5
Evolutionary Game Theory and the Origin of Modern Property

5.1 – Introduction

There are studies of the process of cultural evolution which stress the point that imitation and learning are very complex processes indeed. Luigi Luca Cavalli-Sforza and Marcus W. Feldman undertook a quantitative study of the frequency dynamics and kinetics of the transmission of cultural forms and, in the case of cultural evolution, they add a second mode of selection, the capacity for decision making (Cavalli-Sforza; Feldman, 1981, p. 5-6; 10), an element that can significantly complicate the analysis. In *Culture and the Evolutionary Process*, Robert Boyd and Peter J. Richerson attempt to reach a broader comprehension of the psychological, biological and sociological factors that shape the evolution of cultures by building a variety of simple models in order to capture the diverse qualitative aspects under study (Boyd; Richerson, 1985, p. 24-25). And in the 25th anniversary edition of *Genes, Mind, and Culture*, by Charles J. Lumsden and Edward O. Wilson, one of the first attempts to establish a link between genetic and cultural evolution, Lumsden claims that the scientific advances that occurred during the 25 years since the first edition of the book, in areas like genetics, neuroscience and sociology, indicate that human sociobiology and gene-culture coevolution requires more than atomistic information units (like memes), and observes that "the history of genetic change and cultural change can be thoroughly complex, even in the simplest cases" (Lumsden, 2005, p. lii).

I am in utter accordance with the statements presented above. I acknowledge that cultural evolution involves many factors which cannot be disregarded in any serious attempt to understand even a very particular case of cultural evolution, like the evolution of fundamental institutions. I am also completely aware of the diverse and complicated sociological and philosophical aspects behind the issue of institutional origin and evolution, aspects that engender important debates among sociologists and philosophers of different theoretical trends. There are also historical and geographical specificities and contingencies that undoubtedly participate in the issues under scrutiny, rendering ingenuous any pretension of achieving a generalist understanding of the subject. And all of this without taking into account the rapid advances that continuously arise from scientific areas like evolutionary biology, genetics and neuroscience, placing interdisciplinary approaches under the constant menace of obsolescence. Common answers to all these difficulties are always in danger of falling into deterministic traps, either in the form of the ultra-reductionist belief in a purely genetic determination of human behaviour, or as an expression of the holistically vague belief that all that is human is determined by social construction.

Acknowledging that science does not wear seven-league boots, I do not intend to offer a general and universal explanation of the origin of fundamental institutions. I do not even intend to reach a fully satisfactory understanding of my own analytical focus, which is placed on the specific case of the institution of modern property. What I intend to do with this chapter is to take an almost infinitesimal step, with the hope that a broader understanding of my problem may result from the collaborative process that characterises contemporary science. Hence, I will follow Gregory Chaitin's advice and I will try to keep my model very simple. Chaitin claims - and I agree - that "you do not need much to make evolution work" (Chaitin, 2012, p. 43). Therefore, my aim will be to get as much insight as possible from the minimum required elements for an evolutionary game to work, even at the risk of oversimplifying the matter[83].

The basic components of an evolutionary game theoretic model are the agents, the phenotypes that they express, the specification of the rules that govern the interactions between the agents, the pay-offs that result from those interactions (corresponding to the fitness accumulation) and the functioning of the replication process. In section 5.2, after presenting the technical aspects of a general evolutionary game, I will build and discuss a model for the case of modern property, specifying its components and describing the pertinent environmental changes[84]. In section 5.3, I will perform a computational approach to the problem under study. In the last section of the chapter (5.4), I

[83] Too realistic models, which result from the modeller's attempt to include as much aspects of reality as possible, tend to be operationally useless. This is especially noteworthy in the case of complex non-linear situations. The reason is simple: each variable must correspond to a certain measurable quantity, but in practice it is impossible to achieve measures with absolute precision. Every measure comes with an error term that specifies its precision. The non-linear relations among the variables may lead to the undesirable result of introducing an over-amplified and unmanageable error, which comes from the the non-linear operations over the multitude of errors associated with the introduced variables. Contrary to the common sense, a too realistic model is prone to be also too imprecise to be useful. However, in the other direction, a model which is too simplistic may neglect some relevant aspects that could be introduced, still keeping the model within a safe realm of precision (with some additional computational costs, perhaps). I must stress that my explicit intention to keep the model simple does not mean that it must remain stagnant. According to Myerson, "as in any analytic approach to real-life problems, the best we can hope for is to have a class of models sufficiently rich and flexible that, if anyone objects that our model has neglected some important aspect of the situation that we are trying to analyze, we can generate a more complicated extension of our model that takes this aspect into account" (Myerson, 1991, p. 83). Hence, I am aware that further studies and constructive criticisms are welcome and may result in better refinements of my model.

[84] This is my main difference from approaches like Axelrod's “evolution” of cooperation (Axelrod, 2006). My argument is based on the idea of adaptive evolution, which depends on adaptation to environmental changes. Hence, I cannot work on a closed system.

will discuss both the mathematical and the computational results, and their implications for my argument about the origin of modern property.

5.2 – An EGT-based Model for the Origin of Modern Property

As presented in Chapter 3, EGT began with J. Maynard Smith and G. R. Price's 1973 paper entitled *The Logic of Animal Conflict*. J. Maynard Smith further developed the subject in two essays published in 1974 and in 1976, and respectively entitled *The theory of games and the evolution of animal conflicts* (Maynard Smith, 1974) and *Evolution and the Theory of Games* (Maynard Smith, 1976). In 1982, Maynard Smith published the book *Evolution and the Theory of Games*, in which he presented the advances achieved in the first decade of the applications of the theory of games to the study of biological evolution. In the author's words, "evolutionary game theory is a way of thinking about evolution at the phenotypic level when the fitnesses of particular phenotypes depend on their frequencies in the population" (Maynard Smith, 1982, p. 1)[85]. It is important to remark that J. Maynard Smith acknowledged that classical game theory[86] relies on the central assumption of the player's rational behaviour according to some criterion of self-interest, a criterion that is not fully adequate in the realm of evolutionary theory[87]. In the case of EGT, technical

[85] For a more detailed account of the biography and the contributions of J. Maynard Smith to the fields of EGT and sociobiology, I refer the reader to the beautiful (I apologise for having taken the liberty of incurring in this explicit value judgment) obituary written by Karl Sigmund, a mathematician and another pioneer of EGT (Sigmund, 2005).

[86] That I prefer to call Strategic Choice Game Theory.

[87] I claim, in total consistency with my monistic philosophical stance, that human rationality itself can be regarded as a result of Darwinian evolution by natural selection. I sustain my position based on the results achieved by fields like evolutionary cognitive neuroscience (Goetz *et al*, 2009), by evolutionary perspectives regarding the origin of the conscious mind (Damasio, 2010)

rationality is replaced by population dynamics and stability, and self-interest corresponds to Darwinian fitness (Maynard Smith, 1982, p. 2). It is clear that, in its initial stages, EGT was devised as a promising way to gain theoretical insights about the intricacies of Darwinian evolution. However, EGT gained momentum and now it can now be regarded as an independent field within applied mathematics, related to the study of the evolution of the non-linear dynamical systems associated with situations of strategic[88] interaction among multiple agents.

In mathematical terms, evolutionary games are examples of dynamical systems (Hofbauer; Sigmund, 1998, p. xii). In raw terms, a system is dynamic when its state changes with time (Vincent; Brown, 2005, p. 33). In the case of Darwinian evolution, the dynamics of the system can be related to the environmental changes, and that is the reason that makes an adaptive approach adequate to model such systems. The central idea in evolutionary games is that there is an evolutionary dynamics that translates individual pay-offs obtained in a given generation to heritable phenotypic frequencies expressed in the next generation. Thus, in order to interpret a matrix game as an evolutionary game, it is necessary to explicitly express its dynamics. In most concrete situations modelled by SCGT[89], there is an element of uncertainty that

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and of mind in general (Geary, 2004), by evolutionary studies regarding the evolution of thought in great primates (Russon; Begun, 2004) and by recent researches concerning the adaptive evolution of human intelligence (Cosmides *et al*, 2010; Bradshaw, 2002). Therefore, rationality may be not strictly necessary for EGT-based models, but it is also not incompatible with them. Evolutionary and population games may be also useful to study situations that involve rational strategic planning in international affairs, for example in studies of issues like counter-terrorism (Fokkink; Lindelauf, 2013) and international intelligence cooperation (Munton; Frejd, 2013).

[88] I am referring to the sense explained by Thomas Schelling: "the term 'strategy' (...) is intended to focus on the interdependence of the adversaries' decisions and on their expectations about each other's behavior" (Schelling, 1980, p. 3).

[89] I will not present the basic definitions of SCGT, a subject that is usually well known in the any area that deals with the study of strategic decision making, as is the case with political science.

requires the use of mixed strategies, that is, discrete strategies that each player chooses from a continuous probability distribution. In the case of a game represented by a 2×2 matrix (like, for example, the well-knowns Prisoner's Dilemma, Stag Hunt, Hawk-Dove or the Battle of the Sexes), given the available strategies $\sigma_1$and σ_2, the i-th player can choose between the strategy $\sigma_1$with probability u_i or $\sigma_2$with the correspondent probability $(1-u_i)$.

With mixed strategies, the pay-off function of the i-th player is an expected[90] pay-off with the form:

$$E_i(u_i, u_j),$$

where the i-th player uses the mixed strategy u_i and the other player uses the mixed strategy u_j. If the game is described by the matrix:

$$\boldsymbol{A} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix},$$

and then the expected pay-off function $E_i(u_i, u_j)$ is given by (Vincent; Brown, 2005, p. 69):

$$E_i\left(u_i, u_j\right) = \begin{bmatrix} u_i & 1-u_i \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} u_j \\ 1-u_j \end{bmatrix},$$

For the basic technical details, I refer the reader to any classical treatment of game theory, like for example the elementary presentations offered by Prajit K. Dutta (1999) and Martin J. Osborne (2004), more advanced textbooks like Roger B. Myerson's (1991) and Drew Fudenberg and Jean Tirole's (1991), or the multidisciplinary introductory text written by the computer scientists Kevin Leyton-Brown and Yoav Shoham (2008). In this section, I will follow the mathematical notation used by Vincent and Brown (2005).

[90] In this case, the goal of a rational player is to maximise his expected utility function.

where $[u_i \quad 1-u_i]$ is the strategy vector of the i-th player and $\begin{bmatrix} u_j \\ 1-u_j \end{bmatrix}$ is the strategy vector of the other player. Performing the matrix multiplication[91],

$$E_i(u_i, u_j) = u_i u_j a_{11} + u_i(1-u_j)a_{21} + (1-u_i)u_j a_{12} + (1-u_i)(1-u_j)a_{22}$$

The evolutionary dynamics requires adapting the function above to a population. Now, the rate of change in the number x_i of individuals presenting the phenotype u_i is given by the differential equation[92]:

$$\frac{dx_i}{dt} = x_i H_i(\vec{\boldsymbol{x}}, \vec{\boldsymbol{u}}) \qquad (1)$$

In the differential equation above, t represents time, $\vec{\boldsymbol{u}} = [u_1 \cdots u_n]$ is the vector of heritable phenotypes and $\vec{\boldsymbol{x}} = [x_1 \cdots x_n]$ is the vector that describes the population density (that is, in a given moment of time, there are x_k individuals expressing the phenotype u_k. In other words, the equation above says that the rate of change of the x_i individuals that express the phenotype u_i is proportional to the current population of x_i individuals multiplied by a fitness function H_i[93] of the i-th phenotype. As the fitness that a given individual accumulates depends not only on his expressed phenotype, but also of the phenotypes expressed by

[91] I refer the reader to Chapter 2 of the book by Vincent and Brown (2005) for a review of the basic operations with vectors and matrices.

[92] The basic idea is that the derivative of a function can be interpreted as the instantaneous rate of change of the function. Thus, differential equations represent processes of change (Fowler, 1997, p. 3).

[93] It is equivalent to say that the fitness function is applied over the population of x_i individuals.

the other players, it is reasonable to assume that "the fitness of the strategy [phenotype] i is the sum of the expected payoffs of playing [expressing the phenotype] u_i against all strategies [phenotypes] in proportion to their numbers in the population" (Vincent; Brown, 2005, p. 72). Mathematically, this can be written as:

$$H_i(\vec{\boldsymbol{x}}, \vec{\boldsymbol{u}}) = \omega_0 + \sum_{j=1}^{n} E(u_i, u_j)\frac{x_j}{N} \qquad (2)$$

In the equation above, ω_0 describes the fitness of an individual that does not interact with others (obviously, in such a trivial case, the rest of the expression does not make sense), and N corresponds to the total population size:

$$N = \sum_{k=1}^{n} x_i$$

In the case of an evolutionary game described by the equations (1) and (2), I stress that there are several conceptual differences with respect to SCGT. The players are the individual agents that manifest separate fitnesses (corresponding to the SCGT concept of pay-offs) and that express separate heritable phenotypes (corresponding to the SCGT concept of strategy). Individual agents only carry the units of selection (in my case, the memes), therefore fitness should be understood as the per capita growth rate in the frequency at which a given phenotype is found in the population, and not as a property of an individual agent or of a group[94]. Functioning like genes, memes endow the individual agents with the propensities to express the given phenotypes. This avoids memetic determinism, because those propensities will turn into real expressions only if the environmental conditions are favourable. A more robust mathematical treatment of this could be based, for example, on differential stochastic games, which are games that present probabilistic transitions (Shapley, 1953, p. 1095)[95] and which account for random environmental changes in the form of random noise that can be added to the player's perceptions about the state of the system (Ramachandran; Tsokos, 2012, p. 2). I do not intend to develop such an approach in this thesis, but I do intend to further explore the issue in future works within the realm of international politics, where stochastic differential games have many promising applications.

Furthermore, in EGT the agent of optimisation is natural selection, and not individual rational choices (Vincent; Brown, 2005, p. 74). In the case of EGT, the focus is on the phenotypes instead of the players. Those phenotypes are heritable, but a given player can acquire a different phenotype from the set of heritable phenotypes through mutations. Given a homogeneous population, a mutant phenotype can invade it if the mutant obtains a higher pay-off (in terms of fitness) in comparison to the typical members of the population. If a given homogeneous population cannot be invaded by a mutant phenotype, this means that the native phenotype is evolutionary stable (Axelrod, 2006, p. 56). In other words,

[94] As I stated several times before, group selection must be avoided.

[95] The standard reference for this subject is the book edited by A. Neyman and S. Sorin (2003).

> (…) evolutionary game theory is able to analyse and to predict the evolutionary selection of outcomes in interactive environments in which the behavior of the players is conditioned or pre-programmed to follow biological, sociological or economical rules. (Van der Laan; Tieman, 1998, p. 67)

Hence, it is clear that an EGT-based analysis looks for the evolutionary stable phenotypes that arise in a population (society) of interacting individuals. The main features that an evolutionary game must include are: (i) and identifiable population of agents; (ii) an element of variation, because different types in the population replicate at different rates in the evolutionary process, according to the fitness function; (iii) a mechanism of selection, based on agents' fitness; and (iv) a hill-climbing mechanism of retention/replication, by which the most successful variants in the population are retained and therefore transmissible to the next generation (Smirnov; Johnson, 2011, p. 75). I add, as a fifth element, the description of the system's state, because adaptation requires environmental variation. In the rest of this section, I will describe how these elements are present in the case of the origin and evolution of modern property and I will build the related mathematical model.

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As discussed in the introduction and in Chapter 2, a nuclear element in the origin and evolution of modern property as a fundamental institution it the conjunction between freedom and equality. Property alienability requires free agents that can engage in negotiations. I assume that all the individuals that populate my environments are free agents. I acknowledge that this is a simplification because it could be possible to argue that early modernity presents several degrees and types of freedom. To take this into consideration would make the model much more complicated, hence I will focus only on recognition. Here, I am following Nicholas Onuf's claim that it is recognition what performs a constitutive function for individuals, societies and social/political relations in modernity (Onuf, 2013). Furthermore, the environmental changes must reflect the rapid development of material conditions, economic relations and cultural traits in early modern Europe. And it is reasonable to assume that modern social bonds based on recognition of equality should also include an element of reciprocity between free and equal agents.

I consider the meme as the replication unit and by this I mean that recognition of equality is an inclination attributable to particular agents. That is, some agents may present a greater propensity to recognise equality than others. My whole argument is based on the premise that Darwinian natural selection operates on these "selfish memes" and that the living individuals who carry them are only vehicles. Memes are selected, but not directly; they are selected by proxy, according to their phenotypic effects (that is, the individuals - vehicles - carry the memes that make them more or less prone to express certain heritable phenotypes, and the evolutionary dynamics attributes fitness to the different types of individuals according to the adaptive capacity of their phenotypic expressions to the given environments). To see the predominance of a given phenotype means that the memes which "program" the individuals to express this phenotype were the most selected ones. I am utterly following Richard Dawkins's proposal of the extended phenotype, but in a memetic version. According to Dawkins:

> (…) genes manipulate the world and shape it to assist their replication. (...) Fundamentally, what is going on is that replicating molecules ensure their survival by means of phenotypic effects on the world. (Dawkins, 1999, p. 5)

I must also stress that the idea of a meme for "recognition of equality" means that memes may express phenotypical effects with different degrees of normative force. An individual that is more prone to recognise equality is also more prone to the normative effects of promise keeping. Dawkins's central claim in *The Extended Phenotype* is that "the replicator should be thought of as having extended phenotypic effects, consisting of all its effects on the world at large, not just its effects on the individual body in which it happens to be sitting" (Dawkins, 1999, p. 4). This indicates a possible evolutionary basis to the development of the normative architecture of the social and political realm of modernity. A broader treatment of this pretty ambitious issue should necessarily include a discussion of the relationship between memes and commissive speech acts. I do not intend to embrace such an enterprise here, but in essence I agree with Mikhail Kissine's assertion that:

> (...) the function of a linguistic device explains its reproduction, limited to the relevant features, from earlier tokens: viz, from ancestors within its memetic family. Under such an analysis, that a certain type of utterance is conventionally associated with commissive force means that the performance of commissive speech acts is the function of these utterances. (Kissine, 2013, p. 152)

Besides, promises induce the belief that who made the promise intends to perform a certain action, and not commit to the promise corresponds to the induction of false representations about the future, a behaviour that can present evolutionary consequences:

> (...) cooperative behaviour (e.g. our abstention from inducing false beliefs in others) is an adaptive evolutionary strategy, partly because it helps us to reach long-term gains, even when these are in competition with desire-dependent short-term selfish gains. (...) To be sure, any belief can be revised, but the revision of one's representation of the world always has a certain cost. Therefore, all things being equal, it is evolutionary advantageous for an individual to avoid interaction with those who have repeatedly induced false representations about the future. (Kissine, 2013, p. 158)

As discussed in Chapter 3, memes essentially reproduce by contagion, like infectious diseases. In my research subject, that could be translated as a process of mimicry of successful phenotypes instead of inheritance from one generation to another. I will not address the philosophical debated regarding the relationship between mimesis and normativity, a topic that is extremely broad, multifaceted and controversial, and that encompasses approaches that range from anthropological cultural appropriation (Taussig, 1993) to political philosophy, where mimesis can actively participate in communicative action (Miller, 2011). For my purposes, it is enough to assume that memes can spread by imitation and that there may be a correspondence between the rate of spread of the meme and the normative force of its related phenotypical effects. I suggest that a proper formal modelling of that correspondence could be based on epidemiological dynamics, as in the case of mathematical models of infectious disease transmission (Grassly; Fraser, 2008). In order to keep my model simple, I will not follow this way. Instead, I will just extend the interpretation of inheritance to include mimicry, following Heylighen's claim that "the amount of individuals that can take over a meme from a single individual is almost unlimited" (Heylighen, 1992). In my EGT model, retention and transmission to the next generation must be understood as both survival and spread of the phenotypical effects associated to its respective evolutionary selected meme, an idea that is mathematically expressed as a positive rate of change in the number of the individuals presenting that specific phenotype during time.

In spite of the existence of several types of evolutionary models, all of them contain at least "a representation of the state of the population and a specification of the dynamical laws that tell how the state of the population changes over time" (Alexander, 2007, p. 25). One of the most straightforward approaches at disposal is the study of the replicator dynamics, introduced by Peter D. Taylor and Leo B. Jonker in 1978 as a mathematical foundation for J. Maynard Smith and Price's proposal of evolutionary stability. Taylor and Jonker suppose that the fitness of a given phenotype is an estimation of its growth rate in comparison to the average fitness of the population (Taylor; Jonker, 1978, p. 149; Alexander, 2007, p. 28).

Considering a population of N agents (for N large) and assuming that the population is partitioned in a finite number of n phenotypes (that is, at a given moment of time there are x_i agents presenting the i-th phenotype, for i ranging from 1 to n, and with $\sum x_i = N$), the state of the population at a given time is represented by the vector:

$$\vec{\boldsymbol{s}} = (s_1 \dots s_n)$$

where $s_i = \frac{x_i}{N}$ for all i. If r_i denotes the growth rate of the i-th phenotype, and assuming that the rate of change of x_i is proportional to the size of its subpopulation,

$$\frac{dx_i}{dt} = r_i x_i$$

then the rate of change for the entire population is:

$$\frac{dN}{dt} = \frac{d}{dt}\left(\sum x_i\right) = \sum \frac{dx_i}{dt} = \sum r_i x_i = \sum r_i s_i N = \bar{r}N,$$

where $\bar{r} = \sum r_i s_i$. Now, the rate of change of each phenotype frequency is:

$$\frac{ds_i}{dt} = \frac{d}{dt}\left(\frac{x_i}{N}\right) = \frac{N\frac{dx_i}{dt} - x_i\frac{dN}{dt}}{N^2} = \frac{r_i(s_iN)N - \bar{r}(s_iN)N}{N^2} = s_i(r_i - \bar{r})$$

If the average fitness of the population is given by:

$$F(\vec{\boldsymbol{s}}|\vec{\boldsymbol{s}}) = \sum_{i=1}^{n} s_i F(i|\vec{\boldsymbol{s}})$$

and assuming that $\frac{dx_i}{dt}$ is approximately equal to the expected fitness of the i-th phenotype, then:

$$\frac{ds_i}{dt} = s_i\big(F(i|\vec{\boldsymbol{s}}) - F(\vec{\boldsymbol{s}}|\vec{\boldsymbol{s}})\big),$$

which is the replicator equation.

In the specific case of modern property, R corresponds to the meme that induces recognition of equality, and NR corresponds to the meme that induces non-recognition of equality. It is important to remark, at this point, that what turns property into a modern institution, distinctively modern, is the establishment of an acknowledged distinction between "property as a bundle of things and property as a bundle of rights" (Brace, 2004, p. 1). Recognition of equality is necessary in order to have well-defined property rights. Such recognition implies in a more proneness to commit, which is a cooperative behaviour inasmuch as it avoids conscious induction of false representations about the future. Property cannot be regarded as alienable without the mutual acceptance that promises regarding property transactions are meant to be fulfilled. Before modern property, when property was regarded only as a "bundle of things", it is reasonable to expect that individuals were less prone to commit, and therefore they expressed a mostly non-cooperative behaviour.

The population of the model presents two types: GROTs, which tend to play *NR*, and PUFFs, which tend to play *R*. An isolated game that represents the results of the possible interactions among the agents in the population is the Prisoners' Dilemma, with *R* playing the role of cooperation and *NR* functioning as defection. An additional assumption comes from Douglass North's argument that well-established property rights result in lower transaction costs (North, 1990, p. 34-35). As mutual recognition favours clearer delimitations of rights to use and enjoy (excluding others), when two PUFFs meet and interact, they obtain comparatively higher pay-offs than the pay-offs obtained from the interaction of two GROTs, who experience larger transaction costs and less propensity to engage negotiations. When a PUFF meets a GROT, the PUFF is prone to commit, but the GROT does not recognise the PUFF as an equal. The PUFF's proneness to commit implies that he unilaterally regards the GROT as an equal. Hence, the GROT may face a temptation to cheat, obtaining the best pay-off of the game and leaving the sucker's pay-off to the PUFF.

Following the usual notation for the Prisoners' Dilemma, ρ correspond to the reward for mutual recognition, π is the punishment for mutual non-recognition, τ is the temptation to obtain the highest pay-off and σ is the sucker's pay-off. The Prisoners' Dilemma requires only the satisfaction of the inequalities $\tau > \rho > \pi > \sigma$, but it is usual to require the additional inequality $2\rho > \tau + \sigma$, in order to ensure that the joint pay-off for mutual recognition is larger than unilateral non-recognition (Nowak; Sigmund, 1995, p. 365).

The initial environment corresponds to the period of Hugo Grotius, which presented a property regime characterised by Scholastic reminiscences (as discussed in Chapter 2). Independent of the relative proportions of GROTs and PUFFs in that environment, it is reasonable to assume a high difference between the temptation to non-recognise unilaterally $(\tau - \rho)$ and the gain obtained by mutual recognition $(\rho - \pi)$. I will denote this difference by $\vartheta = (\tau - \rho) - (\rho - \pi)$.

Suppose that the initial population presents p agents of the PUFF type. Therefore, the fraction of GROTs is $(1 - p)$. The expected fitness of the GROTs and the PUFFs are given respectively by:

$$F(GROT|\vec{s}) = pF(GROT|PUFF) + (1-p)F(GROT|GROT) = p\tau + (1-p)\pi$$

$$F(PUFF|\vec{s}) = pF(PUFF|PUFF) + (1-p)F(PUFF|GROT) = p\rho + (1-p)\sigma$$

From the conditions of the Prisoners’ Dilemma, since $\tau > \rho$ and $\pi > \sigma$,

$$F(GROT|\vec{s}) > F(\vec{s}|\vec{s}) > F(PUFF|\vec{s}),$$

where $F(\vec{s}|\vec{s})$ is the average fitness of the population. The replicator dynamics is given by the differential equations:

$$\frac{ds_{GROT}}{dT} = (1-p)[F(GROT|\vec{s}) - F(\vec{s}|\vec{s})] > 0$$

$$\frac{ds_{PUFF}}{dT} = p[F(PUFF|\vec{s}) - F(\vec{s}|\vec{s})] < 0$$

As the rate of change of the frequency of PUFFs is less than zero, the population of the PUFFs is eventually driven towards extinction. For the sake of the analysis, let me consider the fictitious situation of an initial population entirely composed by PUFFs. I am using a replicator dynamics without mutation, therefore the population will remain at that state. However, it is a highly unstable state and the introduction of a very small fraction of GROTs is enough to drive the entire population to a state of only GROTs. If a replicator dynamics based on the general Prisoners’ Dilemma offers such a gloomy perspective, how could recognition (and the concomitant institution of modern property) arise and spread in early modernity?

The epoch of Grotius, corresponding to the initial environment, was not entirely composed by PUFFs. It is reasonable to assume that most agents were of the GROT type. However, it was also a period which experienced a remarkable proliferation of mercantile and banking activities, a feature that was at odds with a regime of property that was still characterised by the influence of a Scholastic-based idea of inalienable property. Therefore, it is reasonable to assume that, with the evolution of the system, the difference ϑ decreases, indicating that the gradual development of commerce, banking and new financial instruments was acting as a selective pressure. In the transition environment, corresponding to the epoch of Pufendorf, the population begins to show more agents of the PUFF type, and the difference ϑ continues decreasing. Eventually, ϑ may become negative, meaning that the joint reward for mutual recognition is greater than the sum of temptation and punishment:$2\rho > \tau + \pi$.

It is enough to study the evolution of the PUFFs, since the GROTs frequency follows from it. From the equations of the model, the replicator equation for the PUFFs, whose fraction in the population is *p*, in terms of the pay-offs is:

$$\frac{dp(t)}{dt} = p^3(\tau - \rho - \pi) + p^2(\rho - \tau + 2\pi) - p\pi$$

From the equation above, the table below shows several replicator equations related to different pay-off choices (parameters). The sucker's pay-off is always set as equal to zero:

	Parameters	**Replicator Equation (PUFFs)**
$\vartheta > 0$	$\rho = 3; \pi = 1; \tau = 6$	$\dot{p} = 2p^3 - p^2 - p$
$\vartheta > 0$	$\rho = 3; \pi = 0.5; \tau = 6$	$\dot{p} = 2.5p^3 - 2p^2 - 0.5p$
$(\tau - \rho) = (\rho - \pi)$	$\rho = 3; \pi = 1; \tau = 5$	$\dot{p} = p^3 - p$
$2\rho > \tau + \pi$	$\rho = 3; \pi = 0.5; \tau = 4$	$\dot{p} = 0.5p^3 - 0.5p$
$2\rho > \tau + \pi$	$\rho = 3; \pi = 0.25; \tau = 3.75$	$\dot{p} = 0.5p^3 - 0.25p^2 - 0.25p$

Table 1: Replicator Equations for the PUFFs, for several values of the parameters ρ, π, τ.

The polynomials above can be plotted together in order to provide a visualisation of the dynamic behaviour for the different sets of parameters:

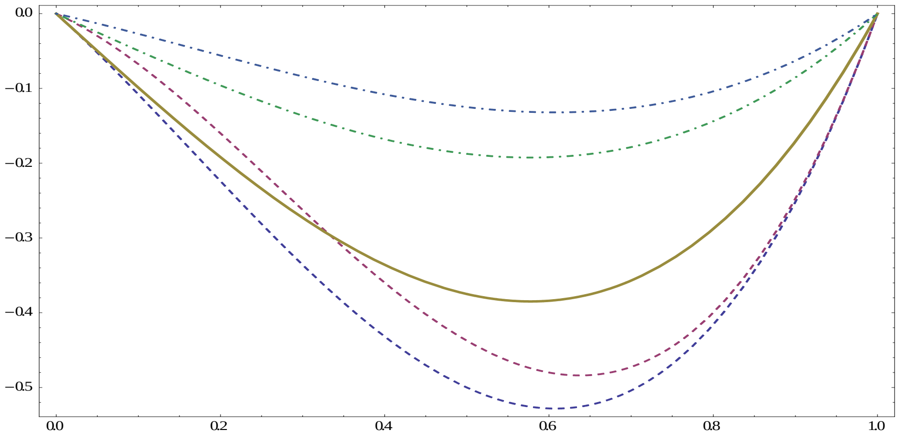

Figure 1: Graphs of the polynomials listed in Table 1.

Figure 1 shows the graphs of the polynomials listed in Table 1. The vertical axis represents the replicator dynamics $\dot{p}$ and in the horizontal axis contain the values of $p \in [0,1]$. The two dashed curves correspond to the first and second entries of the table, with the parameters calibrated for $\vartheta > 0$. The "lowest" curve corresponds to the first entry. The thick curve represents the case $(\tau - \rho) = (\rho - \pi)$. The dot-dashed curves correspond to the last entries of the table, and the "highest" curve corresponds to the last entry. The first thing that must be noticed is that $\dot{p}$ is always negative. This is consistent with the expectation of always strictly decreasing frequencies of PUFFs. The model is based on the replicator dynamics for the Prisoners' Dilemma, and the eventual extinction of the PUFFs was already expected.

However, the origin of modern property would correspond to an eventual increasing frequency of PUFFs, signalling a gradual acceptance of equality recognition. At first sight, it seems that the model shows the opposite. The

GROTs always prevail. I claim that it is not the case. At the moment, the model is showing at least a clear tendency. As the difference ϑ decreases, the PUFFs still show always strictly decreasing frequencies, however the correspondent curves are less and less bowed, and they also increasingly approach the horizontal axis. Furthermore, I only considered the gradual decrease of the difference ϑ. As claimed above, the transition environment would show the gradual appearance of more and more agents of the PUFF type. I did not introduce them in the dynamics because that would require additional assumptions, for example the supposition that the agents periodically review their beliefs and are prone to change their phenotypes. That would provide a more cultural evolutionary model indeed, with individuals switching behaviours according to their belief revisions, a feature that could be modelled by introducing review rates and probabilities of switchings somehow related to their phenotype frequencies (Alexander, 2007, p. 32-33). For the general case, that would correspond to the introduction of mutation rates that conform a stochastic $n \times n$ mutation matrix $Q = [q_{ij}]$ (Novak, 2006b, p. 23).

In spite of having decreased the differences ϑ, I never relaxed the condition $\tau > \rho > \pi > \sigma$. Just for reasons of experimentation, I will extend the analysis for some more values of the parameters:

	Parameters	**Replicator Equation (PUFFs)**
$2\rho > \tau + \pi$	$\rho = 4; \pi = 0.25; \tau = 4.5$	$\dot{p} = 0.25p^3 - 0.25p$
$2\rho > \tau + \pi$	$\rho = 4; \pi = 0.25; \tau = 4.25$	$\dot{p} = 0.25p^2 - 0.25p$
$2\rho > \tau + \pi$	$\rho = 4; \pi = 0.25; \tau = 4$	$\dot{p} = -0.25p^3 + 0.5p^2 - 0.25p$
$2\rho > \tau + \pi$	$\rho = 4.5; \pi = 0.25; \tau = 4$	$\dot{p} = -0.75p^3 + p^2 - 0.25p$
$2\rho > \tau + \pi$	$\rho = 5; \pi = 0.25; \tau = 3$	$\dot{p} = -2.25p^3 + 2.5p^2 - 0.25p$

Table 2: Replicator Equations for the PUFFs, extending for more values of the parameters ρ, π, τ.

Now, the correspondent curves are:

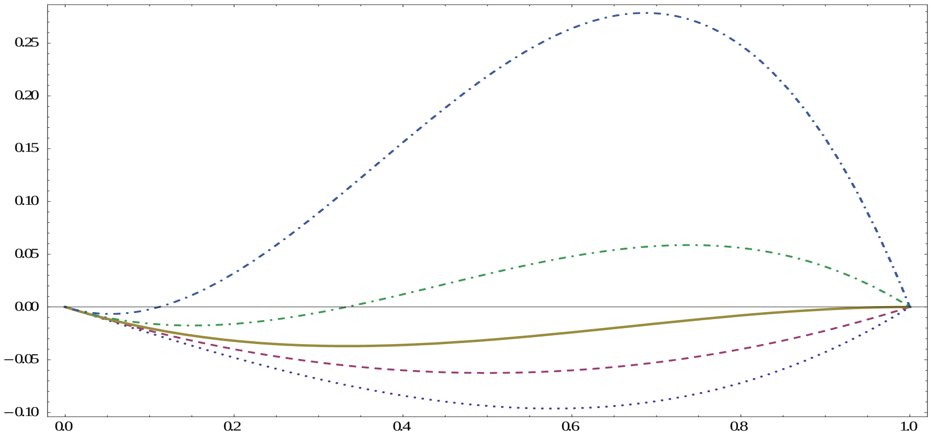

Figure 2: Graphs of the polynomials listed in Table 1.

In Figure 2, the three lower curves correspond to the first entries of Table 2. The two remaining curves correspond to the entries with $\rho > \pi$. Of course, this implies that the game has changed. The two last entries of Table 2, corresponding to the dot-dashed curves, present parameters that are incompatible with the Prisoners' Dilemma. Instead, they represent another game: the Stag Hunt – a game that is well-known for presenting a dynamics that can model the formation of trust (Alexander, 2007, p. 102).

It would be tempting to conclude that, from the specifications of my very simple model, based on the Prisoners' Dilemma and on an environmental dynamics that accounts only for gradual decreases of the difference ϑ, "eventually" the game itself evolves to a Stag Hunt and the PUFFs begin to show increasing frequencies. However, a more detailed analysis of the replicator dynamics of the evolutionary Stag Hunt would be necessary in order to achieve satisfactory conclusions.

The replicator dynamics contains one of the core ideas of EGT, developed from R. A. Fisher's perception, already in the early 1930s, that in a given population, individual fitness depends on the relative fitnesses of the other types in the population (Fisher, 1930)[96]. Fisher's approach was quantitative and tried to statistically address the relationship between phenotypes and underlying genotypes' variability. Several decades later, Taylor and Jonker (1978) proposed the replicator equation, based on a fitness function that incorporates the statistical distribution of the types present in the population. The replicator equation is a deterministic (in the sense of non-stochastic) and non-linear differential equation, and it underlies an aggregative model that excludes differences between individuals. The original replicator equation does not contemplate mutation, but it can be generalised by including a matrix representing the transition probabilities for the mutations between types.

Being a non-linear model itself, the replicator equation may pose several analytical difficulties and resort to numerical methods is usually necessary. Further complicating the equation may permit achieving more robust conclusions, provided that a suitable numerical analysis is made in conjunction. However, the replicator dynamics presents other limitations and even though they are not as handicapping to the study of evolution of biological systems, they are felt more strongly in the case of social systems. Any aggregative model cannot represent social structure, something that is required in order to specify the relational character of interactions among individuals. Regarding the random interactions that characterise the applicability of replicator dynamics to social studies, Alexander states that:

> In human society, our interactions are constrained according to some preexisting network of social relations, or the kinds of tasks we undertake during the course of a given day. One tends to interact with one's friends more often than with total strangers and, more importantly, the *significance* accorded to interactions with one's friends and acquaintances is generally greater than that

[96] It is noteworthy that Ronald Aylmer A. Fisher was one of the originators of the modern synthesis, or neo-Darwinian synthesis, which related Darwin's proposal of natural selection and Mendelian genetics.

> accorded to interactions with total strangers. Interactions with friends typically influence future behavior more readily than interactions with strangers. (Alexander, 2007, p. 26)

The formal model developed in this section is important inasmuch as it indicates a reasonable tendency to increasingly reward recognition compared to non-recognition under the historical conditions of early modernity. However, more details are necessary in order to investigate if the population eventually evolves or not to a significant preponderance of recognition, leading to the origin of a new property regime. It would be possible to develop a formal model for memetic evolution based on the replicator dynamics and with some additional structural features[97], yet such an endeavour would require a significant increase of the model's complexity, at the expense of its analyticity and always running the risk of obtaining numerically intractable results. There are, however, some plausible alternatives which come from the field of computational modelling, as for example the use of agent-based models which, in contrast with aggregative approaches, are based on particular information regarding the individual agents present in the population, such as their mobility, location in a social group, and individual propensities to switch phenotypes (Alexander, 2007, p. 25). In the next section, I will discuss the increasing importance of computational models for the political and social sciences, and I will present a very simple agent-based model for the evolution of modern property, also based on the Prisoners' Dilemma. My point is that both formal models and computer models present advantages and disadvantages, but the

[97] A recent formal approach to study the structural effects on evolutionary dynamics lies at the intersection of combinatorics (graph theory), probability theory and mathematical biology, and it is known as Evolutionary Graph Theory (Lieberman *et al*, 2005). A review of its applications to game theory is provided by Shakarian *et al* (2012).

combination of these two methodological approaches can amplify their advantages.

5.3 – The Evolutionary Origin of Modern Property: A Computational Approach

Claudio Cioffi-Revilla describes computational social science (CSS) as "a fledging interdisciplinary field at the intersection of the social sciences, computational science, and complexity science" (Cioffi-Revilla, 2010, p. 259). Its interdisciplinary character enables the integration and collaboration from several different disciplines and on a broad scope of investigations ranging from the individual to the largest social groups. Another important feature of CSS is that it contemplates both pure science and policy analysis: "(...) CSS seeks fundamental understanding of the social universe for its own sake, as well as for improving the world in which we live" (Cioffi-Revilla, 2014, p. 4). CSS is based on the characterisation of society as a complex adaptive system, reflecting the idea that society undergoes phase transitions in order to deal with changing environmental conditions. Apart from being an interdisciplinary field, CSS presents several areas of concentration, which are often complementary, like automated social information extraction (social data analytics), social networks, social complexity and social simulation modelling, of which agent-based models (multi-agent systems) are a particular case.

Before exposing in more detail what agent-based models are, it is important to stress that they are entirely based on computational simulations and involve the idea of counterfactual experiments. As stated by P. E. Tetlock and A. Belkin, computer-simulation counterfactuals "reveal hitherto latent logical contradictions and gaps in formal theoretical arguments by rerunning 'history' in artificial world that 'capture' key functional properties of the actual world" (Tetlock; Belkin, 1996, p. 6). For being based on "alternative histories" and artificial societies, counterfactuals raise several epistemological as well as normative questions regarding their validity as a research method.

The generic form of a counterfactual can be stated as: "If it had been the case that C (or not C), it would have been the case that E (or not E)" (Fearon, 1991, p. 169). Due to its speculative character, counterfactual-based research faces several objections. Causes may be non-manipulable, affecting the analytical capacity of the model. However, actual human physical intervention is not necessary in order to build an hypothetical framework of the effects associated with causal manipulations (Morgan; Winship, 2007, p. 279). That is particularly sensible in the case of computational simulations, where almost any conceivable physical intervention can be algorithmically implemented to function in an artificial world. In that sense, non-manipulable attributes should be evaluated in terms of its plausibility, and not in terms of their strict manipulability.

Another objection focuses on the emphasis placed on the discovery of the causes of effects. Even admitting that counterfactuals are not adequate to completely elucidate the causes of any effect, the careful formulation of counterfactual thought experiments may help with the less ambitious goal of estimating the effects of particular causes, fostering the progressive advance of scientific knowledge (Morgan; Winship, 2007, p. 281). With a more philosophical hue, another objection is that causal inference should not depend on metaphysical quantities like potential outcomes (Dawid, 2000, p. 409). Such an strict empirical epistemological stance needs to be taken into account, but it should also be pondered against real scientific activity, and not only on the basis of philosophical coherence. Answering to Dawid's objection, Casella and Schwartz claimed that defending that causal analysis "must be based on strict principles that can be verified empirically [leads to] a program [that is] so overly rigid that, in the end, science is not served" (Casella; Schwartz, 2000, p. 425-426). It is clear that the epistemological status of counterfactual models "breaks radically from the positivist-empiricist prescription that analysis must consider only observable quantities" (Morgan; Winship, 2007, p. 284). Does this imply that counterfactuals are valid, but present only a heuristic value?

Taking position on this issue, Bruce Bueno de Mesquita observes that "what really happens is often - perhaps always - the product of expectations about what would had happened had another course of action been chosen" (Bueno de Mesquita, 1996, p. 212). Bueno de Mesquita points to the very way of reasoning of game theoreticians, because game models require taking into account what could happen off the equilibrium and, when multiple equilibria are found, they represent plausible states of the world under scrutiny. It could be objected that this may be valid only for SCGT, but in the case of evolutionary games the concept of evolutionary stable strategy plays the role of equilibrium and, from the analysis of non-linear replicator dynamical systems, multiple attractors may arise, corresponding to potential evolutionary stable phenotypical traits. Besides, even outside of the realm of Game Theory, there are pertinent problems in the social sciences for which history provides insufficient empirical evidence. In those cases, inferences about counterfactuals may help in the process of estimating causal effects, provided that their model dependence is properly assessed (King; Zeng, 2007, p. 209).

From a more critical perspective, a recent contribution by Richard Ned Lebow highlights the importance of counterfactuals in order to show the high level of contingency present in the functioning of the political world. According to Lebow:

> I use counterfactuals to demonstrate the contingency of cases like the origins of World War I that are critical for construction of theories (i.e., balance of power, power transition) or offered as evidence in support of them. (...) I not only raise questions about these theories but, more importantly, show the extent to which our most fundamental assumptions about how the political world works are highly contingent. Counterfactual thought experiments provide a vantage point for taking ourselves outside of our world and our assumptions about it where they can be subjected to active and open interrogation. (...) I do not use counterfactuals to make the case for alternative worlds, but use the construction of those worlds to probe the causes and contingency of the world we know. (Lebow, 2010, p. 5-6)

Regarding the scientific (and not epistemological) status of counterfactuals, Lebow notes that "like all propositions, counterfactuals can be falsified but never validated" (Lebow, 2010, p. 22). That observation is important because I claim that counterfactuals are important not only for their potential to uncover the limits of our theoretical reason and to perform critical evaluations of theories. Counterfactuals are also more than a pragmatic tool that broadens the analytical view to new research perspectives. Counterfactuals, and more specially the case of computational simulations, allow – as Lebow reminds us – performing "active and open interrogation" of our assumptions about the political world. In other words, they enable the realisation of experiments under conditions that would not be normally available for several practical and ethical reasons.

One of the best advantages of computational simulations is that they make room for some degree of experimentation in the social sciences. Computational simulations, if properly used, inasmuch as they enable direct interactions with the object of research, can enhance our learning about social and political dynamics. As posed by Alker and Brunner, "we learn by doing, by operating our theories to discover their surprising implications, and by our own experiences, even if they are artificial ones" (Alker; Brunner, 1969, p. 110). Furthermore, and in spite of the critiques regarding the ontological and epistemological entailments of simulations[98], social simulation modelling advances investigations about social complexity which go far beyond what is possible to achieve using other methodologies. Several additional qualities of computational social simulations can be highlighted: versatility (virtually any statistical and formal model can be simulated, but the inverse is not valid); high dimensionality (insofar as it enables the manipulation of large numbers of variables); the capacity to handle complex non-linear dynamics; the ability of representing coupled dynamics among social, natural and artificial systems; stochasticity, enabling the examination of the relationship between several stochastic dynamics and the resulting patterns of social complexity; testing and comparison of alternative theories; feasibility of experimentation that can be used to explore and test hypotheses; and policy analysis, bridging the gap between theory and practice in the social/political sciences (Cioffi-Revilla, 2014, p. 225-226). Computational simulations also exhibit easy reproductibility, because computer-based experiments can be rerun several as many times as wished (Iba, 2013, p. 1) and the source code can be made available for other

[98] For a more detailed account of these issues, I refer the reader to Thomas B. Pepinsky recent review about the use of computational simulations to model international politics (Pepinsky, 2005).

researchers. Besides, in comparison to other methods, "computer simulations can deliver reliable results beyond the range of analytical tractability" (Helbing, 2012, p. 26).

Among the several possible computational approaches that can be applied to social and political science, agent-based models occupy a prominent place. Beyond their capacity to study interdependencies between several human activities, they are suitable for handling resilience of social systems and can be combined with other computational and formal methods (Helbing, 2012, p. 27), a feature that greatly increases their scientific potential. In general terms, multi-agent systems consist of several micro-level autonomous and proactive entities (agents) that interact through an environment, producing results in the overall system behaviour (Michel et al, 2009, p. 3). Agent-based models are examples of multi-agent systems that focus on the concrete actions and interactions between the agents (Michel et al, 2009, p. 9). In the specific case of EGT, an evolutionary game can be regarded as a dynamic process that integrates multiple agents which repeatedly interact according to the rules of some strategic game, but with more relaxed assumptions related to complete knowledge and perfect rationality (Tuyls; Westra, 2009, p. 215-216). Multi-agent systems are distributed dynamical systems which have several common assumptions with EGT, and thus EGT-based formal models are suitable to be simulated using agent-based models.

Besides, agent-based models enable to include structural features in EGT models, encompassing situations more close to real human interactions (Alexander, 2007, p. 27). In several ways, agent-based models can be regarded as complementary to formal analysis of evolutionary games through the replicator dynamics. First of all, analytical replicator dynamics assumes that populations are essentially infinite and that interactions occur in a random manner. Computational models, otherwise, do not assume infinite populations and pairwise interaction can be set to be not equiprobable (for example, individuals tend to interact more with close neighbours than with distant strangers, a reasonable assumption that can be easily implemented). Second, the replicator dynamics is deterministic and the introduction of mutations can make the model analytically intractable. Agent-based models can handle mutation allowing the agent to switch phenotypic expressions under specified conditions. Third, replicator dynamics' complexity increases significantly with the addition of more than two different types in the population. Agent-based models can be used to investigate more heterogeneous populations without significant additional computational costs. Finally, environmental changes can be introduced and controlled using agent-based models, enabling a better structural framework for the study of social adaptive dynamics.

The direct connection between agent-based computational models and EGT raises again the question of the applicability of *in silico* research techniques to the study of social/political problems. In accordance with Edmund Chattoe-Brown and Bruce Edmonds (2013, p. 456), I acknowledge that biological evolution is not isomorphic with social evolution. Biological evolution occurs over much larger temporal scales and there are no enough evidences (yet) to support the idea of a genetic basis to social behaviour. In my case, I argued that a memetic-based approach to evolution provides satisfactory answers to those two issues. Memetic evolution occurs much faster than genetic-based organic evolution and memes – as replicable units of information

– play practically the same role as genes as units of selection. That is more important, to my purposes, than embark on a quest to find a common material basis for both kinds of processes. And I also agree with Chattoe-Brown and Edmonds in that computer science approaches allow more than mere analogies with biological evolution (after all, genetic-based Darwinian evolution and memetic-based cultural/social evolution share the same algorithm). Computational techniques as Genetic Algorithms (first proposed by J. H. Holland (1975)) and Genetic Programming (Koza, 1992; 1994) are explicitly built on the ideas of biological evolution and are widely applied in social simulations.

With an agent-based model, it is easier to meet the requirements of an EGT-based analysis. I acknowledge – and I do not intend to address that issue – that the term "agent" is widely contested. It is enough to regard agents as computational entities that are autonomous, self-directed, identifiable (modular or self-contained, and endowed with a set of characteristics) and social (they recognise and interact with other agents) (Macal; North, 2009, p. 87). Thus, the specifications of the model provide and identifiable population of agents. The element of variation is set as the different phenotypic types in the population, and the accumulated pay-offs over a fixed number of interactions can be used as a measure of the different replication rates for each type. As a mechanism of selection, individuals who adapt better are selected (leave more offspring), while less adapted individuals are eliminated (in terms of the replicator dynamics, the phenotypical trait corresponding to less adapted individuals is gradually eliminated from the population). For my model, the proposed selection method is by tournament, i.e., based on the hierarchy of the different phenotypes' fitnesses in the population (Iba, 2013, p. 16). That implies in a somewhat higher computational cost, because each individual performances must be monitored by the algorithm. However, for my purposes, as I am comparing only two phenotypes (PUFFs and GROTs), the computational cost is not a problem (further extensions and refinements of the model could require the implementation of alternative selection methods). As a hill-climbing mechanism of retention/replication, more successful phenotypes can be imitated by the agents, which can be programmed to compare their average scores with their neighbours'. Imitation provides a direct connection with the memetic character of EGT applied to social problems. As adaptation requires environmental variation, some structural constrains can be programmed and controlled through the parameters that describe some systemic features (for example, through the careful setting of the relative weights of the pay-offs, as in the case of the ϑ parameter of the last section).

I will use a simple gridscape model written by Sven Orla Kimbrough (2012)[99] to model situations in which the agents play repeated 2×2 games with their close neighbours. The *Symmetric-2x2.nlogo* code is written in NetLogo, a freely available multi-agent programmable and procedural modelling environment designed by Uri Wilensky (Tisue; Wilensky, 2004) and based on the Logo programming language, created in 1967 by Wallace Feurzeig and Seymour Papert as a wide-purpose educational language. Logo presents several features that make it ideal for exploring artificial intelligence (AI), and those characteristics were inherited by NetLogo, which is widely used for programming several kinds of simulations (Gilbert; Troitzsch, 2005, p. 151).

[99] The *Symmetric-2x2.nlogo* code can be obtained from the Kimbrough's book Web site (http://opim.wharton.upenn.edu/~sok/AGEbook/) and requires the installation of NetLogo, freely available at http://ccl.northwestern.edu/netlogo/.

The simulation's world is called the gridscape and consists of a two-dimensional lattice of patches (cells, in NetLogo's terminology)[100]. In the first generation, all individuals are generated and randomly placed in that space, each occupying one patch. The agents are programmed to interact only with their more proximate neighbours (their eight Moore neighbours[101], to be more specific). In each round, each agent plays the specified game (its pay-offs can be introduced using the sliders on the interface) against each one of its neighbours and records both its accumulated result and the results of the neighbours. At the end of the round, each agents compares its total result (for that round only) with the results obtained by the neighbours. If one of the neighbours happened to achieve a higher score, the agent can switch its phenotype to that of the highest-scoring neighbour, according to some previously set chance (designated as the mutation rate). Each round corresponds to one generation (Kimbrough, 2012, p. 73).

The world's surface is a torus with dimensions 329x157, providing a total of 51.653 patches. The initial proportion of agents with the phenotype that corresponds to the meme for recognition of equality (PUFFs) can be specified using the "initial density of PUFFs" slider on the interface. For computational purposes, the PUFFs' phenotype (pure recognition) corresponds to 0 and the GROTs' phenotype (pure non-recognition) corresponds to 1. The feature that enables the agents to interact only with their more proximate neighbours intends to represent the idea that in human societies "interactions are

[100] In fact, the world is the surface of a torus (the mathematical name for a doughnut-shaped geometric surface) in order to enable a complete specification of neighbours to all agents.

[101] In a world modelled by a two-dimensional square lattice, the von Neumann neighbourhood comprises the most proximate cells situated at the north, south, east and west positions surrounding the central cell, and the Moore neighbourhood comprises the eight cells that surround the central cell.

constrained according to some pre-existing network of social relations" (Alexander, 2007, p. 26). It is a more realistic situation than replicator dynamics' assumption of random equiprobable pairings, but it is still a simplification and I do not take account of mobility effects. However, it is an important feature, inasmuch as it enables to include the relational character of social interactions directly in the model framework.

I must stress that the model uses only pure phenotypes that function as the rules that determine the behaviour of individual agents in response to the "encounter another agent" events. Furthermore, no memory was allowed. The computational code can be easily extended to handle memory-based phenotypes with different ranges of memory, but my intention is to keep the model as simple as possible to verify whether recognition of equality can dominate the population under very simple but still reasonable conditions. As for the temporal scale, at each generation a given agent performs eight interactions. I roughly assume that each generation's time span is of approximately one year (seasonality effects were not considered) and each simulation runs for 150 generations. Mutation rate was kept low (0.03), indicating that agents' phenotypes are mutable, but also somehow stable in the sense that individual agents show a certain resistance to change their memetic patterns (that can be regarded as "core beliefs").

As for the parameters ρ, σ, τ and π, they respectively correspond to the pay-off values *A*, *B*, *C* and *D*, that can be freely calibrated for each simulation. I suggest that a decreasing ϑ should correspond to more favourable conditions for recognition of equality. Several simulations were runned with different parameter vectors (ρ,σ,τ,π). σ is always set to zero (corresponding to the sucker's pay-off). Assuming that the changing environment of early modernity was making interactions between GROTs less and less worthy, the parameter π gradually decreases. Furthermore, I assume that acknowledged well-defined property rights (and duties) can diminish transaction costs, making interactions between PUFFs more and more valuable (modelled as a gradual increase of the parameter ρ). I did not alter the parameter τ. In a first moment, I did not relax the conditions of the Prisoners' Dilemma ($\tau > \rho > \pi > \sigma$). However, I did not hold the second inequality $2\rho > \tau + \sigma$, because my agents have no memory and thus they cannot take advantage of more composite phenotypes (like Tit-for-Tat or alternating between *R* and *NR*). I also set the initial density of PUFFs as low (0.10). A summary of the results from the simulation is presented in Table 3[102]:

$(\rho, \sigma, \tau, \pi)$	PUFFs over 50% (Y/N)	Generation over 50% (aprox.)	PUFFs over 90% (Y/N)	Generation over 90% (aprox.)
(3.50, 0.00, 4.00, 0.50)	**N**	**-**	**-**	**-**
(3.55, 0.00, 4.00, 0.45)	**N**	**-**	**-**	**-**
(3.60, 0.00, 4.00, 0.40)	**Y**	**49.5**	**N**	**-**
(3.65, 0.00, 4.00, 0.35)	**Y**	**43.0**	**N**	**-**
(3.70, 0.00, 4.00, 0.30)	**Y**	**41.4**	**N**	**-**
(3.75, 0.00, 4.00, 0.25)	**Y**	**41.0**	**N**	**-**
(3.80, 0.00, 4.00, 0.20)	**Y**	**38.5**	**N**	**-**
(3.85, 0.00, 4.00, 0.15)	**Y**	**38.0**	**N**	**-**

Table 3: Results of the simulations that were runned with different parameter vectors $(\rho, \sigma, \tau, \pi)$.

[102] As the results depend on the initial distribution of the agents, of the formation of clusters and of their proximity, for each set of parameters the simulation was runned 10 times. The highest and the lowest values were discarded and the value presented in the table corresponds to the arithmetic average of the remaining ones.

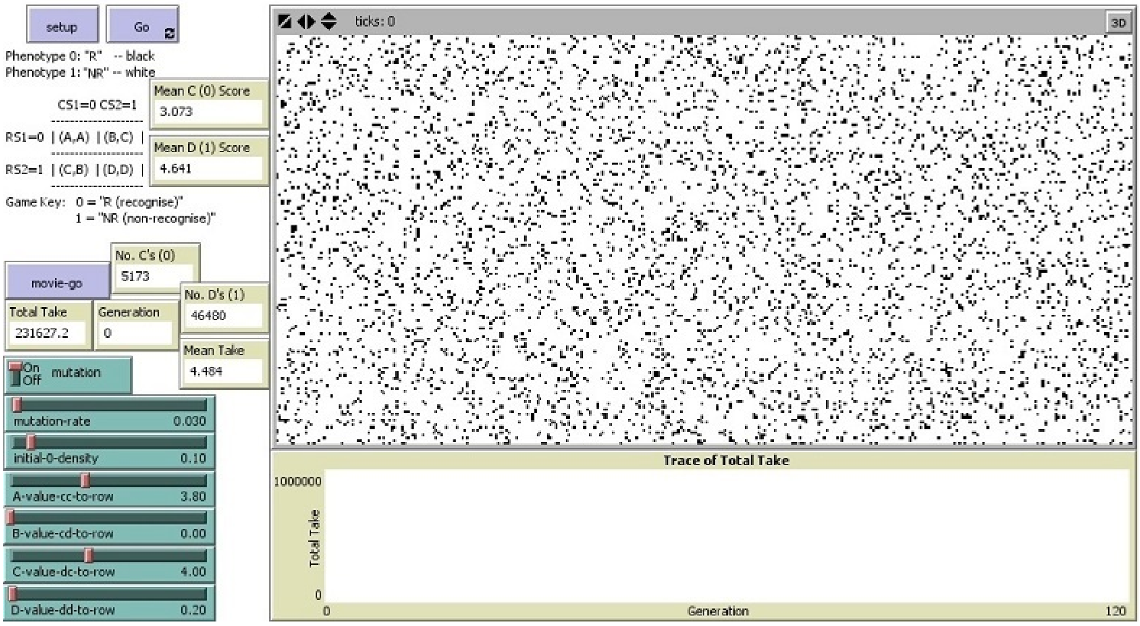

Figure 3: Initial configuration of the gridscape simulation with $(\rho, \sigma, \tau, \pi) = (3.80, 0.00, 4.00, 0.20)$

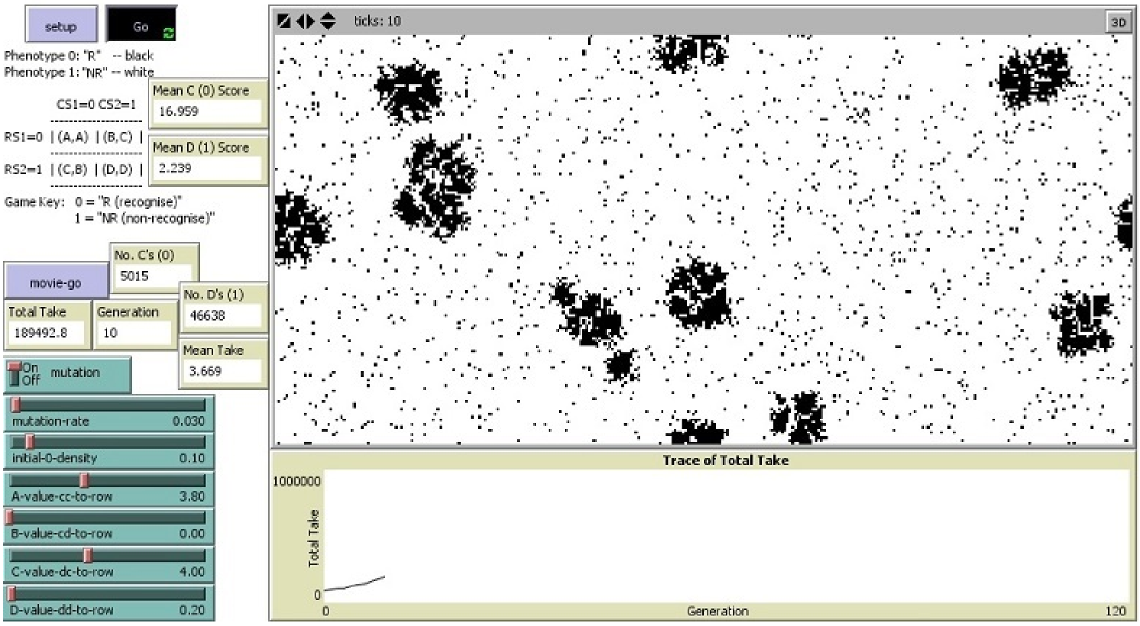

Figure 4: Gridscape simulation after 10 generations.

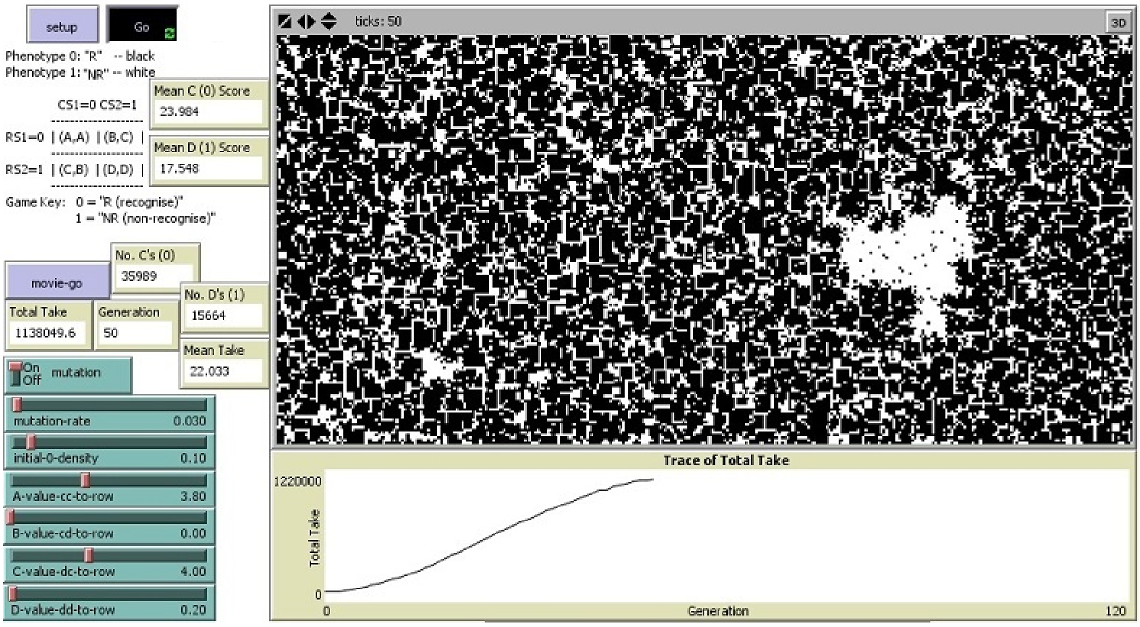

Figure 5: Gridscape simulation after 50 generations.

In a second moment, I explored what happens if the parameters $(\rho, \sigma, \tau, \pi)$ extrapolate the conditions of the Prisoners' Dilemma. I proceeded in two steps. First, I used the same initial proportion of PUFFs (0.10). Second, I repeated the simulations, but this time with a larger initial proportion of PUFFs (0.30). In both cases, I raised back the value of π to 0.60 and kept that parameter fixed. The results are summarised in Table 4:

$(\boldsymbol{\rho}, \boldsymbol{\sigma}, \boldsymbol{\tau}, \boldsymbol{\pi})$	**PUFFs over 90% (Y/N)**	**Generation over 90 (aprox.)**
(4.00, 0.00, 4.00, 0.60) Initial PUFFs = 0.10	**N**	**-**
(4.15, 0.00, 4.00, 0.60) Initial PUFFs = 0.10	**Y**	**68.3**
(4.30, 0.00, 4.00, 0.60) Initial PUFFs = 0.10	**Y**	**56.4**
(4.45, 0.00, 4.00, 0.60) Initial PUFFs = 0.10	**Y**	**48.0**
(4.00, 0.00, 4.00, 0.60) Initial PUFFs = 0.30	**N**	**-**
(4.15, 0.00, 4.00, 0.60) Initial PUFFs = 0.30	**Y**	**17.0**
(4.30, 0.00, 4.00, 0.60) Initial PUFFs = 0.30	**Y**	**14.1**
(4.45, 0.00, 4.00, 0.60) Initial PUFFs = 0.30	**Y**	**09.8**

Table 4: Results with the parameters $(\rho, \sigma, \tau, \pi)$ extrapolating the conditions of the Prisoners' Dilemma.

In the first experiment, as ϑ decreases, the PUFFs begin to slightly proliferate. Their positive rate of change was not allowed by the replicator equation, but this effect was observed in the computational simulation. Obviously, this result was allowed by the random appearance of small clusters of PUFFs in the initial gridscape, a feature that was non-feasible in the replicator dynamics, which pairs individual agents at random and randomly mixes the population at each round. Even holding the conditions of the Prisoners' Dilemma, the analysis of the results shows that the PUFFs finally occupy more than 50% of the gridscape in less than fifty generations in the third row of Table 3, and the threshold generation keeps lowering at each subsequent simulation (that is, as ϑ decreases).

It is important to remark that in the first experiments the PUFFs never occupy more than 90% of the gridscape in less than 150 generations (the limit of the simulation). In fact, the population tends to become stable at the approximate rate of 71% of the entire population. Considering that each round correspond to approximately 1 year, the analysis of the obtained data shows that it is reasonable to conclude that, with the progressive decrease of ϑ, and without introducing changing the initial rate of PUFFs, the memetype for equality recognition occupies more than half of the gridscape in a lapse of time that ranges between approximately 40 to 50 years. However, I must remark that the model does not take into account other factors that could increase even more the rate of growth of the PUFFs in the population (as social mobility, and the appearance of new PUFFs by other means than imitation). The parameters were also not changed during the course of the simulations, something that could be done in order to study the effect of the introduction of small perturbations, yet this additional gain of realism would imply in some operational difficulties.

In the second experiment, I introduced changes in the parameters $(\rho, \sigma, \tau, \pi)$ in what can be regarded as a transition from the Prisoners' Dilemma regime to a Stag Hunt regime. The visible result was an even faster domination of the PUFFs, which occupied more than 90% of the gridscape from the second row of Table 4 on. That could be regarded as a transition from the epoch of Pufendorf to the Lockean period, where a new regime of property (modern property) was already consolidated.

The differences presented by the formal model and the computational approach do not antagonise. In fact, they are complementary. The computational approach provides a better characterisation of the initial state. After all, there was already some operational notion of property in Grotius' epoch, hence the existence of small clusters of PUFFs in that environment is reasonable. The gradual decrease of ϑ depicts the transitional Pufendorfian period. And the final result, achieved with the second experiment, indicates a phase transition to a new regime of property (that can be interpreted as a change from the Prisoners' Dilemma conditions to the Stag Hunt), which presents a rapid stabilisation with the PUFFs rapid domination of more than 90% of the gridscape. That final state of the system represents the Lockean period, when even the capacity to work was considered as alienable property: "Skill was articulated as a property owned by those who worked within the rules and practices of their trade, and so within the bounds of membership of a skilled community" (Brace, 2004, p. 6). Furthermore, the diffusion of the PUFFs appeared in a few rounds of interactions, an effect that can be interpreted as the rapid diffusion of the *R* memetype.

5.4– Discussion of the results

From the formal model based on the replicator dynamics, the PUFFs never become dominant. At most, the progressive decrease of the ϑ parameter shows a tendency to an even slower disappearance. The deterministic aggregative dynamics of the replicator equation indicates that the PUFF phenotype is not evolutionary stable. Even by introducing more changes in the parameters of the model, depicting a transition to a Stag Hunt-based regime of interactions, the analysis at most indicates the possibility of an expansion of the PUFFs population. A detailed analysis of the Stag Hunt regime was not undertaken because I tried to keep the model as simple as possible and my chose was to complement with an agent-based computational model.

While the formal model indicates a reasonable tendency to increasingly reward equality recognition in comparison to non-recognition, more details are necessary to investigate if the population evolves or not to a significant preponderance of equality recognition with the concomitant appearance of a new property regime.

Agent-based models enable to add some structural features, making the situation closer of real social life. According to certain conditions, introducing structural features transforms the recognition of equality from impossible to fairly possible. According to Alexander:

> Population states that are unstable in the replicator dynamics can be stable in structured agent-based models. (...) evolutionary game-theoretic models incorporating structure allow cooperation to persist in the prisoner's dilemma, selection for universal stag hunting in the Stag Hunt (...) [and] the fact that a single family of evolutionary models account for such a wide variety of human behavior, much of it in violation of the 'predictions' of standard game theory, is telling, especially considering that incorporating structure seems to be a necessary requirement for this outcome, since many of these results are not

> obtainable under the replicator dynamics. The structure of evolution plays an important part in the evolution of social norms. (Alexander, 2007, p. 27)

In my case, I verified that recognition of equality, a state that was indeed unstable under the replicator dynamics, became stable in the structured computational approach. In the agent-based model, the PUFFs endowed with the propensity to recognise equality can achieve the domination of the modelled social environment, even beginning with a much lower proportion and – what is still more important – even inside the rules of the Prisoners' Dilemma. Furthermore, extending the parameters into the conditions of the Stag Hunt leads to a much faster preponderance and stabilisation of the PUFFs, a result that can be interpreted as a phase transition from the epoch of Pufendorf to a Lockean era of alienable modern property.

However, a formal analysis of the replicator dynamics is still necessary in order to evaluate the logical possibility of a phase transition from the Prisoners' Dilemma to the Stag Hunt. That would require improving the formal model in order to incorporate continuous changes of the ϑ parameter into the equations. This raises many questions for future research, which I will discuss in more detail in the concluding chapter. For now, it suffices to say that both the formal and the computational analysis performed in this chapter allow to advance the conclusion that they are complementary and they express the relational memetic-evolutionary character of the process of origin of modern property, through its relation with the recognition of equality. I am aware that further studies are necessary, but at this point the analysis seems to indicate that property, as an ordering feature of modern liberal society and modern political (international) relations, indeed evolved according to an adaptive evolutionary process.