Educational Choices and Educational Traps

Gianluca Manzo

fondation maison des sciences de l'homme
Programmes scientifiques

GeWoPs
Working papers du
GEMASS
Groupe d'étude des méthodes de l'Analyse sociologique de la Sorbonne

Educational Choices and Educational Traps

Towards an Integration between Computational and Statistical Modelling in the Sociology of Social Stratification

Gianluca Manzo

N°48 | septembre 2013

From a substantive point of view, the paper analyzes the statistical association between individuals' educations and those of their parents in France and in Italy at the beginning of the twenty-first century – a phenomenon for which a comparison specifically focused on these two countries is still lacking. From a theoretical point of view, the paper develops a formal explanatory model of the macro-level structure of educational inequality - the «interdependent educational choice model» (IECM) - which frames educational choices as the result of both individual benefit/cost evaluations and peer-group pressures. It thus enriches the sociological educational rational-choice approach through the economic perspective of the so-called «membership theory of inequality». (...)

Working Papers Series

Fondation Maison des sciences de l'homme - 190 avenue de France - 75013 Paris - France
http://www.msh-paris.fr - FMSH-WP-2013-48

Educational Choices and Educational Traps

Towards an Integration between Computational and Statistical Modelling in the Sociology of Social Stratification

Gianluca Manzo

Octobre 2013

The author

CNRS, University of Paris IV – Sorbonne (GEMASS)

Gianluca Manzo is a permanent research fellow in sociology at the Centre National de la Recherche Scientifique (CNRS, France) and teaches quantitative and computational methods at the University of Paris-Sorbonne. He is an international research affiliate at the Institute for Futures Studies (Stockholm) and has served as visiting scholar and professor at several universities, which include Columbia University (ISERP) and the University of Oxford (Nuffield College).

E.mail: glmanzo@yahoo.fr

The text

This is the original draft of my contribution to the special issue on « Class and Stratification Analysis » to appear in *Comparative Social Research* (guest editor: Gunn Birkelund). The article eventually published in *Comparative Social Research* (2013, 30: 47-100) as "Educational Choices and Social Interactions: A Formal Model and A Computational Test" is a new, deeply modified version of this draft. Readers are warmly invited to read and quote the published version of my article. It was first published by the GEMASS in November 2011 as GeWoP-1.

This paper is published by the Groupe d'étude des méthodes de l'Analyse sociologique de la Sorbonne (GEMASS - CNRS, Paris Sorbonne, FMSH) in Paris, under the cover of the Fondation Maison des sciences de l'homme's collection of working papers.

Citing this document

Gianluca Manzo, *Educational Choices and Educational Traps*, FMSH-WP-2013-48, GeWoP-1, octobre 2013.

Informations et soumission des textes :

wpfmsh@msh-paris.fr

Fondation Maison des sciences de l'homme
190-196 avenue de France
75013 Paris - France

http://www.msh-paris.fr
http://halshs.archives-ouvertes.fr/FMSH-WP
http://wpfmsh.hypotheses.org

Abstract

From a substantive point of view, the paper analyzes the statistical association between individuals' educations and those of their parents in France and in Italy at the beginning of the twenty-first century – a phenomenon for which a comparison specifically focused on these two countries is still lacking. From a theoretical point of view, the paper develops a formal explanatory model of the macro-level structure of educational inequality - the «interdependent educational choice model» (IECM) - which frames educational choices as the result of both individual benefit/cost evaluations and peer-group pressures. It thus enriches the sociological educational rational-choice approach through the economic perspective of the so-called «membership theory of inequality». From a methodological point of view, the paper adopts agent-based simulations as a means to test the explanatory relevance of the IECM. Three groups of results are discussed. First, the paper demonstrates that simulation of the agent-based implementation of the IECM is able to generate a macro-level association between agents' educational backgrounds and their educational outcomes whose basic structure well reproduces all the qualitative aspects of both educational outflows and opportunities observed in France and in Italy at the beginning of the twenty-first century. Second, by analyzing data collected at the agent-level during the simulation, the paper demonstrates that these macro-level patterns are produced on the basis of micro- and relational-level regularities which qualitatively mimic the real-world counterparts for which we have (at least, partial) empirical evidence. Finally, by manipulating the characteristics of the artificial network in which agents are embedded, the paper demonstrates that the IECM generates a realistic macro-level structure of educational inequalities on the basis of a cumulative process in which highly educationally-homophilic ego-centred dyadic networks fuel educational traps that progressively amplify the initial within- and between-group heterogeneity in agents' perceptions of the benefits and costs of educational levels. Overall, the paper is a preliminary attempt to create, within the sociology of stratification and social mobility, an interface among formal theoretical modelling, the quantitative analysis of empirical data, and computational techniques.

Keywords

educational choices, social interactions, computational agent-based modelling, log-linear and regression models

Choix et pièges éducatifs. Vers une intégration de la modélisation statistique et informatique au sein de la sociologie quantitative de la stratification sociale

Résumé

L'article étudie l'association statistique qui existe entre le niveau scolaire des enfants et celui de leurs parents en France et en Italie au début du vingtième siècle – un lien pour lequel il n'existe pas encore une comparaison systématique centrées sur ces deux pays. D'un point de vue théorique, l'article présente un modèle explicatif de la structure macroscopique des inégalités éducatives qui conceptualise les choix scolaires comme résultant de calculs coûts/bénéfices ainsi que d'influences relationnelles. De cette façon, l'article se propose d'enrichir l'approche du choix éducatif rationnel grâce à la perspective économique de la « théorie de l'inégalité fondée sur l'appartenance ». Sur le plan méthodologique, l'article utilise la simulation à base d'agents artificiels pour tester la pertinence explicative du modèle théorique proposé. L'article discute trois groupes de résultats. Tout d'abord, l'article démontre que tous les aspects de la structure macroscopique de l'association statistique sous étude peuvent être déduits par simulation à partir du modèle théorique proposé. Ensuite, en étudiant le modèle de simulation du point de vue des agents artificiels qui le composent, l'article montre que ces résultats macroscopiques sont produits sur la base d'hypothèses réalistes au niveau micro et relationnel. Enfin, en manipulant les caractéristiques du réseau artificiel dans lequel les agents sont encastrés, l'article démontre que le modèle théorique proposé engendre une structure macroscopique des inégalités éducatives en créant un processus cumulatif dans lequel la ségrégation des liens artificiels reliant les agents amplifie progressivement les différences initiales dans leurs perceptions des bénéfices et des coûts de l'investissement éducatif. Dans son ensemble, l'article constitue une tentative préliminaire pour créer au sein de la sociologie de la mobilité et de la stratification sociale une interface entre la modélisation formelle, l'analyse quantitative de données empiriques et les méthodes de simulation informatique.

Mots-clefs

choix éducatifs, interactions sociales, modèles de simulation à base d'agents artificiels, modèles log-linéaires et de régression

Sommaire

Introduction

A large body of empirical research has documented that the positive correlation between an actor's social background and his/her educational achievement - whereby the higher the former, the greater the probability of achieving the highest educational levels - is one of the strongest and most change-resistant social regularities characterizing the macro-dynamics of social stratification in modern societies (see Shavit and Blossfeld 1993, Erikson and Jonsson 1996, Breen and Jonsson 2005, and Breen *et al.* 2009).

In this paper, by analyzing the most recent and best-quality national survey data available in France and in Italy, I focus more particularly on the cross-sectional statistical association between individuals' educations and the education levels attained by their parents. From a descriptive point of view, this analysis aims at filling a gap in the existing literature. First, the vast majority of studies on educational inequalities adopt social class as the indicator of an individual's social background (for a recent exception, see Pfeffer 2008). Second, to my knowledge, a comparative analysis of educational inequalities specifically focused on France and Italy is still lacking (for a discussion of the limitations of existing social class schemes in comparing these two countries, see Oberti 2002).

From a methodological point of view, the aim of the paper is instead to assess the potentialities of computational modelling – namely, the use of agent-based models (see Macy and Flache 2009) – as a means to test complex sets of theoretical hypotheses on the mechanisms responsible for the genesis of the macro-level structure of the distribution of educational levels and opportunities across social groups.

Since Boudon's (1973: chs. 2 and 4) pioneering study, many scholars have hypothesized that this social structure – and, possibly, its temporal transformations – arises from the composition of the strategies of rational actors who go through the educational system and, under the cultural and economic constraints imposed on them by their families of origin, evaluate the benefits, the costs, and the probabilities of success at each educational branching point (see Gambetta 1987 ; Goldthorpe 1996; Breen and Goldthorpe 1997; Jonsson and Erikson 2000; for criticisms, see also Nash 2003, and Esping-Andersen and Mestres 2000). Over the past two decades, an increasing number of quantitative analyses have sought to evaluate the explanatory power of the micro-sociological premises of this theoretical approach by considering both the micro- and macro-level predictions that should follow from it (see Cobalti 1992; Raftery and Hout 1993; Schizzerotto 1997; Need and de Jong 2000; Ballarino and Bernardi 2001; Davies *et al.* 2002; Becker 2003; Hillmert and Jacob 2003; Breen and Yaish 2006; Manzo 2006; Masterkaasa 2006; Stocké 2007; Van de Werfhorst and Hofstede 2007; Holm and Jaeger 2008; Gabay-Egozi *et al.* 2010).

None of these studies, however, has been able to demonstrate directly that the aggregate statistical structure of the association between actors' social backgrounds and their educational achievements arises from the composition of hundreds of thousands of actors that act and interact according to the mechanisms postulated.

This is not to deny the relevance of the statistical tests performed to date. It is indeed of crucial importance to prove empirically that actors from different social backgrounds perceive the benefits and costs of educational investment differently (see, for instance, Becker 2003, pp. 19-21); that status-maintenance objectives may differ across social groups (Stocké 2007, p. 514; Gabay-Egozi *et al.* 2010); or that actors from different social backgrounds differently believe in their probabilities of success (see, for instance, Need and de Jong 200, pp. 84, 88). It is also essential to establish empirically the extent to which these micro-level factors really impact on individuals' educational decisions, thus discovering, for instance, that status-maintenance may matter less than cultural constraints (Van de Werfhorst and Hofstede 2007) or less than the parents' perception of their child's probability of success (see Stocké 2007).

The issue is instead the capacity of multivariate statistical modelling to represent populations of heterogeneous actors that, driven by these correlations, iteratively evaluate sequential educational levels, influence each other, and generate a given macro-level distribution of educational levels across social groups. In other words, what is at stake is the possibility of directly modelling the complete set of mechanisms postulated by the theory, and of recreating the process associated with them, instead of inferring the configuration of these mechanisms from observation of their aggregate outcomes. That variable-based methods can perform this task seems especially unlikely when – as some analysis is beginning to do (see Morgan 2005 and Jaeger 2007) – dyadic social interactions are considered to be part of the educational decision-making process (for a discussion of this point within economics, see Manski 2000).

The present article suggests that computational modelling can be extremely useful for advancing in this direction. In particular, agent-based models constitute a tool of surprisingly flexibility in designing artificial microcosms in which the actors' behaviour rules, the structure of interactions among actors, as well as the dynamic loops between individual actions and their aggregate consequences can be explicitly and directly modelled. When the computer program containing the algorithms that implement the set of mechanisms postulated is executed, the process potentially associated with these mechanisms is triggered, and it is possible to study the aggregate patterns that these mechanisms are able to generate (for a technical introduction to agent-based models, see Wooldridge 2009; for a non-technical introduction, see Gilbert 2007; for a non-technical overview of the computational approach, see Miller and Page 2007; for the genesis of the computational approach in sociology, see Hummon and Fararo 1995, 1999).

The present article thus follows the research strategy that Hedström and Bearman (2009, p. 16) have recently put on the sociological agenda. They maintain that we should move systematically through five steps: " 1. we start with a clearly delineated social fact that is to be explained; 2. we formulate different hypotheses about relevant micro-level mechanisms; 3. we translate the theoretical hypotheses into computational models**;** 4. we simulate the models to derive the type of social facts that each micro-level mechanism brings about; 5. we compare the social facts generated by each model with the actually observed outcomes."

Within the quantitative sociology of social stratification, Goldthorpe (2001, p. 10) suggested a similar three-phase approach: "(i) establishing the phenomena that form the *explananda*; (ii) hypothesizing generative processes at the level of social action; and (iii) testing the hypotheses". Whilst he placed less emphasis on computer-based techniques to perform (iii), he did not exclude this solution a *priori*: "the simulation approach to hypothesis testing is not at a very advanced stage. None the less, there are by now at least indications that its potential in helping to integrate theoretical and quantitative empirical work is becoming more fully appreciated (see e.g. Halpin, 1998)" (*ibid.*, 14).

The degree of sophistication of agent-based modelling and simulation is at present such that it is reasonable to consider this technique as suited to integrating Hedström and Bearman's proposal into the field of quantitative study of social inequalities. While it is true that this methodology has to date been mostly adopted as a formal theorizing tool (for a review of these studies, see Macy and Willer 2002, Sawyer 2003), some applications suggest that there is nothing to prevent use of the technique in a more empirically-oriented way (see, for instance, Bruch and Mare 2006; Hedström 2005, ch. 6).

To demonstrate this statement, the article is organized as follows: first, I describe the statistical patterns characterizing the statistical association between the educations of individuals and those of their parents in France and in Italy at the beginning of the twenty-first century; second, I present the computational generative model that I devised to generate these empirical observations; third, I analyse the aggregate simulated data in order to assess the extent to which they reproduce the empirical ones; fourth, I perform a statistical analysis of the computational model at the agent-level in order to understand how it works and why it produces the patterns previously described; fifth, I manipulate some of the aspects of the artificial society, namely the characteristics of the artificial network in which agents are embedded, in order to locate the simulated outcomes that best approximate the empirical data within the largest range of outcomes potentially generated by the computational model; finally, I sum up the main substantive results and discuss the limitations of my modelling exercise.[1]

1. Compared to my previous work (see Manzo 2009), the following aspects are original: 1. the empirical data that the computational model presented in section 2 was designed to generate come from two more recent surveys; 2. the empirical regularities that the computational model was designed to generate concern the statistical association between individuals' educations and the education of their parents, while I have previously focused on the statistical association between individuals' educations and the social class of their parents; 3. I extended the computational model to include five groups of agents instead of four; 4. I marginally modified the computational model with respect to agents' scheduling and the way in which educational past performance operates;

Intergenerational Educational Mobility in France and in Italy

To describe the intergenerational transmission of education at its highest level of aggregation, I follow here the contingency table approach instead of the regression-based framework (for a recent discussion of the two perspectives, see Vallet 2004 and Pfeffer 2008). The empirical data on which I draw come from two large national surveys carried out in 2003 by the French and the Italian national bureaus of statistics (the INSEE and the ISTAT, respectively). These surveys are representative of the population aged 18-65 in France and aged 11-65 in Italy.[2] Since I consider here only respondents aged 27-65 in 2003 for whom complete information on their own and at least one of their parents' education achievements was available, the size of French sample analyzed amounts to 33514 individuals while the Italian sample contains 26566 observations.[3]

To maximize the meaningfulness of the comparison, I recoded into the Casmin educational schema (see Muller *et al.* 1989, Brauns et Steinman 1997, and, more recently, Breen 2004, pp. 14-16) the original information on both the respondents' and their parents' highest educational level (according to the "dominance principle", see Erikson and Goldthorpe (1992, p. 238), parental education is measured as the highest educational level between the respondent's father and mother). In order not excessively to increase the number of groups to be represented in the computational model (see section 2), I restricted my analysis to the following five-category version of the original schema: inadequately completed general education (1a); elementary education (1bc); lower-secondary education (2ab); upper-secondary education (2c); and tertiary education (3ab). Since the aim of the computational model that I present in the next section is to generate the vertical stratification of education across groups, this classification seems to be the best compromise among computational constraints, descriptive accuracy, and explanatory aims.

Within this classificatory framework, table 1 provides a first picture of the intergenerational transmission of education in France and in Italy by reporting the distribution of the highest educational destinations attained by respondents within each educational origin.

The figures show three main facts:

1. at the bottom of the two educational hierarchies, the intergenerational transmission of education seems stronger in France than in Italy, given that the proportion of those

5. I complemented the analyses of the computational macro-level outputs with analysis of data simulated at the agent level (see section 4); 6. I rewrote in NetLogo (see Tisue and Wilensky 2004a, b) the original Java implementation of the computational model (the Java code was initially created by Frédéric Amblard): all the results presented here are based on the new NetLogo implementation. The implicit aim of the present paper is thus to check the generalizability of my previous results to new sets of data and empirical patterns, as well as their robustness across programming languages (see also footnote 19).

2. For two recent analyses of educational inequalities based on these data, see, respectively, Duru-Bellat *et al.* (2011) and Barone *et al.* (2010).

3. In order to make it possible to extrapolate the results to the total corresponding population in the two countries, all the analyses have been performed on weighted data (the weights being obtained by multiplying the individual extrapolation coefficients for the total number of cases and dividing this product by the sum of all individual extrapolation coefficients).

Table 1. Educational Outflows: respondents' highest educational level (column) by their parents' highest educational level (row) (row percentages)

	France (2003)						Italy (2003)					
	1a	1bc	2ab	2c	3ab	N	1a	1bc	2ab	2c	3ab	N
1a	**45.69**	27.71	15.22	5.59	5.80	9620	8.50	**42.98**	38.01	8.80	1.71	4598
1bc	16.54	**27.77**	27.02	13.82	14.85	15244	0.79	17.93	**50.93**	24.72	5.63	12708
2ab	9.59	11.06	26.14	20.84	**32.38**	2979	0.45	3.32	36.87	**45.25**	14.11	5606
2c	7.06	9.48	21.20	19.68	**42.58**	2163	0.20	1.56	14.14	**52.10**	32.00	2468
3ab	4.83	3.99	11.26	16.73	**63.19**	3509	0.22	1.95	8.98	33.05	**55.81**	1176

Table 2. Educational opportunities: respondents' propensity to reach a given educational destination rather than each of the other ones compared to all other educational origins (generalized odds ratios)

	France (2003)						Italy (2003)				
	1a	1bc	2ab	2c	3ab		1a	1bc	2ab	2c	3ab
1a	**9.26**	3.90	0.80	0.27	0.13		**29.88**	12.15	1.10	0.09	0.03
1bc	1.22	**2.52**	1.26	0.73	0.35		0.92	**3.90**	2.20	0.58	0.22
2ab	0.57	0.66	1.32	**1.52**	1.32		0.53	0.39	1.84	**2.09**	1.27
2c	0.41	0.60	1.10	1.60	**2.33**		0.25	0.19	0.67	4.20	**7.40**
3ab	0.38	0.26	0.68	2.07	**7.23**		0.28	0.28	0.34	2.11	**18.05**

who experienced some upward educational mobility is substantially lower in the former country;

2. at the top of the educational hierarchies, educational status maintenance is somewhat stronger in France than in Italy, in that the proportion of those who follow their parents in obtaining the highest educational certificates is larger in the former country;
3. in-between, lower- and upper-secondary educational origins tend to reproduce themselves to a lesser extent in France than in Italy, in that the proportion of those who reach the highest educational levels starting from these intermediate positions is larger in France than in Italy.

Table 2 provides a somewhat different picture. The table reports the generalized odds ratios (see Kaufman and Schervish 1987, and, more recently, Zintzaras 2010) describing the "educational fluidity" existing in the two countries, that is to say, the overall configuration of the relative chances of obtaining some or other educational level.[4]

When each educational origin is contrasted to all the others with respect to reaching a given educational destination rather than each of the four other possible educational levels, French educational opportunities seem less rigid than the Italian ones. For instance, while the chances of being trapped in the less desirable educational condition are about nine times higher for the offspring of the lowest-educated parents in France, this ratio is about thirty times greater than that in Italy. Conversely, chances of educational maintenance at the top of the educational hierarchy for those from very well-educated families are more than two times stronger in Italy than in France.

To test the robustness of this difference, I performed a log-linear analysis of the raw cross-tabulation underlying tables 1 and 2. In particular, I estimated two of the models most commonly employed in intergenerational mobility research, namely the "constant association" model - which postulates, in my case, that educational origins and destinations co-vary but that this association is the same within the two countries - and the "uniform difference" model (Erikson and Goldthorpe 1992, pp. 91-92, Xie 1992)- which instead assumes that co-variation in educational origins/destinations also varies across countries by a multiplicative factor β (hereafter, *unidiff* parameter) . As usual, I considered as baseline the "conditional independence" model, which unrealistically posits that only variations of educational origins and destinations across countries matter (for a recent review of these statistical models, see Breen 2004: ch. 2)[5].

The results reported in table 3 show that, whatever goodness-of-fit measure one considers, the log-multiplicative "uniform difference" model outperforms the two other log-linear models,

4. Cobalti (1989) proposed using this measure of association to describe the relative aspect of social mobility in easily interpretable terms. He later extended this proposal to analysis of the inequality of educational opportunities (see Cobalti 1992, p.139-142). Formally, generalized odds ratios are simply the geometric mean of all the "basic sets" forming a given cross-tabulation (see Goodman 1969). As demonstrated by Kaufman and Schervish (1987, p. 233), there is a direct link between log-linear models and generalized odds ratios: for a two-way cross-tabulation, the generalized odds ratios for a given cell can be computed by raising the corresponding multiplicative parameter of the saturated model at power (l * c) / l-1*c-1, where l and c are the number of the table's rows and columns. I built on this relation to compute the coefficients reported in table 2.

5. I performed log-linear model estimations with the functions "loglm" and "gnm" (for the "uniform difference" model) contained in the "MASS" and "gnm" R (version 2.12.1) packages, respectively.

Table 3. Cross-national comparison of educational mobility regimes: fit of «conditional independence», «constant association», and «uniform difference» log-linear(multiplicative) models to French and Italian educational mobility tables (N= 60070)						
	Df	L^2	rL^2	DI	BIC	L^2_A - L^2_{B-C}
(A) Conditional Independence	32	20226.48	-	0.2187	19874.38	
(B) Constant Association	16	1105.93	94.5323	0.0437	929.8777	.000
(C) **Uniform Difference**	15	117.32	99.42	0.0121	-47.7331	.000
Uniform parameters : $Unidiff_{FRANCE}$= 1 $Unidiff_{ITALY}$=1.58387 (95%IC: 1.5475-1.6204)						

thus confirming that the structure of educational opportunity significantly differs between France and Italy. In particular, the estimated value of the unidiff parameter clearly evinces that the Italian educational mobility regime is less open: setting the value for France to 1, the Italian estimated value is about 1.6, and, as testified by the 95% confidence interval, this value significantly differs from the French baseline value.[6]

What about the difference between men and women? A systematic analysis of both educational outflows and generalized odds ratios disaggregated by sex would suggest that the basic structure of the patterns just described is virtually invariant with respect to gender. To prove this statement in the most compact way possible, I report the results of a log-linear analysis of the three-way cross-tabulations of respondents' highest educational levels by their parents' education and sex.

The results shown in table 4 clearly suggest that almost all the variation of respondents' educational attainments is due to their educational background. The "constant association" model, whose meaning here is the assumption that educational origins and destinations co-vary in exactly the same way for men and for women, indeed absorbs more than 99% of the residuals produced by the baseline model – here the "conditional independence" model, which unrealistically postulates that respondents' education only co-varies with gender. The "uniform difference" model, which posits that the educational-origin-destination association differs between men and women by a multiplicative factor β, only adds about 0.01% to the variance explained by the model, and the dissimilarity index is virtually unchanged. Moreover, this very limited fit improvement proves to be statistically significant only on French data.

6. This result echoes that of Breen and Luijkx's (2004, pp. 57-61 and 70-73) comparison of social fluidity in several countries conducted by means of the *unidiff* parameter: they found that France and Italy are among the least fluid nations, Italy being even less fluid than France. Pfeffer (2008, p. 553), whose analysis focuses directly on intergenerational educational mobility, finds similar low levels of educational fluidity in Italy but, unfortunately, his analysis does not deal with France.

Table 4. Women/men Comparison of educational mobility regimes: fit of «conditional independence», «constant association», and «uniform difference» log-linear(multiplicative) models to French and Italian educational mobility tables by respondents' sex						
	Df	L^2	rL^2	DI	BIC	L^2_A - L^2_{B-C}
France (2003) (Men: N=15840 Women: N=17674)						
(A) Conditional Independence	32	10552.26	-	0.2244	10218.83	-
(B) Constant Association	16	41.84318	99.6035	0.0119	-124.8723	.000
(C) **Uniform Difference**	15	24.343	99.7693	0.0091	-131.9524	.000
Uniform Difference parameters : $Unidiff_{MEN}$= 1 $Unidiff_{WOMEN}$=1.092 (95%IC: 1.0487-1.1349)						
Italy (2003) (Men: N=12994 Women: N=13562)						
(A) Conditional Independence	32	9807.065	-	0.2127	9481.08	-
(B) **Constant Association**	16	41.13628	99.5805	0.0105	-121.8559	.000
(C) Uniform Difference	15	37.76	99.615	0.0097	-115.0451	ns
Uniform Difference parameters : $Unidiff_{MEN}$= 1 $Unidiff_{WOMEN}$= 1.0442 (95%IC: 0.9971-1.0914)						

On this basis, since the model containing the three-way interaction only marginally improves the fit to the empirical data, I shall focus in the subsequent analyses on the link between respondents' and their parents' educational attainments irrespectively of respondents' sex. Since the aim of this paper is to develop and test a theoretical model of the basic mechanisms underlying the statistical regularities identified so far, the extent of the variations of educational outflows and opportunities across genders does not seem large enough to justify the introduction of specific hypotheses linking families' educational strategies to offspring's sex (for a recent comparative analysis of gender differences in educational inequality which would justify this simplification, see Breen *et al.* 2009).

The Generative Computational Model: The "Interdependent Educational Choice Model" (IECM)

The agent-based model that I have designed in order to reproduce the macro-level regularities described in the previous section is based on the following logic. I devise an artificial society which contains all the most essential items of information that the theoretical and empirical analyses of educational stratification have accumulated to date.

The pivotal component of this artificial microcosm is a population of individual entities (hereafter called 'artificial agents' or, simply, 'agents') each of which considers four elements in deciding whether or not a given educational level should be chosen: 1. the pay-off of the educational level on the job market (OB term, see [3]); 2. the pay-off of the educational level when this is evaluated from the point of view of the group to which the agent belongs (SB term, see [4]); 3. the cost of the educational level as perceived by the agent, given the cognitive, cultural and economic resources to which s/he has access (C term, see [1]); and 4. the evaluation that the educational level in question has received from agents with which the focal agent is in contact (I term, see [1]).

In order to implement this educational behavioural function, and to make it fully analyzable, several components have been interlocked, viz.: 1. a module defining the social settings in which the artificial agents act (exogenous macro-level); 2. a module specifying how an agent's perception of the benefits and costs of education is constrained by the group to which s/he belongs, as well as how agents consider their educational performances (micro-level); 3. a module defining how an agent's ego-centred dyadic network influences his/her educational choice (the network-related level); 4. a module establishing a link between the diffusion of education at the aggregate level and the agent's perception of the pay-offs from education (the endogenous macro-level).

The Exogenous macro-level. The artificial society comprises five groups of agents, which are ordered along a bottom-up continuum. These groups are assumed to mimic the five educational backgrounds contained in the empirical data that I analyzed in the previous section. Five hierarchically and sequentially ordered educational levels are also present within the artificial society. The task that each agent must perform is to evaluate each of these five educational levels L in sequence. Each educational level is assumed to have a specific value on the job market (the job market is not specifically modelled, however). Let us call this exogenous parameter the "objective return" (OR_{Lt}) to educational level L at time t (I will discuss later where its values come from)[7].

The Micro-level. At the individual level, an agent's evaluation of the educational level L is first assumed to depend on his/her perception of the benefits of the educational level L. Let us call this exogenous parameter the "subjective return" to the educational level L at time t (SR_{Lt}).

If one admits that education is better evaluated within higher socio-economic groups,[8] then it is

7. As testified by Breen and Goldthorpe's (1997) formal model, whilst the return of education on the job market is clearly behind the sociological rational approach to educational choices (in particular, when education is considered a positional good whose value decreases as more people obtain a given educational certificate, see Goldthorpe 1996), this factor does not explicitly appear in the usual way in which actors' subjective perceptions of education benefits are represented in terms of protection against downward social mobility. Since, as we shall see later, my computational model formally represented the inflation process of educational certificates, I decided to keep the "objective" and "subjective" aspects of education pay-offs explicitly separate.

8. Since Keller and Zavalloni's (1964) seminal article, this has been one of the basic assumptions of the sociological rational choice approach to educational choices. From an empirical point of view, whilst the studies by Stocké (2007) and Gabay-Egozi *et al.* (2010) cast doubt on whether this

reasonable to assume that the higher the agent's educational background, and the greater the subjective return SR that the agent attributes to the educational level L, the higher will be his/her propensity to evaluate L positively (I will discuss later how I initialize the SR parameters in the simulation).

The agent's evaluation of the educational level L is also assumed to depend on his/her perception of the costs of the educational level L. Let us call this exogenous parameter the "subjective costs" of the educational level L at time t (SC_L).

If one admits that material and symbolic resources positively co-vary with the place occupied on the social ladder, then it is plausible to postulate that the higher the agent's educational background, and the lower the subjective costs SC that the agent attributes to the educational level L, the higher will be his/her propensity to evaluate L positively (I will discuss later how I initialize the SC parameters in the simulation).[9]

The last individual attribute that the artificial agent is assumed to take into account when evaluating the educational level L is his/her past educational performance. Within the artificial society that I designed, this element was measured in terms of the agent's failures during his/her educational career. Failure here is the reverse of choice: when an agent is unable to choose the educational level L, s/he experiences a failure (to see how agent's final choice is taken, see [6]). Let us call NF_{it}, number of failures, the agent's past educational performances at time t (which is thus an endogenously-created and dynamically-changing individual-related quantity).

As expressed by [1], the agent's past educational performance NF intervenes as a weighting factor of his/her cost perception SR. In particular, I postulated that the better the agent's past educational performance, and the lower the subjective costs that s/he attributes to the educational level L, the higher will be his/her propensity to evaluate L positively.[10]

$$C_{iLt} = \frac{e^{NF_{it}}}{1+e^{NF_{it}}} SC_{GiL}$$

[1]

The Network-related level. Within the artificial society that I designed, agents do not live alone. Besides having their perceptions of the benefits and costs of the various educational levels constrained by their educational background, agents are embedded in a network of (symmetric and non-weighted) dyadic links, which are assumed to represent friendship relationships.

As expressed by [2], each agent is supposed to be (equally) sensitive to the number of his/her direct neighbours who have chosen at the instant t-1 the educational level that the agent is evaluating at time t (Ne^{FLt-1}) divided by the total number of his/her neighbours (Ne_i). As a consequence, the higher the proportion of choices for the educational level L in the agent's neighbourhood , the greater his/her propensity to evaluate L positively.[11]

differential evaluation of benefits of education can be entirely attributed to families' status-maintenance objectives (as Breen and Goldthorpe's (1997) model instead postulates), the evidence shows that education tends to be valued less at the bottom of the social hierarchy than at the top (see, for instance, Need and de Jong 2000, p. 88; Becker 2003, p. 19-21).

9. This is another of the basic mechanisms postulated by the sociological rational approach to educational choices (see Boudon (1973, pp. 75, 115-116, 129-130, 210); Goldthorpe (1996), Breen and Goldthorpe (1997), Jonsonn and Erikson (2000)); and, not surprisingly, it is one of the least disputable on empirical grounds (see, for instance, Becker 2003, pp. 19-21; Stocké (2007, p. 512).

10. Educational performance is the third pillar of the sociological rational approach to educational choices (see Goldthorpe and Breen 1997): empirical evidence shows that this factor systematically varies across social groups and that it powerfully affects educational decisions (see Stocké 2007, pp. 512, 515). Here, by postulating that educational performance affects the probability of an agent making a given educational choice by rendering his/her perception of cost better/worse, I am at the same time providing a possible explanation as to why this relation arises, and formally representing the fact that similar educational performances may differently affect the educational choices of two agents with two different educational backgrounds.

11. Jaeger (2007) suggested extending the rational educational choice approach to include the hypothesis that "students seek to maximize not only the long-term economic payoffs but also the probability of preserving existing peer and friendship relations" (thus following Morgan's (2005: ch. 6) intuition that "I will go to college if I expect other students similar to me will also go to college"). Jaeger's regression-based analysis found that "the higher students' value peer-group relations, the more likely it is that they will opt for the type of education to which the largest proportion of their peers and friends migrate" (*ibid.*, 472). In addition to preserving network solidarity, others' educational choices may matter because: 1. on a cognitive level, the larger the proportion of *ego*'s contacts that choose the educational level L, the higher the probability that *ego* has access to information on this educational level ; 2. on a normative level, the larger the proportion of *ego*'s contacts choosing the educational level L, the higher the probability that *ego* considers

$$I_{iLt} = \frac{\sum_{N_i} N_i E_{t-1}}{N_i}$$

[2]

The extent to which this socially-driven part of the agent's educational behaviour will produce educational conformism inducing him/her to follow the educational choices dominant in the educational group to which s/he belongs is dependent on the amount of educational homogeneity in the agent's neighbourhood.

I built on the structural properties of the "small-world" topologies (see Watts 2004) to create both educational homophily and heterophily in agents' ego-centred networks. In particular, starting with a regular network within each of the five group of agents, each of the agent's K in-group links is rewired outside the agent's group with probability p. The educational group of the potential out-group neighbours is then determined according to one of following criteria: 1. the more distant the focal agent's and potential neighbour's educational backgrounds, the lower the probability that the out-group link will be created (let us call this inter-group relational configuration "short-range out-group link dominance"); 2. the more distant the focal agent's and potential neighbour's educational backgrounds, the higher the probability that the out-group link will be created (let us call this configuration "long-range out-group link dominance"); 3. the probability that an out-group link will be created between two agents with different educational backgrounds is the same whatever the "educational" distance between them (let us call this inter-group relational configuration "out-group link equiprobability").[12]

This network configuration thus makes it possible to combine in-group high relational density areas with varying amounts of bridging ties increasing the probability that agents are connected outside these local areas. In terms of the "biased net theory" (see Skvoretz *et al.* 2004), the agent's educational background constitutes here the biasing factor that heavily alters the probability that each agent is linked to all the others, while the stochastic element determines how many "weak ties" (see Granovetter 1973, 1983) exist in the artificial society, as well as the extent to which, among them, short-range weak ties out-weigh long-range ones.

The Endogenous macro-level. Artificial agents are finally assumed to be sensitive to the overall number of choices that a given educational level L has received in the past from all other agents living in the artificial society. Let us call NC_{Lt}, number of choices, this endogenously-created and dynamically-changing quantity.

As suggested by [3], the diffusion of educational choices at the aggregate level affects the agent's educational choice first by progressively reducing the objective return OR_{Lt} of the educational level L, thereby indirectly depressing the agent's evaluation of the educational level L.[13]

$$\theta_{iL} = \frac{1}{\ln(NC_{L-n})} OR_L$$

[3]

However, it is also assumed that artificial agents actively react to this inflation dynamic of educational levels by iteratively re-adjusting their initial subjective perception SR of the benefits of the educational level L. As expressed by [4], this subjective re-evaluation process is not continuous. Instead, it is triggered whenever the number of choices for a given educational level reach a given proportion of the total number of agents living in the system (NC_{Lt-n}^{prop}) (for a historical outline of education inflation dynamics, see Collins 1979.

$$SR_{iL} = h\left(e + INT\left(\frac{NC_{L-n}}{NC_{L-n}^{prop}}\right)\right) SR_{GiL}$$

[4]

this educational level legitimate; 3. on a practical level, the larger the proportion of *ego*'s contacts choosing the educational level L, the higher the probability that *ego* has access to resources exploitable during school life at the educational level L. The combination of these factors makes it reasonable to assume that educational choices spread among actors by rational imitation (on this concept and on the related one of "mimetic interactions", see, respectively, Hedström 1998 and Orléan 1995).

12. This algorithm extends the algorithm proposed by Watts and Strogatz (1998; see also Watts 1999, pp. 503-506, 524) to the situation where several group of agents are present and the rewiring process must consequently apply to the creation of links among groups. Note also that I adopt here the simplest concept of distance among agents' educational backgrounds, namely the absolute value of the difference between educational group indexes (ranging from 1, the most advantaged educational background, to 5, the most disadvantaged one).

13. I take the natural logarithm of the number of choices simply to avoid a too rapid devaluation of educational levels.

As [5] shows, each agent finally computes his/her propensity P_{it} for the educational level L at the instant t by linearly combining the OB term - expressing the dynamically-changing objective return of the educational level L - the SB term - expressing the agent's dynamically-changing perception of the benefits of the educational level L - the C term - expressing the agent's dynamically-changing perception of the costs of the educational level L - and the I term - expressing the dynamically-changing local diffusion of the educational level L within the agent's ego-centred network.

$$P_{iDt} = \frac{1}{\ln(NC_{L-n})} OB_{L} + h\left(e + ENT\left(\frac{N_{L-n}}{N_{L-n}^{prop}}\right)\right) + SB_{GiLt} - \frac{e^{NIF_{il}}}{1+e^{NIF_{i}}} C_{GiLt} + \frac{\sum_{N_i} N_i^{FLt-1}}{N_i}$$

[5]

Given that several forms of direct and indirect interdependence among agents' educational choices are present, I hereafter refer to this equation as IECM, which stands for "interdependent educational choice model".

As indicated by [6],within the artificial society driven by the IECM, agents determine their final educational choice according to the simplest rule: if their propensity for the educational level L is positive, then they choose the educational level L, otherwise they experience a failure and are obliged to evaluate L once again (the maximum number of permitted trials being three).[14]

$$\text{if } P_{iLt} > 0 \text{ then } choice_L = 1$$
$$\text{if } P_{iLt} > 0 \text{ then } choice_L = 0 \;\&\; N \rightarrow +1$$

[6]

The condition under which the artificial agent will be able to choose the educational level L is given by [7], which can be easily deduced from [5] and [6].

$$\frac{1}{\ln(NC_{L-n})} OB_{L} + h\left(e + ENT\left(\frac{N_{L-n}}{N_{L-n}^{prop}}\right)\right) + SB_{GiLt} + \frac{\sum_{N_i} N_i^{t-1E}}{N_i} > \frac{e^{NIF_i}}{1+e^{NIF_i}} C_{GiLt}$$

[7]

This inequality states that the agent will choose the educational level L when his/her perception of benefits (objective and subjective) plus the dyadic social influence that s/he receives from his/her neighbors out-weigh his/her perception of costs. A less evident but more theoretically meaningful insight is contained in [7]. The inequality also states, in fact, that agents are able to choose the educational level L even if the benefit-minus-cost balance is negative, provided that the network-based social influence is large enough to counterbalance the negative benefit/cost difference. This is the main difference between the IECM and a more standard utilitarian model: in the latter case, benefits must always out-weigh costs for a positive choice to be made.

Before I assess the extent to which the artificial society in which agents are driven by [5] and [6] is able to generate a stratification of educational levels across educational groups which approximates the French and Italian data described in the previous section, it is necessary briefly to discuss the initial conditions of the artificial world that I chose to maximize the probability of achieving this goal, as well as how it evolves over the simulated time.

As table 5 indicates, all the population-level parameters are empirically-calibrated on the French and Italian survey data. Among them, the objective return of each educational level L that agents have to evaluate is initialized by means of the proportion of French and Italian respondents belonging to the highest social class (that is, according to the CASMIN occupational schema adopted here (see Breen 2004, p. 12), the "service class") among those reaching one of the five educational levels.

Given the lack of empirical data sufficiently detailed to initialize agents' perceptions of benefits and costs of the five educational levels, I drew SR and SC values from a family of (twenty) probability distributions (one for each combination of agents' educational origin and educational destination), each of which follows a log-normal distribution with specific means (the standard

14. My mathematical formulation of the agent's educational behavior thus amounts to a deterministic version of a "discrete choice model with externalities" (see Durlauf 1999a, 2001 and Durlauf and Cohen-Cole 2004; for a recent review, see also Rolfe 2009), whose pioneering applications can be found in Schelling (1971,1973), Granovetter (1978) and Granovetter and Soong (1983, 1988).

Table 5. Main starting conditions	
Parameter	Starting value
Population-level	
Number of groups	5 (E)
Population size	France=5000; Italy=10000 (E)
Objective return (OR_L)	Education Level: 1bc=0.10, 2ab=0.21,2c=0.41, 3ab=0.74 (E) Education Level: 1bc=0.01, 2ab=0.05, 2c=0.27, 3ab=0.76 (E)
Agent-level	
Subjective returns (SR_{GiL})	log-normal distribution (M)
Subjective costs (SC_{GiD})	log-normal distribution (M)
Network-level	
Ego's average number of neighbours	4 [0 - 40] (M)
Rewiring probability (p)	0.1 [0-1] (M)
Rewiring probability determining the target group of the rewired in-group link p_{IR}	Short-range out-group link dominance (M) (Long-range out-group link dominance) (M) (out-group link equi-probability) (M)
E=the parameter value derives from empirical information; M=the parameter value is defined by the modeller	

deviation was set to 0.25 for all the distributions). The crucial point concerns the order among these means. Since the two mechanisms referring to SR and SC postulate that the higher the agent's educational group, the higher/lower should be his/her perception of the benefits/costs of the educational level L, the main objective of the simulation exercise will be to determine whether there is at least one set of probability distributions that at the same time expresses this relation and reproduces the French and Italian empirical educational stratifications.[15]

In regard to the network-level parameters, agents' average number of dyadic links was set to 4 in order to represent the empirical regularity whereby, despite the fact that people may have numerous different types of contacts, the average number of significant others substantially affecting specific behaviours tends to be relatively small (see, for instance, Fowler and Christakis 2008). The relatively small proportion of out-group links (about 10% of the total number of links present in the system), as well as the decision to heavily overestimate among them those relative to agents with similar educational origins ("short-range out-group-link-dominance" structure) represent the overwhelmingly homophilic nature of friendship relations (see McPherson *et al.* 2001) (the values will be manipulated with an experimental purpose in section 5, however).

Given these initial conditions, the temporal schedule on which the artificial society evolves is quite simple. At each iteration, twenty percent of the agents are selected at random and, in random order, their propensity for the educational level L is computed according to [5], and their final choice about L is determined according to [6]. The total number of choices in favour of the five educational levels – the variable NC_{Lt}, –, is computed every fifty-two iterations and reinserted into the agents' education behavioural function [6]. The artificial society iteratively evolves along this two-level temporal scale - so that while the network-based social influence is continuously activated, the feedback effects of the diffusion of education at the aggregate level work only discretely - until all the agents have reached a stable educational destination.

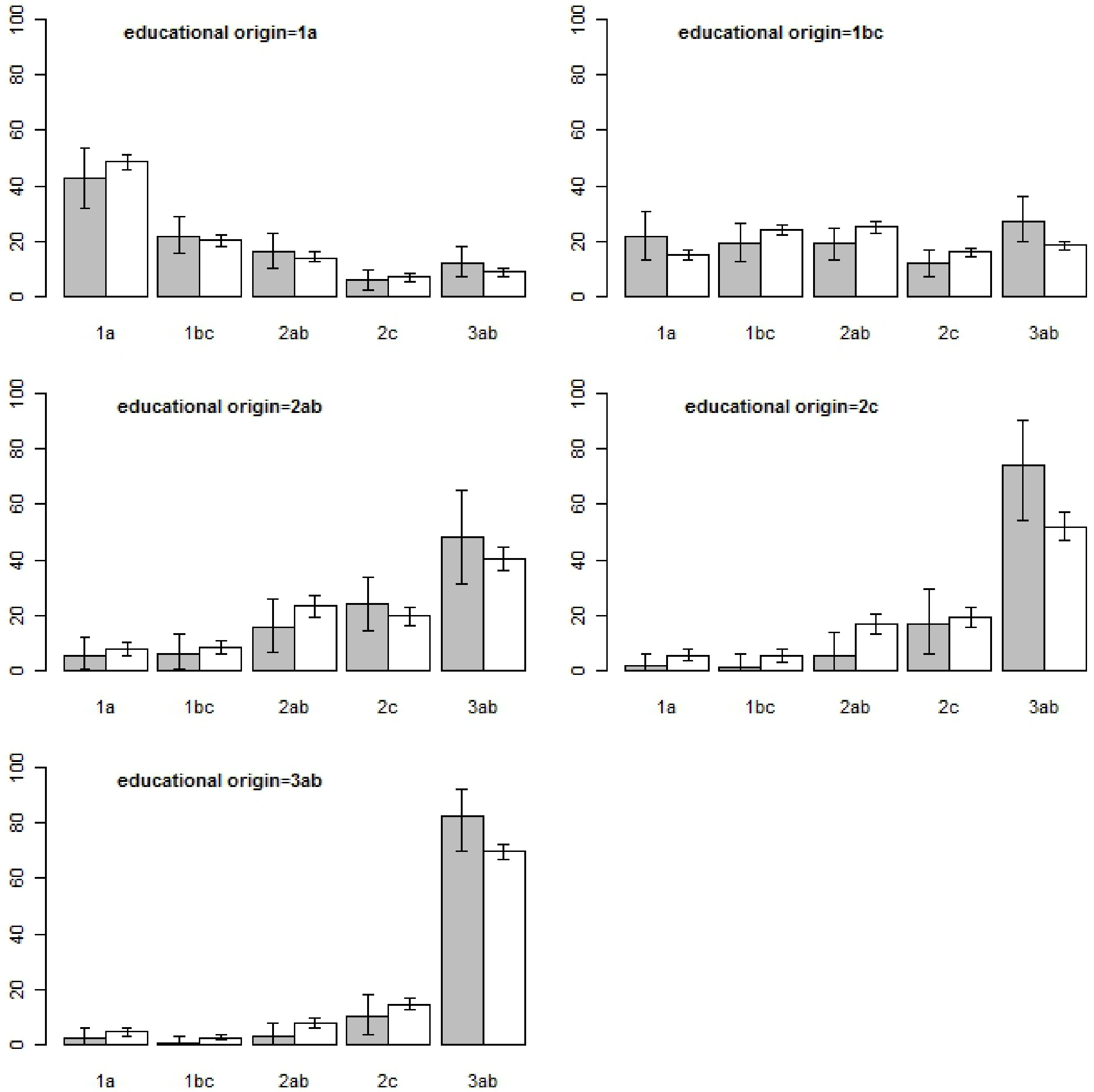
15. The two sets of twenty mean values finally adopted for France and for Italy are available upon request. I do not report them here because they are less meaningful than the relations among groups that they express with respect to their perception of the benefits and costs of educational levels. I will study these relations in section 4.

The Macro-level Patterns Generated by the IECM

To establish whether or not an artificial society driven by the IECM can generate realistic forms of educational stratification, I compared the macro-level patterns that the simulation of the computational model generated with the structure of the French and Italian empirical educational outflows and opportunities.

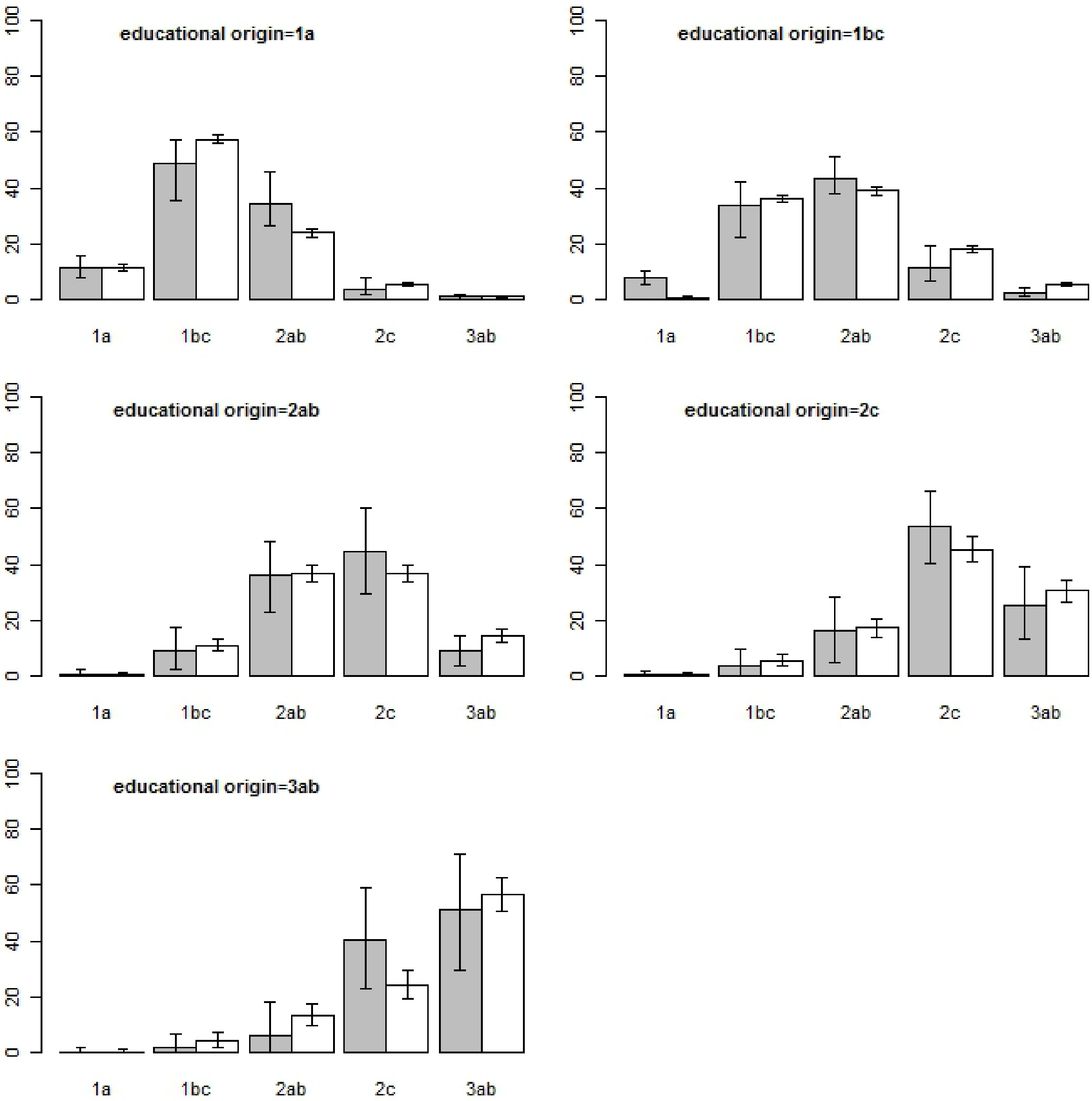
More specifically, I matched the distribution of the simulated outcomes for a given educational origin/destination combination across 1000 replicates of the computational model against the distribution of the empirically observed corresponding educational situations across 1000

Figure 1: simulated and empirical French educational outflows (N=5000).



The graphs compare, separately for each educational origin, the percentage of artificial agents (gray bars) and real respondents (white bars) who reach a given educational level as their highest educational destination. The height of the gray bars shows the simulated percentage averaged over 1000 replications of the computational model, while the height of the white bars shows the empirical percentage averaged over 1000 bootstrapped educational-origin-destination cross-tabulations drawn from the original French sample. The error bars report the 0.025- and 0.975-percentiles of the distribution of the outcomes across simulated and bootstrapped replicates.

Figure 2: simulated and empirical Italian educational outflows (N=10000)



See figure 1 for the explanation of graphs.

bootstrapped educational origin/destination cross-tabulations. If the variability surrounding the two series of data overlapped, I authorized myself to conclude that the educational stratification generated by the simulation of the IECM did not significantly differ from the educational stratification observed in the French and Italian survey data.[16]

16. I decided to match the simulated data generated by the IECM against a set of bootstrapped educational origin/destination cross-tabulations instead of comparing them with the single cross-tabulation computed on the French and Italian total samples (which I described in section 1) because the analysis of both the computational model and of the empirical data can be framed in terms of analyzing distributions of outcomes over multiple realizations of combinations of random variables. For the empirical data, this arises from the fact that the estimates of the empirical educational outflows and opportunities vary across samples drawn from the same population, while, for the simulated data, it derives from the fact that the IECM contains several stochastic components - agents' perception of the benefits and costs of educational levels, for instance, or the specific configuration of dyadic links between artificial agents. Like any other computational model, the simulation of the IECM can thus be conceived as "a computer-based statistical sampling experiment" (Law 2007, p. 485), in that each replicate of the simulation under a given set of parameter values constitutes a particular realization of a combination of random variables. As a consequence, in order to infer some regularities from the compu-

Figures 1 and 2 report the results of this analysis for the French and the Italian data with respect to the percentages of agents/respondents who reach a given educational level as the highest educational destination within each educational group of origin.[17] Needless to say, the match between the average simulated and empirical bootstrapped values is far from being perfect, but the variability areas around the two series of point estimates widely overlap. The qualitative structure of the aggregate educational outflows generated by several thousands of agents acting and interacting according to equations [5] and [6] is quite close to the empirical patterns observed in the French and the Italian samples.[18]

Firstly, artificial agents, similarly to their real *alter-egos*, tend to attain the highest educational levels 3ab with a frequency that increases as their educational origin is higher. Second, artificial agents who do not reproduce the educational status of their educational group of origin tend to reach close educational destinations more frequently than distant ones. Finally, the main difference between French and Italian educational outflows – that the highest educational level 3ab is more frequently attained in France than in Italy whatever the agent's educational origin – also appears in the artificial societies driven by the IECM.

The statistical analyses performed earlier showed that the main consequence of this difference between French and Italian educational outflows is that the overall structure of the relative chances of attaining some or other educational destination tends to be less open in Italy than in France (see tables 2-3). Does the statistical association between artificial agents' educational origins and destinations exhibit a similar pattern at the aggregate level?

Figure 3 shows that this is the case to a large extent. The black circles report the value of the log-multiplicative coefficient of the "uniform difference model", the *unidiff* parameter, which I obtained by estimating this log-linear model on each of the 1000 bootstrapped educational origin/destination cross-tabulations drawn from the total French and Italian samples, and, on the other hand, on each educational origin/destination cross-tabulation generated by replicating 1000 times the simulation of the computational model for France and for Italy. As the reader may remember from section 1, the meaning of the *unidiff* coefficient is that, compared to France taken as reference category (for which the *unidiff* coefficient is set to 1, the continuous line in figure 3), there is less educational fluidity in Italy if the *unidiff* coefficient is higher than 1 in that country.

Figure 3 thus shows two main facts. First, the empirical bootstrapped estimates (upper graph) confirm the result obtained on the total samples and according to which the Italian educational fluidity is lower than the French one. In all of the 1000 bootstrapped estimations, the constant association model was outperformed by the uniform difference model. The estimates of the *unidiff* coefficient are also very close. In fact, 95% of the bootstrapped ones vary between 1.40 and 1.55, while the 95% confidence interval for the total empirical sample was estimated at 1.55-1.62.

The second major fact shown by figure 3 is that this difference between the French and the Italian educational opportunity structures also appears in the data generated by the simulation of the IECM (lower graph). Except in 22 out of 1000 estimations (which correspond to the point estimates in figure 3 whose confidence intervals cross the reference category line), the uniform difference model fits the simulated data generated for France and for Italy better than does the constant association model.

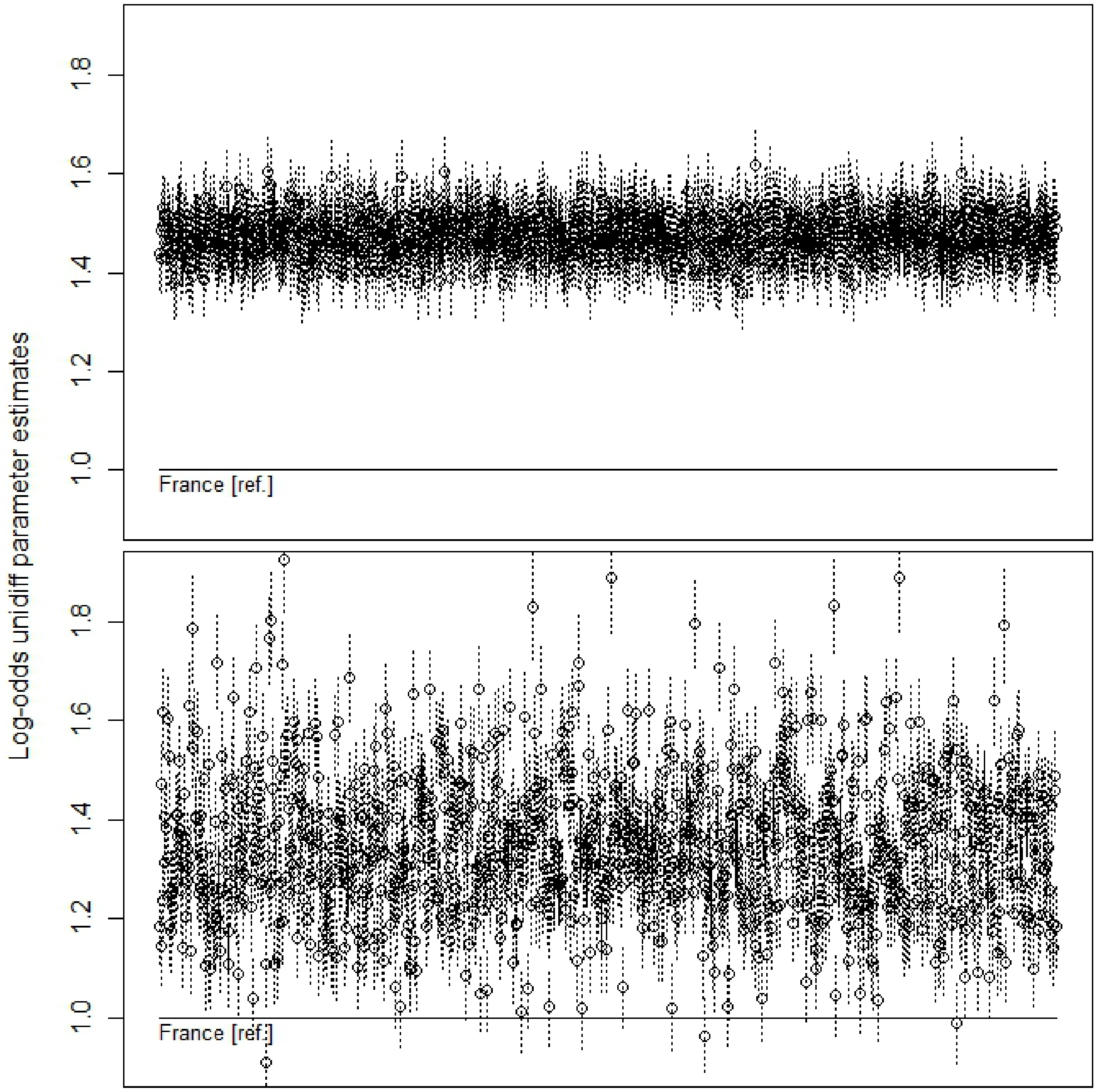
It is certainly true that the simulated estimates vary to a larger extent than the empirical bootstrapped estimates; their magnitude, however, is

tation model, the distribution of simulated outcomes across replicates matters more than the outcome of a single run.

17. Compared to the original sample sizes, the choice of bootstrapping 5000-case cross-tabulations for France and 10000-case cross-tabulations for Italy was taken in order to find the best balance between obtaining bootstrapped educational outflows that reproduce all the basic patterns of the original-size educational origin/destination cross-tabulation and, on the other hand, obtaining population sizes that reduce the computation time needed to simulate the agent-based implementation of the IECM.

18. Confidence intervals were computed as non-parametric percentile confidence intervals: that is, I looked for the bootstrapped values containing 95% percent of the distribution of the bootstrapped values (see Davison and Hinkley 1997, ch. 5). Confidence intervals for the simulated data were computed in the same way. Thus, while I followed Law's (2007, pp. 269-271) IC-based approach for comparing simulated and real-system outcomes, I adopted non-parametric instead of parametric confidence intervals.

Figure 3: Empirical (upper graph) and simulated (lower graph) estimates of the Unidiff parameters.



Note: the upper graph reports the *Unidiff* parameters of the log-multiplicative "uniform difference" model estimated on 1000 bootstrapped educational-origin-destination-by-country cross-tabulations. The lower graph reports the results of the estimations of the same log-multiplicative model on the 1000 educational-origin-destination cross-tabulations generated by replicating 1000 times the simulation of the IECM for the two countries. The vertical dashed bars provide the 95% confidence interval around the point estimates. Coefficients higher than 1 and not crossing the continuous horizontal line indicate that the association between respondents' (artificial agents') educational origins and their highest educational destinations attained is significantly stronger in Italy than in France (reference category).

comparable and largely overlapping. In fact, the median of the empirical bootstrapped estimates is 1.47, while that of the simulated ones is 1.34. Around the median values, then, 95% of the empirical bootstrapped estimates vary between 1.40 and 1.55, while 95% of the simulated ones vary between 1.12 and 1.66.

Overall, these results seem to provide strong evidence that an artificial society in which each agent evaluates the educational levels according to the mechanisms formalized by equation [5] is sufficient to generate a macro-level association between agents' educational destinations and origins whose basic structure exhibits all the traits observed in the French and Italian empirical data.

Agents and networks at work within the artificial society driven by the IECM

In the previous section, I tried to demonstrate that the macro-level consequences of the IECM are structurally homologous to the cross-sectional aggregate educational stratification observed in the French and Italian survey data. In the present section, I dissect the artificial society in order to demonstrate that this result has been reached on the basis of highly plausible and realistic micro- and relational-level regularities.[19]

To do so, I will apply standard multivariate techniques to agent-level data collected during simulations of the IECM that satisfyingly reproduced the French and Italian aggregate data (for a similar strategy applied to simulated outcomes variability across parameter space, see Fararo and Butts 1999, pp. 51-52).[20] In particular, I first analyse the relation within the artificial society between agents' educational backgrounds and their perceptions of the benefits and costs of educational levels, their educational performances, as well as the dyadic neighbours with whom they are in contact. Second, I assess the relative importance of the four components of the agents' educational behaviour function [5] at each educational transition. Finally, I evaluate the relative weights of the main factors underlying this function choice for the educational outcome finally reached by the agents. While this three-step analysis considers the artificial society driven by the IECM from a static point of view, its by-product will be some light shed also on the low-level dynamic underlying the macro-level patterns generated by the computational model (for a discussion of this problem with agent-based models, see Macy and Flache 2009, pp. 261-264).

Agents' perceptions of education benefits and costs, agents' failures and agents' neighbourhoods

Let us start with agents' perceptions of the benefits (SR, subjective returns) and the costs (SC, subjective costs) of the four educational levels that agents must evaluate within the artificial society. As stressed earlier, I drew the SR and SC values from a set of log-normal distributions. In particular, I looked for the means of these distributions which, at the same time, maximize the fit of simulated data to empirical data and respect order constraints expressing the fact that higher social groups tend to evaluate education more positively than lower social groups and perceive it as less costly.

To investigate the relation created by the probability distributions adopted to initialize agents' perceptions of the benefits (the parameter SR of [5]) and the costs (the parameter SC of [5]) of the four educational levels that they must evaluate within the artificial society driven by the IECM between these two agents' attributes and agents' educational background, I regressed agents' SR and SC values on the agents' group (see table 6).[21]

19. In Manzo (2007, pp. 28-39) and Manzo (2009, pp. 160-166, 245-254), I attempted to demonstrate that the IECM is able to generate the basic diachronic patterns of the association between social class and education observed on a series of French and Italian cohorts covering the first two-thirds of the twentieth century. In the present paper, I preferred to deepen the analysis of the internal functioning of the computational model instead of trying to reproduce the diachronic analysis on the new data studied in the this paper.

20. Since information was collected at the agent-level, the analysis of the complete set of 1000 replicates underlying the results commented on in the previous section would have required working on files containing 5,000,000 and 10,000,000 cases for France and Italy, respectively. Because of memory limitations, I was unable to load the Italian agent-level simulated file. The following analysis is thus restricted to a sub-sample of 100 replicates.

21. In this analysis, as well as in those reported in tables 8, 9, 10 and 11, I followed the same strategy, namely estimating the regression model separately on agent-level data collected during each of the 100 replicates of the simulation. The reported coefficients are thus averages of the 100 estimated coefficients across replicates, and standard errors (in parentheses) give coefficient uncertainty across replicates (all the regression estimations were performed with the "lmList" function contained in the "lme4" R package). A more elegant way of dealing with simulated replicates variability would have been to frame replicates as repeated measures and accordingly estimate mixed-effect models - or multilevel models if one prefers - with both intercept and slope varying across levels (here the replicates) (see Gelman and Hill 2009, chap. 11-13). The estimation of fixed-effect models is computationally demanding, however. Moreover, the larger the within-level population and the more numerous the levels, the less mixed-effect models perform better than formally equivalent standard regression models separately estimated within each level. Given that my agent-level simulated datasets contained both large within-level populations (5000/1000 cases) and many levels (100 replicates), I finally opted to return to the basic single-level regression strate-

TABLE 6. OLS regression estimates of the effects of agents' educational group of origin on agents' subjective evaluations of the benefit, SR, and cost, SC, of educational levels (reference category: lower 2, the lowest education background).

	French Artificial Society (N=5000)					Italian Artificial Society (N=10000)			
	SR - level 1bc		SC - level 1bc			SR - level 1bc		SC - level 1bc	
intercept	0.1317	0,0002	0.6241	0,0005		0.1831	0,0002	0.5420	0,0004
Upper	0.0744	0,0004	-0.0925	0,0008		0.0448	0,0009	-0.0446	0,0013
Intermediate 1	0.0177	0,0004	-0.0769	0,0011		0.0234	0,0006	-0.0367	0,0010
Intermediate 2	0.0166	0,0004	-0.0657	0,0010		0.0123	0,0003	-0.0294	0,0008
Lower 1	0.0140	0,0003	-0.0600	0,0007		0.0114	0,0002	-0.0239	0,0005
	SR - level 2ab		SC - level 2ab			SR - level 2ab		SC - level 2ab	
intercept	0.1292	0,0002	0.6426	0,0006		0.1610	0,0001	0.5857	0,0004
Upper	0.0986	0,0004	-0.0949	0,0009		0.1034	0,0009	-0.0796	0,0014
Intermediate 1	0.0214	0,0004	-0.0609	0,0012		0.0894	0,0006	-0.0705	0,0010
Intermediate 2	0.0214	0,0003	-0.0537	0,0010		0.0783	0,0004	-0.0636	0,0005
Lower 1	0.0190	0,0003	-0.0192	0,0007		0.0392	0,0002	-0.0279	0,0005
	SR - level 2c		SC - level 2c			SR - level 2c		SC - level 2c	
intercept	0.1229	0,0002	0.7388	0,0005		0.1530	0,0002	0.6753	0,0002
Upper	0.1162	0,0004	-0.0882	0,0008		0.1522	0,0001	-0.1478	0,0011
Intermediate 1	0.0315	0,0004	-0.0720	0,0011		0.1231	0,0006	-0.1216	0,0008
Intermediate 2	0.0296	0,0004	-0.0638	0,0009		0.1107	0,0005	-0.0802	0,0005
Lower 1	0.0023	0,0002	-0.0470	0,0006		0.0431	0,0002	-0.0072	0,0002
	SR - level 3ab		SC - level 3ab			SR - level 3ab		SC - level 3ab	
intercept	0.1134	0,0002	0.8595	0,0003		0.1168	0,0001	0.8598	0,0002
Upper	0.1366	0,0005	-0.0663	0,0006		0.2311	0,0012	-0.1341	0,0011
Intermediate 1	0.0368	0,0004	-0.0620	0,0009		0.1469	0,0006	-0.1216	0,0008
Intermediate 2	0.0161	0,0004	-0.0547	0,0007		0.1339	0,0005	-0.0802	0,0005
Lower 1	0.0009	0,0002	-0.0077	0,0004		0.0022	0,0002	-0.0072	0,0002
	Average SR - SR difference					Average SR - SR difference			
intercept	-0.5774 (0,0003)					-0.4934 (0.0002)			
Upper	0.1904 (0,0005)					0.2238 (0.0008)			
Intermediate 1	0.0985 (0,0006)					0.1785 (0.0006)			
Intermediate 2	0.0835 (0,0006)					0.1461 (0.0004)			
Lower 1	0.0461 (0,0003)					0.0440 (0.0003)			

Note: the regression model has been estimated on the agent-level data collected during each of 100 replicates of the simulation: each reported coefficient is thus the average of the 100 estimated coefficients across replicates (the standard errors of each series of coefficients is given in parentheses). This holds for tables 8, 9, and 11

As the first column of table 6 shows, whatever educational level one considers, the higher the agent's educational background (the lowest group is taken as reference category), the more positive, on average, are the subjective benefits that the agent associates with the educational level. Within this hierarchy, agents with the highest educational backgrounds tend to evaluate each educational level especially positively compared to the groups. The distinctive position of this group of agents, however, is more pronounced within the French artificial society than within the Italian one.

The inverse relation holds for agents' perceptions of costs (tables 6, column 2). At each educational level, the higher the agent's educational background the lower, on average, tends to be the cost that the agent attributes to the educational level concerned.

As equation [5] suggests, however, what drives agents' educational choices is the difference between the benefit and the cost that they attribute to each educational level that they must evaluate. The bottom section of table 6 thus reports the effect of agents' educational background on this difference averaged across the four educational levels (that is, I computed the difference between the geometric mean of SR values and that of SC values). The figures clearly suggest that the higher the agent's educational background, the less negatively, on average, s/he perceives educational levels. Within this hierarchy, agents with the highest educational backgrounds occupy a distinctive favourable position, which, again, is more marked within the French artificial society than within the Italian one[22].

gy (however, for the French agent-level simulated dataset, which is smaller than the Italian one, I also estimated mixed-effect models - by means of the "lmer" function contained in the "lme4" R package: parameter fixed effects estimates as well as their standard errors only differ from the average single-level standard regression estimates reported in what follows at the level of the fourth decimal).

22. Explaining in detail the SR and SC settings finally adopted for the two artificial societies would fall outside the scope of this article. Elsewhere (see Manzo 2009, ch. 5 and, ch. 7, pp. 169-175), I have argued that the different initializations are intended to represent, within the artificial microcosm driven by the IECM, the link that may exist in the real world between the horizontal and vertical stratification of the French and the Italian educational systems, and, on the other hand, individuals' perceptions of the benefits and costs of education (for two comparative empirical studies focused on this link, see, for instance, Muller and Karle 1993, and Pfeffer 2008).

While agents' perceptions of the benefits and costs of educational levels constitute the main parameter manipulated in the simulation, inequality [7] indicates that the second major initial condition potentially heavily affecting agents' educational choices is the set of dyadic influences in which each agent is embedded. Consequently, it is important to know what the composition of the agents' neighbourhood looks like at the beginning of the simulation.

Table 7 shows that the parameter values chosen for the artificial network at the outset (see table 5) generate agents' ego-centred networks with two major characteristics. First, whatever educational background one considers (rows), the majority of the agent's neighbours tend to belong to the same educational background as him/her. On average, agents tend to have about 3 neighbours out of 4 in-group neighbours. Second, the few out-group links established by agents exhibit a clear pattern: the larger the distance between the agent's educational background and the educational backgrounds of the potential neighbours, the smaller the number of out-group neighbours. This basic relational pattern does not differ significantly between the French and the Italian virtual societies.

Thus, at the individual level, agents' subjective benefit/cost balances tend to be more positive as agents' educational backgrounds are higher (which qualitatively corresponds to the partial empirical evidence available on the real world: see, for instance, Becker (2003, p. 19-21), and, Stocké (2007, pp. 512)), and, on a network-level, in-group links tend to outweigh out-group links – among which, moreover, short-range links tend to be more frequent than long-range links (which qualitatively mimic the robust empirical regularity of the overwhelmingly educationally-homophilic character of social relations: see McPherson *et al.* 2001, pp. 426-427).

On the basis of these two initial conditions, two expectations may be formulated as to what should be observed within the artificial society driven by the IECM as it evolves over the simulated time. First, the less favourable benefit/cost balance characterizing agents with lower educational backgrounds should structurally expose them to the risk of educational failures more than agents with higher educational backgrounds. Second, given that

Table 7. Agents' average number of neighbours as a function of the educational distance between the focal agent's educational background and neighbour's educational background (averaged values over 100 replications)											
	French Artificial Society						Italian Artificial Society				
	1a	1bc	2ab	2c	3ab		1a	1bc	2ab	2c	3ab
1a	**3.24**	0.42	0.12	0.04	0.03		**3.24**	0.47	0.11	0.04	0.02
1bc	0.33	**3.24**	0.19	0.07	0.04		0.29	**3.24**	0.18	0.07	0.02
2ab	0.31	0.63	**3.24**	0.24	0.22		0.35	0.87	**3.24**	0.21	0.08
2c	0.00	0.16	0.35	**3.24**	0.69		0.24	0.64	0.40	**3.24**	0.25
3ab	0.05	0.08	0.13	0.29	**3.24**		0.28	0.54	0.35	0.58	**3.23**
Note: variability across replications is extremely low: the standard deviation of the reported values varies between 0.01 and 0.07.											
F: Averaged Agents' Average degree:1=3.79,2=4.78,3=4.65,4=3.87,5=3.84											
I: Averaged Agents' Average degree:1=4.97,2=4.78,3=4.75,4=3.79,5=3.89											

agents tend to be linked with each other predominantly within their own group, agents with lower educational backgrounds should be structurally exposed to neighbours with less good educational outcomes than agents with higher educational backgrounds.

Table 8 proves that the first deduction on the micro-level educational dynamics sustained by the IECM is correct. On average, in fact, there is a negative correlation within the artificial society between agents' educational backgrounds and the overall number of failures that agents accumulate during their educational careers (the parameter NF of [5]). By taking agents with the lowest educational background as the baseline, bivariate regression coefficients show that the higher the agent's group, the less numerous tend to be the failures accumulated during the simulation (which is another association which closely corresponds to what we know about the relation between social background and educational performance in the real world: see, for instance, Need and de Jong (2000, p. 84).

Table 9 provides, on the other hand, some indications on the existence of the second phenomenon. In particular, I examined in this case the difference between the proportion of an agent's neighbors who reached the highest or the full secondary educational level, and the proportion of those who only reached one of the three other lower educational levels. This measure of the educational quality of the agent's neighborhood - separately computed on the agent's in-group and out-group neighbors - thus varies between -1, when none of the agent's neighbors obtain one of the two highest educational levels, and 1, when all the agent's neighbors obtain one of these two educational levels.

TABLE 8. OLS regression estimates of the effects of agents' educational group of origin on the agent's number of failures accumulated during his/her educational career (reference category: lower 2, the lowest education background).				
	French Artificial Society (N=5000)		Italian Artificial Society (N=10000)	
	Failures			
intercept	3.1982	0.0107	4.2531	0.0042
Upper	-2.2138	0.0242	-1.6831	0.0376
Intermediate 1	-1.8864	0.0344	-0.8181	0.0287
Intermediate 2	-0.9963	0.0276	-0.1974	0.0126
Lower 1	-0.3618	0.0118	-0.0226	0.0044

TABLE 9. OLS regression estimates of the effects of the agent's educational group of origin on the educational quality of the agent's in-group and out-group neighbours (reference category: lower 2, the lowest education background).

French Artificial Society (N=5000)				
	In-group neighbourhood educational quality		Out-group neighbour-hood educational quality	
intercept	-0.6555	0.0085	-0.9001	0.0034
Upper	1.5054	0.0084	1.7198	0.0089
Intermediate 1	1.4671	0.0110	1.4747	0.0143
Intermediate 2	1.1145	0.0143	0.9584	0.0165
Lower 1	0.4331	0.0072	0.1849	0.0048
Italian Artificial Society (N=10000)				
	In-group neighbourhood educational quality		Out-group neighbour-hood educational quality	
intercept	-0.0307	0.0126	-0.5076	0.0097
Upper	0.6570	0.0066	0.6447	0.0072
Intermediate 1	0.5912	0.0070	0.4700	0.0061
Intermediate 2	0.2515	0.0051	0.1678	0.0039
Lower 1	0.0190	0.0039	0.1433	0.0029

NOTE: An agent's neighborhood educational quality is measured as the difference between the proportion of neighbours who have reached the highest or the full secondary educational level and the proportion of those who have reached one of the three other educational levels. Hence the index varies between -1, when none of the agent's neighbours attain one of the two highest educational levels, and 1, when all the agent's neighbours attain one of these two educational levels

The structure of the coefficients reported in the first column of the table clearly shows that, on average, the higher the agent's group, the larger the proportion of his/her in-group neighbours who ended up with the highest educational level. Similarly, because short-range out-group links dominated long-range out-group links, the higher the agent's group, the larger, on average, the proportion of his/her out-group neighbours who ended up with the highest educational level. These are strong indications that the micro-level dynamics generated by the IECM progressively generate local neighbourhoods of agents with similar educational performances which reinforce each other: in other words, this is what one may call an "educational trap" (by analogy with the concept of "poverty trap": see Durlauf 2006 and Durlauf and Cohen-Cole 2004).

The relative importance of objective returns, subjective returns, costs and social influence

Before I try to prove the existence of this phenomenon more directly, let us assess the extent to which each of the four components of the agents' educational choice function (see eq. 5) affects the overall evaluation that the agents give to each educational level.

To obtain some insights, I regressed the propensity P observed during the simulation for each educational level on the computed values of the four main components of equation [5], namely the terms expressing the objective benefits (OB) (see eq. [3]), the subjective benefits (SB) (see eq. [4]), the costs (C) (see eq. [1]), and the diffusion of the educational level L in the agent's neighbourhood (I) (see eq. [2]). By introducing each of these terms sequentially in the regression models, one can evaluate the extent to which the four

TABLE 10. Average (over 100 replicates) predictive contribution (R^2) of each component of the agent's educational behavioural function (see Eq. [5]) to the agent's propensity P for each educational level.				
	Level 1bc	level 2ab	level 2c	level 3ab
French Artificial Society (N=5000)				
OB	0.0572 (0.0193)	0.3628 (0.0346)	0.6287 (0.0286)	0.8384 (0.0153)
OB + SB	0.0591 (0.0191)	0.4103 (0.0348)	0.6557 (0.0280)	0.8410 (0.0157)
OB + SB+ C	0.3435 (0.0123)	0.5028 (0.0275)	0.7327 (0.0192)	0.8958 (0.0079)
OB + SB + C + I	1	1	1	1
Italian Artificial Society (N=10000)				
OB	0.0016 (0.0012)	0.0521 (0.0092)	0.0878 (0.0260)	0.2293 (0.0690)
OB + SB	0.0053 (0.0027)	0.0556 (0.0088)	0.0920 (0.0265)	0.3440 (0.0690)
OB + SB+ C	0.3137 (0.0139)	0.3112 (0.0229)	0.5648 (0.0515)	0.8571 (0.0243)
OB + SB + C + I	1	1	1	1

terms contribute to the final values of the agent's propensity P_i at each educational level. Table 10 reports the overall fit (R^2) of each of these OLS regression models.

The main result is that the relative contribution of the social influence term (I) is very strong at the two first educational levels that agents have to evaluate - about 70% and 50% of the variance of P_i across agents is left unpredicted when the social influence term is absent (within the Italian artificial society this is still the case at the third education level that agents must pass) - while the objective benefit term (OB) largely outweighs the other terms at the subsequent educational levels: more than 60% and 80% respectively of the variance of P_i across agents is absorbed at the third and fourth educational level when only the term containing the objective returns is introduced (within the Italian artificial society this is the case only of the highest educational level that agents must pass). The contribution of agents' subjective perceptions of educational benefits is small at each level, while the subjective cost term contributes by about one third at the first educational level (the first three within the Italian artificial society).[23]

This analysis thus provides a quite clear overall picture of which mechanisms drive most of the agents' education behaviour within the artificial society. The mathematical structure of the IECM makes agents very sensitive to the educational behaviour of others when the market return of educational levels is not sufficiently large to offset subjective benefit/cost balances which tend to be negative. In this respect, the observed differences between the French and the Italian artificial societies are meaningful. Objective educational returns are lower in the latter (see table 5), and it is precisely within the virtual Italian society that the importance of the social influence term persists longer throughout agents' educational careers.

The determinants of an agent's final educational outcome

However, to gain deeper understanding of the micro-level dynamic at work within the artificial society driven by the IECM, one must more directly evaluate the extent to which agents' final educational outcomes are related to the various micro- and network-level factors underlying their educational choice functions [5]. I addressed this issue by regressing the highest educational level obtained by the agent at the end of the simulation on some of the agent's attributes, as well as on some characteristics of the agent's ego-centred network.[24]

23. Because of space constraints, I omit the fit of this series of regression models when they are estimated separately for each group agents. The basic structure of the relative contribution of the four terms that I have described for the total population is in fact largely invariant across groups of agents.

24. The simulated agent's highest educational level is coded as a five-point scale where 0 means "no educational level (1a)" and 4 indicates "highest educational level (3ab)". Given that the number of categories is limited and that the assumption of equidistance between them is questionable, the ideal statistical model would be the ordered logistic regression (see Fullerton 2009; Gelman and Hill 2007, p. 123). The

TABLE 11. OLS regression estimates of the effects of several agents' attributes and agents' ego-centred network characteristics on agents' final educational outcomes

	French Artificial Society (N=5000)	Italian Artificial Society (N=10000)
(1) intercept	3.5095 (0.0170)	3.3282 (0.0167)
(2) Average Subj. Benefit-cost Balance	1.3313 (0.0180)	1.5616 (0.0111)
(3) No. of Failures	-0.1362 (0.0021)	-0.0234 (0.0038)
(4) No. of in-group neighbours	-0.2337 (0.0050)	-0.1559 (0.0027)
(5) No. of in-group neighbours : Upper	0.1922 (0.0057)	0.1612 (0.0061)
(6) No. of in-group neighbours : Intermediate 1	0.2024 (0.0067)	0.1350 (0.0046)
(7) No. of in-group neighbours : Intermediate 2	0.1865 (0.0070)	0.1406 (0.0037)
(8) No. of in-group neighbours : Lower 1	0.0887 (0.0059)	0.0414 (0.0031)
(9) Difference between higher- and lower-group neighbours	0.0332 (0.0014)	0.0444 (0.0009)
(10) In-group neighbourhood Educational Quality	1.4773 (0.0045)	0.6896 (0.0030)
(11) Out-group neighbourhood Educational Quality	0.2508 (0.0025)	0.1611 (0.0018)

The regression coefficients reported in table 11 first show that the agent's subjective perception of educational level benefit positively affects the final amount of education that s/he obtains (coefficient 2); in particular, the more favourable is the average perception of benefit of educational levels compared to their costs, the higher the educational level finally reached by the agent. By contrast, the number of failures that the agent accumulates during his/her educational career (coefficient 3) negatively impacts on the final amount of education obtained (recall that failures act within the artificial society as a costs-boosting factor: see equation [5]). It should be noted that both these associations are qualitatively very much in line with the effect that the perception of education benefits and educational performances have on educational decisions in the real world (see, respectively, Becker 2003, p. 10, and Stocké 2007, p. 515 and Gabay-Egozi *et al.* 2010).

Variable coefficients which refer to the characteristics of the agent's set of dyadic links add information relevant to understanding his/her final educational outcome within the artificial society driven by the IECM.

Firstly, the number of the agent's neighbours with the same educational background negatively affects his/her final educational outcome (coefficient 4). The statistical interaction between the agent's in-group degree and his/her educational background suggests, however, that this average effect differs across groups of agents (coefficients 5-8). In particular, the higher the agent's group, the less negative is the net effect of being connected with many same-group agents (the effect becomes even positive for upper agents within the Italian artificial society).

estimation of this more complex statistical model does not lead, however, to different coefficient estimates with respect to their sign and order. For ease of interpretation, I thus preferred the simpler OLS regression model. Note also that the agent's educational background as well as his/her total number of neighbours are included in the regression model as controlling variables.

This statistical interaction effect is easily interpretable. If, as I demonstrated earlier (see table 9), agents from lower groups tend to be surrounded by poorly educationally-performing neighbours more frequently than do higher group agents, then the social influence term of equation [5] will positively contribute to agents' educational choices less for the former than for the latter, thereby depressing agents' final educational outcomes more for the lower group agents than for agents with higher educational backgrounds.

The positive effect of being connected with agents with higher educational backgrounds on agents' educational outcome is testified by the sign of the parameter (coefficient 9) measuring the difference between the number of contacts with neighbours belonging to a group higher than *ego*'s and the number of contacts with neighbours belonging to a group lower than *ego*'s: the greater this difference, the larger, on average, the amount of education that the agent finally obtains.[25]

The two last parameters reported in table 12 directly show the importance of being connected with educationally successful agents (thus providing computational evidence in line with the existing empirical evidence on "neighborhood effects": see the review by Sobel 2006). In particular, the more the agent is surrounded by other agents reaching the two highest educational levels, the larger the amount of education that s/he finally obtains. This positive effect of the educational quality of the agent's neighbourhood is especially strong where in-group neighbours are concerned (coefficient 10).

The set of variable coefficients which refer to the characteristics of the agent's neighbourhood thus consistently demonstrate the extent of the "educational traps" generated by the IECM within the artificial society: that is to say, the "*collection of behaviours that are mutually reinforcing and consequently individually rational*" (Durlauf and Cohen-Cole 2006). Starting with subjective perceptions of the benefits and costs of educational levels that expose them to higher(lower) risks of failing according to their educational background, agents tend to be linked mainly with agents having similar benefit/cost balances, so that, if an educational choice is potentially feasible for an agent belonging to a given educational group, then the dyadic social interactions in which s/he is embedded make the choice even more feasible, while, if the educational choice is potentially hard to make, then the dyadic interactions make it even harder (for a similar description of how unemployment spreads across actors, see Hedstrom 2006, p. 135). The micro-level dynamic generated by the IECM is thus a nice illustration of a cumulative process, as originally defined by Merton (1968, p. 606, 610), in which the amplification mechanism (on this concept, see Boudon 1979, pp. 156-157) progressively differentiating agents' private incentives - the social multiplier, if one prefers (on this concept, see Durlauf 2006, Durlauf and Cohen-Cole 2004) - is the socially segregated composition of agents' ego-centred dyadic networks.

The explanatory power of this dynamic may be tested on the educational outcomes whose statistical frequency is low within the artificial society driven by the IECM. The most extreme of them concern agents with the highest educational backgrounds who fail to obtain any educational level or, conversely, agents with the lowest educational backgrounds who attain the highest educational level. According to the analyses performed so far, these statistically rare educational outcomes should be related to exceptional constellations of agents' benefit and cost perceptions, as well as to specific relational configurations in which these "deviant" agents are embedded.

The figures reported in table 12 largely confirm this expectation. If one compares, for instance, the around 3% of agents with the upper educational background who do not attain any educational level within the French artificial society (first row of the table) with the around 82% of those from this same group who attain the highest educational level (second row of the table), one can see that both the subjective benefit/cost balances at the first educational level to be passed and the benefit/cost balance averaged across all educational levels is less positive for the former, the "deviant" agents, than for the latter. On the relational side, then, failing

25. Since agents with the highest educational background cannot have contacts with agents belonging to a group higher than theirs, the variable is upper-bounded at 0, so that this variable gives for these agents the number of links they establish with agents belonging to groups lower than theirs. The positive coefficient thus means here that the less agents from the highest educational group are connected with agents from lower groups (hence the closer the variable's value is to zero), the better is their final educational outcome.

TABLE 12. Benefit/cost difference at the first (second, for the Italian artificial society) educational level (first column), average benefit/cost difference across all educational levels, in- and out-group neighbourhood educational quality for agents from the highest (lowest) educational background attaining the lowest (highest) educational destinations (all measure are averaged across 100 replicates; standard deviation is given in parenthesis)

		SR1bc-SC1bc	SR-SC Average Diff.	In-group neighbourhood educational quality	Out-group neighbourhood educational quality
	French Artificial Society (N=5000)				
Upper Agents	Level 1a	-0.5265 (0.0549)	-0.4387 (0.0272)	-0.6757 (0.1245)	-0.1203 (0.4623)
	Level 3ab	-0.3102 (0.0074)	-0.3797 (0.0042)	0.9783 (0.0098)	0.703 (0.0743)
Lowest Agents	Level 1a	-0.5686 (0.0087)	-0.5993 (0.0045)	-0.9471 (0.0128)	-0.2876 (0.106)
	Level 3ab	-0.3512 (0.0211)	-0.3797 (0.0088)	0.5455 (0.0872)	0.7075 (0.0952)
	Italian Artificial Society (N=10000)				
		SR2ab-SC2ab	SR-SC Average Diff.	In-group neighbourhood educational quality	Out-group neighbourhood educational quality
Upper Agents	Level 1bc	-0.6106 (0.1202)	-0.3699 (0.0776)	-0.0682 (0.5677)	-0.7273 (0.2757)
	Level 3ab	-0.2293 (0.0208)	-0.2446 (0.0104)	0.958 (0.0298)	0.278 (0.106)
Lowest Agents	Level 1bc	-0.4955(0.0099)	-0.5075 (0.0035)	-0.9813 (0.0058)	-0.6547 (0.0722)
	Level 3ab	-0.3749 (0.037)	-0.2446 (0.0165)	0.511 (0.1965)	0.5218 (0.206)

upper agents tend to be embedded in dyadic neighbourhoods where educational performances are worse, no matter whether in-group neighbours or out-groups neighbours are considered. A similar constellation of factors characterizes the around 12% of agents with the lowest educational backgrounds who are able to attain the highest educational level (fourth row of the table). Compared to the around 44% of agents belonging to the same group but falling in the less desirable educational situation (third row of the table), "deviant" successful lower group agents tend to evaluate the first as well as the subsequent educational levels more favourably, and benefit from the better educational quality of the dyadic neighbourhoods in which they are embedded (I leave to the reader analysis of the bottom part of the table concerning the Italian artificial society).

Within the artificial society driven by the IECM, the same set of mechanisms thus generates at the aggregate level, and explains at the micro-level, both frequent and infrequent educational choices.

Network manipulations and the macro-level patterns generated by the IECM

In the two previous sections, I tried to demonstrate, on the one hand, that the macro-level consequences of the IECM are structurally homologous to the cross-sectional aggregate educational stratification observed in France and in Italy, and, on the other hand, that the IECM produced this macro-level pattern on the basis of highly plausible and realistic micro-and relational-level regularities. In addition, the statistical analysis performed on the simulated agent-level data has demonstrated that the IECM generates macro-level realistic forms of educational stratification through a cumulative process in which the composition of agents' neighbourhoods plays a crucial role in progressively differentiating agents' final educational outcomes across groups of agents.

One of the objections that might be raised against this result is that the regression-based analysis performed on the agent-level simulated data is unable effectively to disentangle the "social interaction effect" from the other mechanisms driving agents' educational behaviours. After all, looking at the artificial world driven by the IECM from a static perspective, as I did, may have the same drawbacks as the empirical analysis of the neighbourhood effect in which "selection biases" (see, for instance, Mouw 2006) and the "reflection problem" (Manski 1993a,b) make it extremely difficult both to estimate the real impact of social influence and grasp the mechanisms at work (see Sobel 2006; Sampson *et al.* 2002; see also Breen and Jonsson 2005, pp. 228-229).

In the present section, I apply a manipulationist strategy to the IECM in order to demonstrate more directly the specific effect that dyadic social influences exert on artificial agents' educational choices. In particular, I will manipulate the three parameters defining the network that links agents to each other - viz. the average number of the agent's neighbours, the specific configuration of inter-group links, and the overall proportion of these links (see table 5) - and I compare the educational outflows obtained under these different settings to the educational outflows produced by the model under the parametric configuration that allowed approximation of the French and the Italian empirical patterns. Since all other parameter values will be unchanged, all the modifications possibly observed at the aggregate level under these network manipulations can only be imputed to the way in which agents' educational choices influence each other through dyadic links tying them.

The quantity of dyadic links

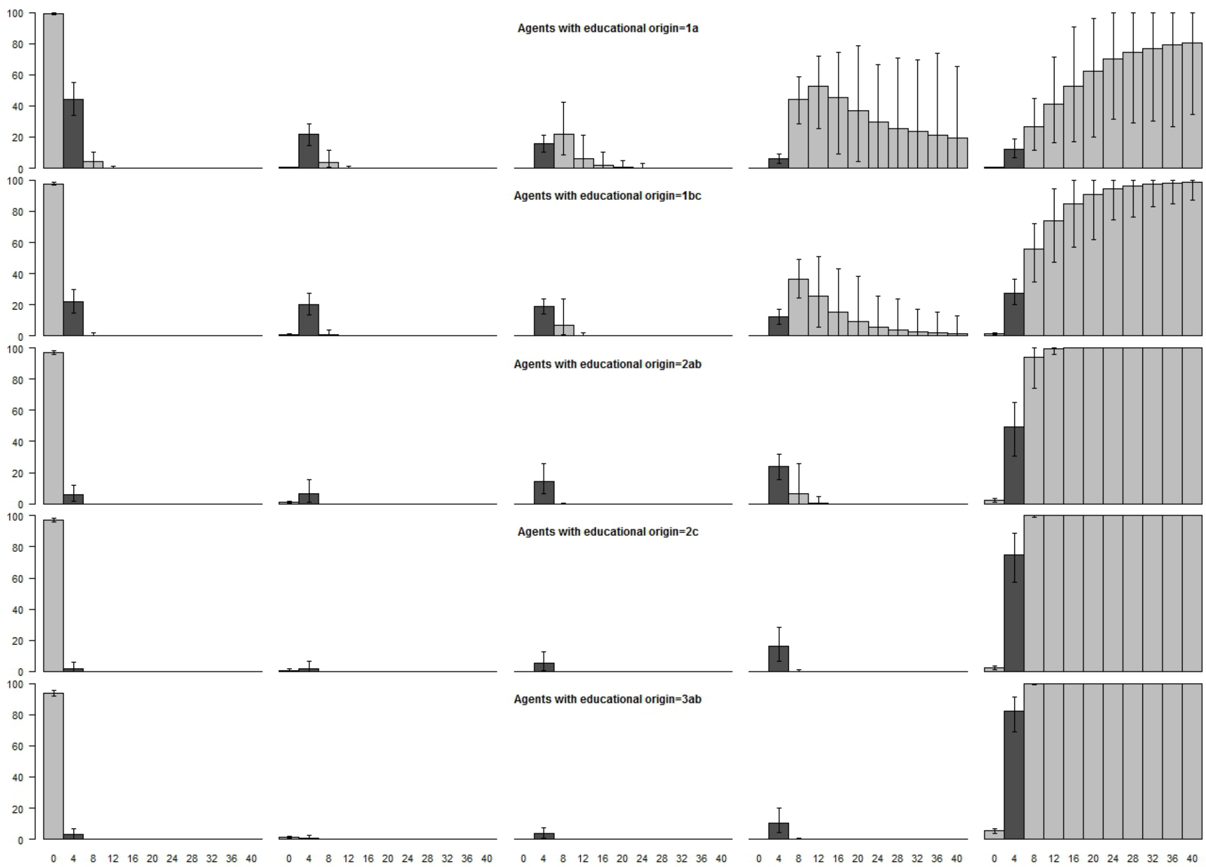
Let us start with study of the macro-level consequences of modifying the average degree of the network in which agents are embedded: that is, the average number of neighbours to which each of them has access. Each of the horizontal graph panels shown in figure 4 thus reports the percentage of agents that attain one of the five educational destinations (from the lowest one (1a), on the left, to the highest one (3ab), on the right) within a given group of agents (the lowest being on the top panel of graphs, the highest on the bottom one) for eleven increasing values of the average number of neighbours with which agents are linked. It will be recalled (see table 5) that the simulations of the IECM that allow reproduction of the French and Italian empirical data were performed with an average number of neighbours per agent equal to 4 (the dark gray bars in figure 4).[26]

Two computational regularities can be clearly identified. First, when the dyadic network is completely eliminated from the artificial society, the overwhelming majority of agents within each group falls in the lowest educational destination (left column of the left graphs). Only about 1% of the agents with the lowest educational background, about 3% of those from the three middle groups, and about 7% of those with the highest educational background, escape this undesirable condition. Among them, about 5%, 2% and 0.50%, respectively, are then able to reach the highest educational level.

The origin of this extreme aggregate outcome within the artificial society is easily identifiable. Setting the average network degree to zero amounts to removing the term expressing the dyadic social influence from the agents' educational choice function (see eq. 5). Under this condition, only the objective return of educational levels and agents' perceptions of their benefits and costs matter, so that when the benefit/cost balance tends to be negative, only the objective return of educational levels may counterbalance it.

26. Note that, to save computation time, all the exploratory results reported in the present section were based on 100 replicates of the simulation, while the simulated results that I matched in section 3 against empirical data – simulated results that constitute my benchmark here – were produced on the basis of 1000 replicates. The structure of the simulated educational outflows obtained under 100 and 1000 replicates is almost identical, however, the dissimilarity index between the two averaged tables being 0.01. Note also that, because of space limitations, I only report and comment on the results obtained for the French artificial society (results for the Italian one, available upon request, are qualitatively the same).

Figure 4: Simulated educational outflows as a function of an increasing average number of agents' neighbours (x-axis: from 0 to 40 by 4-unit increments).



Bar heights report the percentages of agents (averaged over 100 replicates of the simulation) who reach a given educational level (from left to right: level 1a, 1bc, 2ab, 2c, 3ab, respectively) within a given group of agents (from the top to the bottom: educational background 1a, 1bc, 2ab, 2c, 3ab, respectevely). The error bars report the 0.025- and 0.975-percentiles of the distribution of simulated outcomes across the 100 replicates. The dark gray bar - corresponding to an average degree equal to 4 - indicates the simulated outcomes that I previously matched against French empirical data (see figure 1).

As a consequence, given the agents' decision rule - educational level L is chosen when the agent's propensity for it is strictly positive (see eq. 6) - agents who can escape the less desirable educational destination when the social influence term is absent correspond to those whose propensity for a given educational level is strictly positive *irrespectively of what other agents do*. Since, as table 5 indicates, the value of the objective return of the first educational levels is especially low, few agents will be in a position to make the first transition.

This computational result thus provides the most direct proof that dyadic social influences among agents have a specific impact on their educational choices: at the scale of a single educational transition, when an agent's subjective benefit/cost balance tends to be negative, a certain amount of dyadic linkage is crucial in making the choice.

The aggregate computational traces of the contagion process fuelled by dyadic links are clearly apparent in figure 4 when considering values of the average degree higher than 4. In fact, the bar heights show that, as the average number of agents' neighbours increases, the percentage of agents who reach the highest educational level increases as well. But if we consider the error bars, figure 4 tells a more complex story. By quantifying educational outcome variability across replicates of the simulation, these bars clearly indicate that the five groups of agents are exposed to the educational contagion process to different extents.

Under average degrees higher than 8, agents with the three highest educational backgrounds (three graph panels from the bottom) attaining the highest educational level outweigh those who stop at the educational level 2c, and this modification seems robust (the error bars for the two educational destinations do not overlap). Agents with educational background 1bc experience a similar situation under a slightly higher average degree (=12). Among them, however, the positive effect of having more contacts on the probability of ending up with the highest educational level is more nuanced (the error bars for this educational destination tend to overlap). Agents with the lowest educational background experience the least virtuous situation. Whilst a trend towards an upgrading of educational outflows is certainly visible as average degree increases, there is no certain sign of a generalized diffusion process at the highest educational levels (the error bars largely overlap).

The origin of this non-linear relation among network degree, agent's educational outcome, and agent's group is easily identifiable within the artificial society driven by the IECM. Increasing the agent's average number of neighbours can make the social influence term of the agents' educational choice function more positive - thereby increasing the probability that the agent's propensity for a given educational level becomes positive - provided that the agent's new contacts are able to accomplish the educational level that the focal agent is evaluating. Given that the higher the educational level the heavier the cost, and, on the other hand, given that the lower the agent's group the higher this cost, this condition will be met with a decreasing frequency as the multiplication of dyadic links concerns agents from the lower groups. Since the proportion of inter-group links is, under the experimental conditions adopted here, very limited (only about 10% of the overall number of links available within the artificial system), being more connected with agents similarly unable to overcome largely negative benefit/cost balances cannot contribute to making the agent's social influence term more positive. As a consequence, lower-group agents will tend to benefit less than upper-group agents from an increasing number of dyadic ties in which they are embedded, and this is especially so at the highest educational levels.

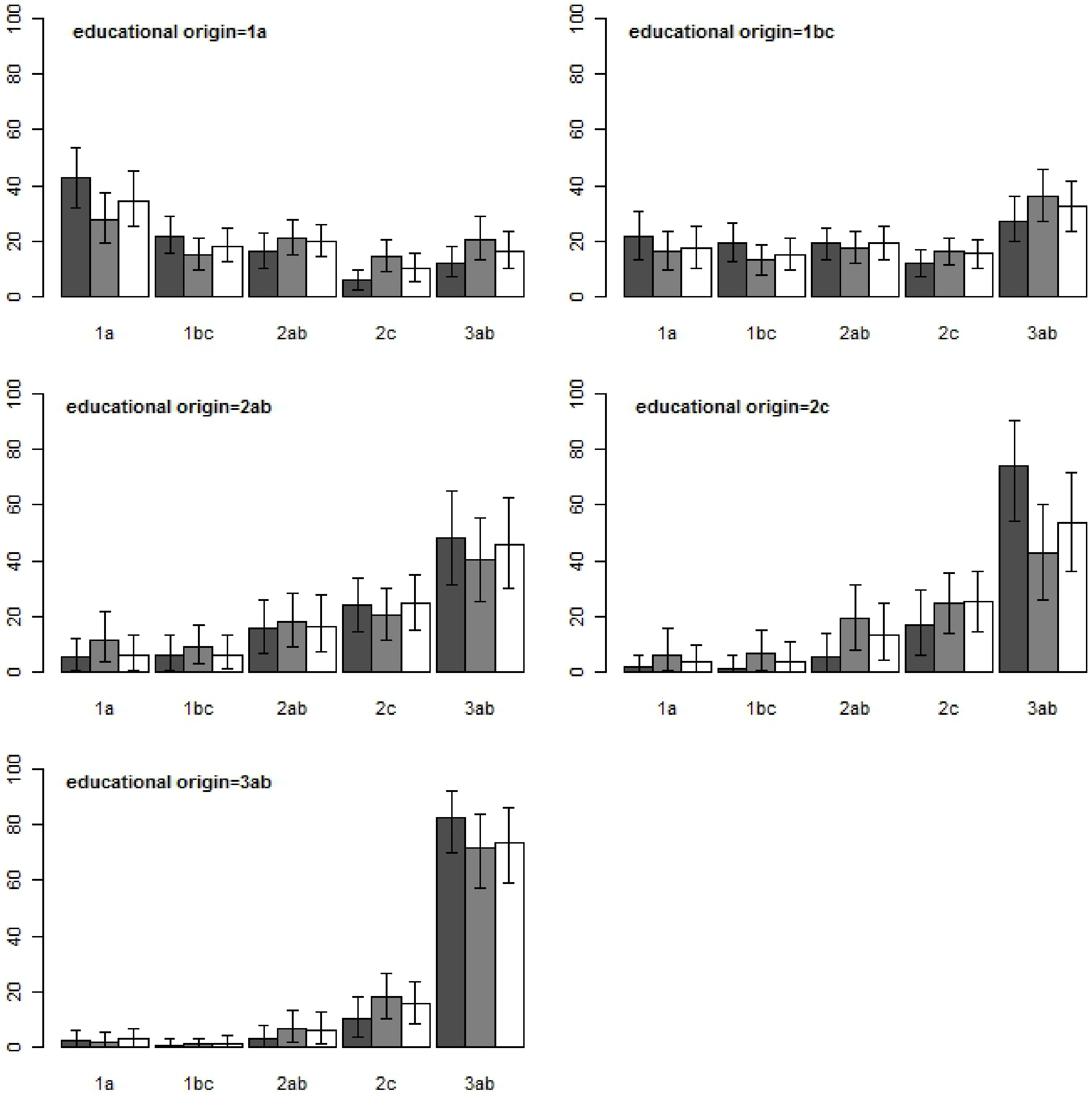
Thus, in line with the original intuition of Granovetter (1978), "strong ties" – which within the simplified artificial world driven by the IECM are approximated by in-group links – may slow down the diffusion of desirable outcomes within some group of agents. However, as the extreme computational outcome generated when in-group links are completely absent suggests, "strong ties" may also have the positive effect of driving the diffusion of costly educational choices at the first transition (I will provide later an additional proof of this function of in-group links). But what about the strength of "weak ties", which, within the simplified artificial world driven by the IECM, are approximated by out-group links? Do they always have positive effects?

The configuration of the inter-group links

To answer this question, let us first study the configuration of the inter-group links. Figure 5 reports the results that I obtained by simulating the IECM under (i) the configuration in which the more distant the educational backgrounds of the two agents to be linked together, the higher the probability that the link between them will be finally created ("long-range out-group link dominance", light gray bars); and (ii) the configuration where the probability that an inter-group link will be created between two agents with two different educational backgrounds is the same whatever the "educational" distance between them ("inter-group link equiprobability", white bars). The benchmark is represented by the configuration that I have adopted so far, in particular to reproduce the French and the Italian empirical data, in which the more distant the educational backgrounds of the two agents to be linked together, the lower the probability that the link between them will be finally created ("short-range out-group link dominance", dark gray bar).

The basic aggregate pattern generated by the IECM under these new conditions is quite clear. Compared to the artificial society where short-range out-group links dominate the inter-group side of the network, agents with the two lowest educational backgrounds (first two bar plots) tend to reach the highest educational level 3ab more frequently when the probability of being linked to upper agents is higher than the probability of being linked to lower agents and, although to a less extent, when the probability of establishing

Figure 5: Simulated educational outflows as a function of the type of configuration of the intergroup dyadic links (dark gray bars = "short-range inter-group link dominance"; light gray bars = "long-range inter-group link dominance"; white bars = "inter-group link equiprobability").



Bar heights report the percentages of agents (averaged over 100 replicates of the simulation) who reach a given educational level within a given group of agents. The error bars report the 0.025- and 0.975-percentiles of the distribution of simulated outcomes across the 100 replicates. The dark gray bar - corresponding to configuration of "short-range inter-group link dominance" - indicates the simulated outcomes that I previously matched against French empirical data (see figure 1).

an out-group link is independent from the agents' educational backgrounds. Conversely, agents with middle and upper educational backgrounds attain the highest educational level more frequently when the probability of being linked to lower agents is lower than the probability of being linked to upper agents.

Comparison among these three alternative configurations of the inter-group links thus directly demonstrates that network segregation (here in terms of educational background) depresses the educational outcomes of lower agents while it sustains that of upper agents, which is line with Granovetter's original intuition concerning the "strength of weak ties".

One should admit, however, that the extent of the modifications of the simulated educational outflows is generally limited. This can be easily explained. On the one hand, dyadic links are not weighted within the artificial society driven by the IECM, which means that the educational choice of an upper-group agent matters for the educational choice of a lower-group agent exactly to the same extent as the choice of the latter matters for the choice of the former. On the other hand, since the network-building algorithm requires the network degree to be kept constant, each inter-group link that has been created replaces one in-group link.[27] Under these conditions, while a lower-group agent may profit from being in contact with an upper-group agent to make a costly educational choice, the latter may no longer be able to build on his/her in-group links to sustain such a costly choice. As a result of a cascade of dyadic influences which cancel each other out, the potential equalizing effects of less-segregated ego-centred networks may not be visible at the aggregate level.

The quantity of inter-group links

The existence of this phenomenon can be checked by varying the overall proportion of inter-group links existing within the artificial society driven by the IECM. Figure 6 reports the percentage of agents who attain one of the five educational destinations (from the lowest one, on the left, to the highest one, on the right) within a given group of agents (the lowest being on the top panel of graphs and the highest on the bottom one) for eleven increasing values of the probability that agents' in-group links are rewired outside their educational group of origin (the results are generated under the "short-range out-group link dominance" type of inter-group link configuration).

This series of scenarios amounts to moving progressively from five disconnected regular networks where the probability of inter-group linkage is 0 - under this condition, agents only have in-group links - to a single random network where the probability of inter-group linkage is 1 - here agents only have out-group links (for the case of a one-group population, see Watts 1999, pp. 503-509).

27. The rationale behind this choice is that it enables evaluation of the relative impact on the outcome of interest of the local density of the network or of the fraction of long ties (see Centola and Macy 2007, p. 711).

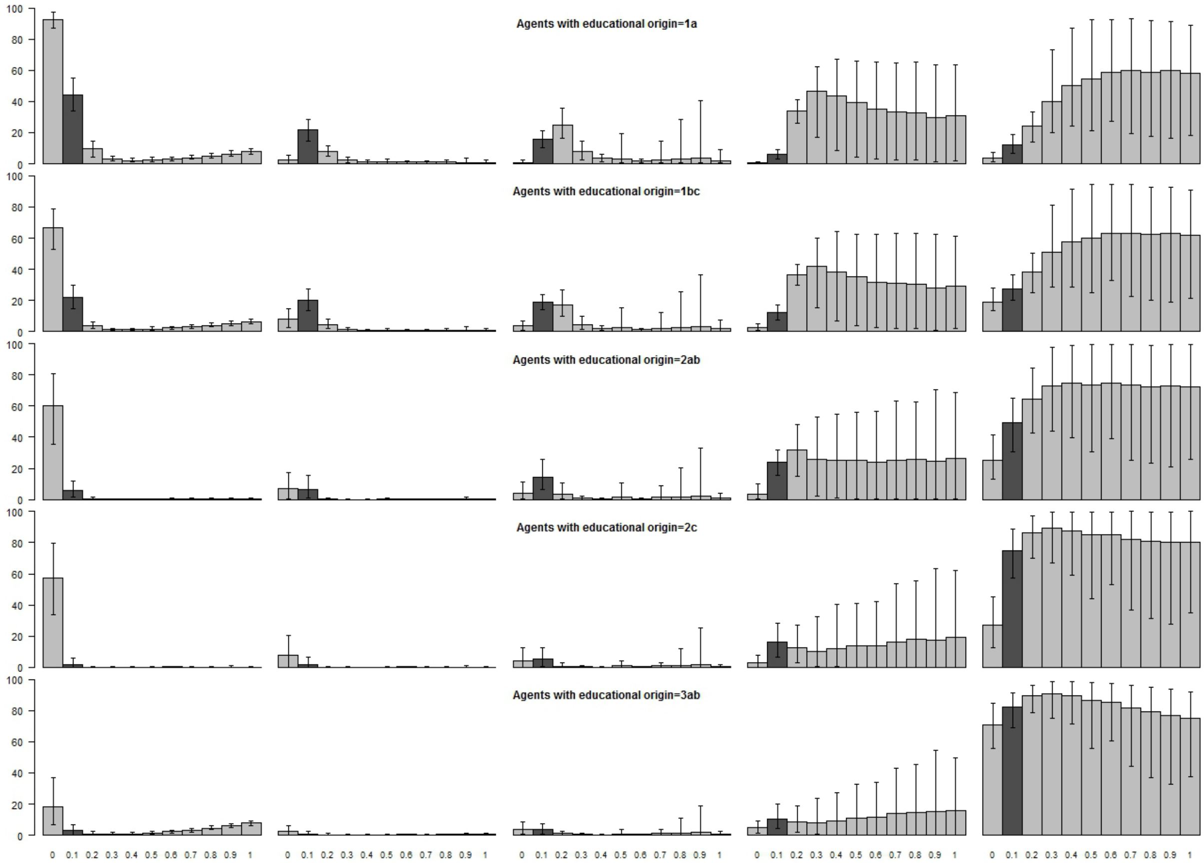
Two computational facts can be identified in figure 6. First, compared to the artificial society where the probability of creating an inter-group link is 0.1 (dark gray bars; this was the condition under which I was able to reproduce the French and Italian educational data), completely destroying the inter-group-links side of the artificial network leads more agents to fall in the most undesirable educational destination (first-left column of each bar plot on the left side). The extent of this modification of the educational outflows is not the same within all group agents, however. In fact, whilst more than 80% of the upper-group agents are still able to go beyond the first educational transition (bottom panel), this is the case of only about 10% of the agents with the lowest educational background (top panel), which clearly suggests that lower-group agents are dependent on out-group links much more than are upper group agents.[28]

This computational result thus proves that inter-group links indeed have the capacity to equalize the structure of educational outflows across groups of agents. When groups are completed separated, in fact, the aggregate distribution of educational levels across educational groups is even more segregated than when a small amount of group inter-connections exists. Again, Granovetter's original intuition concerning the "strength of weak ties" seems confirmed.

On this basis, one may expect to find that increasing the proportion of links relating agents with different educational backgrounds fuels a virtuous diffusion of the highest educational levels within all the groups of agents. Figure 6 bar plots show, however, that the simulation of the IECM does not generate this macro-level result. When the overall proportion of inter-group links increases from 10% to 20% or 30%, there is some sign that the highest educational level tends to spread on average within all the groups of agents. However, the error bars are so large that it is impossible to

28. If the reader compares these modifications to those generated by the complete suppression of the dyadic network linking agents (see figure 4, extreme-left bars of the left-column graphs), s/he will obtain additional proof of the positive role played by in-group links within the artificial society driven by the IECM. In fact, when upper-group agents do not have any in-group links, the percentage of those who fall in the less desirable educational destination is four times larger than the percentage simulated under the absence of out-group links. This is the clearest signal of the importance of in-group links in sustaining costly choices.

Figure 6: Simulated educational outflows as a function of an increasing probability of creating intergroup dyadic links (x-axis: from 0 to 1 by 0.1-unit increments).



Bar heights report the percentages of agents (averaged over 100 replicates of the simulation) who reach a given educational level (from right to left: level 1a, 1bc, 2ab, 2c, 3ab, respectively) within a given group of agents (from the top to the bottom: educational background 1a, 1bc, 2ab, 2c, 3ab, respectively). The error bars report the 0.025- and 0.975-percentiles of the distribution of the simulated outcomes across the 100 replicates. The dark gray bars - corresponding to a rewiring rate equal to 0.1 - indicate the simulated outcomes that I previously matched against French empirical data (see figure 1).

distinguish an increasing/decreasing trend clearly from a trendless pattern.

That the "strength of weak ties" does not seem to operate in this area of the parameter space can be explained by returning to the way in which the artificial network is built within the artificial society driven by the IECM. I pointed out earlier that inter-group links are created at the expense of in-group links. As a consequence, as the probability of creating inter-group links increases, agents' neighbourhoods are increasingly filled with agents with different educational backgrounds. This structural modification explains why the IECM does not produce any stable generalized diffusion of the highest educational levels within the population of agents as the social heterogeneity of agents' ego-centred networks increases. Insofar as the choice of the highest educational levels is costly even for upper-group agents, these agents need the other agents with whom they are in contact to make the same choice so that their potentially negative cost/benefit balances can be off-set by the choices of their contacts. When these agents progressively lose contacts with agents in the best position to sustain costly choices – that is, agents with the same educational background – the probability that they will finally choose the highest educational level decreases. Under this condition, lower-group agents can benefit to an increasingly less extent from being in contact with upper-group agents because these agents are themselves increasingly less able to make the most costly educational choices. In the end, a higher educational level fails to spread through the artificial population.

This result thus illustrates, in the context of a theoretical model of a specific relevant social behaviour, i.e. educational choices, the phenomenon abstractly analyzed by Centola and Macy (2007), who convincingly demonstrated that "*for simple contagions, too much clustering means too few long ties, which slows down cascades. For complex contagions, too little clustering means too few wide bridges, which not only slows downs cascades but can prevent them entirely*" (ibid., 723). Within the IECM, the complexity of contagions derives from the fact that educational choices are costly, so that the choices of *ego*'s neighbours are crucial for overcoming these costs.

Conclusion

From a descriptive point of view, this paper has sought to produce empirical knowledge on the statistical association between individuals' educations and those of their parents in France and in Italy at the beginning of the twenty-first century – a phenomenon for which a comparison specifically focused on these two countries is still lacking. The analysis has mainly shown that the highest educational level is reached more frequently in France than in Italy, not only by individuals belonging to highly educated families but also by those whose families have only a secondary educational background. The main consequence of this difference on the structure of educational opportunity is that the overall level of educational fluidity is higher in France than in Italy.

From a theoretical point of view, the paper has instead sought to develop a formal explanatory model of the macro-level structure of educational inequality - the "interdependent educational choice model" (IECM) - which frames educational choices as the result of both individual benefit/cost evaluations and peer-group pressures. It thus enriches the sociological educational rational-choice approach (Breen and Goldthorpe 1997) through the economic perspective of the so-called "membership theory of inequality" (Durlauf 1999b, 2006). The basic novelties of this theoretical framework consist, on the one hand, in suggesting that social interactions may help actors to endorse costly educational choices, and on the other hand, that the specific social composition of an actor's ego-centred dyadic network may reinforce or obstruct the educational choice that the actor would have made on the basis of a purely private benefit/cost reasoning. The model's theoretical interest is therefore that it links the macro-level structure of educational inequalities with the way in which group belonging biases the heterogeneity of actors in preferences, resources and social contacts.

From a methodological point of view, finally, this paper has developed an interface among formal theoretical modelling, the quantitative analysis of empirical data, and computational techniques – a research strategy which is still too rarely followed within the sociology of stratification and social mobility. In particular, the paper has argued that agent-based models are powerful tools with which to design and test both the macro- and micro-level consequences of a complex set of hypotheses linking structures, actors, and networks.

In this regard, the paper has obtained two groups of results that may be respectively termed "confirmatory" and "exploratory".

The "confirmatory" results concern the part of the analysis in which I attempted to demonstrate that simulation of the agent-based implementation of the "interdependent educational choice model" (IECM) is able to generate a macro-level association between agents' educational backgrounds and their educational outcomes whose basic structure well reproduces all the qualitative aspects of both educational outflows and opportunities observed in France and in Italy at the beginning of the twenty-first century. This demonstration was produced by systematically comparing the aggregate simulated data with the aggregate empirical data, and by showing that the variability observed across replicates of the computational model largely overlapped with the variability observed across empirical sub-samples drawn from the original French and Italian samples.

A strong objection to this result would be that it does not prove the explanatory power of the formal theoretical model, but only its generative sufficiency (see Epstein 2006, chs. 1-2), in that it cannot be excluded that another set of micro- and network-level hypotheses would lead to a similarly satisfying fit between the simulated and empirical macro-level data. Until it is demonstrated that how I have represented (i) agents' perceptions of benefits and costs, and (2) the roles of past success and social influence, does not correspond to the ways in which these factors operate in the educational decisions of real actors, it is not in principle possible to exclude concurrent models.

In reply to this objection, in the absence of micro- and relational-level data sufficiently detailed to calibrate all the aspect of the "interdependent educational choice model" (IECM) empirically, I collected data at the agent-level during the simulation and I statistically analyzed them to evaluate the extent to which the artificial society worked in a realistic way. The main result was demonstration that, on the one hand, the distribution across artificial educational backgrounds of education benefit and cost perceptions, of educational performances, as well as of network composition, and, on the other hand, the net effects of each of these factors on agents' final educational outcomes, qualitatively mimic the real-world counterparts for which we have (at least, partial) empirical evidence.

The statistical analysis performed on the simulated agent-level data produced three additional noteworthy explanatory insights. First, it demonstrated that the "interdependent educational choice model" (IECM) generated a realistic macro-level structure of educational inequalities on the basis of a cumulative process in which highly educationally-homophilic ego-centred dyadic networks fuel educational traps that progressively amplify the initial within- and between-group heterogeneity in agents' perceptions of the benefits and costs of educational levels. Second, "deviant" educational outcomes – that is, educational outcomes which are rare within a given educational milieu – can be explained on the basis of this process: within the artificial society, educationally "deviant" agents are precisely those who have more (less) positive benefit/cost balances compared to the average of the educational group to which they belong, as well as a better (worse) educational neighbourhood. Finally, the statistical analysis performed on the simulated agent-level data sheds some light on the way in which the computational model generates different macro-level patterns for France and for Italy. Upper-group agents within the French artificial society have benefit/cost balances at the highest educational levels that tend to be more positive than those of their artificial Italian counterparts: the probability that French artificial upper-group agents will end up with the highest educational level is higher, and so is the probability that this educational level will spread through the group of agents with which they are most frequently in contact.

By using the computational model as an "outcome-range-oriented" tool, the paper has finally attempted to prove more directly the role that dyadic social interactions play within the cumulative process fuelled by the "interdependent educational choice model" (IECM). Here I have studied the macro-level educational stratifications generated by the model under several network parameter configurations in order to design the space of model outcomes as a function of the model's parameter space. It is for this reason that I proposed earlier that the results obtained in this part of the paper should be called "exploratory".

The results have essentially shown that there exists within the artificial society driven by the "interdependent educational choice model" (IECM) a subtle interplay between in- and out-group dyadic links. Whilst a certain amount of in-group links is necessary to make it possible to choose educational levels for which objective payoffs on the job market are not sufficiently large to counterbalance private benefit/cost balances that tend to be negative (which constitutes what one may call the "strength of strong ties"), too many in-group links per agent reduce the probability that agents, in particular with lower educational backgrounds, will deviate from the educational outcomes most frequently achieved in the group to which they belong (which corresponds to the "weakness of strong ties"). Out-group links perform precisely this role, i.e. making educational choices less dependent on the private benefit/costs balances characterizing on average a given educational milieu (which confirms the intuition concerning the "strength of strong ties"). Within the artificial society driven by the "interdependent educational choice model" (IECM), however, this equalizing effect of out-group links is attenuated when they become too numerous (more than forty percent of the total amount of links present in the system). The computational model analyzed here conditions this result on the fact that out-group links are created at the expense of in-group links, thus progressively destroying the basis on which costly educational choices become possible, in particular among upper-group agents.

This is what one may call the "weakness of weak ties" (see Centola and Macy 2007).

Overall, the main substantive contribution of the paper is thus, on the one hand, that it proves that a population of artificial agents in which each entity acts according to realistic associations between the group to which they belong and their educational behaviour can produce realistic macro-level structures of educational inequalities, and, on the other hand, that it shows the complex role played by dyadic social interactions in the micro-level dynamic leading to these high-level outcomes. The main methodological contribution of the paper is instead to suggest that, while it seems unlikely that similar results could be obtained by simply relying on variable-based quantitative methods, multivariate statistics is still a crucial tool with which both to compare simulated with empirical data and to help solve the complex technical problem of how to understand the dynamics generated by a computational model. However, the reader will have no difficulty in identifying the limitations that weaken the proposals contained in the paper.

References

Ballarino G., Bernardi F. (2001), Uso di dati time-budget per lo studio delle risorse familiari: capitale sociale e culturale dei genitori dei bambini in età scolare in Italia, *Quaderni di sociologia*, 2, pp. 7-36.

Barone C., Luijkx R., Schizzerotto A. (2010), "Elogio dei grandi numeri: il lento declino delle disuguaglianze nelle opportunità di istruzione", *Polis*, XXIV, 1, pp. 5-34.

Becker, R. (2003) "Educational Expansion and Persistent Inequality of Education. Utilizing Subjective Expected Utility Theory to Explain Increasing Participation Rates in Upper Secondary School in the Federal Republic of Germany", *European sociological review,* 19, 1, pp. 1-24.

Boudon, R. (1973), *L'inégalité des chances. La mobilité sociale dans les sociétés industrielles*, Armand Colin, Paris.

Boudon, R. (1979), *La logique du social*, Presses Universitaires de France, Paris.

Brauns, H. and Steinman, S. (1997), "Educational Reforms in France, West-Germany, the United Kingdom and Ungary: Updating the Casmin Educational Classification", *Working Papers 21*, Mannheim.

Breen, R. (Ed.) (2004), *Social mobility in Europe*, Oxford University Press, Oxford.

Breen, R. and Goldthorpe, J. (1997), "Explaining Educational Differentials: Towards a Formal Rational Choice Theory", *Rationality and Society*, vol. 9 no. 3, pp. 275-305.

Breen, R. and Jonsson, J. O. (2005), "Inequality of Opportunity in Comparative Perspective: Recent Research on Educational Attainment and Social Mobility", *Annual Review of sociology*, 31, pp. 223-243.

Breen, R. and Luijkx, R. (2004), "Social Mobility in Europe between 1970 and 2000", in Richard B. (Ed.) (2004), *Social Mobility in Europe*, Oxford University Press, Oxford, p. 17-36.

Breen, R. and Yaish, M. (2006), "Testing the Breen-Goldthorpe Model of Educational Decision Making", in Stephen, L., Morgan, D. B., Grusky, D. and Fields, G. S., (Eds.) (2006) *Frontiers in Social and Economic Mobility*, Stanford University Press.

Breen, R., Luijkx, R., Müller, W. and Pollak, R. (2009), "Nonpersistent Inequality in Educational Attainment: Evidence from Eight European Countries ", *American Journal of Sociology*, vol. 114, no. 5, pp. 1475–1521.

Bruch, E. and Mare, R. (2006), "Neighborhood Choice and Neighborhood Change", *American journal of sociology,* 112, 3, pp. 667–709.

Centola, D. and Macy, M. W. (2007), "Complex Contagions and the Weakness of Long Ties", *American Journal of Sociology*, vol. 113, n° 3 (November), p. 702-734.

Cobalti, A. (1989), "A Relative Mobility Table. A Modest Proposal", *Quality and Quantity*, vol. 23, n° 2, p. 205-220.

Cobalti, A. (1992), "Origine sociale e livello di istruzione: un modello", *Polis*, vol. 6, n° 1, p. 117-145.

Davison, A. and Hinkley, D. (1997), *Bootstrap Methods and Their Application*, Cambridge University Press, Cambridge.

Davies, R., Heinesen, E. and Holm, A. (2002), "The Relative Risk Aversion Hypothesis of Educational Choice", *Journal of Population Economics,* 15, 4, pp. 683-713.

Durlauf, S. (1999a), "How Statistical Mechanics Contribute to Study of Science", *Proceedings of the national academy of sciences*, 96, 19, pp. 10582–10584.

Durlauf, S. (1999b), "The Memberships Theory of Inequality: Ideas and Implications", in Brezis, E. and Temin, P. (eds.) (1999), *Elites, Minorities, and Economic Growth*, North Holland.

Durlauf, S. (2001), "A Framework for the Study of Individual Behaviour and Social Interactions", *Sociological Methodology*, 31, 1, pp. 47-87.

Durlauf, S. (2006), "Groups, Social Influences, and Inequality: A Memberships Theory Perspective on Poverty Traps", in Bowles, S., Durlauf, S. and Hoff, K. (Eds.) (2006), *Poverty Traps*, Princeton University Press, Princeton.

Durlauf, S. and Cohen-Cole, E. (2004), "Social Interactions Models", in Lempf-Leonard K. (Ed.) (2004), *Encyclopedia of Social Measurement*, Academic Press.

Duru-Bellat, M., Kieffer, A. and Reimer, D. (2011), «Les inégalités d'accès à l'enseignement supérieur : le rôle des filières et des spécialités. Une comparaison entre l'Allemagne de l'Ouest et la France», *Économie et statistique, n° 433-434*, pp. 3-22.

Erikson, R. and Goldthorpe, J. (1992), *The Constant Flux: A Study of Class Mobility in Industrial Society*, Clarendon Press, Oxford.

Erikson, R. and Jonsson, J. (1996), *Can education be equalized?: The Swedish case in comparative perspective*, Boulder (Colo.), Westview Press.

Esping-Andersen, G. and Mestres, J. (2003), *Ineguaglianza delle opportunità ed eredità sociale*, *Stato e Mercato*, 67, pp. 123-152.

Fararo, T. J. and Butts, C. T. (1999) "Advance in Generative Structuralism: Structured Agency and Multilevel Dynamics", *Journal of Mathematical Sociology*, vol. 24, n° 1, pp. 1-65.

Fowler, J.H. and Christakis, N.A. (2008) "Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study", *British Medical Journal,* 338 (768): a2338.

Fullerton, A. S. (2009), "A Conceptual Framework for Ordered Logistic Regression Models", *Sociological Methods and Research*, 38, 2, pp. 306-347.

Gabay-Egozi, L., Shavit, Y. and Yaish, M. (2010), "Curricular Choice: A Test of a Rational Choice Model of Education", European Sociological Review, 26, 4, pp. 447-463.

Gambetta, D. (1987), *Where They Pushed or Did They Jump? Individual Decision Mechanisms in Education*, Cambridge University Press, Cambridge.

Gelman, A. and Hill, J.(2007), *Data Analysis Using Regression and Multilevel/Hierarchical Models*, Cambridge University Press, Cambridge.

Gilbert, N. (2007), *Agent-Based Models*, Sage Publications, London.

Goldthorpe, J. (1996), "Class Analysis and the Reorientation of Class Theory: The Case of Persisting Differentials in Educational Attainment", *The British Journal of Sociology*, Vol. 47, No. 3, pp. 481-505.

Goldthorpe, J. (2001), "Causation, Statistics, and Sociology", *European Sociological Review*, 17, 1, pp. 1-20.

Goodman, Leo A. (1969), "How to "Ransack" Social Mobility Tables and other Kinds of Cross Classification Tables", *American Journal of Sociology*, vol. 75, n° 1, pp. 1-40.

Granovetter, M. (1973), "The Strength of Weak Ties", *American Journal of Sociology*, 78, 6, pp. 1360-1380.

Granovetter, M. (1978), "Threshold Models of Collective Behavior", *American Journal of Sociology*, 83, 6, pp. 1420-1443.

Granovetter, M. (1983), "The Strength Of Weak Ties: A Network Theory Revisited", *Sociological Theory*, 1, pp. 201-233.

Granovetter, M. and Soong, R. (1983), "Threshold Models of Diffusion and Collective Behavior", *Journal of mathematical sociology*, 9, pp. 165-179.

Granovetter, M. (1988), "Threshold Models of Diversity: Chinese Restaurants, Residential Segregation and the Spiral of Silence", *Sociological* Methodology, 18, pp. 69-104.

Hedstrom, P. (1998), "Rational Imitation", in Hedstrom P. and Swedberg R., (eds.) (1998), *Social Mechanisms. An Analytical Approach to Social Theory*, Cambridge University Press, Cambridge.

Hedstrom, P. (2005), *Dissecting the Social: On the Principles of Analytical Sociology*, Cambridge University Press, Cambridge.

Hedström, P. and Bearman, P. (2009), "What is analytical sociology all about? An introductory essay", in Hedström, P. and Bearman, P. (Eds.) *The Oxford Handbook of Analytical Sociology*, Oxford University Press, Oxford, ch. 1, pp. 3 - 24.

Hillmert, S. and Jacob, M. (2003), "Social Inequality in Higher Education. Is Vocational Training a Pathway Leading to or away From University?", *European Sociological Review*, 19, 3, pp. 319-334.

Holm, A. and Jaeger, M.M. (2008), "Does Relative Risk Aversion explain educational inequality? A dynamic choice approach", *Research in Social Stratification and Mobility*, 26 (3), pp. 199-219.

Hummon, N. P. and Fararo, T. J. (1995), "The Emergence of Computational Sociology", *Journal of Mathematical Sociology,* 20, 2-3, pp. 79-87.

Hummon, N. P. and Fararo, T. J., (1999), "Actors and networks as objects", *Social Networks*, 17, 1, pp. 1-26.

Jaeger, M. M. (2007), "Economic and Social Returns To Educational Choices. Extending The Utility Function", *Rationality and Society*, 19, 4, pp. 451–483.

Jonsson, J. O. and Erikson, R. (2000), "Understanding Educational Inequality: the Swedish Experience", *L'Année Sociologique*, 50, 2, pp. 345-382.

Kaufman, R. L. and Schervish, P. G. (1987), "Variations on a Theme. More Uses of Odds Ratios to Interpret Log-linear Parameters", *Sociological Methods and Research*, 16, 2, pp. 218-255.

Keller, S. and Zavalloni, M. (1964), « Ambition and Social Class: A Respecification », *Social Forces*, vol. 43, n° 1, p. 58-70.

Law, A. M. (2007), *Simulation Modeling and Analysis,* McGraw-Hill, New York.

Macy, M. W. and Flache, A. (2009), "Social dynamics from the bottom up: Agent-based models of social interaction", *in* Hedström, P. and Bearman, P., (Eds.), *The Oxford Handbook of Analytical Sociology*, Oxford University Press, Oxford, ch. 11, pp. 245-269.

Macy, W. M. and Willer, R. (2002), "From Factors to Actors: Computational Sociology and Agent-based Modeling", *Annual Review of Sociology,* 28, pp. 143-166.

Manski, Ch. (1993a), "Identification of Endogenous Social Effects: the Reflection Problem", *Review of Economic Studies*, 60, 3, pp. 531-542.

Manski, Ch. (1993b), "Identification Problems in Social Sciences", *Sociological Methodology*, 23, pp. 1-56.

Manski, Ch. (2000), "Economic Analysis of Social Interaction", *Journal of Economic Perspectives*, 14, 3, pp. 115-136.

Manzo, G. (2006), "Generative Mechanisms and Multivariate Statistical Analysis. Modeling Educational Opportunity Inequality by Multi-Matrix Log-Linear Topological Model: Contributions and Limits", *Quality and Quantity*, 40, 5, pp. 721-758.

Manzo, G. (2009), *La spirale des inégalités. Choix scolaires en France et en Italie au XX siècle*, Presses de l'Université Paris-Sorbonne, Paris.

Mastekaasa, A. (2006)," Educational Transitions at Graduate Level: Social Origins and Enrolment in PhD Programmes in Norway", *Acta sociologica*, 49, 4, pp. 437-453.

McPherson, J., Smith-Lovin, L. and Cook, J. (2001), "Birds of a Feather: Homophily in Social Networks", *Annual Review of Sociology*, 27, pp. 415-444.

Merton, R. K. (1968), "The Matthew Effect in Science. The Reward and Communication Systems of Science Are Considered", *Science*, 159, 810, pp. 55-63.

Miller, J. H. and Scott, E. P. (2007), *Complex Adaptive Systems: An Introduction to Computational Models of Social Life,* Princeton University Press, Princeton.

Morgan, S. L. (2005), *On the Edge of Commitment: Educational Attainment and Race in the United States*, Stanford University Press, Stanford.

Mouw, T. (2006), "Estimating the Causal Effect of Social Capital: A Review of Recent Research", *Annual Review of Sociology*, 32, pp. 79-102.

Müller W., Lüttinger P., König W. and Karle W. (1989), "Class and Education in Industrial Nations", *International Journal of Sociology*, vol. 19, n° 3, p. 3-39.

Müller W., Karle W. (1993), "Social Selection in Educational Systems in Europe", *European Sociological Review*, vol. 9, n° 1, p. 1-23.

Nash, R. (2003), "Inequality/Difference in Education: Is a Real Explanation of Primary and Secondary Effects Possible?", *British journal of sociology*, 54, 4, pp. 433-451.

Need, A. and de Jong, U. (2000), "Educational Differentials in the Netherlands: Testing Rational Choice Theory", *Rationality and Society*, 13, pp. 71–98.

Oberti, M. (2002), «Usage et limites des nomenclatures socioprofessionnelles pour l'analyse sociologique: le cas italien», *Sociétés contemporaines,* 45-46, 1, pp. 43-75.

Orléan, A. (1995), "Bayesian interactions and collective dynamics of opinion: Herd behavior and mimetic contagion", *Journal of Economic Behavior and Organization*, 28, 2, pp. 257-274.

Pfeffer, F. T., 2008, « Persistent Inequality in Educational Attainment and its Institutional Context », *European Sociological Review,* European Sociological Review, 24, 5, pp. 543-565.

Raftery A. E., Hout M. (1993), "Maximally Maintained Inequality: Expansion, Reform and Opportunity in Irish Education, *1921-1975*", *Sociology of Education,* 66, pp. 41-62.

Rolfe, M. (2009), "Conditional Choice", in Hedström P. and Bearman P. (eds.) *The Oxford Handbook of Analytical Sociology*, Oxford University Press, Oxford, ch. 18, pp. 419 - 447.

Sampson, R., Morenoff, J. D. and Gannon-Rowley, T. (2002), "Assessing Neighbourhood Effects: Social Processes and New Directions in Research", *Annual Review of Sociology,* 28, pp. 443–78.

Sawyer, R. K. (2003), "Artificial Societies. Multiagent Systems and the Micro-macro Link in Sociological Theory", *Sociological Methods and Research,* 31, 3, pp. 325-363.

Schelling, T. C. (1971), "Dynamic Models of Segregation", *Journal of Mathematical Sociology*, 1, pp. 143-186.

Schelling, T. C. (1973), "Hockey Helmets, Concealed Weapons and Daylight Saving. A Study of Binary Choices with Externalities", *Journal of Conflict Resolution*, 17, 3, pp. 381-428.

Schizzerotto, A. (1997), "Perché in Italia ci sono pochi diplomati e pochi laureati ? Vincoli strutturali e decisioni razionali degli attori come cause della contenuta espansione della scolarità superiore", *Polis,* 11, 3, pp. 345-365.

Shavit Y., and Blossfeld, H.-P. (eds.), (1993), *Persistent Inequality: Changes Educational Attainment in Thirteen Countries*, Westwiew Press, Boulder.

Skvoretz J., Fararo, T. and Agneessens, F. (2004), "Advances in Biased Net Theory: Definitions, derivations, and estimations", *Social Networks*, vol. 26, n° 2, pp. 113-139.

Sobel, M. E. (2006), "Spatial Concentration and Social Stratification: Does the Clustering of Disadvantage 'Beget' Bad Outcomes?", in Bowles, S., Durlauf, S. N. and Hoff, K. (Eds.), (2006), *Poverty Traps*, Russell Sage Foundation, New York, pp. 204-229.

Stocké, V. (2007), "Explaining Educational Decision and Effects of Families Social Class Position: An Empirical Test of the Breen–Goldthorpe Model of Educational Attainment", *European Sociological Review*, 23, 4, pp. 505-519.

Tisue, S. and Wilensky U., (2004a), "NetLogo: Design and Implementation of a Multi-Agent Modeling Environment", Evanston, IL, Center for Connected Learning and Computer-Based Modeling, Northwestern University< http://ccl.northwestern.edu/papers/>.

Tisue, S. and Wilensky, U., (2004b), "NetLogo: A simple environment for modeling complexity", Evanston, IL, Center for Connected Learning and Computer-Based Modeling, Northwestern University < http://ccl.northwestern.edu/papers/>.

Vallet, L.-A. (2004), "State of the Art, Current Issues, and Future Prospects in Comparative Educational Stratification Research", Comparative Analysis of Intergenerational Inheritance Theme, Final workshop of the Changequal Network on Economic Change, Unequal Life-Chances and Quality of Life, University of Stockholm, November 23rd-25th 2004.

Van De Werfhorst, H. G. and Hofstede, S. (2007), "Cultural capital or relative risk aversion? Two mechanisms for educational inequality compared", *The British Journal of Sociology*, 58, pp. 391–415.

Watts, D. J. (1999), "Networks, Dynamics, and the Small-World Phenomenon", *American Journal of Sociology*, 105, 2, pp. 493-527.

Watts, D. J. (2004), "The "New" Science of Networks", *Annual Review of Sociology*, 30, pp. 243-270.

Watts, D. J. and Strogatz, S. H. (1998), "Collective Dynamics of 'Small-world' Networks", *Nature*, 393, pp. 440-442.

Wooldridge, M. (2009), *An Introduction to MultiAgent Systems*, John Wiley and Sons, Ldt.

Xie, Y. (1992), "The Log-Multiplicative Layer Effect Model for Comparing Mobility Tables", *American Sociological Review*, 57, 3, pp. 380-395.

Zintzaras, E. (2010), "The Generalized Odds Ratio as a Measure of Genetic Risk Effect in the Analysis and Meta-Analysis of Association Studies", *Statistical Applications in Genetics and Molecular Biology*, vol. 9, n. 1, article 21.

Working Papers : la liste

Hervé Le Bras, Jean-Luc Racine & Michel Wieviorka, *National Debates on Race Statistics: towards an International Comparison*, FMSH-WP-2012-01, février 2012.

Manuel Castells, *Ni dieu ni maître : les réseaux*, FMSH-WP-2012-02, février 2012.

François Jullien, *L'écart et l'entre. Ou comment penser l'altérité*, FMSH-WP-2012-03, février 2012.

Itamar Rabinovich, *The Web of Relationship*, FMSH-WP-2012-04, février 2012.

Bruno Maggi, *Interpréter l'agir : un défi théorique*, FMSH-WP-2012-05, février 2012.

Pierre Salama, *Chine – Brésil : industrialisation et « désindustrialisation précoce »*, FMSH-WP-2012-06, mars 2012.

Guilhem Fabre & Stéphane Grumbach, *The World upside down,China's R&D and innovation strategy,* FMSH-WP-2012-07, avril 2012.

Joy Y. Zhang, *The De-nationalization and Re-nationalization of the Life Sciences in China: A Cosmopolitan Practicality?,* FMSH-WP-2012-08, avril 2012.

John P. Sullivan, *From Drug Wars to Criminal Insurgency: Mexican Cartels, Criminal Enclaves and Criminal Insurgency in Mexico and Central America. Implications for Global Security,* FMSH-WP-2012-09, avril 2012.

Marc Fleurbaey, *Economics is not what you think: A defense of the economic approach to taxation,* FMSH-WP-2012-10, may 2012.

Marc Fleurbaey, *The Facets of Exploitation,* FMSH-WP-2012-11, may 2012.

Jacques Sapir, *Pour l'Euro, l'heure du bilan a sonné : Quinze leçons et six conclusions,* FMSH-WP-2012-12, juin 2012.

Rodolphe De Koninck & Jean-François Rousseau, *Pourquoi et jusqu'où la fuite en avant des agricultures sud-est asiatiques ?,* FMSH-WP-2012-13, juin 2012.

Jacques Sapir, *Inflation monétaire ou inflation structurelle ? Un modèle hétérodoxe bi-sectoriel,* FMSH-WP-2012-14, juin 2012.

Franson Manjali, *The 'Social' and the 'Cognitive' in Language. A Reading of Saussure, and Beyond,* FMSH-WP-2012-15, july 2012.

Michel Wieviorka, *Du concept de sujet à celui de subjectivation/dé-subjectivation*, FMSH-WP-2012-16, juillet 2012.

Nancy Fraser, *Feminism, Capitalism, and the Cunning of History: An Introduction,* FMSH-WP-2012-17 august 2012.

Nancy Fraser, *Can society be commodities all the way down? Polanyian reflections on capitalist crisis,* FMSH-WP-2012-18, august 2012.

Marc Fleurbaey & Stéphane Zuber, *Climate policies deserve a negative discount rate,* FMSH-WP-2012-19, september 2012.

Roger Waldinger, *La politique au-delà des frontières : la sociologie politique de l'émigration,* FMSH-WP-2012-20, septembre 2012.

Antonio De Lauri, *Inaccessible Normative Pluralism and Human Rights in Afghanistan,* FMSH-WP-2012-21, september 2012.

Dominique Méda, *Redéfinir le progrès à la lumière de la crise écologique,* FMSH-WP-2012-22, octobre 2012.

Ibrahima Thioub, *Stigmates et mémoires de l'esclavage en Afrique de l'Ouest : le sang et la couleur de peau comme lignes de fracture,* FMSH-WP-2012-23, octobre 2012.

Danièle Joly, *Race, ethnicity and religion: social actors and policies,* FMSH-WP-2012-24, novembre 2012.

Dominique Méda, *Redefining Progress in Light of the Ecological Crisis,* FMSH-WP-2012-25, décembre 2012.

Ulrich Beck & Daniel Levy, *Cosmopolitanized Nations: Reimagining Collectivity in World Risk Society,* FMSH-WP-2013-26, february 2013.

Xavier Richet, *L'internationalisation des firmes chinoises : croissance, motivations, stratégies,* FMSH-WP-2013-27, février 2013.

Alain Naze, *Le féminisme critique de Pasolini, avec un commentaire de Stefania Tarantino*, FMSH-WP-2013-28, février 2013.

Thalia Magioglou, *What is the role of "Culture" for conceptualization in Political Psychology? Presentation of a dialogical model of lay thinking in two cultural contexts*, FMSH-WP-2013-29, mars 2013.

Byasdeb Dasgupta, *Some Aspects of External Dimensions of Indian*

Economy in the Age of Globalisation, FMSH-WP-2013-30, april 2013.

Ulrich Beck, *Risk, class, crisis, hazards and cosmopolitan solidarity/risk community – conceptual and methodological clarifications*, FMSH-WP-2013-31, april 2013.

Immanuel Wallerstein, *Tout se transforme. Vraiment tout ?*, FMSH-WP-2013-32, mai 2013.

Christian Walter, *Les origines du modèle de marche au hasard en finance*, FMSH-WP-2013-33, juin 2013.

Byasdeb Dasgupta, *Financialization, Labour Market Flexibility, Global Crisis and New Imperialism – A Marxist Perspective*, FMSH-WP-2013-34, juin 2013.

Kiyomitsu Yui, *Climate Change in Visual Communication: From 'This is Not a Pipe' to 'This is Not Fukushima'*, FMSH-WP-2013-35, juin 2013.

Gilles Lhuilier, *Minerais de guerre. Une nouvelle théorie de la mondialisation du droit*, FMSH-WP-2013-36, juillet 2013.

David Tyfield, *The Coal Renaissance and Cosmopolitized Low-Carbon Societies*, FMSH-WP-2013-37, juillet 2013.

Lotte Pelckmans, *Moving Memories of Slavery: how hierarchies travel among West African Migrants in Urban Contexts (Bamako, Paris)*, FMSH-WP-2013-38, juillet 2013.

Amy Dahan, *Historic Overview of Climate Framing*, FMSH-WP-2013-39, août 2013.

Rosa Rius Gatell & Stefania Tarantino, *Philosophie et genre: Réflexions et questions sur la production philosophique féminine en Europe du Sud au XX*[e] *siècle (Espagne, Italie)*, FMSH-WP-2013-40, août 2013.

Angela Axworthy *The ontological status of geometrical objects in the commentary on the Elements of Euclid of Jacques Peletier du Mans (1517-1582)*, FMSH-WP-2013-41, août 2013.

Pierre Salama, *Les économies émergentes, le plongeon ?*, FMSH-WP-2013-42, août 2013.

Alexis Nuselovici (Nouss), *L'exil comme expérience*, FMSH-WP-2013-43, septembre 2013.

Alexis Nuselovici (Nouss), *Exiliance : condition et conscience*, FMSH-WP-2013-44, septembre 2013.

Alexis Nuselovici (Nouss), *Exil et post-exil*, FMSH-WP-2013-45, septembre 2013.

Alexandra Galitzine-Loumpet, *Pour une typologie des objets de l'exil*, FMSH-WP-2013-46, septembre 2013.

Hosham Dawod, *Les réactions irakiennes à la crise syrienne*, FMSH-WP-2013-47, septembre 2013.

Gianluca Manzo, *Understanding the Marriage Effect: Changes in Criminal Offending Around the Time of Marriage*, FMSH-WP-2013-48, GeWoP-1, octobre 2013.

Torkild Hovde Lyngstad & Torbjørn Skarðhamar, *Understanding the Marriage Effect: Changes in Criminal Offending Around the Time of Marriage*, FMSH-WP-2013-49, GeWoP-2, octobre 2013.

Gunn Elisabeth Birkelund & Yannick Lemel, *Lifestyles and Social Stratification: An Explorative Study of France and Norway*, FMSH-WP-2013-48, GeWoP-3, octobre 2013.

Franck Varenne, *Chains of Reference in Computer Simulations*, FMSH-WP-2013-51, GeWoP-4, octobre 2013.

Olivier Galland & Yannick Lemel, avec la collaboration d'Alexandra Frenod, *Comment expliquer la perception des inégalités en France ?*, FMSH-WP-2013-52, GeWoP-5, octobre 2013.

Position Papers : la liste

Jean-François Sabouret, *Mars 2012 : Un an après Fukushima, le Japon entre catastrophes et résilience*, FMSH-PP-2012-01, mars 2012.

Ajay K. Mehra, *Public Security and the Indian State*, FMSH-PP-2012-02, mars 2012.

Timm Beichelt, *La nouvelle politique européenne de l'Allemagne : L'émergence de modèles de légitimité en concurrence ?*, FMSH-PP-2012-03, mars 2012.

Antonio Sérgio Alfredo Guimarães, *Race, colour, and skin colour in Brazil*, FMSH-PP-2012-04, july 2012.

Mitchell Cohen, *Verdi, Wagner, and Politics in Opera. Bicentennial Ruminations*, FMSH-PP-2012-05, may 2013.

Ingrid Brena, *Les soins médicaux portés aux patients âgés incapables de s'autogérer,* FMSH-PP-2013-06, avril 2013.

Thalia Magioglou, *Refaire l'Europe ou refaire le « monde » ? Un commentaire sur l'ouvrage : « Refaire l'Europe avec Jürgen Habermas »,* FMSH-PP-2013-07, septembre 2013.

Samadia Sadouni, *Cosmopolitisme et prédication islamique transfrontalière : le cas de Maulana Abdul Aleem Siddiqui,* FMSH-PP-2013-08, septembre 2013.

Alexis Nuselovici (Nouss), *Étudier l'exil,* FMSH-PP-2013-09, septembre 2013.