deduce that the right hand side is nonnegative from (i) of the definition of more sensitive than. This is derived as follows. Let K be the min k such that both $\widehat{p}_K \geq 0$ and $(p_K'-p_K) \geq 0$. First, suppose it is the case that $(p_{K+1}'-p_{K-1}) < 0$. Then

$$\sum_{k\geq K} \mu_k^{-i}\widehat{p}_k(p_k'-p_k) \geq \widehat{p}_K \sum_{k\geq K} \mu_k^{-i}(p_k'-p_k),$$

and

$$\sum_{k<K} \mu_k^{-i}\widehat{p}_k(p_k'-p_k) \geq \widehat{p}_K \sum_{k<K} \mu_k^{-i}(p_k'-p_k).$$

Thus,

$$\sum_{k} \mu_k^{-i}\widehat{p}_k(p_k'-p_k) \geq \widehat{p}_K \sum_{k} \mu_k^{-i}(p_k'-p_k),$$

and the right hand side is nonnegative by (1). By analogous reasoning, in the case where $\widehat{p}_{K-1} < 0$, we deduce that

$$\sum_{k} \mu_k^{-i}\widehat{p}_k(p_k'-p_k) \geq (p_{k'}'-p_{k'}) \sum_{k} \mu_k^{-i}\widehat{p}_k,$$

where k' minimizes $(p'_{k'} - p_{k'})$ subject to $k' \geq K$. Since $\sum_k \mu_k^{-i} \widehat{p}_k = 0$, the result again follows. ■

Proof of Theorem 2: For all $m < m'$ let

$$S_m^{m'}(p) = \sum_{k=m}^{m'} \mu_k^{-i} |p_k - \overline{p}| \geq 0.$$

Let $m(p)$ be such that $p_{m(p)-1} \leq \overline{p}$ and $p_{m(p)} > \overline{p}$. Then,

$$\sum_{k \geq 0} \mu_k^{-i} (p_k - \overline{p}) = S_{m(p)}^{n-1}(p) - S_0^{m(p)-1}(p).$$

First, consider a case where $m(p') < m(p)$. Then, (2) and p' is more sensitive than p for $K = m(p)$ imply that

$$S_{m(p)}^{n-1}(p') \geq S_{m(p)}^{n-1}(p).$$

But, recall that

$$S_{m(p)}^{n-1}(p') + S_{m(p')}^{m(p)-1}(p') - S_0^{m(p')-1}(p') = S_{m(p)}^{n-1}(p) - S_0^{m(p)-1}(p) = 0.$$

Thus,

$$-S_{m(p')}^{m(p)-1}(p') + S_0^{m(p')}(p') \geq S_0^{m(p)-1}(p).$$

Therefore,

$$\begin{aligned} Spread(p') &= S_{m(p)}^{n-1}(p') + S_{m(p')}^{m(p)-1}(p') + S_0^{m(p')-1}(p') \\ &\geq S_{m(p)}^{n-1}(p') - S_{m(p')}^{m(p)-1}(p') + S_0^{m(p')-1}(p') \\ &\geq S_{m(p)}^{n-1}(p) + S_0^{m(p)-1}(p) = Spread(p). \end{aligned}$$

Next, consider the case where $m(p') \geq m(p)$. Then, p' is more sensitive than p for $K = m(p)$ implies that

$$S_{m(p')}^{n-1}(p') - S_{m(p)}^{m(p')-1}(p') \geq S_{m(p)}^{n-1}(p).$$

But, recall that

$$S_{m(p')}^{n-1}(p') - S_{m(p)}^{m(p')-1}(p') - S_0^{m(p)-1}(p') = S_{m(p)}^{n-1}(p) - S_0^{m(p)-1}(p) = 0.$$

Thus,

$$S_0^{m(p)-1}(p') \geq S_0^{m(p)-1}(p).$$

Therefore,

$$\begin{aligned} Spread(p') &= S_{m(p')}^{n-1}(p') + S_{m(p)}^{m(p')-1}(p') + S_0^{m(p)-1}(p') \\ &\geq S_{m(p')}^{n-1}(p') - S_{m(p)}^{m(p')-1}(p') + S_0^{m(p)-1}(p') \\ &\geq S_{m(p)}^{n-1}(p) + S_0^{m(p)-1}(p) = Spread(p). \end{aligned}$$

■

Proof of Theorem 3: We write

$$Cost(p) = \sum_{k=0}^{n-1} \frac{\mu_k^{-i} p_k}{\overline{p}} \frac{C}{2} p_k. \tag{8}$$

Thus,

$$Cost(p) = \frac{C}{2\overline{p}} \left[Cov(p) + \overline{p}^2 \right].$$

The result then follows from Theorem 1 and the fact that $\overline{p}(p') = \overline{p}(p)$. ■