Information Economy and Institutional Dynamics: Four Essays

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Thesis Abstract

The thesis studies the evolution of economic institutions in the information economy. Overall, the thesis seeks to answer two crucial questions: (1) does (if so, how) the move to a networked and knowledge-based economy affect the emergence and persistence of different institutions of information production? And (2) what are the factors that affect the firms' propensity to adopt knowledge-intensive productions? In order to answer these questions, three different domains of institutional analysis are considered: the interplay between technology and property rights, and its role in explaining the emergence (Chapter 1) and the co-existence (Chapter 2) of open and closed systems of information production; the interplay between platform designs and individual motivation, and its role in explaining the evolution of control in the digital space (Chapter 3); and the role of organizational capabilities in explaining the firm's propensity to accumulate intangible assets (Chapter 4). The theoretical and empirical analysis employed shows that: First, the diffusion of digital technologies is a necessary but not sufficient condition to explain the emergence of open systems of information production, a similarly important role being played also by the specific set of norms that formed the early culture of the networked environment; second, in the case of software development, production efficiency is not a necessary condition for a specific type (open vs. closed) of system to be adopted, and institutional diversity can indeed persist; third, in the long-run there exist two stable cultural-institutional equilibria in the digital economy: one (relatively efficient) with intrinsically motivated users and low control; and the other (relatively inefficient) with purely extrinsically motivated users and high control; the convergence towards the latter as opposed to the former tends to be favored by many of the recent policy proposals on Internet regulation. Fourth, and finally, firm-specific factors (such as size, human capital, organizational complexity and the historical intangible asset base) tend to be more powerful than industry related effects in explaining the firms' propensity to accumulate intangible assets.

Contents

Chapter 1

Institutional Change and Information Production

Abstract: The organization of information production is undergoing a deep transformation. Alongside media corporations, which have been for long time the predominant institutions of information production, new organizational forms have emerged, e.g. free software communities, open-content on-line wikis, collective blogs, distributed platforms for resource sharing. The chapter investigates the factors that favored the emergence of these alternative systems, called peer production. Differently from most of the previous literature, the chapter does so by considering technology (i.e. digital code) as an endogenous variable in the process of organizational design. On this basis the chapter argues that the diffusion of digital technologies is a necessary but not sufficient condition to explain the emergence of peer production. A similarly important role has been played by the specific set of ethics that motivated the early adherents to the free software movement. Such an ethics indeed operated as a sort of "cultural subsidy" that helped to overcome the complementarities existing among distinct design domains, and let a new organizational species to form.

JEL: B52; D23; K20; L17; O34.
Keywords: peer production, organizational equilibria, institutional complementarities, transaction costs

1.1 Introduction

Economists, since long time, have been interested in the existence of different ways of organizing production (Coase, 1937). Using as a benchmark the view according to which 'in a competitive economy it really does not matter who hires whom' (Samuelson, 1957, p. 894), several authors have gradually relaxed the standard assumptions about market completeness and discussed the viability and persistence of organizations based on different property rights regimes (Alchian and Demsetz, 1972; Demsetz, 1966; Grossman and Hart, 1986; Jensen and Meckling, 1976; Craig and Pencavel, 1992; Dow, 1993; Dow and Putterman, 2000). Although such a debate may seem to some extent an out-of-date residual of the economy of "grain and steal", it is not necessarily so. On the contrary, it turns out that the competition among distinct institutions of production is an issue that plays a central role in a key sector of the present networked economy, namely the information industry.[1]

Over the course of the last 150 years, the organization of information production has undergone a deep transformation. For more than a century, due to the specific investments necessary to the creation of long-distance mass distribution systems and the low marginal cost of production, the media corporation has been the predominant institution of information production. Such an institution has characterized by the combination of exclusive intellectual property rights on the one hand, and vast capital investments as well as highly hierarchical managerial structures on the other, typifying examples being Hollywood, the broadcast networks and the recording industry. Today, the move to a communication environment dominated by the Internet is changing all that. Alongside media corporations, we have begun to observe the emergence of radically decentralized systems of production, where loosely connected communities of volunteers openly share information on the basis of non-exclusive property rights claims. These systems have been generally referred to as peer production[2] and include communities of free software developers (e.g. GNU/Linux, Apache, LibreOffice), open-content on-line wikis (e.g. Wikipedia), collective blogs (e.g. Global Voices, OhmyNews), massive multi-players on-line games (e.g. Second Life, EverQuest) and distributed platforms for resource sharing (e.g. SETI@Home, YouTube, Flickr). In some sectors of the economy (e.g. software, on-line encyclopedia) the introduction of peer production has proven capable of generating impressive intellectual outcomes and started to represent a serious threat to the

[1] By "information industry" it is meant the set of all economic activities that deal with the production and distribution of information, including entertainment, advertising and marketing, computer programming, publishing and printing.

[2] The notion of peer production was first introduced by Yochai Benkler (2002a) and refers to a non-proprietary and commons-based mode of production in which widely distributed and loosely connected individuals voluntary cooperate with each other and without relying on either market signals or managerial commands, in order to produce unified intellectual outcomes. According to Benkler (2002a, 2006) three main features differentiate peer production from other organizations of production (e.g. firm): a marginal use of monetary payments and compensation, the absence of employment contract and hierarchical commands, and the application of non-exclusive property rights on produced information.

survival of media corporations.

Based on this evidence, an increasing number of works have recently investigated the origins of this deep transformation (Benkler, 2002a, 2003, 2006; Lerner and Tirole, 2002, 2005; von Hippel, 2005; Baldwin and von Hippel, 2011). This literature, which relies mainly on the so-called New Institutional approach - see for instance Williamson (1985), explains the emergence of peer production by placing particular emphasis on the role played by the diffusion of digital technologies (i.e. cheap processors, computer networks, and highly modular software architectures). It is argued, in fact, that such technologies have created an environment where organizations based on non-exclusive property rights regimes have become relatively more effective than the ones based on exclusive regimes in reducing the transaction costs associated with information production.[3] This, at least for certain type of information goods, has in turn generated an efficiency advantage for peer production, which has indeed favored its proliferation in the economy. Obviously, if this interpretation is correct, its implications for the future of information production are remarkable. A consistent application of the New Institutional approach would indeed suggest that if in the present technological environment peer production is relatively more efficient than firm production - i.e. the same output can be produced at a lower cost per unit of transaction, the former is inevitably going to displace the latter as the predominant institution of information production.

The application of the New Institutional approach to the study of peer production, however, suffers of one important limitation. One of the key assumption of this approach is that technology represents an exogenous variable in the process of organizational design. Such an assumption is a necessary condition if one wants to compare the transaction costs associated with distinct property rights regimes and argue in favor of a selection process that is effectively capable of rewarding the most efficient organizations. As soon as technology becomes endogenous, in fact, the transaction costs associated with each mode of organization become endogenous too and an efficiency-enhancing change in property rights is not guaranteed to occur.

Although the treatment of technology as an exogenous variable has been

[3]Benkler (2002a, 2006) argues that, in a context where cheap-processor-based computer networks have dramatically reduced the cost of information sharing (and thus eliminated the incentive problem that the latter generally entails), a system based on non-exclusive property rights regime generates two main types of transaction costs savings: first, because there is very limited used of hired labor, it eliminates the monitoring costs associated with knowledge-intensive and difficult-to-measure human inputs; and second, because individual tasks are self-identified rather than hierarchically assigned, it reduces the coordination costs associated with the allocation of human capital. In addition to this, von Hippel (2005) and Baldwin and von Hippel (2011) suggest that organizations employing non-exclusive property rights enjoy a direct transaction costs advantage because they need to invest little resources in the protection and enforcement of intellectual property rights.

largely predominant in the economic literature, it seems to be inadequate when we deal with productions taking place in a digital environment. Several authors have indeed recognized that the increased adaptability of digital code to a given structure of legal relations transforms technology into a variable that is from all respects endogenous to the process of institutional design (see Lessig, 2006; Reidenberg, 1998a; Wu, 2003b). This point, in particular, has been made clear by Elkin-Loren and Salzberger (2000, p.578) who argue that:

> The Cyberian world is very different from Coase's example of straying cattle [...]. In the latter, technological change as a result of change in legal rules is, indeed, a remote option. In Cyberspace, [on the contrary] technologies are constantly changing the substance of legal rules that may indeed affect technological development and vice versa. The apparent shortcomings of the [standard] economic approach are that it takes technological development as static and overlooks the correlation and reciprocity between technological development and legal rules. [...] [In Cyberspace] technology should become endogenous to the analysis, and the economic discourse should be expanded to address it.

Obviously, the fact that such an "expansion" is effectively undertaken is not at all neutral with respect to the meaning of the theory. The treatment of technology as an endogenous variable, in fact, affects both the interpretation that is given on the emergence of peer production (e.g. it undermines the purely technology-driven explanation) and the predictions that are made on how it will evolve.

On this basis, the present chapter will suggest that, rather than by relying on the New Institutional view, a better understanding of the factors that have favored the emergence of peer production can be grasped by referring to the literature on organizational equilibria. Such a literature, which was first originated by Pagano (1993) and Pagano and Rowthorn (1994b), presents two main advantages: first, and most prominently, it extends the New Institutional view by considering both property rights and technology as endogenous variables in the process of organizational design; and second, it explicitly models the selection process leading to the emergence of new organizational forms. By combining these two components, such an approach may offer a much better sense of the origin of peer production and eventually highlights some possible trajectories for its future development.

To simplify the analysis, the chapter will present a very simple model. In the model two (representative) agents are involved in the production of a composite information good and must choose how to organize production. The organization of production is defined along two dimensions: technology and property rights. The nature of technology is defined in terms of the ratio between modularity and labor commitment. Technologies for which this ratio is relatively high (low) are defined as modularity-intensive (labor-intensive). Each organizational dimension is assumed to be endogenous with respect to the other, in the sense that technology is designed in order to maximize profit taking as given property rights, and *vice versa*. In this framework the diffusion of digital technologies is modeled as a sudden increase in the malleability of technology, i.e. the extent to which the design of technology can be modularized. Overall, the model shows that when technical malleability is low and the *status quo* technology is labor-intensive, firm-based production is the only viable organizational equilibrium. Starting from this condition, an increase in the degree of technical malleability (i.e. the diffusion of digital technologies) enlarges the set of parameters for which peer production is effectively viable. When peer production becomes viable, two organizational equilibria exist in the economy, namely peer and firm-based production.

The fact that within this framework the diffusion of digital technologies leads to the existence of multiple organizational equilibria poses a challenge in explaining the emergence of peer production. When multiple organizational equilibria exist, in fact, the increased viability of one of them does not by itself ensure that it will effectively emerge as a productive solution in the economy. In these cases, the emergence of new organizational species generally requires the existence of some form of protection mechanism that, by reducing the selection pressure running against hybrids organizations (i.e. organizations employing a non-optimal combination of technology and property rights), allows the new equilibrium condition to be identified. On this respect, it will be argued that in the case of peer production such a protection mechanism indeed existed and is associated with the cultural backdrop that motivated the adherents to the free software movement (in particular the GNU/Linux community) in the early 1990s. By sustaining the adoption of free software packages on moral grounds rather than actual performance such culture reduced the competitive pressure generated by the proprietary packages available in the market and in turn allowed the various communities to optimize their internal organization. Once peer production could emerge within this "protected environment", it extended to other sectors of the information industry (e.g. on-line encyclopedia, video sharing) and eventually became an effective institution of information production.

Overall, the chapter adds to the previous literature in two ways. First, it models information production by considering both technology and property rights as endogenous variables. On this basis, the chapter offers a much more realistic representation of information production taking place in a digital environment than previous contributions. Moreover, it suggests that the main effect of the diffusion of digital technologies has not simply been to increase the relative efficiency of peer production, but rather to expand the set of organizational equilibria in information production. This has interesting policy implications too. Second, the chapter argues that, in addition to the diffusion of digital technologies, a crucial role in the emergence of peer production has been played by the set of values that formed the early culture of the free software movement. The latter, in particular, did not only motivate programmers to get engaged in free software development, but also worked as a sort of "cultural subsidy" that helped peer production to evolve as an effective institution of production.

The chapter is organized as follows. Section 1.2 introduces the notion of organizational equilibrium and surveys the related literature. Section 1.3 presents the model. Section 1.4 discusses the main results. Section 1.5 focuses on the role played by the free software culture in favoring the emergence of peer production. Section 1.6 finally concludes.

1.2 Organizational equilibria

The notion of organizational equilibria was originally introduced by Ugo Pagano (1993) and refers to "technological-institutional equilibria" satisfying two key conditions: (a) the technological characteristics of the resources used in production bring about a set of rights which is consistent with this technology; and (b) the set of rights brings about technological characteristics of the resources which are consistent with these rights. This notion results from the combination of two distinct views concerning the relationship between technology and property rights. The first one is the New Institutional view, according to which in economic organizations technology causes the allocation of property rights (i.e. only property rights are endogenous). The second one is the so-called "reversed view", i.e. the idea that it is the allocation of property rights that actually causes the design of technology (i.e. only technology is endogenous). Both views have been rather popular in the economic literature.

The New institutional view originates from the contributions by Coase (1937, 1960), and is then extended in what are sometimes called the Transaction Costs (Williamson, 1985) and Property Rights Literature (Grossman and Hart, 1986; Hart and Moore, 1990; Hart, 1995). The starting point of this approach is the recognition that, in complex economic systems, the execution of transactions is inevitably characterized by some positive costs (i.e. transaction costs). The latter generally reflect the resources that are dissipated during the process of negotiating, drafting and enforcing a contractual agreement and can be conceived as the economic equivalent of friction in physical systems.[4] When these positive costs exist, the formal specification of all events that may be of relevance for a transaction becomes extremely costly and contracts turn out to be incomplete.

When it is impossible to write complete contract, the characteristics of the resources used in production (i.e. the nature of technology) inevitably affect the attribution of property rights. Contract incompleteness, in fact, implies the existence of positive agency costs (i.e the costs of structuring and bonding contracts between agents), whose relative value strictly depends on the type of assets employed in the organization. Such costs, in particular, take two main forms: monitoring costs and specificity insurance costs. Monitoring costs are the costs incurred by the organization in order to increase the measurability of individual performances. Specificity insurance costs are instead the costs sustained in order to reduce the exposition of partners in the transaction to the hazards of opportunistic behavior. In presence of these costs, the force of competition will push property rights in the hands of those agents who owns the most firm-specific and difficult-to-monitor assets. By doing so, in fact, the organization can save the most on agency costs, and increases production efficiency. Organizations characterized by this allocation of property rights will in turn enjoy a competitive advantage in the market, and thus tend to proliferate in the economy.

The New Institutional way of reasoning, however, can be inverted. In contexts characterized by contractual incompleteness, in fact, it could also be the case that it is the initial allocation of property rights that affects the nature of technology, and not the reverse. This view has been supported by several authors in the literature[5] and relies on two main points. First, the agents who hold property rights on the organization have relatively fewer inhibitions about developing resources specific to that organization compared to their non-owning counterparts, and may be thus inclined to employ a technology that is more intensive in this kind of assets. Second, the very same subjects may also have a direct incentive to exploit information asymmetries to their own advantage, and thus design technology in a way that make their own individual performance relatively more difficult to monitor. The result is that also according to this view we should expect the owners of the organization to be also the owners of the most firm-specific and difficult-to-monitor assets, with the exception that

[4]Kenneth Arrow (1969, p.48), for instance, has defined transaction costs as the 'costs of running the economic system'. This definition has led Williamson (1985) to establish a parallel between transaction costs and physical friction. While recognizing the success of physics in ascertaining the attributes of complex system by assuming the absence of friction, Williamson underlines the unrealistic nature of such an assumption and argues in favor of a more realistic view of economics.

[5]See, for instance, Marglin (1974), Braverman (1974), Putterman (1982), Bowles (1985) and Bowles and Gintis (2000).

this time the direction of causality is reversed. Whereas in the New Institutional view this causality runs from technology to property rights, in this approach it runs from property rights to technology.

Although these two views have often been considered antithetic in the literature - see for instance the critique of the reversed view in Williamson (1985, ch.9), their causal opposition does not imply that they are mutually exclusive. On the contrary, as suggested by Pagano (1993) and Pagano and Rowthorn (1994b), it can well happen that both directions of causality hold at the same time. When this is the case, economic organizations qualify as self-sustaining institutions in which for any given technology there exist an optimal allocation of property rights, and for any given allocation of property rights there exist an optimal technology. When these conditions obtain, we can say that we are in situations of "organizational equilibrium" where property rights self-reinforce via technology and *vice versa*. By relying on Aoki (2001), this self-reinforcing relation can be viewed as the source of institutional complementarities between technology and property rights, with the obvious consequence that, when such complementarities obtain, multiple organizational equilibria may exist.

The notion of organizational equilibria has been employed in several contexts to study the evolution of organizational forms. Pagano and Rowthorn (1994a), for instance, use this notion to study the competitive selection of democratic and capitalist firms. Pagano and Rossi (2004) rely on a similar approach to model the complementarity between skills development and intellectual property rights (IPRs) protection, and use this model to suggest the existence of divergent trajectories of knowledge accumulation across countries. Earle et al. (2006), similarly, use the framework of organizational equilibria to investigate the relationship between ownership dispersion and the adoption of information technologies in a sample of Eastern European firms.

Recently, Pagano (2011) has expanded on the notion of organizational equilibria by studying the role of interlocking complementarities between technology and property rights in the evolution of complex institutions. In analogy with epistatic interactions for natural species, interlocking complementarities are defined as synchronic interdependences existing across different institutional domains which can be the source of built-in inertia in the process of organizational evolution. When interlocking complementarities exist, in fact, institutional speciation cannot be approached by gradual one-by-one adjustments, and necessarily requires simultaneous and complementary modifications across distinct domains. Such modifications, however, are very difficult to accomplish (e.g. due to mis-coordination) and *status-quo* institutions tend to be highly persistent. In all these cases the emergence of new organizations requires the existence of some kind of protection mechanism that attenuates the selective pressure running against hybrid forms. In general, such mechanism can be of two main types: the equivalent of protectionism, which allows organizations to experiment with different combinations of technology and property rights in a "safe" environment; and some form of unintended subsidy, which helps to shift the pressure of the selection mechanism away from production efficiency. Pagano (2011) argues that similar factors indeed played a major role in favoring both the emergence of managerial capitalism in U.S. and Germany at the end of the nineteenth century, and the evolution of distinct corporate governance models in Japan and Italy after the Second World War.

So far, to the best of my knowledge, there is no contribution that applied the notion of organizational equilibria to the study of institutional change in information production. On the contrary, this is precisely the aim of the present chapter.

One of the reason why the notion of organizational equilibria is particularly well suited to study information production in a digital environment is related to the specific way in which technology is treated. As argued above, in fact, one of the necessary condition for the theory of organizational equilibria to apply is that technology be effectively endogenous to the process of organizational design. Although such a condition has always been a controversial issue in social sciences - see for instance the debate on 'hard' and 'soft' technological determinism (Smith and Marx, 1994), it is often regarded as one of the key features that has characterized the move to a production environment dominated by digital code. In virtue of its high malleability and nearly perfect enforceability, digital code represents today a key design variable in defining systems of information production. In both off- and on-line productions, digital code is used to organize and coordinate production tasks, to structure individual interactions and monitor behavior, to punish individual decisions as well as to reward them.[6] In a similar context, a coherent approach to the study of information production can not prescind from treating technology as an endogenous variable, and the theory of organizational equilibria represents in this sense the most direct

[6]The idea of digital code as a tool to regulate on-line behavior was first proposed by cyberlaw scholars such as Lawrence Lessig (2006) and Joel Reidenberg (1998a), and captured by the well known catch phrase 'code is law'. Although the original argument was mainly concerned with government regulation, the same principle applies to the organization of information production. Even at this layer of the Internet, in fact, the end-users' activities need to be somewhat regulated in order to ensure a sustained path of information production, and code turns out to be an extremely powerful device to this end. A nice example is reported by Strahilevitz (2003) and concerns the design of peer-to-peer file-sharing networks. Early designs of such networks tended to introduce very little incentives for users to act selflessly (e.g. Gnutella). This had a negative impact on the performance of the platforms. In more recent versions, however, some changes in code were introduced that made the individual history of files contribution to be compelling for clients' requests to be accepted (e.g. KaZaA, Limewire, Bearshare). These changes reduced the degree of free-riding in the network and in turn increased the performance of the platform.

extension of the standard approach.

In order to apply the notion of organizational equilibria to the study of information production, I will proceed as follows. First, I will define a simplified model on the basis of which the interaction between technology and property rights in information production can be studied. Then, I will find the equilibrium conditions of the model. Finally, I will discuss how such conditions can eventually explain the emergence of peer production.

1.3 A Simple Model

Following Pagano (1993), I define an organization of production on the basis of two domains: the first is technology (T), i.e. the technological characteristics of the resources used in production; the second is property rights (R), i.e. the set of rights on the resources employed in the organization and on the organization itself. Depending on the way R and T combines, different organizations of production may exist. The necessary and sufficient condition for these organizations to be organizational equilibria is that the allocation of property rights be optimal given the technology, and the technology be optimal given the allocation of property rights. Formally, such condition can be defined as follows. Write $\Pi(R,T)$ as the profit obtained under a particular organization of production. Then,

Definition 1.1. *An organization of production is a an organizational equilibrium if* ***(a)*** *R maximizes $\Pi(R,T)$ given T; and* ***(b)*** *T maximizes $\Pi(R,T)$ given R.*

The application of this definition to the study of information production requires a detailed characterization of domains R and T. In domain R, as argued by Benkler (2002a), the nature of property rights employed in information production generally extends beyond the simple licensing terms on the information good, so far as to include the use of employment contracts and the ownership of physical capital. On this basis, although some hybrid forms may exist, I assume that only two main alternatives are available:

Definition 1.2. *An open property rights regime $R^O \in R$, which combines a marginal (or absent) use of employment contracts with non-exclusive copyrights claims and a decentralized ownership of physical capital.*

Definition 1.3. *A closed property rights regime $R^C \in R$, which combines a wide use of employment contracts with exclusive copyrights claims and a cen-*

tralized ownership of physical capital.

Both such regimes are widely used in the field of information production , and tend to be associated with fairly different organizational structure: flat communities of self-selected volunteers in the case of R^O (e.g. free software, Wikipedia, YouTube) and managerial hierarchies based on hired labor in the case of R^C (e.g. proprietary software, Encarta, broadcast networks).

In domain T, the characterization of the alternative resources employed in the production of information is far more complex. In such a domain, in fact, several variables ranging from publicly available information to physical equipments play a crucial role in determining how information is produced, and a comprehensive representation of technology is difficult to obtain. For this reason, in this chapter, I choose to follow Landini (2012) and focus on two variables only: i) the degree of modularity of the production system (M) and ii) the employment of cognitive labor across production modules (L).

M reflects the number of dependences that exist across the different tasks necessary to produce a composite information good. In this framework by "composite information good" is meant a unified and complex intellectual outcome, such as a software package, an encyclopedia, a movie or a newspaper. When M is high, many tasks are independent and modules (i.e. the collections of interdependent tasks) are on average small; on the contrary, when M is low, many tasks are interdependent and modules tend to be large. The value of M can be constrained by different factors such as the intrinsic complexity of the information good that is to be produced (e.g. a movie) or the type of physical equipments employed in production (e.g. printing press). In general, M is a measure of how finely grained the system of production is.

L reflects instead the units of cognitive work (say, hours) assigned to each production module per unit of time (say, a day). When L is high it means that, on average, each production module requires a large amount of cognitive work. On the contrary, when L is low such an amount is limited.[7]

This definition of M and L allows one to treat such variables as two factors of production in the standard economic sense. Both M and L, in fact, positively contribute to production[8], and can to a certain extent be considered substitute of each other. For a given information good, in fact, an increase (decrease) in M tends to decrease (increases) the average size of the production modules and therefore reduces (augments) the amount of cognitive labor L that is to be assigned to each module. Obviously, the extend to which M and L can be

[7] For a more formal treatment of M and L with specific reference to software production see Landini (2012).

[8] For the positive impact of modularity on production see Langlois and Garzarelli (2008).

effectively substitute depends on some external exogenous component, such as the physical equipments that are necessary to produce information. Under this interpretation the nature of a generic technology i can be defined by the factors proportion (or intensity) $T^i = M^i/L^i$. Such a technology can be then defined as M-intensive with respect to a benchmark j when the following holds:

Definition 1.4. *Take any pair of technologies $T^i = M^i/L^i$ and $T^j = M^j/L^j$. Then, T^i is M-intensive relative to T^j if and only if $T^i > T^j$.*

Given this characterization of domains R and T, I consider an economy with two representative agents r and t who want to produce a composite information good (say, an encyclopedia). In order to do so, and before production can actually take place, they need to decide how to organize production, i.e. they need to make a choice within two domains of the choice set S: the property rights domain $R \in S$, in which the two available options are R^C and R^O; and the technology domain $T \in S$, in which they need to set the factors proportion $T = M/L$. For the sake of simplicity I restrict the model at the design phase only, without expressly modeling actual production. I simply assume that the necessary conditions for the latter to take place are satisfied. This in turn implies that there exist a market and a demand for the information good, as well as an adequate factors endowment, especially in terms of L. When R^O is chosen in domain R the latter condition amounts to assume that there exit a community of volunteers that could be willing to contribute to production (remember that no employment contract is used under R^O). The model abstract from both the way in which such community is gathered and the way in which such community works (for more detailed work on these issues see for instance Reagle, 2010).

The decision making process is modeled as follows. Agents r and t make an independent choice in the property rights and technology domain respectively. To lend some concreteness to the model we can imagine r as being a 'financier' who owns the organization and is responsible for selecting the property rights regime to be adopted in production (e.g. an entrepreneur), and t as being the 'production manager' who is a member of the organization and is responsible for the design of technology (e.g. a web designer). In both domains, choices are made in order to maximize individual payoff, i.e. r will choose the property rights regime that maximizes π_r for a given technology, while t will choose the technology that maximizes π_t for a given property rights regime. Notice that, abstracting from the problem at stake, r stands as representative of the causality mechanism that runs from technology to property rights (i.e. the New Institutional view), while t stands as representative of the causality mechanism that runs from property rights to technology (i.e. the "reversed view").

Agents' payoffs depend on the costs and benefits that are associated with the distinct design options. On the side of costs, I assume that two main typologies exist: design costs and transaction costs.[9] I call d the design cost of modularity, i.e. the cost of modularizing the production system; l the transaction cost of labor, i.e. the cost of inducing actual effort from labor; and m the transaction cost of modularity, i.e. the cost associated with the allocation of cognitive skills within the production system. The latter, in particular, can be interpreted as the information cost that is incurred in screening individual skills first, and then in assigning subjects to the development of specific modules within the system (e.g. the allocation of people who is knowledgeable on particle physics to the draft of an encyclopedic entry on solar neutrinos). Since skills are costly to evaluate (both subjectively and from a third-party), the value of m can be relatively high. l is assumed to be monotonically increasing in L, while d and m to be monotonically increasing in M. In this sense I assume, in line with Langlois and Garzarelli (2008), that an increase in M generally entails an increase in the specialization of modules and thus a greater transaction cost for the allocation of cognitive skills. In order to account for asymmetric relations within the organization I also assume that while transaction costs m and l enters the payoff of both agents r and t, design cost d are paid only by the agent involved in the modularization of the technology, i.e. agent t.

Given this definition of the costs, I assume that each property rights regime R^O and R^C is characterized by a different transaction cost advantage. Under R^O the allocation of cognitive skills is not hierarchically determined, but rather relies on the self-identification of community members into the modules they wish to contribute (e.g. a professor of particle physics who spontaneously chooses to write an entry on solar neutrinos). For this reason, as suggested by Benkler (2002a), under R^O there tends to be a cost advantage in terms of m as compared to R^C, because community members are likely to know better than any manager which tasks they are best at doing. I will call such cost advantage x ($< m$). At the same time, as partly suggested by David and Rullani (2008) with specific reference to software, the fact that in an organization based on R^C most of the subjects are hired rather volunteer, makes it easier for such an organization to mobilize labor (i.e. to induce effort) as compared to an organization based on R^O. For this reason I assume that under R^C there is a cost advantage in terms l. I will call the latter y ($< l$). On this basis, I write the transaction costs

[9] For a similar approach see Baldwin and von Hippel (2011).

function as follows

$$C(M, L, R) = \begin{cases} (m-x)M + lL, & \text{if } R = R^O \\ \\ mM + (l-y)L, & \text{if } R = R^C \end{cases} \tag{1.1}$$

where $m > l - y$ and $l > m - x$, the latter conditions meaning that there exist transaction cost advantages in the use of different factors of production not only between but also within the same organization of production. In addition to this I write the total design cost of modularity as dM. Such cost, however, is assumed to be the same under both property rights regimes.

On the side of the benefit, I assume that the information good give rise to two main types of return. The first is the expected rents on the sale of the information good (e.g. the sale of proprietary copies of the encyclopedia), which I call $z(L, R)$ and is appropriated by the agent who owns the organization, i.e. agent r. Since such rents exist only under R^C, I assume $z(L, R)$ to take the following form:

$$z(L, R) = \begin{cases} 0, & \text{if } R = R^O \\ \\ zL, & \text{if } R = R^C \end{cases} \tag{1.2}$$

where $z > 0$ captures the positive effects of labor commitment on the marketability of the information good. The second type of return is instead associated with any other kind of expected return that can be earned from the distribution of information apart from rents, including the sale of services, advertisement and network effects. This type of return, which exist also under R^O, is equally shared between the two agents and is captured by a function $Q(M, L)$ such that $\partial Q/\partial M > 0$ and $\partial Q/\partial L > 0$. The shape of this function is assumed to be independent of the property rights regime.

Under these assumptions, the payoffs of agent r and t can be respectively written as follows:

$$\pi_r(R, T(M, L)) = z(R, L) + \frac{[Q(M, L) - C(M, L, R)]}{2} \tag{1.3}$$

$$\pi_t(R, T(M, L)) = \frac{[Q(M, L) - C(M, L, R)]}{2} - dM \tag{1.4}$$

Agents are assumed to be risk neutral and the price of the information good is equal 1. The model is solved by simply studying the associated maximization problems.

In domain R, given equations (1.3) and (1.4), and considering a generic technology T^j, r will choose to adopt an open property rights regime as long as

$\pi_r(R^O, T^j) \geq \pi_r(R^C, T^j)$, which is the case if and only if:

$$T^j = \frac{M^j}{L^j} \geq \frac{y+2z}{x} \tag{1.5}$$

Similarly, r will choose to adopt a closed property rights regime as long as $\pi_r(R^C, T^j) \geq \pi_r(R^O, T^j)$, which is the case if and only if:

$$T^j = \frac{M^j}{L^j} \leq \frac{y+2z}{x} \tag{1.6}$$

From equation (1.5) and (1.6) the following proposition hold (proofs for all Propositions are reported in Appendix 1):

Proposition 1.1. *In the domain of property rights R, the incremental benefit from choosing an open regime R^O (instead of choosing R^C) is greater when an M-intensive technology is selected in the domain T, i.e. when T^M is selected instead of T^L.*

Let's now consider domain T. Under the above described decision-making process, t will set M and L so as to maximize $\pi_t(R^C, T(M,L))$ and $\pi_t(R^O, T(M,L))$. Let:

$$(M^C, L^C) = \arg\max \pi_t(R^C, T(M,L)) \tag{1.7}$$

$$(M^O, L^O) = \arg\max \pi_t(R^O, T(M,L)) \tag{1.8}$$

Then, from equations (1.3) and (1.4) above and under standard assumptions about the shape of the marginal product, i.e. $\partial^2 Q/\partial M^2 < 0$ and $\partial^2 Q/\partial L^2 < 0$, it follows that $M^C \leq M^O$ and $L^C \geq L^O$. From the latter conditions it is straightforward to derive the following relation:

$$T^O = \frac{M^O}{L^O} \geq \frac{M^C}{L^C} = T^C \tag{1.9}$$

Relation (1.9) in turn implies that:

Proposition 1.2. *In the domain of technology T, the incremental benefit from choosing an M-intensive technology T^M (instead of choosing an L-intensive technology T^L), is greater when an open property rights regime is selected in the domain R, i.e. when R^O is selected instead of R^C.*

The combination of Propositions (1.1) and (1.2) implies that the choices made in the property rights domain R and the choices made in the technology domain T satisfy the standard supermodularity conditions (see Milgrom and Roberts, 1990; Aoki, 2001). Under the supermodularity conditions there can be two pure Nash equilibria in the system comprised of domains R and T. Each of these equilibria is an organizational equilibrium according to Definition 1.1. The first, $\{R^O, T^M\}$, is characterized by an open property rights regime and a relatively modular technology; I will call this equilibrium *peer production*. The second, $\{R^C, T^L\}$, is characterized by a closed-source regime and a relatively non-modular technology; I will call this equilibrium *firm-based production*. When these two equilibria exist, using Aoki (2001)'s terminology, R^O and T^M as well as R^C and T^L are institutional complements.

The technical conditions supporting the existence of distinct organizational equilibria in information production can be summarized in the following proposition:

Proposition 1.3. **(a)** *Suppose* $T^O = T^M \geq (y+2z)/x \geq T^L = T^C$. *Then there exist two pure strategy Nash equilibria* $\{R^O, T^M\}$ *and* $\{R^C, T^L\}$, *i.e. multiple organizational equilibria exist.* **(b)** *Suppose* $T^O = T^M \geq T^L = T^C \geq (y+2z)/x$. *Then there exist only one pure strategy Nash equilibrium* $\{R^O, T^M\}$, *i.e. only peer production is an equilibrium.* **(c)** *Suppose* $(y + 2z)/x \geq T^O = T^M \geq T^L = T^C$. *Then there exist only one pure strategy Nash equilibrium* $\{R^C, T^L\}$, *i.e. only firm-based production is an equilibrium.* **(d)** *For any ratio* $(y+2z)/x$ *there exists at least one pure strategy Nash equilibrium, i.e. there always exist at least one organizational equilibrium.*

Proposition 1.3 suggests that if the ratio between the cost advantages $(y + 2z)/x$ falls into the closed intervals defined by the factors proportions that optimize under the different property rights regimes, two distinct ways of organizing information production exist. The key question, then, becomes to understand how likely it is that such condition obtains. Intuition suggests that the 'malleability' of technology plays an important role in this respect because it ensures that, for any given property rights regime, factors proportion can be adjusted so as to minimize production costs. Under the standard assumption of decreasing marginal product, in particular, it can be proved that:

Proposition 1.4. **(a)** *For any standard production function* $Q(M, L)$ *and for any set of costs* (m, l, d), *there exists at least one triple* (x, y, z) *such that multiple organizational equilibria exist.* **(b)** *If the elasticity of substitution is equal zero, i.e. if* M *and* L *are perfect complements, then there exist only one triple* (x, y, z) *such that multiple organizational equilibria exist.* **(c)** *If the elasticity of substitution is infinite, i.e. if* M *and* L *are perfect substitutes, then any positive triple* (x, y, z) *will imply that multiple organizational equilibria exist.* **(d)** *Any* *neutral increase in the elasticity of substitution between M and L enlarges the set of the triple (x, y, z) for which multiple organizational equilibria exist.*

In addition to the 'malleability' of technology another variable that plays a crucial role in determining the existence of multiple equilibria in information production is the value of rent z. In particular, the following holds:

Proposition 1.5. *Suppose that M and L are not perfect substitute. Then, for any $T^M \geq T^L$, and for any set of costs (m, l, d), the set of points for which a peer production equilibrium exists is smaller the greater z.*

1.4 Discussion

The results of the model can be usefully employed to interpret the effects that the diffusion of digital technologies had on the organization of information production. By marking the passage from an analog to a digital environment, these technologies indeed had a crucial impact on the features of the resources used in production, and thus affected both the type and number of organizational equilibria existing in the economy.

Let's consider first the technological features of the analog environment, i.e. the world as it were up until the 1980s. In such an environment the production and distribution of information required large physical equipments such as high-volume mechanical presses, radio and television relay stations. The large scale and complexity of such equipments imposed serious constraints on the possibility to decompose the production process in finer and independent modules, with the result that technology turned out to be extremely rigid and costly to modularize. Most of the tasks were interdependent (low M), and most production modules were likely to require high involvement of cognitive labor (high L). The production environment was therefore characterized by a fairly inelastic (i.e. low malleability) and relatively labor-intensive production technology. This made firm-based production (i.e. the media corporation) the only viable organizational equilibrium (see Propositions 1.3 and 1.4).

Staring from this condition, the diffusion of digital technologies taking place during the late 1980s and (especially) the 1990s had a dramatic impact on features of the production environment. Following the developments in data transmission, cheap-processors-based computer networks gradually replaced capital-intensive equipments as the predominant communication devices. This suddenly increased the flexibility and adaptability of technology. The reduced size of personal computers, together with the huge improvements in computational capabilities and sophistication of software architectures, enabled the design of increasingly modular production platforms (high M). At the same time, the rising number of on-line users, created a pool of human resources that could be easily involved in the execution of short tasks (low L). The combination of these two effects radically increased the degree of substitutability between cognitive labor and modularity (i.e. high malleability), and in turn made peer production increasingly viable. As a result (in line with Propositions 1.3 and 1.4) two organizational equilibria started to exist in the economy, namely firm-based and peer production.

The increased viability of peer production as a consequence of a rise in technical malleability, however, is not by itself sufficient to explain its effective emergence as an institution of production. The reason for this is twofolds. First of all, as suggested by Proposition 1.5, even in the presence of high technical malleability, the viability of peer production could still be constrained by the existence of high expected rents on the information good. In this sense, the progressive tightening of the legislation on IPRs that occurred in the early 1990s did surely play a role in limiting the sectors where peer production could effectively emerge (on this see Benkler, 2002b). Secondly, even in those sectors where peer production became effectively viable, the fact that incumbent organizations were primarily represented by media corporations was likely to generate strong barriers to the emergence of new (although relatively efficient) organizational forms. The reason, as discussed in Section 1.2, is that when multiple organizational equilibria exist, technology and property rights tend to be affected by interlocking complementarities, which make the process of institutional change extremely difficult to occur.

The role played by interlocking complementarities is particularly relevant in the case of peer production. Because the media corporation had been for long time the *status-quo* institution in most sectors of the information industry, the effective emergence of peer production required not only a switch from a closed to an open property rights regime, but also a complementary change in the domain of technology, i.e. from a non-modular to a modular design. Such a change, however, could be anything but immediate, and required sometime before the new equilibrium condition could be identified. In the meantime, the media corporation could enjoy greater performances than any hybrid forms and thus exercised a strong selective pressure running against the latter. Were this selective pressure sufficiently strong, no hybrid organization would have ever had the time to make the path through the optimal design and peer production would have not probably emerged. This, independently of the productive efficiency of the two equilibria.

Obviously, the fact that nowadays we do observe peer production reveals that the convergence towards the new equilibrium condition was finally accomplished. The above discussion, however, is relevant in pointing out a missing link between production efficiency and institutional change. When multiple organizational equilibria exist, in fact, production efficiency ceases to be a necessary condition for institutional stability to obtain, with the consequence that relatively inefficient organizations can persist. This implies that, even if the technological environment of the early 1990s could have made firm production relatively inefficient with respect to peer production, e.g. in the allocation of human capital (Benkler, 2002a) and/or exploitation of innovative potential (von Hippel, 2005), this is not sufficient to explain why peer production emerged. Some other factors must have necessarily played an important role.

Once again the literature on organizational equilibria can be usefully employed in identifying what these "other factors" can possibly be. As discussed in Section 1.2, in fact, when interlocking complementarities exist the emergence of new institutions is favored by existence of some form of protectionism and/or unintended subsidy which help reducing the selective pressure running against hybrid organizations (see Pagano, 2011). In the case of peer production an external subsidy of this sort indeed existed and is related to the set of ethics that motivated the early adherents to the free software movement. As the next section will show, in fact, such an ethics tended to motivate individual decisions on software adoption more on moral ground then on actual performance, thus shifting the selective pressure away from production efficiency alone. This in turn gave the new system the time necessary to optimize its internal structure and eventually expand in other sectors of the economy.

1.5 GNU/Linux and the emergence of a new organizational species

According to the technology historian Glyn Moody (2001) the origin of free software development can be associated with a precise moment in history, namely the launch of the GNU project in September 1984. Founded by former MIT Artificial Intelligence Lab programmer Richard M. Stallman (RMS), the GNU project aimed at reproducing a non-proprietary version of many components of Unix, one of the leading operating systems (OS) of the time. Although the project started as a single-person endeavor, it soon attracted the attention of a large community of programmers. As of 2010 it is estimated that more than 200 people contributed software to the GNU system.[10]

The reasons why RMS choose to start the GNU project are rooted in the evolution that the U.S. software industry was undergoing in the early 1980s.

[10]See `http://www.gnu.org/people/` (Last time checked: May 30, 2010).

This period, as suggested by Nuvolari (2005), saw an increased commercialization of software production, which started with the AT&T's decision to begin to sell licenses of Unix. After that, a growing number of companies began to sell copies of software packages without granting full access to the underlying source code[11] and to bound the work of hired programmers by the mean of non-disclosure agreements. This represented a substantial departure from the sharing-based culture that had characterized the world of computer programming since the 1970s. In those early days, the users of mainframe computers were primarily universities and corporate research laboratories, which saw computer programs eminently as research tools. For this reason, it was common practice among programmers to share the source code of their works, and to develop new programs by improving upon the code written by others. From this perspective, the source code of programs represented a sort of public good which was freely available to anyone in the users community to read, study and hack.

Having as a reference this cultural background, RMS and other programmers like him perceived the growing commercialization of software programs as a direct attack to their individual freedom. As members of the worldwide community of hackers[12], they rebelled against the idea that the underlying source code of programs could be anyhow enclosed. For them, as suggested by Moody (2001, p.4), these special texts represented 'a new kind of literature that forms part of the common heritage of humanity: to be published, read, studied and even added to, not chained to desks in inaccessible monastic libraries for a few authorized adepts to handle reverently'. For this reason, this community started to look at the GNU project as something that went far beyond the simple technicalities of code programming, and had instead strict relations with the defense of individual freedom. Commenting on the origins of GNU, for instance, RMS observed that:

> the overall purpose [of GNU] is to give the users freedom by giving them free software they can use and to extend the boundaries of what you can do with entirely free software as far as possible. Because the idea of GNU is to make possible for people to do things

[11] The source code is a sequence of instructions to be executed by a computer to accomplish a program's purpose. Programmers usually write computer software in the form of source code (using different programming language, e.g. C, Java) and then use what is called a software compiler in order to convert the code in binary format that can operate a computer, i.e. instructions consisting of strings of ones and zeros. Binary format, however, is difficult to read and interpret, and softwares that comes without source code are very difficult to understand and modify (von Hippel and von Krogh, 2003).

[12] The word "hacker" in this context is not to be confused with its malevolent version of "crackers", who break into computer systems. As defined by RMS, a *hacker* is more generally referred to as 'someone who loves to program and enjoys being cleaver about it' (Stallman, 2002, p.17).

> with their computers without accepting [the] domination by somebody else. Without letting some owner of software say, 'I won't let you understand how this works; I'm going to keep you helplessly dependent on me and if you share with your friends, I'll call you a pirate and put you in jail.' [...] I consider that immoral, and I'm working to put an end to that way of life. [...] That's what GNU is for, it's to give people the alternative of living in freedom. (Moody, 2001, p.38)

In order to strengthen the efficacy and sustainability of the GNU project, RMS extended his own range of activities beyond sole programming. In 1985 he founded the Free Software Foundation and introduced a new licensing procedure for software called General Public License (GPL, also known as "copyleft"). Thanks to a cleaver use of the standard copyrights legislation, the GPL permits free redistribution, modification and redistribution of the modified version of the programs it covers, without depriving programmers of their own individual authorship (see McGowan, 2001). As reported by Moody (2001, p.27-28), RMS 'created in the GNU GPL a kind of written constitution for the hacker world that enshrined basic assumptions about how their community should function. In doing so, he enabled that world to progress far more efficiently than it had in the past when all these "laws" were unwritten. [...] [And] yet for Stallman, this emphasis on inherent efficiency misses the point about the GNU project and the GNU GPL. His essential concern is freedom, and the GNU project a means to an end rather than an end in itself.' From this perspective, 'Stallman's work is significant not only because it engendered many of the key elements [...] that made the success of what came to be the combined GNU/Linux operating system possible but also because it provided an ethical backdrop against which the entire free software and open source story is unfolding.' (p.30)

The existence of this ethical backdrop turned out to be of crucial importance for the success of free software, and more generally peer production. The characterization of free software (as the "GPLed" software came to be known) as a mean to an end rather than as an end in itself, had in fact a powerful impact on the way in which software programs started to be consumed. For a large portion of users the "free" nature of source code became a condition that was often more important than the degree of technical performance in determining the adoption of a particular program. By direct admission of RMS, in fact, the early applications of the GNU system

> had no technical advantage over Unix. [...] [Yet, they had] a social advantage, allowing users to cooperate, and an ethical advantage, respecting the user's freedom (Stallman, 2002, p.24).

The combination of these "non-technical" features created an environment where "source code freedom" rather than "technical performance" became the principal domain in which competing applications were compared. This, at least for set of programs that attracted the attention of hackers, generated a kind of "cultural subsidy" in favor of free software production (and as a consequence peer production), because it reduced the selective pressure that the latter had to face.

The protection ensured by this "cultural subsidy" played an important role not only during the initial launch of the GNU project, but also when the history of free software had its second important twist. On August 25 1991 a Finnish undergraduate student named Linus Torvalds posted on the comp.os.minix newsgroup[13] a message concerning his work on a free Unix kernel called Linux. The kernel represents the main component of most OS, in that it works as a sort bridge between applications and the actual data processing done at the hardware level. Although the development of a Unix kernel (eventually called Hurd) had always been in the waiting list of the GNU project, it was still lacking in 1991 and indeed represented the missing step towards the realization of a complete free system. For this reason, the degree of excitement that welcomed the first news about Linux comes at no surprise. As reported by Moody (2001, p.42), less than four hours after Torvalds's original message there were already positive reactions in the newsgroup:

> a fellow Finn wrote:'Tell us more!' and asked:'What difficulties will there be in porting?'. [Similarly,] a Minix user from Australia said:'I am very interested in this OS. I have already thoughts of writing my own OS, but decided I wouldn't never have the time to write everything from scratch. But I guess I could find the time to help raising a baby OS:-)'.

As suggested by Moody, this was just 'a portent of the huge wave of hacker talent that Linux would soon ride' (ibid.).

Similarly to the first versions of the GNU applications, also Linux did not exhibit excellent technical properties at its birth. In the comments attached to version 0.01 of the code (released in October 1991), for instance, Torvalds himself admits:

> this isn't yet the 'mother of all operating system', and anyone who hoped for that will have to wait for the first real release (1.0), and

[13] The comp.os.minix newsgroup was one of the many Usenet newsgroups operating at the time. The topic being discussed in this particular newsgroup concerned Minix, a Unix-like OS based on a microkernel architecture created by Andrew S. Tanenbaum for educational purposes in 1987.

> even then you might not want to change for Minix (Moody, 2001, p.45).

Also in this case, however, the appeal for programmers to start using and studying Linux was not primarily a matter of performance. In the same posting accompanying the release of this version, Torvalds in fact writes:

> I can (well, almost) hear you asking yourselves "Why?". Hurd will be out in a year (or two, or next month, who knows), and I've already got Minix. This is a program for hackers by a hacker. I've enjoyed doing it, and somebody might enjoy looking at it and even modifying it for their own needs. It is still small enough to understand, use and modify, and I'm looking forward to any comments you might have (Moody, 2001:45).

And the strength of the appeal was indeed sufficient to meet an extraordinary success. As argued by Nuvolari (2005), when Torvalds released version 1.0 of Linux in 1994, the OS could compete successfully in stability and reliability with most commercial versions of Unix. Starting from that release, Linux was further refined, incorporating a number of new features. The community of developers grew exponentially, outnumbering the thousands. In 1999 the effective potential of Linux received also its "official recognition" in the so-called "Halloween document", an unofficial document leaked out from Microsoft which mentioned Linux (and, generally, the diffusion of the open-source modality of production) as a major competitive threat to the company.

If we look at the overall period that went from the launch of the GNU project to the success of Linux, it is then possible to observe a clear pattern of organizational evolution. Starting from the idea of a small group of programmers which had deep roots in the hacker culture of the early 1970s, the GNU project served as an example for an alternative non-proprietary way of developing software. The use of exclusive copyrights terms was substituted by GPL-like licenses, and the hiring of paid programmers was replaced by the voluntary participation in communities of peer developers. At the beginning, this way of producing software encountered some difficulties and the quality of "free" programs could not compete with their proprietary counterparts. Nevertheless, the attachment of strong social and ethical values to these works compensated (at least partly) for their inferior quality and supported their diffusion in spite of the technical deficiencies. With the passage of time, and in virtue of this "cultural subsidy", the communities of free software developers could improve their internal organization and define in a clearer way the rules that could sustain their performance - see for instance Raymond (1999). The result was the impressive success that free software enjoyed in the second half of the 1990s, with programs such as

Linux (OS), Apache (web server), MySQL (relational database), and Sendmail (mail transport agent) becoming widely popular also outside the hacker world (see Moody, 2001). It is indeed with the success of these programs that peer production made its first appearance on the "stage" of information production.

This brief history of free software, however, rises some important questions. The most relevant, for the sake of the argument that is presented here, is whether there exist some sectors of the economy other than just software development where peer production could have possibly emerged within the same period of time. If this is not the case, in fact, the role played by the specific culture of free software would be significantly undermined, because essentially indistinguishable from that of other purely technological factors. On this respect, although a more robust empirical analysis is required, some supporting evidence can be gained by looking at the status of information technology at the beginning of the 1990s. Such an analysis reveals in fact that, beyond the specific domain of software production, many of the technologies generally associated with peer production were already available at that time. The first proposal for the WWW system - i.e. the easy-to-use system of interlinked hypertexts that facilitates the transmission of information over the Internet, for instance, was written by Tim Berners-Lee already in 1989 (Berners-Lee, 1999). Even earlier, in 1978, Ward Christensen developed the first Bulletin Board System, which can be considered one of the technological antecedent of Internet forums, and then blogs (Stone, 2004). Similarly, as early as 1972, a group of researchers at Carnegie-Mellow University developed a system called ZOG multi-user database, which is many respects an indirect predecessor of the wiki-style web page (i.e. WikiWikiWeb) created by Ward Cunningam in 1994. Finally, with specific reference to the design of peer-to-peer (P2P) network, the Usenet developed by Tom Truscott and Jim Ellis in 1980 can be viewed as one of the first clients-server architecture where the principle of P2P servers interactions was directly employed (Fristrup, 1994). In spite of this technological *substratum*, however, highly successful and non-software-related examples of peer production such as Napster (P2P networks), Wikipedia (on-line encyclopedia), and the myriad of individual and collective blogs, did not emerge until the early 2000s. Not only, but in most of these cases (see for instance Wikipedia)[14] the evolution of GNU/Linux was indeed considered as the main example to follow in the design of the digital platforms. This, although only at an intuitive level, tends to support the interpretation according to which peer production first emerged in the particular niche of software production, and only afterward it extended to other sectors of the economy.

[14]On the role that the free software movement and in particular RMS played as a source of inspiration for Wikipedia see Reagle (2010).

1.6 Conclusion

Commenting on the relationship between information and institutions in modern economies, Kenneth Arrow (1999, p.25) once observed that:

> Information, one of the fundamental economic determinants, leaps over from one firm to another, yet the firm has so far seemed reasonably defined in terms of legal ownership. It seams to me that there must be an increasing tension between legal relations and fundamental economic determinants. [...] We are just beginning to face the contradictions between the system of private property and of information acquisition and dissemination

Although in making this statement Arrow was not directly referring to peer production, he still captured the essence of the institutional change that the information economy is facing. In the decade that followed Arrow's intuition there has been a dramatic diffusion of non-proprietary forms of production that spawned across different information goods. As suggested by Benkler (2006, p.5), instead of treating such forms of production as mere curiosities, 'we should see them for what they are, namely a new mode of production emerging in the middle of the most advanced economies in the world'.

Based on this evidence, the chapter investigated the factors that favored the emergence of this new mode of information production. Differently from most of the previous literature, the chapter did so by modeling technology as an endogenous variable in the process of organizational design. In this way, it integrated the intuition derived from part of the cyberlaw literature, according to which the endogenity of technology is indeed one of the crucial features that characterizes the move to a digital production environment.

On the basis of a simple model, the chapter suggested that the diffusion of digital technologies is a necessary but not sufficient condition to explain the emergence of peer production. The reason is that, when technology is endogenous, there may exist multiple organizational equilibria in the economy. In the latter case, the emergence of a new organizational form necessarily requires some form of protection mechanisms that, by reducing the selection pressure running against hybrids organizations, allows the new equilibrium condition to be identified. With respect to peer production, the chapter suggested that such protection mechanism can be associated with the cultural backdrop that characterized the early adherents to the free software movement. By sustaining the adoption of software programs on moral grounds rather than on actual performance, this culture created a sort of protected environment where peer production could first emerge and then proliferate.

If this interpretation is correct, then there exist interesting implications for the future of peer production. The existence of multiple organizational equilibria, in fact, limits the possibility of establishing any direct link between production efficiency and institutional change. This implies that even if in the present technological environment peer production can be deemed as more efficient than standard firm-based production, this does not necessarily mean that the former will spontaneously replace the latter as the predominant institution of information production. Such a replacement depends on several factors, among which the frequency of the two institutions and the speed of the selection process. Moreover, depending on the type of institution that we believe as more valuable for the society as a whole - see on this Benkler and Nissenbaum (2006) and Benkler (2002b), it can also be affected by different types of policy interventions, such as for instance a reform of IPRs legislation.

1.7 Appendix 1

1.7.1 Proof of Proposition 1.1.

For a given value of x, y and z, consider two technologies T^M and T^L such that conditions (5) and (6) are simultaneously satisfied, i.e. $T^M \geq (y + 2z)/x \geq T^L$. Then, it follows directly from (5) and (6) that:

$$\pi_r(R^O, T^M) \geq \pi_r(R^C, T^M) \tag{1.10}$$

$$\pi_r(R^C, T^L) \geq \pi_r(R^O, T^L) \tag{1.11}$$

Adding equations (1.10) and (1.11) side by side and rearranging, we obtain the following relation:

$$\pi_r(R^O, T^M) - \pi_r(R^C, T^M) \geq \pi_r(R^O, T^L) - \pi_r(R^C, T^L) \tag{1.12}$$

which proves the proposition.

1.7.2 Proof of Proposition 1.2.

Consider two technologies T^M and T^L such that conditions (1.9) is satisfied, i.e. $T^M \geq T^L$ and T^M maximizes π_t under R^O as well as T^L maximizes π_t under R^C. Then, it follows directly from (1.9) that:

$$\pi_t(R^O, T^M) \geq \pi_t(R^O, T^L) \tag{1.13}$$

$$\pi_t(R^C, T^L) \geq \pi_t(R^C, T^M) \tag{1.14}$$

Adding equations (1.13) and (1.14) side by side and rearranging, we obtain the following relation:

$$\pi_t(R^O, T^M) - \pi_t(R^O, T^L) \geq \pi_t(R^C, T^M) - \pi_r(R^C, T^L) \tag{1.15}$$

which proves the proposition.

1.7.3 Proof of Proposition 1.3.

Points **(a)**, **(b)** and **(c)** follow directly from conditions (1.5), (1.6) and (1.9) above. Point **(d)** is a direct consequence of points **(a)**, **(b)** and **(c)**.

1.7.4 Proof of Propositions 1.4 and 1.5.

See Pagano and Rowthorn (1994b), Propositions (2), (3), (4) and (5). Proposition 1.5 follows directly from Propositions 1.3 and 1.4.

Chapter 2

Technology, Property Rights and Organizational Diversity in the Software Industry

Abstract: Why do open- and closed-source productions co-exist? To address this question, the chapter studies the viability of distinct systems for software development. The model shows that: a) for low design costs of modularity, both open- and closed-source productions are viable systems; b) closed-source production is more likely to be adopted the greater the expected rents on software; and (c) production efficiency is not a necessary condition for the stochastic stability of a system to obtain. These three results can shed light on the emergence of organizational diversity in the software industry. The chapter adds to the literature in three ways: first, it considers property rights and technology as endogenous variables in the process of system design; second it argues that in producing software multiple equilibrium designs may exist; and third, it shows that, in because of high rents and low design costs of modularity, production inefficiency can be persistent.

JEL: C73; D23; L17; O34.
Keywords: software production, system design, institutional diversity, transaction costs, evolutionary games

2.1 Introduction

In the software industry there presently exist two distinct ways of organizing production. On one hand there exist closed-source production, which relies on exclusive copyright claims, hired workforce and hierarchical coordination. On the other open-source production, which combines non-exclusive copyright claims, (mainly) unpaid work and peering-based coordination. Although both forms of production have existed since long time in the software industry[1], none of them seems to effectively prevail. On the contrary, open- and closed-source productions tend to co-exist in most market segments.[2] This is clearly the case, for instance, in the market for web servers, where the competition between Apache (open-source) and Microsoft Web Server (closed-source) is more than 15 years long. A similar trend can be observed in the market for web browsers, where Internet Explorer (closed-source) has been steadily competing with Mozilla Firefox (open-source), and now also with Google Chrome (open-source). An almost equivalent situation exists in the market for database, with MySQL (open-source) competing against Oracle and SQL Server (closed-source), and in the market for mobile and desktop operating systems, with iPhone, RIM and Windows Mobile (closed-source) competing against Symbian and Android (open-source), and Microsoft Windows (closed-source) competing against GNU/Linux (open-source). Overall, looking at these as well as other market segments (e.g. office suites, finance and accountability packages, mail servers), it seems that for most part of the last two decades open- and closed-source software packages have simply co-existed in the market.

From the perspective of the standard organizational economics literature - e.g. Williamson (1985), the sustained co-existence of open- and closed-source productions is somewhat puzzling. According to this view, in fact, for any given set of available technologies, systems of production based on relatively inefficient allocations of property rights should be less likely to be adopted than more efficient ones, and thus a tendency towards organizational uniformity should emerge (at least for technologically equivalent products). In the software industry, on

[1]The free sharing of software among programmers (mainly working for public institutions such as universities) was an established practice in the early 70's, and it has survived side by side to the production of proprietary software all the way through the present days. On this point see Lerner and Tirole (2002, 2005) and McGowan (2001).

[2]For detailed information on the trend of market shares within the distinct market segments see: Netcraft, web server survey, July 2010. URL `http://news.netcraft.com/archives/2010/` (Last time checked: July 29, 2010). NetApplications, Top browser share trend, 2010 `http://marketshare.hitslink.com/browser-market-share.aspx?qprid=1` (Last time checked: July 29, 2010). Gartner Inc., Competitive landscape: Mobile devices, 1q10, 2010. URL `http://www.gartner.com/DisplayDocument?doc_cd=200946l\ref=g_rss` (Last time checked: July 29, 2010). For data on both database and desktop operating systems see David A. Wheeler (2007), Why Open Source Software/Free Software (OSS/FS, FLOSS, or FOSS)? Look at the Numbers! URL `http://www.dwheeler.com/oss_fs_why.html.` (Last time checked: August 16, 2010).

the contrary, we observe that for almost any kind of software package, two systems of production based on different property rights regimes co-exist. Why, then, do open- and closed-source productions co-exist? When both systems are effectively viable, what leads an organization to adopt one type of production rather than the other? Does this choice always entail that production efficiency is achieved? These are the main questions addressed in the chapter.

The chapter takes a system design approach to study software production. A system design is defined as a specific combination of two domains: technology and property rights. Both domains are assumed to be endogenous relative to each other, in the sense that technology is designed in order to adjust to the characteristics of property rights and *viceversa*.[3] On this basis, the model focuses on the decision-making dynamics leading to the adoption of a particular system design, and not on actual production. Although such an approach is highly abstract, it offers a useful representation of the complementarities that may exist among distinct design domains. The model shows that: a) for sufficiently low design costs of modularity, both open- and closed-source productions are viable systems for software development; b) when both systems are viable, closed-source production is more likely to be adopted the greater the expected rents on software; and (c) production efficiency is not a necessary condition for the stochastic stability of a system to obtain.

These three results, together with the widespread diffusion of digital technologies in the mid '90s, may offer an explanation for the exceptional degree of organizational diversity that we presently observe. The intuition is an analogy with the process of biological speciation. Acting as an exogenous shock, the diffusion of digital technologies has suddenly enlarged the set of software packages for which both open- and closed-source productions became viable systems. In consequence of the complementarities existing among distinct design domains, however, some organizations faced important constraints in the process of adapting their system to the new environment, and divergent trajectories of organizational speciation have emerged.[4] Only the organizations that, in because of low expected rents, lose little by shifting to open-source production were in the position of actually making the move, while the others got locked into the old system. As a result open- and closed-source productions have increasingly co-existed.

In the literature on free/open-source software (FOSS) several works have investigated the viability of open-source production from both a theoretical and empirical point of view - see Benkler (2002a) Johnson (2006) Baldwin and

[3]The system design approach adopted in this chapter is inspired by the analysis of cooperative human systems design outlined by Benkler (2011). For a similar focus on a two-dimensional system defined in terms of technology and property rights see Pagano (1993).

[4]On the concept of organizational speciation see Pagano (2001).

Clark (2006) David and Rullani (2008) and von Hippel (2007) among the others. Significant emphasis, in particular, has been placed on the role and functioning of on-line communities of developers - see Lerner and Tirole (2002), David and Shapiro (2008), Lakhani and Wolf (2005), Lakhani and von Hippel (2003), den Besten et al. (2008) and Shah (2006). Less attention, however, has been paid on the effective co-existence of alternative systems for software development, and on the factors leading to the adoption of one system design when multiple options are available. This chapter is explicitly aimed at filling such gap.

The chapter is also related with the more general literature on the evolution of economic diversity (see Pagano and Nicita, 2001). The latter includes the evolutionary theories of the firm (Nelson and Winter, 1982) as well as the comparative studies on institutions and their emergence (Aoki, 2001, 1998). In this respect the chapter presents one of the first attempt to apply the analysis of institutional diversity to the case of software production. For a similar approach see Baldwin and von Hippel (2011).

The structure of the chapter is the following. Section 2.2 defines the concept of system design, and characterizes the domains of technology and property rights. Section 2.3 presents the model. Section 2.4 studies the asymptotic stability of the equilibrium designs. Section 2.5 transforms the decision-making dynamics defined in Section 2.4 into an ergodic process and studies stochastic stability. Section 2.6 discuses the model's results and uses them to explain the emergence of organizational diversity in the software industry.

2.2 Technology, property rights and system design

A simple definition of a system for software development can be based on two domains: the first is technology (T), i.e. the technological characteristics of the resources used in software production; the second is property rights (R), i.e. the set of rights on the resources employed in the system (including software, human labor and hardware) and on the system itself. Depending on the way in which R and T combine, different systems for software development may exist.

In domain R, as suggested by Benkler (2002a), software developers generally have two main options: an open-source regime $R^O \in R$, in which a marginal (or absent) use of employment contracts is combined with non-exclusive copyrights claims and decentralized hardware ownership; and a closed-source regime $R^C \in R$, in which a wide use of employment contracts is combined with exclusive copyrights claims and centralized hardware ownership. Both such regimes are widely used in the software industry, and tend to be associated with fairly different organizational structures: flat communities of self-selected peer producers in the case of R^O and managerial hierarchies based on hired labor in the case of R^C.

In domain T, the characterization of the alternative resources available to developers is far more complex. In such a domain, in fact, several variables ranging from procedural routines to physical equipments play a crucial role in determining how a piece of software is produced. A comprehensive representation of technology is thus difficult to obtain. For this reason, in this chapter, I choose to focus on two variables only: i) the degree of modularity in code architecture and ii) the distribution of cognitive labor across software modules. The combination of these two variables, I believe, can offer a general enough characterization of technology, although at a cost in terms of exhaustiveness.[5]

Modularity is a well known concept in the literature on system design and refers to the way in which a system is decomposed (Simon, 1962). Baldwin and Clark (2000) describes a modular system as one in which the elements (e.g. tasks) are partitioned into subsets called modules. Within each module, elements of the system are densely dependent and interconnected. Across modules, elements are independent or nearly so. As suggested by Parnas (1972) modularity is a crucial property of a system since it facilitates coordination by reducing the amount of information that needs to be exchanged. At the same time, as argued by Langlois and Garzarelli (2008), modularity militates in favor of specialization, and thus it increases productivity.

Although authors tend to agree on the general principles underlying modularity, they vary in their definitions and measurements. In the context of this chapter, and with particular reference to software production, I will define the degree of modularity as follows. Consider a piece of software as represented by set $S = \{s_1, s_2, ..., s_m\}$ where $s_i \in S$ for $i = 1, ..., m$ is the i-th task that is to be performed. Define a code design $\overline{s}$ as a set of dependences among the different tasks in S, and call $\overline{S} = \{\overline{s}_1, \overline{s}_2, ..., \overline{s}_o\}$ the set of all possible designs. Define $|\overline{s}_j|$ for $j = 1, ..., o$ as the cardinality of $\overline{s}_j$, i.e. the number of dependences included in design j. Call $|\overline{s}|^{max} = max\{|\overline{s}_1|, |\overline{s}_2|, ..., |\overline{s}_o|\}$ the design with the greatest number of dependences. Then, the degree of code modularity associated with design j can be defined as $M^j = 1 - (|\overline{s}_j|/|\overline{s}|^{max})$. When $M^j = 1$ all tasks are independent and code modularity is maximum. On the contrary, when $M^j = 0$ design j corresponds to the one with the greatest number of dependences and modularity is minimum. Overall, the value of M^j tells how finely grained is the code architecture associated to design j.[6]

[5]For studies that place similar emphasis on modularity and cognitive labor while studying the nature of the resources employed in software production see Baldwin and Clark (2006), West and O'Mahony (2008) and Langlois and Garzarelli (2008).

[6]This way of measuring modularity is a simplified version of the one employed in Mac Cor-

In addition to code modularity, the other main resource that I consider as a component of technology is cognitive labor. The latter, in particular, takes the form of problem solving activities and creative tinkering aimed at source code development. As suggested by Benkler (2006) cognitive human labor of this sort has by far become the most important input in the production of information goods, and software, in because of its complexity, represents a particularly relevant case in this category.

A simple way of accounting for cognitive labor is by considering the average units of work (say, hours) devoted to the development of each software module. Define a module as a collection of interdependent tasks. Given any design $\overline{s}_j$, call $P_j = \{p_1, p_2, ..., p_v\}$ the set of modules associated with j. Define L_{jk} for $k = 1, ..., v$ the hours of work devoted to the development of module k in j. Then, the average units of cognitive labor employed in design j can be defined as $L^j = (\Sigma_k L_{jk})/|P_j|$ where $|P_j|$ is the cardinality of set P_j. For the sake of simplicity I will assume L^j to be normalized in such a way that it ranges from 0 to 1. When $L^j = 1$ the average amount of cognitive labor employed in the development of design j is maximum, i.e. equal to the maximum amount of cognitive labor effectively (or legally) available for each module. On the contrary, when $L^j = 0$ such an amount is minimum. Notice that $L^j = 0$ does not mean that no cognitive labor is used at all, but rather that the average amount of work devoted to the development of each software module is so small that it is almost negligible.

This definition of M and L allows one to treat such variables as two factors of production in the standard economic sense. Both M and L, in fact, positively contribute to production, and can to a certain extent be considered substitute of each other. For a given size of software S, in fact, an increase (decrease) in M tends to decrease (increases) the average size of the software modules and therefore reduces (augments) the amount of cognitive labor L needed to develop each module. Under this interpretation the nature of a generic technology T^j can be defined by the factor proportion (or intensity) $T^j = M^j/L^j$. A technology T^j is defined as relatively modular when compared to a technology T^h if and only if $T^j > T^h$. The idea is that while in a modular technology highly modular software (high M^j) is developed by programmers devoting relatively small portions of time to programming (low L^j), in a non-modular technology weakly modular software (low M^h) is developed by programmers devoting large portion of time to programming (high L^h). In this framework, the nature of the choice that is open to developers in domain T can be reduced to set the factor

mack et al. (2006). In both cases modularity is evaluated by looking at the pattern of dependences in the overall software architecture. Also in Mac Cormack et al. (2006) the degree of modularity associated with a given code architecture can be evaluated only in relative terms.

proportion M/L.

Given this characterization of domains R and T, the remaining sections of the chapter will study the viability and persistence of systems for software development based on different combinations of R and T. In particular, the attention will be placed on the factors that make one system design more or less likely to be adopted as compared to another, and on the existing link between systemic efficiency and actual adoption.

2.3 The model

2.3.1 General setting and assumptions

The type of interaction that I model in this chapter is one in which a group of agents (possibly a group of programmers) projects to develop a new piece of software. In order to do so, and before production can actually take place, they need to choose how to design the system of production, i.e. they need to set a specific combination of R and T. Once the system is designed, production occurs and the agents earn the associated payoffs. The model is based on six distinctive assumptions, that I believe are of broad empirical relevance.

First, both property rights and technology are treated as endogenous variable in the model, i.e. both R and T are choice variables in the system. In particular, I assume that R is set in order to maximize expected profits given T, and T is set in order to maximize expected profits given R. While the first causality is a standard assumption in organizational economics - see for instance Williamson (1985) - the one running from property rights to technology is less common. Some of the early authors making a point in favor of this type of causality were Marglin (1974), Putterman (1982) and Bowles (1985), and lately it has been defended also by Pagano and Rowthorn (1994b), Pagano and Rossi (2004) and Pagano (2011). The main argument that is put forward by these authors is that, similarly to the case in which property rights are allocated so as to minimize the transaction costs associated with a given technology, also technology may by designed so as to optimally adjust to given rights. Although this argument has received some critiques in the literature (Williamson, 1985), it is very reasonable when applied to the case of digital productions, such as software. As suggested by Elkin-Loren and Salzberger (2000), in fact, in this type of productions technology is so flexible and cheap to adapt that its design is likely to be endogenous to the nature of legal relations. In this respect, there are several examples of software packages in which the code architecture has been expressly modified in order to fit with a given allocation of property rights.[7]

[7] A good example of this causality comes from the common practice of refactoring the

Second, I assume that technology is not only flexible, i.e. cheap to modify - but also malleable. In particular, I assume M and L to be perfect substitute, i.e. the very same piece of software can be produced by substituting each fraction of M with a fraction of L and *vice versa*. This in turn implies that the structure of S is so malleable that there always exist a design $\overline{s}$ such that M can be increased and/or reduced at wish, and that an increase (decrease) in M is always associated with a reduction (increment) in the average size of the software modules. Moreover, perfect substitutability implies that, below the maximum amount available, there are no (physical or legal) constraints in the amount L that can be employed in each module. These implications are fairly stringent, but are reasonable so long as digital production is considered.

Third, I assume that software gives rise to two main types of return. The first is the expected rents on the sale of the software package, which I call $z(M, L, R)$. Since such rents exist only under R^C, I assume $z(M, L, R)$ to take the following form:

$$z(M, L, R) = \begin{cases} 0, & \text{if } R = R^O \\ z(M, L), & \text{if } R = R^C \end{cases} \tag{2.1}$$

where $\partial z/\partial M > 0$ and $\partial z/\partial L > 0$. The second type of return is instead associated with any other kind of expected return that can be earned from software apart from rents, including the sale of services, advertisements and network effects. This type of return, which exist also under R^O, is captured by a function $Q(M, L)$ such that $\partial Q/\partial M > 0$ and $\partial Q/\partial L > 0$. The shape of this function is assumed to be independent of the property rights regime. Hence, in line with most of the authors in the literature, I model R^C and R^O as being associated with two distinct revenue generation models: one that gives rise to $z(M, L, R) + Q(M, L)$ in the first case, and another that generates only $Q(M, L)$ in the second. As we will see, this distinction will play a crucial role in the model.

Fourth, I assume that different property rights regimes entail different costs. In particular, I consider two main types of costs: design costs and transaction costs.[8] On the side of design costs, I call d the design cost of modularity, i.e. the cost of modularizing the code architecture. On the side of transaction costs, I call l the transaction cost of labor, i.e. the cost of inducing actual effort from

source code before going open-source. Code refactoring, i.e. the process of changing the non-functional attributes of a software in order to foster the source code's maintainability and extensibility, indeed entails an improved readability and modularity of the code architecture. The author is grateful to Yochai Benkler for pointing out the analogy between code refactoring and the causality running from property rights to technology.

[8]For a similar approach see Baldwin and von Hippel (2011).

labor; and m the transaction cost of skills allocation, i.e. the information cost associated with the allocation of cognitive skills across software modules. The latter, in particular, can be interpreted as the information cost that is incurred in screening the skills of individual programmers first, and then in assigning programmers to the development of specific modules within the system. Since skills are costly to evaluate (both subjectively and from a third-party), the value of m can be relatively high, and tends to increase in the level of M. The reason is that the higher (lower) M, the more (less) modules exist in the system, the greater (smaller) the division of labor, and thus the more (less) complex and costly to evaluate the set of all possible allocations of programmers to modules.[9] At the same time, I assume l to be monotonically increasing in L, and d to be monotonically increasing in M.[10]

Given this definition of the costs included in the model, I assume that each property rights regime R^O and R^C is characterized by a different transaction cost advantage. Under R^O the allocation of cognitive skills is not hierarchically determined, but rather relies on the self-identification of programmers into the modules they wish to contribute. For this reason, as suggested by Benkler (2002a), under R^O there tends to be a cost advantage in terms of m as compared to R^C, because neither screening nor allocation of individual skills is to be undertaken on the side of the organization.[11] I will call such cost advantage x ($< m$). At the same time, as partly suggested by David and Rullani (2008), the fact that in a system based on R^C most of the programmers are hired rather volunteers, makes it easier for such a system to mobilize labor as compared to a system based on R^O. For this reason I assume that under R^C there is a cost advantage in terms l. I will call the latter y ($< l$). On this basis, I write the

[9] A high level of M has also the positive effect of reducing the average size of each module. This in turn increases the probability to find a good matching between the skills of programmers, and the set of tasks that are to be developed in any given module. Such a positive effect tends to hold under both property right regimes, and in the model is captured by the fact that $\partial Q/\partial M > 0$. At the same time, however, the fact that modules are small does not imply that the number of individual skills that need to be evaluated is small too. Even when modules are as small as a single task, an optimal allocation of programmers to modules still requires a detailed mapping of individual skills, including inter- and intra-individual differences. Only on the basis of this information, in fact, the organization is able to balance the skills and talents of each single programmer, and thus guarantee an optimal allocation of skills within the system.

[10] Surely there exist other transaction costs that can be associated with both labor and modularity. With respect to the latter, in particular, the coordination costs among programmers certainly play an important role (Parnas, 1972). For the sake of traceability, however, I choose to focus only on the transaction costs whose value is likely to change according to the type of property rights regime. This is not the case, for instance, if we consider coordination costs, which have instead a structural (or architecture-based) nature.

[11] Also under R^O there is still need of some skills comparison among peers, to decide who does what within the system. With respect to a hierarchical organization, however, each programmer can at least save on the costs of screening her own skills. Moreover, I assume that each member of the peer group faces a cost in acquiring information about the skills of others which is not greater (and possibly lower) than the one of a manager in a standard firm.

transaction costs function as follows

$$C(M, L, R) = \begin{cases} (m-x)M + lL, & \text{if } R = R^O \\ \\ mM + (l-y)L, & \text{if } R = R^C \end{cases} \tag{2.2}$$

where $m > l - y$ and $l > m - x$, the latter conditions meaning that there exist transaction cost advantages in the use of different factors of production not only between but also within production systems. In addition to this, I write the total design cost of modularity as dM. Such a cost, however, is assumed to be the same under both property rights regimes.

The fifth assumption that I consider is that, independently of the system which is effectively designed, the necessary conditions for production to take place are satisfied. This in turn implies that there exist a market and a demand for the software package, as well as an adequate factors endowment, especially in terms of L. When R^O is chosen in domain R the latter condition amounts to assume that there exit a community of developers willing to volunteer in writing the source code (remember that no employment contract is used under R^O). The model abstracts from both the way in which such community is gathered and the way in which the community works. Previous studies on participation in FOSS communities have successfully dealt with both these issues (Lerner and Tirole, 2002; David and Shapiro, 2008; Lakhani and Wolf, 2005; Lakhani and von Hippel, 2003; den Besten et al., 2008; Shah, 2006; von Hippel and von Krogh, 2003; Gambardella and Hall, 2006; Bonaccorsi and Rossi, 2003; David and Rullani, 2008), hence I take them as given in the model. On the contrary, I mainly focus on the dynamics of system design.

Finally, I assume that agents have limited cognition and come to a choice through a process of adaptive learning. This does not mean to disregard the intention of each agent to maximize his own payoffs. As we will see such an intention plays a crucial role in the model. By 'limited cognition' I simply mean the limited capacity and predisposition to engage in extraordinary complex and costly cognitive exercises, such as making advanced inferences about what others will do and about the way the world works. Several contributions in both cognitive psychology and behavioral economics provide empirical evidence in support of this assumption - e.g. Kahneman (2003).

2.3.2 A simple game of system design

Given the above assumptions, a simple model of system design can be defined as follows. Let us consider an economy in which a voluntary association of economic agents projects to develop a piece of software. We could think of it as a standard organization such as a software house, or more generally a group of programmers, involved in the development of a new software package. In such an economy, in order for this package to be produced, a specific system for software development has to be designed.

The organization is composed of two distinct groups of agents: n_r (> 0) identical 'financiers' (r), who own the organization and are responsible for selecting the property rights regime R; and n_t (> 0) identical 'production managers' (t) who are members of the organization and are responsible for the design of technology T. Agents in both groups make their choices in order to maximize individual payoffs, which in turn depend on the expected returns and costs of software production.[12]

As described in the previous section software is assumed to give rise to two types of expected return: the rents on software sales $z(M, L, R)$ and the returns other than rents, indicated by $Q(M, L)$. In order to account for asymmetric relations within the organization, I assume the former to be appropriated in equal shares only by the members of group r (r-agents), while the latter to be earned in equal shares by the members of both groups. Similarly, the production of software is assumed to generate two types of costs: transaction costs m and l, which are sustained by all members of the organization; and design costs d, which are sustained only by the agents involved in the modularization of code architecture, i.e. the members of group t (t-agents). On this basis, given equations (1) and (2), the payoffs of r- and t-agents can be written as follows:

$$\pi_r(R, T(M, L)) = \frac{z(R, L)}{n_r} + \frac{[Q(M, L) - C(M, L, R)]}{n} \tag{2.3}$$

$$\pi_t(R, T(M, L)) = \frac{[Q(M, L) - C(M, L, R)]}{n} - \frac{dM}{n_t} \tag{2.4}$$

where π_i (for $i = r, t$) is the payoff of an i-agent and $n = n_r + n_t$ is the size of the organization. Given equations (2.3) and (2.4), the choice of the agents takes the following form: r-agents choose that property rights regime that maximizes ownership rents given the existing technology, i.e. they choose $R = \arg\max \pi_r(R, T(M, L))$, taking as given the combination of M and L; while t-agents choose that technology that maximizes profits given the existing property rights regime, i.e. they choose $(M, L) = \arg\max \pi_t(R, T(M, L))$, taking as given the value of R.

For the sake of simplicity, and without loss of generality, I assume that in both domains R and T the choice set Σ_i (for $i = r, t$) consists of only two alternatives. In domain R, r-agents can choose between an open-source regime R^O and a closed-source regime R^C, i.e. $\Sigma_r = \{R^O, R^C\}$. In domain T, t-agents

[12] For a similar distinction between 'financiers' and 'production managers' see Pagano (2011).

Technology (t) (→) Copyright (r) (↓)	Modular (T^M)	Non-modular (T^L)
Open-source (R^O)	$\dfrac{Q-(m-x)}{n}, \dfrac{Q-(m-x)}{n} - \dfrac{d}{n_t}$	$\dfrac{Q-l}{n}, \dfrac{Q-l}{n}$
Closed-source (R^C)	$\dfrac{Q-m}{n} + \dfrac{z}{n_r}, \dfrac{Q-m}{n} - \dfrac{d}{n_t}$	$\dfrac{Q-(l-y)}{n} + \dfrac{z}{n_r}, \dfrac{Q-(l-y)}{n}$

Table 2.1: Strategic game of system design, matrix of payoffs. Note: each cell of the matrix corresponds to a different system for software development; the reported payoffs are the ones that the agents get if production takes place in each alternative system.

can choose between a modularity-intensive technology $T^M = M^M/L^M$ and a labor-intensive technology $T^L = M^L/L^L$, i.e. $\Sigma_t = \{T^M, T^L\}$. To simplify the analysis, given the assumption of perfect substitutability between M and L, I assume $M^M = 1$, $L^M = 0$, $M^L = 0$ and $L^L = 1$, which in turn implies $\infty = T^M > T^L = 0$. Moreover, I also assume $Q(1,0) = Q(0,1) = Q > 0$, $z(1,0,R^C) = z(0,1,R^C) = z > 0$, and $m = l$.

Since agents are assumed to be identical within the same group, we can now consider two representative agents r and t. On this ground, a strategic game of system design can be defined by the triplet $\Gamma = (I, \Sigma, \pi)$ where $I = \{r, t\}$ is the set of players, $\Sigma = \Sigma_r \times \Sigma_t$ is the set of strategy profiles and $\pi = \{\pi_r(\sigma), \pi_t(\sigma)\}$ for $\sigma \in \Sigma$ is the vector function of players' payoffs, where $\pi_r(\sigma)$ and $\pi_t(\sigma)$ are given by equations (2.3) and (2.4) respectively. Table 2.1 reports a normal-form representation of Γ. With respect to the latter I introduce the following definitions:

Definition 2.1. *A system design in game Γ corresponds to a pure strategy profile $\sigma = \{\sigma_r, \sigma_t\} \in \times_{i \in I} \Sigma_i$, where $\sigma_r \in \Sigma_r$ and $\sigma_t \in \Sigma_t$ is the pure strategy adopted by player r and t respectively.*

Definition 2.2. *A system design $\sigma^* = \{\sigma_r^*, \sigma_t^*\}$ is an equilibrium design, if the correspondent pure strategy profile is a Nash equilibrium of game Γ.*[13]

Game Γ is characterized by four distinct system designs: $\{R^O, T^M\}$, $\{R^C, T^M\}$, $\{R^O, T^L\}$ and $\{R^C, T^L\}$. I now determine the conditions under which each of the four system designs is an equilibrium design (proofs for all Propositions are reported in Appendix 2).

[13]According to this definition an equilibrium design represents what Pagano and Rowthorn (1994b) call an organizational equilibria.

Proposition 2.1. *Suppose $Q > 0$, $z > 0$, $l = m > 0$, $x > 0$ and $y > 0$. Then:* **(a)** *For any $d > 0$, $\{R^C, T^L\}$ is always an equilibrium design;* **(b)** *For any $d > 0$, $\{R^C, T^M\}$ and $\{R^O, T^L\}$ are never equilibrium designs;* **(c)** *If the transaction cost advantage under R^O is sufficiently large, i.e. $x \geq z/\delta$ where $\delta = n_r/n$, and the design cost of modularity d is sufficiently small, i.e. $d \leq x\xi$ where $\xi = n_t/n$, then $\{R^O, T^M\}$ is an equilibrium design.*

When point (c) in Proposition 2.1 holds, game Γ is affected by strategic complementarities and multiple equilibrium designs exist. In the latter case, it is interesting to characterize the degree of efficiency of each such design. Let's consider the following:

Definition 2.3. *Take any system design $\sigma^j = \{\sigma_r^j, \sigma_t^j\} \in \times_{i \in I} \Sigma_i$. The degree of efficiency ψ^j is defined as the total joint surplus generated by design j, i.e $\psi^j = \pi_r(\sigma^j)n_r + \pi_t(\sigma^j)n_t$.*

Taking equilibrium $\{R^C, T^L\}$ as the benchmark (let's call it design 0), the efficiency properties of $\{R^O, T^M\}$ (let's call it design 1) can be thus defined as follows:

Proposition 2.2. *Suppose that multiple equilibrium designs exist. Then:* **(a)** *$\{R^O, T^M\}$ is relatively efficient (i.e. $\psi^1 > \psi^0$) if and only if $x \geq y + d$ and $z < x - y - d$;* **(b)** *$\{R^O, T^M\}$ is Pareto superior if and only if $x > y$, $z < \delta(x - y)$ and $d < \xi(x - y)$.*

Propositions 2.1 and 2.2 point towards the existence of an interesting relationship between technology, property rights and the exogenous factors influencing the environment in which software production takes place. When both z and d are high, because for instance competition in the industry is low and/or the process of code modularization is subject to some fixed rigidities, $\{R^C, T^L\}$ is the only equilibrium design and it is also efficient. This can reflect situations in which standard firm-based productions is the predominant way of developing software, e.g. in the early years of the software industry when digital technologies were not as fully developed as today and the number of firms operating in the market was limited. On the contrary, when both z and d are relatively small compared to x, the game is characterized by multiple equilibria. In this case, alongside $\{R^C, T^L\}$, also $\{R^O, T^M\}$ qualifies as an equilibrium design and under certain conditions it turns out to be relatively efficient. The intuition is that if x is sufficiently large - because for instance the self-identification of programmers into modules is particularly effective - the reduction in transaction costs associated with R^O more than compensate both the loss in rents that affect r-agents when R^O is chosen in place of R^C, and the greater cost which is incurred by t-agents when the code architecture has to be modularized. Thanks to the combination of these two effects, $\{R^O, T^M\}$ is able to generate a greater surplus than $\{R^C, T^L\}$.

The cases in which both $\{R^O, T^M\}$ and $\{R^C, T^L\}$ are equilibrium designs reflect situations in which, for the same software package, both open- and closed-source productions are viable. The main difference between these two productions, beside the adoption of a different property rights regime, is in the design of technology, with open-source production adopting a relatively more modular technology than closed-source production. Some empirical evidence in support of these distinct property rights-technology combinations comes from Mac Cormack et al. (2006). In this sense, the above game provides a relatively simple micro-foundation of their results.

Viability, however, is not a synonym of actual adoption. When multiple equilibrium designs are viable, in fact, an organization still has an incentive to adopt the solution that ensures the greatest economic return, with the consequence that some viable options may not be even tried (or if they are tried, they are readily abandoned). What remains to be investigated, therefore, are the factors that may lead an organization to adopt one specific design as opposed to another when both options are available - i.e. to play one particular Nash equilibrium in the above game, and that may eventually cause similar organizations to diverge in their choices. In order to understand that, a model of the decision-making dynamics leading to the actual adoption of a system design has to be introduced.

2.4 Dynamics

To provide a framework for understanding the process through which a particular system design is adopted, I now study the asymptotic stability of the two equilibria $\{R^O, T^M\}$ and $\{R^C, T^L\}$. In order to do so, I explicitly model the governance process that leads r- and t-agents to come to a final choice, starting from the assumption that two equilibrium designs exist. Such a governance process takes the form of a decision-making dynamics through which the design of domains R and T co-evolve, before production can actually take place. Instead of assuming an exogenous law of motion, I model the dynamics by adopting the now-standard evolutionary game theoretic approach (Gintis, 2009). This approach has two main advantages: first, it easily allows one to extend the previous static game into a dynamic game; second, it micro-founds the evolution of decision-making on credible behavioral rules, including adaptive learning and limited cognition. This obviously comes at a cost, which is mainly due to the high degree of abstraction in modeling the interaction. In the context of this chapter, such an abstraction takes the form of a repeated voting mechanism thanks to which the agents in the two groups can express their preferred design choice.

The dynamics of voting is modeled as follows. At the beginning of every time period τ agents in both groups express an individual and autonomous vote in their own domain of choice, i.e. r-agents vote in domain R having $\Sigma_r = \{R^O, R^C\}$ as choice set, and t-agents vote in domain T having $\Sigma_t = \{T^M, T^L\}$ as choice set. Let

$$\rho_\tau = \frac{n_\tau^O}{n_\tau^O + n_\tau^C} \quad \omega_\tau = \frac{n_\tau^M}{n_\tau^M + n_\tau^L} \tag{2.5}$$

be the fraction of agents voting R^O and T^M respectively, with n_τ^j being the number of agents voting for option j at time τ and $n_r = n_\tau^O + n_\tau^C$ as well as $n_t = n_\tau^M + n_\tau^L$ for all $\tau = 1, ..., \infty$. At τ_0 these votes are exogenously determined by causes not expressly modeled (it can be due to preferences or previous experience). Then, for any $\tau > \tau_0$, each agent updates her vote following the updating process described below. Once votes are expressed, agents are paired across the two groups to compare their individual decisions. To lend some concreteness to the model we can imagine such pairings as periodic meetings between 'financiers' and 'production managers' to discuss the costs and benefits of distinct system design. In the course of such meetings each agent receives two pieces of information. The first one is the distribution of votes in each group. The second one consists of the payoffs reported in Table 2.1 - i.e. the payoffs that each agent would receive if the software were to be developed under each system design. Such payoffs, however, do not immediately translate in individual earnings since production takes place only when "near" unanimity obtains, where the latter means that the following conditions hold: $\rho_\tau < \varepsilon$ or $\rho_\tau > 1 - \varepsilon$ and $\omega_\tau < \varepsilon$ or $\omega_\tau > 1 - \varepsilon$ with $\varepsilon > 0$ being arbitrarily small, i.e. only a negligible portion of agents disagrees with the majority in both groups. Once production takes place, agents earn the payoffs associated with the system design chosen by the majority, i.e. version 1.0 of the software package comes out. In this framework the "near" unanimity condition can be simply interpreted as a managerial rule which ensures that consistent practices are maintained within the organization. Once production has taken place, the process of vote updating starts anew with the initial distribution of votes being the one associated with the organization of production actually adopted. For the sake of simplicity I assume that agents have a time discount factor equal 1.

The process of vote updating takes the following form. At the beginning of every time period $\tau > \tau_0$ each agent in a group uses the two pieces of information

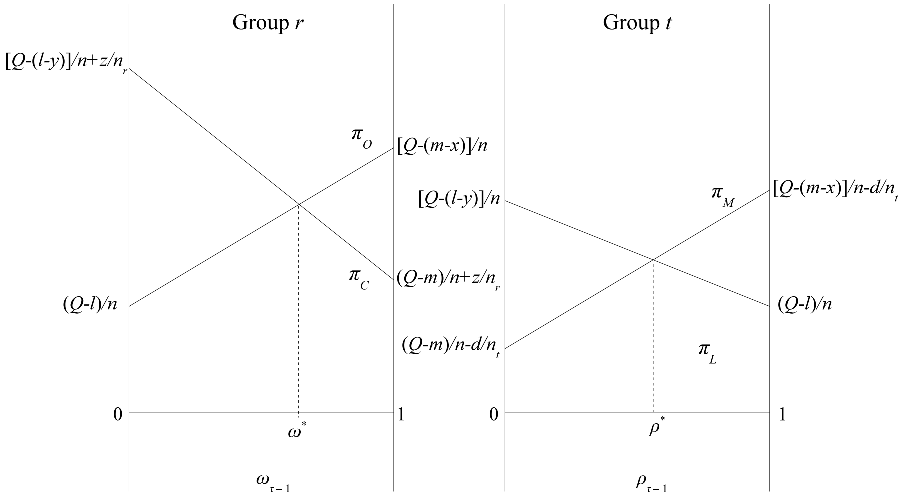

Figure 2.1: Expected payoffs to agents from sub-groups r and t. Note that $\omega_{\tau-1}$ and $\rho_{\tau-1}$ are respectively the fractions of agent voting T^M and R^O in the previous period.

obtained during the meeting occurred in the previous period in order to compute her expected final payoffs, where expectations are formed on the basis of the distribution of votes in the other group. Using the payoffs in Table 2.1 the expected payoffs to t-agents voting T^M and T^L can be written as

$$V_\tau^M(\rho_{\tau-1}) = \rho_{\tau-1}\left[\frac{Q-(m-x)}{n} - \frac{d}{n_t}\right] + (1-\rho_{\tau-1})\left[\frac{(Q-m)}{n} - \frac{d}{n_t}\right] \quad (2.6)$$

$$V_\tau^L(\rho_{\tau-1}) = \rho_{\tau-1}\frac{(Q-l)}{n} + (1-\rho_{\tau-1})\left[\frac{Q-(l-y)}{n}\right] \quad (2.7)$$

Similarly, the expected payoffs to r-agents voting R^O and R^C are respectively

$$V_\tau^O(\omega_{\tau-1}) = \omega_{\tau-1}\left[\frac{Q-(m-x)}{n}\right] + (1-\omega_{\tau-1})\frac{(Q-l)}{n} \quad (2.8)$$

$$V_\tau^C(\omega_{\tau-1}) = \omega_{\tau-1}\left[\frac{(Q-m)}{n} + \frac{z}{n_r}\right] + (1-\omega_{\tau-1})\left\{\left[\frac{Q-(l-y)}{n}\right] + \frac{z}{n_r}\right\} \quad (2.9)$$

These expected payoff functions are reported in Figure 2.1, assuming $x > y$. Once such functions have been computed and before choosing on a new vote, each agent meets with another agent randomly selected from her sub-group and compares the respective decisions. For instance, an agent a in group t has the opportunity to observe the vote expressed by another t-agent, named b, and to know her expected payoffs with a probability $\gamma d\tau$. If b expressed the same vote as a, a does not update. But if b expressed a different vote, a compares the two expected payoffs and, if b has a greater expected payoffs, switches to b's vote with a probability equal to $\beta > 0$ times the payoff difference, retaining her own vote otherwise. While this updating process is not very sophisticated, it may realistically reflect individual cognitive capacities and it ensures that the standard economic assumption of utility maximization is preserved - i.e. each agent votes for the outcome that, given the distribution of votes in the other group, maximizes her expected payoffs.

Specifically, writing the probability that an agent who voted option j switches to option k at time τ as α_τ^{jk} we have:

$$\alpha_\tau^{jk} = \begin{cases} \beta\left(V_\tau^k - V_\tau^j\right), & \text{if } V_\tau^k > V_\tau^j \\ \\ 0, & \text{if } V_\tau^k \leq V_\tau^j \end{cases} \tag{2.10}$$

for $j, k = T^M, T^L$ and $j \neq k$ in the case of t-agents and $j, k = R^O, R^C$ and $j \neq k$ in the case of r-agents. On this basis the expected fraction of r-agents who votes R^O (R^O-voters) in period $\tau + d\tau$ is given by:

$$\begin{aligned} \rho_{\tau+d\tau} = \rho_\tau - \rho_\tau(1-\rho_\tau)\gamma d\tau\ \eta^C \beta(V_\tau^C - V_\tau^O) + \\ +(1-\rho_\tau)\rho_\tau \gamma d\tau\ \eta^O \beta(V_\tau^O - V_\tau^C) \end{aligned} \tag{2.11}$$

where η^C and η^O are two binary functions such that $\eta^C = 1$ if $V_\tau^C > V_\tau^O$ and is zero otherwise, $\eta^O = 1$ if $V_\tau^O > V_\tau^C$ and is zero otherwise, and $\eta^C + \eta^O = 1$. Equation (2.11) reads as follows: the expected fraction of R^O-voters at $\tau + d\tau$ is given by the fraction of R^O-voters at τ (first term), minus the fraction of R^O-voters who are paired with a R^C-voter and switch their type (second term), plus the fraction of R^C-voters who are paired with a R^O-voter and switch their type (third term). Similarly, the expected fraction of agents who votes T^M (T^M-voters) in period $\tau + d\tau$ is given by:

$$\begin{aligned} \omega_{\tau+d\tau} = \omega_\tau - \omega_\tau(1-\omega_\tau)\gamma d\tau\ \eta^L \beta(V_\tau^L - V_\tau^M) + \\ +(1-\omega_\tau)\omega_\tau \gamma d\tau\ \eta^M \beta(V_\tau^M - V_\tau^L) \end{aligned} \tag{2.12}$$

where $\eta^L = 1$ if $V_\tau^L > V_\tau^M$ and is zero otherwise, $\eta^M = 1$ if $V_\tau^M > V_\tau^L$ and is zero otherwise, and $\eta^L + \eta^M = 1$. Subtracting ρ_τ and ω_τ from both sides of equation (2.11) and (2.12) respectively, dividing both equations by $d\tau$, and taking the limit as $d\tau \to 0$, we get:

$$\dot{\rho_\tau} = \rho_\tau(1-\rho_\tau)(V_\tau^O(\omega_\tau) - V_\tau^C(\omega_\tau)) \tag{2.13}$$

$$\dot{\omega_\tau} = \omega_\tau(1-\omega_\tau)(V_\tau^M(\rho_\tau) - V_\tau^L(\rho_\tau)) \tag{2.14}$$

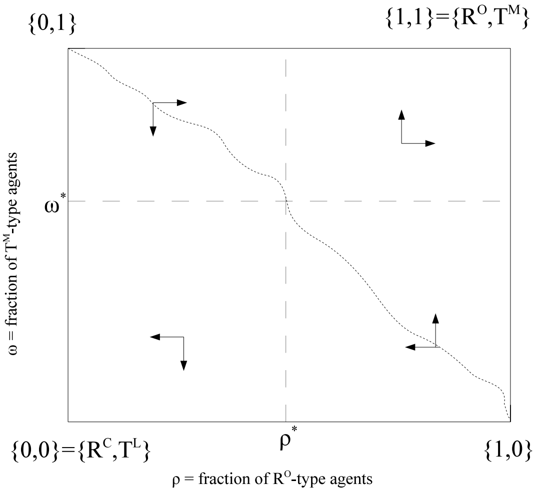

Figure 2.2: Asymptotically stable states and out-of-equilibrium dynamics. Note: the arrows represent the disequilibrium adjustment in the number of voting agents (horizontal movements for the property rights domain and vertical for the technology domain).

where, for the sake of simplicity, I assume $\gamma\beta = 1$. Equations (2.13) and (2.14) represent a system of differential equations which describes how the distribution of votes $\{\rho_\tau, \omega_\tau\}$ evolves over time. Given this dynamics, we are mainly interested in the stationary states, namely the states for which $\dot{\rho_\tau} = 0$ and $\dot{\omega_\tau} = 0$. Such states qualify as fixed-points of the dynamical system, and as voting equilibria of the organization.

Proposition 2.3. *The dynamical system composed of equations* (2.13) *and* (2.14) *is characterized by five voting equilibria:* $\{0,0\}$*,* $\{0,1\}$*,* $\{1,0\}$*,* $\{1,1\}$ *and* $\{\rho^*, \omega^*\}$*, where* $\rho^* = (y + d/\xi)/(x + y)$ *and* $\omega^* = (y + z/\delta)/(x + y)$*. Out of these five equilibria, only two are asymptotically stable, namely* $\{0,0\}$ *and* $\{1,1\}$*; equilibrium* $\{\rho^*, \omega^*\}$ *is a saddle, whereas equilibria* $\{0,1\}$ *and* $\{1,0\}$ *are unstable.*

Figure 2.2 offers a graphical representation of the dynamical system composed of equations (2.13) and (2.14). The arrows indicate the out-of-equilibrium adjustment. For a distribution of votes such that $\rho_\tau < \rho^*$ and $\omega_\tau < \omega^*$ (i.e. in the southwest region of Figure 2.2), $\Delta\rho_\tau$ and $\Delta\omega_\tau$ are both negative and the organization will move towards the $\{0,0\}$ equilibrium. This equilibrium corresponds to closed-source production where all r- and t-agents vote for R^C and T^L respectively; I will call the latter Equilibrium 0 (E_0). As reported in Proposition 2.3, such an equilibrium qualifies as an asymptotically stable state of the dynamics, meaning that when the organization is at this equilibrium it will never leave. Analogous reasoning holds for the northeast region of Figure 2.2, where the organization converges towards the $\{1, 1\}$ equilibrium. In this case the asymptotically stable state corresponds to open-source production where r- and t-agents vote for R^O and T^M respectively; I will call the latter Equilibrium 1 (E_1). In the remaining regions of the state space, namely northwest and southeast, we may define a locus of states from which the system will transit to the interior equilibrium $\{\rho^*, \omega^*\}$ (the dashed line in Figure 2.2). Such a state is stationary, but is a saddle: small movements away from ρ^* and ω^* are not self-correcting. For all the states below the locus transiting to $\{\rho^*, \omega^*\}$ the system will move to E_0. On the contrary, for all the states above that locus the system will move to E_1. As a consequence, there is no set of points for which the system converges to the equilibria $\{0, 1\}$ and $\{1, 0\}$. Such voting equilibria qualify as unstable states of the dynamics and they will never be reached.

2.5 Stochastic process

Under the present formulation, there being more than one absorbing state, the dynamic process modeled in Section 2.4 is non-ergodic, i.e. its long-run average behavior depends on initial conditions. If the organization starts with a distribution of votes in the area below the dashed downward-sloping line in Figure 2.2 - i.e. in the basin of attraction of E_0, the organization will adopt design $\{R^C, T^L\}$ and thus closed-source production. On the contrary, if the initial state is a point in the area above the dashed line - i.e. in the basin of attraction of E_1, the organization will adopt design $\{R^O, T^M\}$ and thus open-source production. In this framework, for any exogenously given staring point, the likelihood that any system design is actually adopted is greater the larger the basin of attraction of its correspondent voting equilibrium, whereas the following holds:

Remark 2.1 $\partial\rho^*/\partial x < 0$, $\partial\omega^*/\partial x < 0$, $\partial\rho^*/\partial d > 0$ and $\partial\omega^*/\partial z > 0$ imply that the basin of attraction of E_1 (E_0) is larger (smaller) the greater (smaller) x and the smaller (greater) d and z.

Such dynamics may certainly offer some useful insights on the process of system design, especially in highlighting the role that conventions and routines may play as sources of path dependency. In the model of Section 2.4, in fact, we assumed that the initial distribution of votes was exogenously given. The latter, however, may clearly be a function of what the organization did in the past, and in particular of the type of systems the organization has learned to design. If most of the software packages produced in the past were developed through design $\{R^C, T^L\}$, for instance, it is reasonable to expect most of the agents in both groups to have evolved a set of routines according to which such system is the conventional way of producing software within the organization. By relying on such routines, the agents may be thus inclined to vote for $\{R^C, T^L\}$ also in this case. The result is that, for any new package that is to be developed, the distribution of votes within this organization is highly likely to start in the southwest region of Figure 2.2, and closed-source production is likely to be adopted. This sort of path dependency in the process of organizational design plays a crucial role in the evolutionary theories of the firm - see for instance Nelson and Winter (1982), and is surely of crucial importance in the field of software development.

At the same time, however, the non-ergodic nature of the above dynamics limits the possibility of explaining the reason why a specific path of system design is embarked in the first place. This can be an important limit, especially if we wish to explain the existence of organizational diversity in newly emerging market segments, where start-up companies play an important role. In order to avoid such limitation we need to transform the dynamical system into an ergodic process. Following Young (1998) and in particular Bowles (2006) and Naidu et al. (2010), I do so by introducing the possibility that agents engage in intentional idiosyncratic plays.

Suppose that every period there is a probability $\lambda \in (0, 1)$ that each agent is selected to undertake an intentional non-best response meant at explicitly influencing the voting process in favor of the system design that she prefers, i.e. the one that ensures the greatest individual payoffs. The idiosyncratic plays accounting for non-best responses need not be irrational; it can be simply the result of experimentation. These stochastic events transform the dynamics into an ergodic process.

If one system design ensures to all agents in both groups payoffs greater than the other - i.e. $\{R^C, T^L\}$ and $\{R^O, T^M\}$ can be Pareto ranked, once the voting equilibrium associated with that system is reached, no idiosyncratic play occurs and the organization will remain in that state forever. In line with the mainstream approach to organizational evolution , therefore, highly efficient and conflictless designs tend to be favored in the dynamics. The result is different, however, if we consider situations in which none of the equilibrium designs is Pareto superior. Let's consider, for instance, the following range of the parameters:

$$x > y + d \quad , \quad d < (x - y)\xi \quad , \quad (x - y)\delta < z < x - y - d \tag{2.15}$$

With reference to the payoffs in Table 2.1, the first three inequalities imply that the payoffs to t-agents are greater in $\{R^O, T^M\}$ than in $\{R^C, T^L\}$, whereas the payoffs to r-agents are greater in $\{R^C, T^L\}$ than in $\{R^O, T^M\}$, i.e. none of the designs is Pareto superior . The third inequality (together with the first), in line with Proposition 2.2, means instead that $\{R^O, T^M\}$ (or design 1) is more efficient than $\{R^C, T^L\}$ (or design 0), i.e. $\psi^1 > \psi^0$. Under these conditions, when the organization's state is in the basin of attraction of E_1, the r-agents that are selected for idiosyncratic play have an incentive to vote for R^C because in so doing they may induce their best responding partners to vote T^L next period. For the same reason t-agents have an incentive to idiosyncratically vote for T^M when the organization's state is in the basin of attraction of E_0. The combination of these effects may lead to the "tipping" of the group from one basin of attraction to the other.

The introduction of intentional idiosyncratic plays means that, independently of the initial conditions, each asymptotically stable state can be reached. This, however, does not mean that all states are equally likely. Intuition suggests that the voting equilibrium that requires a large amount of idiosyncratic plays to dislodge, while requiring little idiosyncratic plays to access, will tend to persist longer time than the other. At the same time, if dislodged, it will tend to reemerge readily. This is the equilibrium that is most likely to be associated with a persistent adoption of a system design.

In order to formalize the above intuition consider the following definitions:

Definition 2.4. (Young, 1998:105) *Let r_{jk}, the reduced resistance on the path from E_j to E_k, be the minimal number of agents voting for E_j that, should they idiosyncratically switch their vote, would induce their best-responding partners to switch theirs. Then, $r_{01} = \min\{\rho^*, \omega^*\}$ and $r_{10} = \min\{1 - \rho^*, 1 - \omega^*\}$.*

Definition 2.5. (Bowles, 2006:413) *The stochastically stable equilibrium (SSE) is the one that occurs with non-negligible probability when the rate of idiosyncratic plays is arbitrarily small. In a 2×2 coordination game with two asymptotically stable equilibria E_j and E_k, E_j is SSE if and only if $r_{kj} < r_{jk}$.*

Definitions 2.4 and 2.5 can be used in order to find the condition under which each of the two asymptotically stable voting equilibria identified in Proposition 2.3 qualifies as SSE. In particular, I obtain the following result :

Proposition 2.4. *Suppose $\lambda > 0$. Then, in the dynamic system composed of equations (13) and (14) there exist a $z^* = \delta(x - y - d/\xi)$ such that if $z < z^*$ E_1 is SSE.*

The intuition behind Proposition 2.4 is straightforward. So long as the rents obtainable from the sale of proprietary software is sufficiently small (i.e. $z < z^*$), r-agents do not have much to loose in adopting design $\{R^O, T^M\}$ and therefore are more vulnerable to the idiosyncratic plays of t-agents. At the same time, when the transaction cost advantage (disadvantage) associated with an open-source regime is large (low) - notice that $\partial z^*/\partial x > 0$ and $\partial z^*/\partial y < 0$, t-agents strictly prefer design $\{R^O, T^M\}$ to $\{R^C, T^L\}$, and will try their best to get it. The combination of these two effects, makes design $\{R^O, T^M\}$ at the same time more likely to be adopted and less likely to be abandoned.

For any given value of z, x and y, the range of values for which $\{R^O, T^M\}$ is relatively persistent in the voting dynamics strictly depends on two additional factors: the design cost of modularity d and the relative sizes of the two groups δ and ξ. For what concerns d it is easily shown that $\partial z^*/\partial d < 0$, so that $\{R^O, T^M\}$ is more likely to be persistent the lower the value of d. This result could be used to interpret the impact of the so-called "digital revolution": by enabling a greater modularization of software components, the advent of digital computing has dramatically reduced d and has therefore increased the rate of adoption of open-source productions. A similar point has been made also by Benkler (2002a, 2006) and Baldwin and von Hippel (2011) among the others.

With respect instead to δ and ξ, their impact on the dynamics is less clearcut. In order to simplify the analysis, I report in Figure 2.3 the value of z^* (vertical axis) for different combinations of δ and ξ, assuming $x = 10$, $y = 2$ and normalizing the size of the group to one (i.e. $n = 1$).[14] The horizontal axis reports the ratio $\xi/\delta = n_t/n_r$, and the curves are drawn for $d = 0.7, 0.5, 0.3$. The graph shows that, if we start from a situation in which the group is composed mainly by r-agents and we progressively increase the ratio n_t/n_r, z^* first increases - therefore making $\{R^O, T^M\}$ relatively more persistent for a given z, and then (after a certain threshold) decreases. The reasons behind such a behavior are related to the combination of two main forces that operate as the relative size of the two groups changes. The first force is associated with an effect on the value of the payoffs at the two equilibrium designs. As n_t increases and n_r decreases, in fact, the share of d that goes to each t-agent in $\{R^O, T^M\}$ diminishes, while the share of the benefits remains constant (n is fixed). This makes $\{R^O, T^M\}$ relatively more attractive. The same, obviously, holds for r-agents, since a reduction in n_r increases the share of the rents that would go to each of them in the case $\{R^C, T^L\}$ were to be adopted. For low value of n_t/n_r, however, the effect of an increase in n_t for t-agents is predominant over a reduction in n_r for r-agents, and the range of parameter for which $\{R^O, T^M\}$ is SSE enlarges (i.e.

[14] These values are chosen for convenience in such a way that the effects are expressed in the right order of magnitude. The general results, however, do not depend on them.

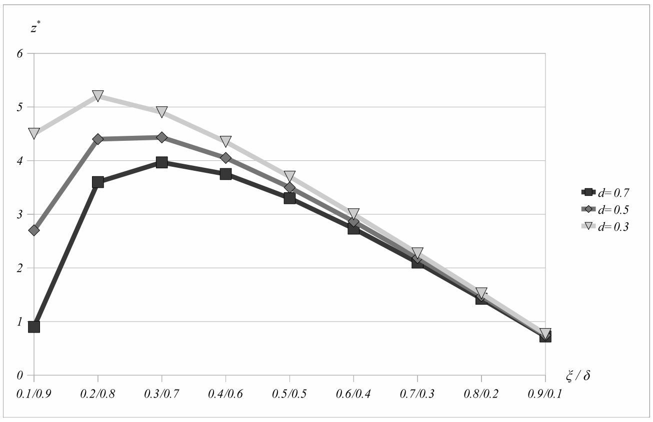

Figure 2.3: Variation of z^* as a function of the ratio ξ/δ. Notice that for $z \leq z^*$ $\{R^O, T^M\}$ is SSE. The curves are drawn assuming $x = 10$, $y = 2$, and $n = 1$. Three different values of d are considered: 0.7, 0.5 and 0.3. As the ratio n_t/n_r increases, z^* presents and inverted-U-shaped behavior, therefore making $\{R^O, T^M\}$ initially more and then less persistent for any given value of z and x.

z^* increases).

After a certain threshold, however, this trend is inverted. As n_t and n_r begin to have similar dimensions, the reduction in the share of d which is due to an increase in n_t is more than offset by the increase in the share of z that follows a reduction in n_r, and z^* diminishes. In addition, when n_r becomes particularly small there is a second force that starts to play a role against the persistence of $\{R^O, T^M\}$, which is associated with an increase in the voting power of r-agents. For a given level of λ, in fact, the smaller n_r, the more r-agents can influence the voting process in favor of the equilibrium design that they prefer. When z is sufficiently large and n_r sufficiently small, such a preferred equilibrium is $\{R^C, T^L\}$. Notice that in this model such a power does not depend on their ability to coordinate on a common and advantageous position. Rather it is a consequence of the fact that, being small, they experience more "tipping" opportunities.

This inverted-U-shaped behavior of z^* with respect to the ratio n_t/n_r is partially related to the fact that, in this setting, the design of a modular code architecture assumes the characteristics of a quasi-public good. In order to have the degree of modularity which is necessary for open-source production to emerge, in fact, a big initial investment has to be put forward by one group (i.e. the t-agents) with the resulting benefits being shared by the organization as a whole.[15] Referring to the literature on the theory of economic organizations (e.g. Alchian and Demsetz, 1972) this result could be interpreted as a version of the "$1/n$ problem" where, as long as n_t is too small compared to n_r, the marginal cost of modularity is higher than its marginal benefit, therefore making design $\{R^O, T^M\}$ unsuitable.

In ultimate instance, Proposition 2.4, together with Proposition 2.2 and Definition 2.3 can be used in order to investigate the relationship between production efficiency and stochastic stability. The following proposition, in particular, summarizes the main finding:

Proposition 2.5. *Suppose design $\{R^O, T^M\}$ is more efficient than $\{R^C, T^L\}$ in the sense of Definition 2.3 and no Pareto superior design exists. Assume also $x > y + d$. Then, there exist a range of values for the couple (z, d) such that E_0 (despite being inefficient) is SSE.*

2.6 Discussion

Figure 2.4 summarizes the main results of the model and suggests a useful way of interpreting the content of Proposition 2.5. The downward sloping 45-degree line defines the portions of the plane for which open-source production as opposed to close-source production is efficient: any point above the line identifies a combination of parameters (x, y, z, d) for which closed-source production is efficient, while any point below the line is a combination for which open-source production is efficient. The entire line represents instead z^*, so that for any point above such line closed-source production is SSE. z^* has been drawn by assuming $n_r < n_t$. As suggested in Proposition 2.5, so long as z^* has a vertical intercept which is lower than $x - y$, there exist a whole set of points (the shaded area in the graph) for which closed-source production is at the same time relatively inefficient *and* stochastically stable.

The fact that some organizations in the software industry effectively locate in this area of the graph is difficult to say theoretically, and it turns out to be mainly an empirical question. What Figure 2.4 shows is the possibility that, under some plausible assumptions, relatively inefficient systems for software development *can* be persistently adopted. In this sense, Figure 2.4 can be used in order to make sense of the process of systems differentiation that, following the development of digital technologies, has led to the high degree of organizational diversity that we presently observe.

[15] The author is grateful to Ugo Pagano for the idea of modularity as a quasi-public good.

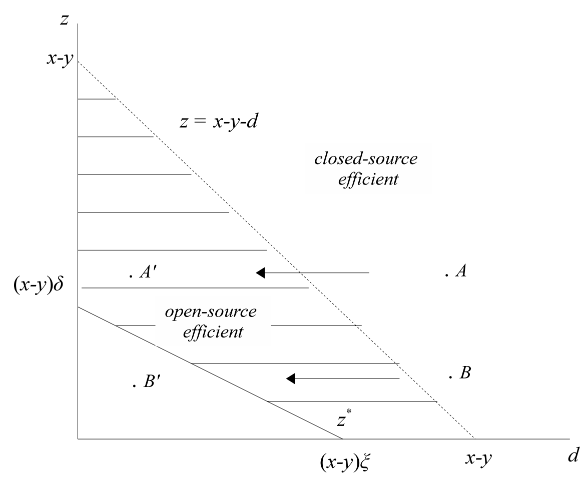

Figure 2.4: Production efficiency and stochastic stability. Note: the shaded area reflects the set of points for which closed-source production is at the same time inefficient and stochastically stable. The arrows indicate the shift caused by the diffusion of digital technologies. Starting from an economy mainly populated by closed-source productions, the reduction in the design cost of modularity brought about the emergence of an ecology of organizational forms in which open- and closed-source production co-exist.

Let's consider for instance points A and B in the graph, which represent a combination of parameters characterized by given rents (higher in A than in B) and high design costs of modularity (the same for both). These points could be interpreted as two pieces of software that were developed prior to the so-called digital revolution, let's say in the late '80s, by two distinct companies operating in the industry. At that time technology made it very expensive to design modular platforms (relatively high d), so that closed-source production tended to be the only viable and efficient solution. The economy, as a consequence, exhibited a relatively homogeneous nature in terms of organizational demography, with close-source production being the prevailing form (both A and B fall, in fact, in this category).

After the technological shock represented by the widespread diffusion of the Internet and the huge fragmentation of computational capabilities, however, the design cost of modularity has sensibly dropped. At the same time, in the domain of property rights, the diffusion of FOSS licenses had only a negligible effect on the rents that could be earned from proprietary software, so that the latter remained close to their initial level. As a consequence the systems of production experienced a horizontal shift in the (d, z) space as the one depicted in the figure ($A \to A'$ and $B \to B'$). In the cases in which the rents prior to the drop in d were low, point B in the graph, the organizations most likely experienced a change from closed- to open-source production (point B') which had become, by that time, relatively efficient and profitable (e.g. Netscape Communicator 4.0 turned into Mozilla Firefox). On the contrary, when the rents before the reduction in d were high, point A, the organization still had an incentive in maintaining a closed-source type of production (point A') despite the fact that, under the new technological environment, it had become relatively inefficient (e.g. Internet Explorer). As a result, in analogy with the process of biological speciation, distinct trajectories of organizational change have gradually emerged. The organizations that, in because of low expected rents, had little to lose by switching to open-source production made the move, while the others kept the design associated with the old system. Such a divergence has in turn led to a variegated ecology of organizational forms in which open- and closed-source productions have increasingly co-existed, *independently of* their relative (in)efficiency. As long as each form was able to sustain a sufficiently high degree of economic performance (e.g. through the development of different revenue generation models), no selective pressure could readily wipe out the relatively unfit systems and organizational diversity could persist.

Overall, the model offers one possible explanation for the reason why we observe both open- and closed-source productions in the software industry. In light of the obtained results, some additional research should be carried out in order to test its validity. In particular, the attention should be placed on the hypothesis of persistent systemic inefficiency. If such an hypothesis were to be verified, in fact, there could be room to argue in favor of government interventions in order to restore efficiency in the economy. In this sense, policy interventions could go along two main lines: i) a reform of the intellectual property rights law aimed at reducing rents from software sales; and ii) a deeper involvement of public institutions (e.g. Universities) in the design of modular platforms with the objective of reducing the 'under-supply' of modularity which follows from its own quasi-public good nature.

As a concluding remark let me highlight some limitations of the chapter. Apart from the already mentioned degree of abstractness, one important limit is that there is no direct account of the competitive interaction between open- and closed-source productions. In this sense, while offering an explanation for the emergence of organizational diversity, the chapter does not study if and for how long such diversity is effectively going to last. Several factors could play an important role in these terms, including the actual frequency of the two systems in the overall economy and the time span over which the selection of the fittest can take place. A careful analysis of such factors, however, requires a completely different approach to the issue and is thus left for future research.

2.7 Appendix 2

2.7.1 Proof of Proposition 2.1

Let's consider $Q > 0$, $z > 0$, $l = m > 0$, $x > 0$ and $y > 0$. **(a)** $\{R^C, T^L\}$ is proven to be a Nash equilibria as long as: *(i)* $[Q-(l-y)]/n + z/n_r \geq (Q-l)/n$, and *(ii)* $[Q-(l-y)]/n \geq (Q-m)/n - d/n_t$. Both conditions are self-explained. **(b)** For $\{R^C, T^M\}$ and $\{R^O, T^L\}$ to be Nash equilibria two necessary conditions are that T^M is a best response to R^C and R^O is a best response to T^L. These conditions, however, can never be verified because otherwise they would violate point (a) above. **(c)** $\{R^O, T^M\}$ is proven to be a Nash equilibria as long as: *(i)* $[Q-(m-x)]/n \geq (Q-m)/n + z/n_r$, and *(ii)* $[Q-(m-x)]/n - d/n_t \geq (Q-l)/n$. Simple algebra shows that the latter conditions reduce to $x \geq z(n/n_r) = z/\delta$ and $d \leq x(n_t/n) = x\xi$.

2.7.2 Proof of Proposition 2.2

(a) Let's call $\{R^C, T^L\}$ design 0 (benchmark) and $\{R^O, T^M\}$ design 1. From Definition 2.3 it follows that:

$$\psi^0 = \left[\frac{Q-(l-y)}{n} + \frac{z}{n_r}\right] n_r + \left[\frac{Q-(l-y)}{n}\right] n_t \tag{2.16}$$

$$\psi^1 = \left[\frac{Q-(m-x)}{n}\right] n_r + \left[\frac{Q-(m-x)}{n} - + \frac{d}{n_t}\right] n_t \tag{2.17}$$

Simple algebra shows that $\psi^1 > \psi^0$ if and only if:

$$z < x - y - d \tag{2.18}$$

Since $z \geq 0$ by assumption, $x \geq y + d$ is a necessary condition for inequality 2.18 to hold. **(b)** Two necessary and sufficient conditions for $\{R^O, T^M\}$ to be Pareto superior are that: $[Q-(m-x)]/n \geq [Q-(l-y)]/n + z/n_r$ and $[Q-(m-x)]/n - d/n_t \geq [Q-(l-y)]/n$. After some simple algebra such conditions reduces to:

$$z \geq (x-y)\delta \qquad d \leq (x-y)\xi \tag{2.19}$$

Since both $z \geq 0$ and $d \geq 0$ by assumption, $x \geq y$ is a necessary condition for inequalities 2.19 to hold.

2.7.3 Proof of Proposition 2.3

The five voting equilibria are derived by simply solving the system (2.13)-(2.14) for $\dot{\omega_\tau} = 0$ and $\dot{\rho_\tau} = 0$. The proof in this case is omitted. The asymptotic properties of each equilibrium are derived by analyzing the Jacobean Matrix J associated to system (2.13)-(2.14):

- At $\{0,0\}$, $\mathrm{Tr}(J) = -\beta/n(2y + z/\delta + d/\xi) < 0$, $\mathrm{Det}(J) = \beta^2(y/n + z/n_r)(y/n + d/n_t) > 0$. Hence, $\{0,0\}$ is asymptotically stable.
- At $\{1,0\}$, $\mathrm{Tr}(J) = \beta/n(y + z/\delta + x - d/\xi) > 0$ for any $d < x\xi$, $\mathrm{Det}(J) = \beta^2(y/n+z/n_r)(x/n - d/n_t) > 0$ for any $d < x\xi$. Hence, $\{1,0\}$ is unstable.
- At $\{0,1\}$, $\mathrm{Tr}(J) = \beta/n(x - z/\delta + y + d/\xi) > 0$ for any $x > z/\delta$, $\mathrm{Det}(J) = \beta^2(x/n-z/n_r)(y/n+d/n_t) > 0$ for any $x > z/\delta$. Hence, $\{0,1\}$ is unstable.
- At $\{1,1\}$, $\mathrm{Tr}(J) = \beta(z/n_r - x/n + d/n_t - x/n) < 0$ for any $x > z/\delta$ and $d < x\xi$, $\mathrm{Det}(J) = \beta^2(z/n_r - x/n)(d/n_t - x/n) > 0$ for any $x > z/\delta$ and $d < x\xi$. Hence, $\{1,1\}$ is asymptotically stable.
- At $\{\rho^*,\omega^*\}$, $\mathrm{Det}(J) = -\beta^2(y+d/\xi)(x-d/\xi)(y+z/\delta)(x-z/\delta)/n^2(x+y)^2 < 0$ for any $x > z/\delta$ and $d < x\xi$. Hence, $\{\rho^*,\omega^*\}$ is a saddle.

2.7.4 Proof of Proposition 2.4

From Definition 2.4 and the value of ρ^* and ω^* reported in Proposition 2.3 it follows that:

$$r_{01} = \omega^* = \frac{y + z/\delta}{x + y} \quad \textit{and} \quad r_{10} = 1-\rho^* = \frac{x - d/\xi}{x + y} \qquad \Longleftrightarrow \qquad z\xi \leq d\delta \quad (2.20)$$

$$r_{01} = \rho^* = \frac{y + d/\xi}{x + y} \quad \textit{and} \quad r_{10} = 1-\omega^* = \frac{x - z/\delta}{x + y} \qquad \Longleftrightarrow \qquad z\xi > d\delta \quad (2.21)$$

According to Definition 2.5, E_1 is SSE if and only if $r_{01} < r_{10}$. Simple algebra shows that, given equations 2.20 and 2.21, the latter condition holds if and only if $z < \delta(x - y - d/\xi) = z^*$.

2.7.5 Proof of Proposition 2.5

From Proposition 2.4 it follows that E_0 is SSE if and only if:

$$z > \delta(x - y - d/\xi) = z^* \tag{2.22}$$

Considering equation (2.22) jointly with Proposition 2.2, E_0 can be SSE while being relatively inefficient as long as the following holds:

$$\delta(x - y - d/\xi) < z < x - y - d \tag{2.23}$$

For $d = 0$, the closed interval defined by (2.23) always exists, since $\delta < 1$ by definition. This, together with the fact that $\partial z^*/\partial d < 0$, proves the proposition.

Chapter 3

The Evolution of Control in the Digital Economy

Abstract: Control is becoming increasingly frequent in cyberspace, to an extent that puts into question the latter's traditional openness. In order to investigate the origins and effects of such change the chapter formally model the historical evolution of digital control. In the model, the economy-wide features of the digital space emerge as a result of endogenous differences in culture (users' preferences including motivation) and institutions (platform designs). The model shows that: a) in the long-run there exist two stable cultural-institutional equilibria in the digital economy: one with intrinsically motivated users and low control; and the other with purely extrinsically motivated users and high control; b) under a closed economy - i.e. before the opening of the network to commerce, the initial emergence of a low-control-intrinsic-motivation equilibrium can be explained by the specific set of norms and values that formed the early culture of the networked environment; and c) the opening of the network to commerce can indeed cause a transition to a high-control-extrinsic-motivation equilibrium, even if the latter is Pareto inferior. Although it is too early to say whether such a transition is actually taking place, these results call for a great deal of attention in evaluating policy proposals on Internet regulation.

JEL: C73; D02; K00; L23.
Keywords: Internet control, Internet regulation, motivation, on-line law enforcement, institutions, endogenous preferences, evolutionary games

3.1 Introduction

Control - i.e. the ability of those in power to direct and constraint the actions of others, is a crucial feature of many social institutions. Influential scholars from different disciplines - such as Marx (1970); Parsons (1963); Weber (1978) - have indeed dedicated a great deal of intellectual effort in understanding both its role and consequences. Significant emphasis, in particular, has been placed on the different modalities in which control could be exercised, with the distinction between psychological (Deci and Ryan, 1985), legal (Simon, 1951) and technological factors (Bowles, 1985).

Despite some notable early exceptions (e.g. Lessig, 1996; Reidenberg, 1998b; Mitchell, 1995), the digital economy - i.e. the set of economic and social transactions that take place over the Internet, has been for long time considered as a place that is relatively exempt from strong forms of control. The reasons have been often associated with both the high cost of on-line rules enforcement (Johnson and Post, 1996; Elkin-Loren and Salzberger, 2000) and the advantage that loose forms of control may sometime have in sustaining innovation (Benkler, 2002a; von Hippel, 2005). It is not by chance the some of the most successful platforms in the last two decades have all included the giving up of control on some (or most) of their users' actions as key component of their internal design.[1]

Recently, however, there has been several signs of a turnround in the implementation of digital control. At the national level, for instance, there has been frequently reported cases of public authorities increasing their actual control over the Internet, going from the implementation of surveillance system to improve on-line security[2], to the recent controversy on Wikileaks's shutdown (Benkler, 2012a). At the corporate level, similarly, companies such as Google, Facebook and Apple have been all repeatedly accused of privacy and/or free-speech law infringements in because of the tight control they exercise on their digital platforms (MacKinnon, 2012). At the policy level, finally, three of the most recent and important initiatives to reform the Internet governance, such as the Anti-Counterfeiting Trade Agreement (ACTA)[3], the Stop On-line Piracy Act (SOPA) and Preventing Real On-line Threats to Economic Creativity and

[1] The intentional absence of control over users' actions (e.g. in the provision of content) is a key feature of most sharing-based platforms such as Wikipedia, YouTube, Flickr as well as the communities of free software developers and peer-to-peer file sharing networks. Similarly, the lack of control plays an important role also in the decentralized mechanisms of relevance and accreditation that are implemented in on-line marketplaces such as Amazon and eBay. All these platforms can be generally considered as instances of what Benkler (2006) calls peer production. For a detailed discussion of the role that users' decisional autonomy plays in peer production see Benkler and Nissenbaum (2006).

[2] See Robert Booth, *Government plans increased email and social network surveillance*, The Guardian, April 1, 2012, available at: `http://www.guardian.co.uk/world/2012/apr/01/government-email-social-network-surveillance` (last time checked: April 24, 2012).

[3] For a detailed analysis of ACTA and related criticisms see McManis (2008).

Theft of Intellectual Property Act (PIPA) in the U.S.[4] and the Google-Verizon Proposal on network neutrality[5], all look at control over users' on-line actions as a critical component of the proposed legislative framework. Overall, what seems to be undeniable, is that at present the digital economy has become radically different from the open and anarchic place it was at its origin. The effective direction in which it will further evolve, however, is still an open question; one whose answer is likely to have a direct impact on the way in which we, as citizens, contribute to society.

In this chapter, I propose a behavioral economic model to study the evolution of digital control. By *digital control* I mean any coerced limitation of users' action which is imposed and enforced by the mean of digital code. In this sense I follow Lessig (1999, 2006) in considering *code* as the main instrument of rules enforcement in the digital space.[6] According to this definition, the deletion of a user's account because it is has proven responsible for illegal or controversial activities (e.g. diffusion of viruses, spamming, copyrights infringement) is a form of digital control.[7] The automatic removal of copyrighted files (e.g. songs, e-books) once they have been copied for a fixed number of times is another.[8] The discretionary choice of a marketplace owner concerning the types of applications that can be uploaded in her platform is a third one.[9] Obviously, these forms of control can be introduced and enforced at different layers of the overall Internet architecture (Lessig, 1999). For the sake of simplicity, I will focus only on the forms of control that can be enforced at the content layer, i.e. those that directly affect the organization of information production.[10]

I present a dynamic model where a group of platform designers and of users interact to produce information. Production is governed by the designers' choice on the degree of control, where the latter presents both costs and benefits. A

[4]See Jonathan Weisman, *After an Online Firestorm, Congress Shelves Antipiracy Bills*, The New York Times, January 20, 2012, available at:`http://www.nytimes.com/2012/01/21/technology/senate-postpones-piracy-vote.html?_r=1` (last time checked: April 24, 2012).

[5]See Claire Cain Miller and Miguel Helft, *Web Plan From Google and Verizon Is Criticized*, The New York Times, August 9, 2010, available at:`http://www.nytimes.com/2010/08/10/technology/10net.html?_r=2&ref=technology` (last time checked: April 25, 2012). For more detail on the concept of "net neutrality" see Wu (2003a).

[6]Lessig (1999, 2006) coined the well-known catchphrase "Code is Law" capturing the idea that in the digital space software code - as opposed to law, market and social norms - becomes the most powerful regulators of all. This is due to two main factors: first, the weaknesses of traditional law as a tool of on-line regulation; and second, the specific features of code that are associated with its malleability and nearly perfect enforceability. Overall, it is the combination of these specific features of code that, according to Lessig, makes cyberspace an arena of (potentially) perfect control.

[7]Similar provisions are included in the terms of service of most digital platforms, see for instance art. 5.5 in Facebook's Terms of Service: "if you repeatedly infringe other people's intellectual property rights, we will disable your account when appropriate", available at `http://www.facebook.com/legal/terms` (last time checked: April 25, 2012).

[8]See Zittrain (2000) on the creation of so-called trusted systems.

[9]See MacKinnon (2012) on Apple's App censorship practices.

[10]For a similar approach see Benkler (2002b).

high degree of control limits the set of tasks that can be performed by users and thus reduces the probability that a noisy activity is undertaken, where by *noisy activity* it is meant a task that may cause designers to incur a positive cost (e.g. illegal redistribution of copyrighted material, diffusion of worms and viruses, submission of malfunctioning applications). At the same time, control affects the users' preferences (and the behavior they support) for contributing information, in that it crowds out intrinsic motivation (e.g. desire for self-expression, ethical values, social norms). When intrinsic motivation is an important determinant of individual behavior this may generate a trade-off in the use of control. Given this setting, I study the evolution of control through a two-designers/two-users dynamic model. Designers can choose between two types of design, characterized by either high or low control. I refer to such distinction as an institutional difference. The relevant preference differences are instead captured by assuming that users are either intrinsically or purely extrinsically motivated. The digital space is initially modeled as a closed economy, with no access from the outside. Then, a positive rate of accesses is allowed. This shift is aimed at capturing the opening of the network to commercial uses occurred in 1995. By studying the long-run equilibrium distributions of preferences and designs under these two different settings, I can make sense the overall evolution of digital control from the origin of cyberspace up to the present days. On this basis, I can also make some predictions on future trends.

This approach is characterized by two main novelties. The first one is that it takes into account the long-run effect of control on the distribution of on-line users' preferences. Most of the literature on digital control, especially on the legal side, has tended to neglect this effect. The attention, on the contrary, has been placed on the direct costs and benefits of control for information production. On the side of benefits, for instance, Zittrain (2000, 2008) extensively discusses the role that digital control can play in both reducing the degree of information noise at the content layer and improving the security of on-line transactions. For what concerns the costs, Lessig (2006) and Benkler (2002b) widely discuss the economic and political costs associated with a limitation of users' desires to access and redistribute data. On this respect, the present chapter introduces an additional effect of control which consists of its influence on the type of culture (i.e. preference distribution) that characterizes on-line participation. As we will see, under certain conditions, this effect may also have normative implications.

The second novelty of this approach is that, instead of treating control and motivations as exogenous or determined by an economy-level institutional bargain, it exploits evolutionary game theory to model the interacting dynamics of both as the result of decentralized non-cooperative interactions among agents.

In doing so the chapter adopts a methodological approach which is similar to Bowles et al. (2003), Naidu et al. (2010), Belloc and Bowles (2011), Bisin and Verdier (2001) and Landini (2012). None of this paper, however, studies the evolution of digital control.

On the basis of the model, I derive three main results. First, in the long-run there exist two stable cultural-institutional equilibria in the digital economy: one in which all users are intrinsically motivated and designers exercise low control; and the other in which all users are purely extrinsically motivated and designers exercise high control. In this sense, the model reflects Lessig's view on the existence of two extremely different social spaces the digital economy could eventually evolve into. The emergence of one of these two spaces depends on several factors, among which the actual costs and effectiveness of control.

Second, during the early days of the digital economy (i.e. period 1969-1995) the closure of the network to commercial uses favored both the emergence and persistence of a low-control-intrinsic-motivation equilibrium. In that period, in fact, most of the network users looked at the emerging public Internet more as an instrument to enable free and open communication rather than as a tool for running businesses, and were thus characterized by fairly strong intrinsic motivation. This, combined with the relatively high costs of digital control, favored the initial emergence of a cultural-institutional equilibrium dominated by low-control designs. At the same time, the ban to exploit the network for commercial purposes, transformed the digital space in a sort of closed system, characterized by relatively few accesses from the outside. This closure imposed a limit on the possibility that some forms of idiosyncratic shock could induce a transition to a different type of equilibrium, thus sustaining the persistence of the low control status-quo.

Third, the opening of the network to commercial uses can indeed cause the transition to a different type of cultural-institutional equilibrium. In particular, by allowing for a positive rate of exogenous variation, the long-run effect of such opening may be to displace the low-control-intrinsic-motivation equilibrium in favor of the high-control-extrinsic-motivation one. Quite interestingly, I find that such displacement may occur even if the high-control-extrinsic-motivation equilibrium is Pareto inferior. Although it is too early to say whether such a transition is actually taking place, this result calls for a great deal of attention in evaluating the role and pace of government intervention in the digital space.

The chapter is related with two main streams of literature. The first one is the law and economics literature on rule-making in cyberspace, which includes the seminal contributions by Johnson and Post (1996), Lessig (1996, 1999), Post (1995), Mitchell (1995) and Reidenberg (1998b), as well as more recent works by Wu (2003b), Zittrain (2003, 2006, 2008), Strahilevitz (2003), Goldsmith and

Wu (2006), and Deibert et al. (2010). While these contributions are mainly concerned with the governance of the overall Internet architecture, this chapter exploits some insights from these works - namely the idea of code as an efficient enforcement device - to study the organization of information production at the content layer. It does so by adopting a bottom-up, dynamic and emergence-based approach to the analysis of institutional change in the digital space. In this way the chapter directly addresses the call by Elkin-Loren and Salzberger (2000) for new approaches to the study of economic institutions in cyberspace.

In its behavioral assumptions the chapter is also related to the social psychology and behavioral economics literature on intrinsic and extrinsic motivation (Deci and Ryan, 1985; Frey, 1997; Frey and Jegen, 2001). Such literature has provided solid empirical and experimental evidence supporting both the role of intrinsic motivation and the existence of motivational crowding out as a result of exogenous incentives - for a recent survey of the empirical results see Bowles and Polania-Reyes (2012). Although the interplay between different types of motivation has been already considered in formal economic modeling (Benabou and Tirole, 2003), less emphasis has been placed on the interaction between control and motivation in the digital space. This aspect, on the contrary, is at the core of the present chapter.

The chapter is organized as follows. Section 3.2 describes the setting of the model and defines the main assumptions. Section 3.3 introduces the model's dynamics and finds the equilibrium conditions in a closed economy (i.e. for the period 1969-1995). Section 3.4 adds the possibility of external entrance and studies stochastic stability. Section 3.5 discusses the major policy implications. Section 3.6, finally, concludes.

3.2 Code, control and motivation

A digital economy is populated by n_d (> 0) platform designers (d) and n_u (> 0) users (u), with $n_d < n_u$. Each designer owns a platform and repeatedly interact with users to produce information, the single interaction being a random user-designer match in which a generic user i performs action a_i being offered a given design. Designs differ according to the degree of digital control they support. The payoffs of users and designers are modeled as follows.

A digital platform is represented as a set of tasks. For any given platform type (e.g. social networks, wikis, peer-to-peer services, apps store), I call T the set of all feasible tasks that are enabled by the features of the available technology (e.g. upload and/or download of files, interaction with other users, provision of particular on-line services). Given T, and the specific interests of the platform designer, I assume the existence of a non-empty set of noisy tasks $T_k \subseteq T$ such that if any $t_k \in T_k$ is performed by a user, the platform designer incurs a cost k (> 0). Such tasks may include, for instance, the illegal redistribution of copyrighted material, where k corresponds to the state-enforced sanction on the platform owners that are deemed to facilitate copyright law infringement. Another example consists of undesired users' messaging, where k corresponds to the (designer's expected) reduction in the number of accesses to the platform caused by an increased noisiness of the information environment. In order to avoid this cost, the platform designer may choose to define a set of censored tasks $T_{ce} \subseteq T_k$, such that any $t_{ce} \in T_{ce}$ cannot be performed by any user. Such censoring is enforced by the mean of digital code, in the sense that all $t_{ce} \in T_{ce}$ are simply made "not available" to users (see Lessig, 2006). On this basis, the degree of digital control supported by the platform design can be represented by the ratio $t = |T_{ce}|/|T_k| \in [0, 1]$ where $|T_{ce}|$ and $|T_k|$ are the cardinality of sets T_{ce} and T_k respectively.

The degree of digital control t plays two main roles in the model. On one hand it affects the probability that a noisy task $t_k \in T_k$ is performed. In particular, the higher t, the lower such probability. On the other, it affects the user's motivation for performing action a_i, where the latter is defined as the effort exercised in performing some (or all) of the available tasks. Tasks availability obviously depends on the degree of censoring, and can be represented by set $T_{av} = T \setminus T_{ce}$. When there is no censoring (i.e. $T_{ce} = \oslash$ and $t = 0$), the set of available tasks coincides with the set of feasible tasks, so that $T_{av} = T$. On the contrary, when censoring is maximum (i.e. $T_{ce} = T_k$ and $t = 1$), the set of available tasks contains only "non-noisy" tasks and $T_{av} = T \setminus T_k$.

Given these definitions, I model individual motivation as follows. Each user i can obtain two main types of reward from performing action a_i. The first type consists of the extrinsic benefits associated with *participation in* the platform, and (depending on the type of platform) includes things such as (present or delayed) monetary rewards, increased reputation and access to fast communication tools. The second type of reward coincides with the non-monetary and intrinsic benefits associated with the *contribution to* the platform, and (again depending on the type of platform) includes the pure pleasure of information sharing, the desire for self-expression, and the utility derived from cooperating with others.

In line with the results reported in several studies coming from both social psychology and behavioral economics, I assume that the degree of digital control is not neutral with respect to the nature of individual motivation. In particular, I assume that an increase in t has two main effects. First, it crowds out intrinsic motivation, i.e. for any given level of extrinsic motives, it reduces the total marginal benefit that a user derives from performing a_i.[11] In the off-line world, this effect has been found in a large number of natural environments (Gagne and Deci, 2005) and experimental settings (Irlenbusch and Ruchala, 2008), and there are reasons to believe that it holds also on-line. Second, I assume that an increase in t generates a net positive disutility for the users with intrinsic motives, whose value is independent of a_i. On this respect, some supporting evidence comes from the growing experimental economics literature on control-aversion (Falk and Kosfeld, 2006; Fehr et al., 2010; Charness et al., 2011).

Formally, I call ϕ and $\lambda_i(t)$ the extrinsic and intrinsic marginal benefit of a_i. In line with the crowding-out hypothesis, I assume $\lambda_i(0) = \lambda_i > 0$ and $\lambda_i' < 0$. While ϕ is user-generic, I consider $\lambda_i(t)$ to be user-specific. This captures the idea that while most individuals are motivated by some forms of extrinsic reward, only some of them exhibit also intrinsic motivation. As a behavioral model, this is a fair compromise between the standard economic view of self-interested and purely extrinsically motivated agents, and the behavioral and psychological approach based on a more complex mix of motivations. With respect to the costs, I call $c(a_i)$ the opportunity cost of the time spend in performing a_i and $\mu_i(t)$ the psychological cost associated with control aversion, where $c' > 0$, $c'' > 0$ and $\mu_i' > 0$. On this basis, following Bowles and Hwang (2008), I assume i's (risk-neutral) utility function to be additive in motivations, and I write:

$$U_i = [\phi + \lambda_i(t)]a_i - c(a_i) - \mu(t) \tag{3.1}$$

From the maximization of equation (3.1) with respect to a_i it follows that:

Remark 3.1 The optimal level of a_i is given by condition $c' = \phi + \lambda_i(t)$. Since $\lambda' < 0$, an increase in t reduces *ceteris paribus* the optimal level of a_i for intrinsically motivated users.

At an intuitive level, the relationship between motivation and control on one hand, and the level of a_i on the other can be thought in terms of number and typology of tasks being performed by users. Within set T_{av}, in fact, we can generally distinguish between two main typologies of tasks. On one hand there are tasks that can be directly exploited for extrinsic purposes. They include, for instance, the possibility to share information that advertise the user's last piece of work (e.g. song, book, or academic article depending on the platform). On the other, there exist "self-policing" tasks that tend to be associated only with the intrinsic pleasure of contributing to the platform's well-functioning. They

[11] This way of modeling motivational crowding out is generally called "marginal". An alternative is to assume "categorical" crowding out. On the distinction between marginal and categorical crowding out see Bowles and Polania-Reyes (2012).

include, in the order, the self-reporting of bugs and errors, the sanctioning of other users' misbehavior and the updating of missing information. On this basis, the positive relationship between the value of $\lambda_i(t)$ and the optimal level of a_i can be interpreted with the fact that, for any given level of t, intrinsically motivated users are willing to perform both typologies of tasks (and thus to exert high effort), whereas purely extrinsically motivated ones tend to undertake only the former. Starting from this condition, an increase in t tends to reduce the effort of intrinsically motivated users because by undermining the degree of self-commitment to the platform it decreases their willingness to undertake "self-policing" acts.

Given this behavioral model for users, I now consider the payoff of designers. Each designer owns a platform and earns a reward that is positively related to the amount of information produced by users. For any given user-designer match, I write the return of the designer as $q(a_i) = qa_i$, where $q > 0$ is the marginal contribution of i's action to the overall stock of information. The decision of each designer is then concerned with the degree of control t to be implemented. Depending on users' motivation, control presents both costs and benefits. On the side of costs, as reported in Remark 3.1, control reduces the level of a_i whenever the designer is matched with an intrinsically motivated user. I call the latter the motivational cost of control. Moreover, control forces the designer to spend both cognitive and digital resources (e.g. lines of code) to define the tasks to be included in T_{ce}. This can be termed the design cost of control and is represented by function $\delta(t)$, with $\delta' > 0$ and $\delta'' > 0$. On the side of benefits, on the contrary, control limits the number of tasks in T_k that are effectively available to users and thus reduces the probability of incurring cost k. Such probability obviously depends also on the willingness of users to undertake tasks included in set $T_k \setminus T_{ce}$, i.e. noisy tasks that are not censored by the designer. On this respect, given the association between intrinsic motivation and social/ethical norms, I will assume that such willingness is lower the more intrinsically motivated the user.

On this basis I write the expected reward of a generic (risk-neutral) designer d as follows:

$$\pi_d = qa_i - \delta(t) - \gamma(1-t)\eta(\lambda_i)k \tag{3.2}$$

where $\eta(\lambda_i) \in [0,1] \ \forall \ \lambda_i \geq 0$ with $\eta' < 0$ is the probability that i performs a task in T_k and $\gamma \in [0,1]$ represents the effectiveness of censoring in reducing the probability of incurring cost k. At an intuitive level, γ captures both the status of the control-enhancing technologies and the users' capabilities to hack the limitations imposed by designers, where the more effective the former and weaker the latter, the higher the value of γ.

Before going deeper into the analysis, I want now to point out three key assumptions that are related to the way in which users and designers interact in the economy. First, I assume that there are no strategic interactions among users. Every period, a user decides on her optimal level of a_i by looking only at the degree of t implemented by the designer she is matched with, and on the basis of the preferences described by equation (3.1). In this way I abstract from any form of free-riding problem that may arise when users simultaneously contribute to the same platform. Although this is a fairly strong assumption, it heavily simplifies the analysis and it allows me to focus on the motivational effect of control. Moreover, several studies have shown that the incentives to free-ride do not represent a big problem in most digital platforms, especially when the standard money maximizer behavioral model is expanded to include also intrinsic motivation (see Benkler, 2006). On this basis, I simply choose to take free-riding incentives out of the analysis.

Second, I assume that there is no assortment in the matching between users and designers. In other words, neither users nor designers can choose the type of partner to interact with. This is due to the fact that both intrinsic motivations and digital control are assumed to be unobservable ex-ante, and thus cannot be used to condition the matching dynamics. This is a standard assumption in most evolutionary game theoretic model.

Finally, I assume that while both motivation and control change over time, none is the result of instantaneous individual maximization. Rather, they are durable features of users and designers that evolve in a decentralized environment under the influence of long-run economy-wide payoff differences. Users, in particular, periodically update their motivation by best responding to the distribution of designs in the past. Similarly, designers occasionally update the degree of control by best responding to the past distribution of users' motivation. The main objective of the analysis is then to identify the long-run equilibrium distribution of both motivation and designs.

3.3 The closed economy, 1969-1995

3.3.1 Stage game

Given the setting described in Section 3.2, I now study the evolution of digital control under the assumption of no external access into the economy. In every period, the members of both populations of users and designers remain the same, and interactions evolve through their continuous re-matching. Such an assumption is aimed at capturing the status of the digital economy as of the period 1969-1995, when the prohibition to use the public Internet for commercial purposes brought a relative closure of cyberspace. Such an assumption will be later removed (see Section 3.4), when I study the opening of the network to commerce.

From the technical point of view, I also introduce three important simplifications that will be maintained throughout the model. First, I assume an explicit form for functions $\lambda(t)$, $\mu(t)$, $\delta(t)$, $c(a)$ and $\eta(\lambda)$. In particular, I assume $\lambda(t) = \lambda(1-t)$ with $\lambda > 0$, $\mu(t) = \mu t$ with $\mu > 0$, $\delta(t) = \delta t^2/2$, $c(a) = a^2/2$ and

$$\eta(\lambda) = \begin{cases} 1, & \text{if } \lambda = 0 \\ \\ \eta, & \text{if } \lambda > 0 \end{cases} \tag{3.3}$$

where $0 < \eta < 1$. This simplifies the analysis, without affecting the final results. Second, I assume that there exist only two available control technologies in the economy, namely a full-control ($t = 1$) and a no-control ($t = 0$) technology. Designers employing the full-control technology are called high control designers (H-type), whereas those employing the no-control technology are called low control designers (L-type). This distinction is obviously an oversimplification, which however makes the model analytically traceable. Finally, I assume that users are either purely extrinsically motivated (E-type), or both extrinsically and intrinsically motivated (I-type). Within the population of I-users I assume that no difference exists in terms of the degree of intrinsic motivation, so that there are only two behavioral types. Looking at the explicit functions defined above, such types can be defined by the pair (λ, μ), with I-user $\sim (\lambda, \mu)$ and E-user $\sim (0, 0)$. This, when combined with equation (3.1), gives us the following utility functions for I- and E-users respectively:

$$U_I = [\phi + \lambda(1-t)]a - \frac{a^2}{2} - \mu(t) \quad \textit{and} \quad U_E = \phi a - \frac{a^2}{2} \tag{3.4}$$

We can thus derive the following (proofs for all Lemmas and Propositions are reported in Appendix 3.1):

Lemma 3.1. Call $a_{i,j}$ the best-response level of a for an i-type user when matched with a j-type designer. From Remark 3.1 and Eqs. (4) it follows that: $a_{I,L} = \phi + \lambda$ and $a_{I,H} = a_{E,H} = a_{E,L} = \phi$.

Given these simplifications, it is now possible to represent the single interaction taking place between a user u and a designer d in game theoretic form as follows. Let's interpret each behavioral and technological type as the strategy of a game, which we can call the stage game. We thus have $\Sigma_u = \{I, E\}$ and $\Sigma_d = \{L, H\}$, where $\Sigma_i =$ (for $i = u, d$) is the strategy set of player i. On this

Designers ($\rightarrow$) **Users**($\downarrow$)	**L-type** ($t = 0$)	**H-type** ($t = 1$)
I-type $\sim (\lambda, \mu)$	$\frac{(\phi+\lambda)^2}{2}$, $q(\phi+\lambda) - \gamma\eta k$	$\frac{\phi^2}{2} - \mu$, $q\phi - \frac{\delta}{2}$
E-type $\sim (0, 0)$	$\frac{\phi^2}{2}$, $q\phi - \gamma k$	$\frac{\phi^2}{2}$, $q\phi - \frac{\delta}{2}$

Table 3.1: Stage game matrix of payoffs. Note: each cell of the matrix represents a different preference-design matching that may occur in the economy.

ground, a stage game of information production can be defined by the triplet $\Gamma = (I, \Sigma, \pi)$ where $I = \{u, d\}$ is the set of players, $\Sigma = \Sigma_u \times \Sigma_d$ is the set of strategy profiles and $\pi = \{\pi_u(\sigma), \pi_d(\sigma)\}$ for $\sigma \in \Sigma$ is the vector function of players' payoffs, where $\pi_u(\sigma)$ and $\pi_d(\sigma)$ are given by equations (3.1) and (3.2) respectively. Table 3.1 reports a normal-form representation of Γ, taking into consideration that functions $\lambda(t)$, $\mu(t)$, $\delta(t)$, $c(a)$ and $\eta(\lambda)$ take the explicit form defined above (for the derivation of the payoffs in Table 3.1 see Appendix 3.2). With respect to Γ, I thus introduce the following definitions:

Definition 3.1. *A preference-design matching in game Γ corresponds to a pure strategy profile $\sigma = \{\sigma_u, \sigma_d\} \in \times_{i \in I} \Sigma_i$, where $\sigma_u \in \Sigma_u$ and $\sigma_d \in \Sigma_d$ is the pure strategy adopted by player u and d respectively.*

Definition 3.2. *A preference-design matching $\sigma^* = \{\sigma_u^*, \sigma_d^*\}$ is a preference-design equilibrium, if the correspondent pure strategy profile is a Nash equilibrium of game Γ.*

Game Γ offers a mapping of all possible preference-design matchings that may occur in the economy, namely: $\{I, L\}$, $\{E, L\}$, $\{I, H\}$ and $\{E, H\}$. I now determine the conditions under which each of the four matchings is also an equilibrium.

Proposition 3.1. *Suppose $\lambda > 0$, $0 < \eta < 1$, $k > 0$ and $\mu > 0$. Then, $\exists$ two values $\underline{\delta} = 2(\gamma\eta k - q\lambda)$ and $\overline{\delta} = 2\gamma k$ (for $\overline{\delta} > \underline{\delta}$) s.t.: (i) if $\delta > \overline{\delta}$, then $\{I, L\}$ is the only preference-design equilibrium; (ii) if $\delta < \underline{\delta}$, then $\{E, H\}$ is the only preference-design equilibrium; and (iii) if $\underline{\delta} < \delta < \overline{\delta}$, then there exist two preference-design equilibria, namely $\{I, L\}$ and $\{E, H\}$.*

Corollary 3.1.1 *For any value of δ, $\{E, L\}$ and $\{I, H\}$ are never preference-design equilibria.*

Corollary 3.1.2 *For any value of δ, there always exist at least one preference-design equilibrium in game Γ.*

At the population level a preference-design equilibrium represents a cultural-institutional convention, meaning that conforming to it is a mutual best response as long as virtually all members of each population (users and designers) expect virtually all members of the other to conform to it. According to Proposition 3.1, the number and types of conventions existing in the economy depend on the design cost of control δ. When the latter is greater than an upper threshold $\overline{\delta}$ (because for instance technology is costly to manipulate), $\{I, L\}$ is the only cultural-institutional convention in the economy, and is thus likely to proliferate. On the contrary, when δ is smaller than a lower threshold $\underline{\delta}$ ($< \overline{\delta}$), the only cultural-institutional convention is $\{E, H\}$. Quite interestingly, I find that when δ is intermediate between these two values, two cultural-institutional conventions exist in the economy, namely $\{I, L\}$ and $\{E, H\}$. In this case, the convention that will emerge as the long-run cultural-institutional equilibrium of the economy depends on the asymptotic stability properties of the two conventions. From the analytical point of view, this is clearly the most interesting case to study.

Before going into the details of asymptotic stability, it is interesting to characterize the efficiency properties of the two conventions. In this sense I find that, if anything, convention $\{I, L\}$ tends to exhibit an efficiency advantage with respect to $\{E, H\}$. In particular, I derive the following result:

Proposition 3.2. *If in the economy there exist only one cultural-institutional convention, then the associated preference-design equilibrium is Pareto efficient. If in the economy there exist two cultural-institutional conventions, then $\{I, L\}$ Pareto dominates $\{E, H\}$.*

The intuition behind Proposition 3.2 is straightforward, and essentially relates to the combined effect of λ and δ. Since $\lambda > 0$, users are always better-off under $\{I, L\}$, because they can enjoy the additional utility that derives from being intrinsically motivated. This implies that $\{I, L\}$ will never be Pareto dominated. At the same time, the payoff condition of designers depends on the specific value of δ. When δ is sufficiently low (i.e. $\delta < \underline{\delta}$), designers are better-off under $\{E, H\}$, because control is cheap and allows one to avoid cost k. In the latter case $\{E, H\}$ is the only convention of the economy and it is also Pareto efficient. When δ is sufficiently high (i.e. $\delta > \underline{\delta}$), on the contrary, designers are better-off under $\{I, L\}$, because the cost of designing an architecture of control is less than compensated by the reduced likelihood of incurring cost k. This implies that for the range of values in which both $\{I, L\}$ and $\{E, H\}$ are cultural-institutional conventions (i.e. for $\underline{\delta} < \delta > \overline{\delta}$), the former Pareto dominates the latter. As we will see later in the chapter, the Pareto dominance of $\{I, L\}$ over $\{E, H\}$ turns out to be a critical feature of the model, which has interesting policy implications.

3.3.2 Dynamics

To provide a framework for studying asymptotic stability I now restrict the analysis to the space of parameter in which two conventions exist (i.e. I assume $\underline{\delta} \leq \delta \leq \overline{\delta}$) and introduce an explicit model of the dynamics of change. In particular, I model such dynamics as follows. In every time period $d\tau$ users and designers are randomly paired to play the stage game described above. Give their own type and the degree of control chosen by the designer, users choose their level of effort according to the best response functions reported in Lemma 3.1. Once production has taken place, designers and users earn the payoffs reported in Table 3.1. Let:

$$\omega_I^\tau = \frac{n_I^\tau}{n_I^\tau + n_E^\tau} \quad \omega_L^\tau = \frac{n_L^\tau}{n_H^\tau + n_L^\tau} \tag{3.5}$$

be the fractions of I-users and L-designers operating in the economy at any τ, where n_i^τ (for $i = I, E, L, H$) is the number of agents (users and designers) of type i in period τ. The pair $\{\omega_I^\tau, \omega_L^\tau\}$ represents the state of the economy, i.e. it gives the overall distribution of motivation and control. Assuming that the size of the economy is sufficiently large, ω_I^τ and ω_L^τ will also denote the probability with which users and designers are paired across types. On this basis, for any given value of ω_L^τ and taking into consideration the payoffs reported in Table 3.1, we can write the expected payoffs of I- and E-users at any τ as follows:

$$V_I^\tau(\omega_L^\tau) = \omega_L^\tau \left[\frac{(\phi+\lambda)^2}{2}\right] + (1-\omega_L^\tau)\left[\frac{\phi^2}{2} - \mu\right] \tag{3.6}$$

$$V_E^\tau(\omega_L^\tau) = \omega_L^\tau \frac{\phi^2}{2} + (1-\omega_L^\tau)\frac{\phi^2}{2} \tag{3.7}$$

Similarly, for any given value of ω_I^τ, the expected payoffs to L- and H-designers are respectively:

$$V_L^\tau(\omega_I^\tau) = \omega_I^\tau \left[q(\phi+\lambda) - \gamma\eta k\right] + (1-\omega_I^\tau)\left[q\phi - \gamma k\right] \tag{3.8}$$

$$V_H^\tau(\omega_I^\tau) = \omega_I^\tau \left[q\phi - \frac{\delta}{2}\right] + (1-\omega_I^\tau)\left[q\phi - \frac{\delta}{2}\right] \tag{3.9}$$

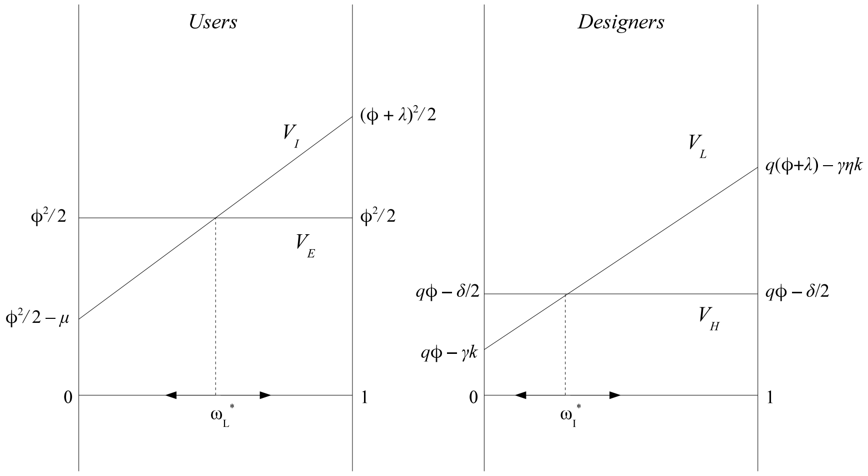

Figure 3.1: Expected payoffs to I- and E-users and L- and H-designers. Note: ω_I^τ is the fractions of users who are intrinsically motivated and ω_L^τ the fraction of designers who exercise low code-based control at time τ. The vertical intercepts are from Table 3.1.

These expected payoff functions are illustrated in Figure 3.1.

To model the co-evolution of motivations and control, suppose that both users and designers update the preferences and the designs (respectively) by best responding to the distribution of types in the previous period. In particular, suppose the updating process works as follows. In any time period $d\tau$ both users and designers are exposed to a cultural or institutional model randomly selected from their subpopulation. For instance, a designers, named A, has the opportunity to observe the degree of control exercised by another designers, named B, and to know her expected payoff with a probability $\alpha d\tau$. If B is the same type as A, A does not update. But if B is of a different type, A compares the two payoffs and, if B has a greater payoff, switches to B's type with a probability equal to β (> 0) times the payoff difference, retaining her own type otherwise. The same procedure takes place among users. Specifically, writing the probability that an agent (user and designer) of type i switches to type j at time τ as p_{ij}^τ we have:

$$p_{ij}^\tau = \begin{cases} \beta\left(V_j^\tau - V_i^\tau\right), & \text{if } V_j^\tau > V_i^\tau \\ \\ 0, & \text{if } V_j^\tau \leq V_i^\tau \end{cases} \tag{3.10}$$

for $i, j = I, E$ and $i \neq j$ in the case of users and $i, j = L, H$ and $i \neq j$ in the case of designers. On this basis the expected fractions of I-users in period $\tau + d\tau$ is given by:

$$\omega_I^{\tau+d\tau} = \omega_I^\tau - \omega_I^\tau(1-\omega_I^\tau)\alpha d\tau\sigma_E\beta(V_E^\tau - V_I^\tau) + (1-\omega_I^\tau)\omega_I^\tau\alpha d\tau\sigma_I\beta(V_I^\tau - V_E^\tau) \quad (3.11)$$

where σ_E and σ_I are two binary functions such that $\sigma_E = 1$ if $V_E^\tau > V_I^\tau$ and is zero otherwise, $\sigma_I = 1$ if $V_I^\tau \geq V_E^\tau$ and is zero otherwise, and $\sigma_E + \sigma_I = 1$. Equation (3.11) reads as follows: the expected fraction of I-users at $\tau + d\tau$ is given by the fraction of I-users at τ (first term), minus the fraction of I-users who are paired with an E-user and switch their type (second term), plus the fraction of E-users who are paired with an I-user and switch their type (third term). Similarly, the expected fractions of L-designers in period $\tau + d\tau$ is given by:

$$\omega_L^{\tau+d\tau} = \omega_L^\tau - \omega_L^\tau(1-\omega_L^\tau)\alpha d\tau\sigma_H\beta(V_H^\tau - V_L^\tau) + (1-\omega_L^\tau)\omega_L^\tau\alpha d\tau\sigma_L\beta(V_L^\tau - V_H^\tau) \quad (3.12)$$

where $\sigma_H = 1$ if $V_H^\tau > V_L^\tau$ and is zero otherwise, $\sigma_L = 1$ if $V_L^\tau \geq V_H^\tau$ and is zero otherwise, and $\sigma_H + \sigma_L = 1$. Subtracting ω_I^τ and ω_L^τ from both sides of Equations (3.11) and (3.12) respectively, dividing both equations by $d\tau$, and taking the limit as $d\tau \to 0$, we get:

$$\dot{\omega}_I^\tau = \omega_I^\tau(1-\omega_I^\tau)(V_I^\tau(\omega_L^\tau) - V_E^\tau(\omega_L^\tau)) \quad (3.13)$$

$$\dot{\omega}_L^\tau = \omega_L^\tau(1-\omega_L^\tau)(V_L^\tau(\omega_I^\tau) - V_H^\tau(\omega_I^\tau)) \quad (3.14)$$

where, for the sake of simplicity, I have assumed $\alpha\beta = 1$. Equations (3.13) and (3.14) represent a system of differential equations which describes how the distribution of types $\{\omega_I^\tau, \omega_L^\tau\}$ evolve over time. Given this dynamics, we are mainly interested in the stationary states of the economy, namely the states for which $\dot{\omega}_I^\tau = 0$ and $\dot{\omega}_L^\tau = 0$. Such states represents fixed-points of the dynamical system, and cultural-institutional equilibria of the economy.

Proposition 3.3. *The dynamical system composed of Equations* (3.13) *and* (3.14) *is characterized by five cultural-institutional equilibria:* $\{0,0\}$, $\{0,1\}$, $\{1,0\}$, $\{1,1\}$ *and* $\{\omega_I^*, \omega_L^*\}$, *where*

$$\omega_I^* = \frac{2\gamma k - \delta}{2\left[q\lambda + \gamma k(1-\eta)\right]} \qquad \omega_L^* = \frac{2\mu}{\lambda(\lambda + 2\phi) + 2\mu} \quad (3.15)$$

Out of these five equilibria, only two are asymptotically stable, namely $\{0,0\}$ *and* $\{1,1\}$; *equilibrium* $\{\omega_I^*, \omega_L^*\}$ *is a saddle, whereas equilibria* $\{0,1\}$ *and* $\{1,0\}$ *are unstable.*

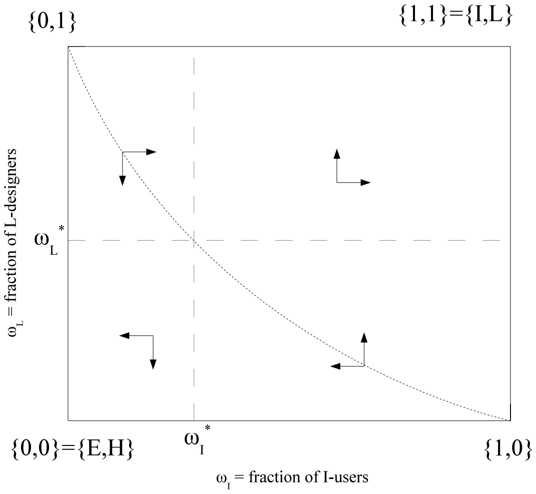

Figure 3.2: Asymptotically stable states and out-of-equilibrium dynamics. Note: the arrows represent the disequilibrium adjustment in the number of I-users (horizontal movements) and L-designers (vertical movements).

Because $\underline{\delta} \leq \delta \leq \overline{\delta}$, both ω_I^* and ω_L^* are included in the close interval $[0, 1]$. The vector field in Figure 3.2 offers a graphical representation of the dynamical system composed of equations (3.13) and (3.14), and of the content of Proposition 3.3. The arrows indicate the out-of-equilibrium adjustment. For states $\omega_I^\tau < \omega_I^*$ and $\omega_L^\tau < \omega_L^*$ (i.e. in the southwest region of Figure 3.2), both $\dot{\omega}_I^\tau$ and $\dot{\omega}_L^\tau$ are negative and the economy will move to $\{0, 0\}$. This state corresponds to a cultural-institutional equilibrium in which H-type designers interact with E-type users; I will call the latter Equilibrium 0 (E_0). Analogous reasoning holds for the northeast region of Figure 3.2, where the economy converges to $\{1, 1\}$. In this case the stable state corresponds to a cultural-institutional equilibrium in which L-type designers interact with I-type users; I will call the latter Equilibrium 1 (E_1). In the remaining regions of the state space, namely northwest and southeast, we may identify a locus of states (dashed downward-sloping line) for which the system will transit to the interior equilibrium $\{\omega_I^*, \omega_L^*\}$, with states below that locus transiting to E_0, and above the locus to E_1. State $\{\omega_I^*, \omega_L^*\}$ is stationary, but is a saddle: small movement away from it are not self-correcting. Two additional unstable stationary states are $\{1, 0\}$ and $\{0, 1\}$, but are of no interest. All the area below the dashed downward-sloping line represents instead the basin of attraction of E_0, and all the area above it the one of E_1. These two corner solutions are thus the absorbing states of the dynamic process. If the economy is ever at either of these states, it will never leave.

The dynamics represented in Figure 3.2 suggests that, overtime, the economy is likely to converge to one of two very different equilibria. In one of them, namely E_0, a homogeneous population of extrinsically motivated users interact overtime with designers employing high control technologies. In the other, namely E_1, a population dominated by intrinsically motivated users interact with designers exercising low control. According to Proposition 3.2, the convergence to one equilibrium as opposed to the other does indeed have implications in terms of overall efficiency, in that E_1 is Pareto dominant over E_0. The extent to which one of these two equilibria will actually be the cultural-institutional equilibrium of the economy depends on two interrelated factors. First of all, for any given size of the basins of attraction, the emergence of E_1 as opposed to E_0 (and *viceversa*) is more likely, the more probable the initial distribution of types in the economy to fall within E_1's (or E_0's in the opposite case) basin of attraction. This implies that, in this closed setting, there exist path dependency in the way in which the economy evolves. Secondly, for any given initial distribution of types, the emergence of one of the two absorbing states as the final resting point of the dynamics depends on the size of its basin of attraction. In particular, the greater the basin of attraction of one state relative to the other, the more likely such state to become the cultural-institutional equilibrium of the economy. On this respect, it is important to notice that:

Remark 3.2. $\partial\omega_I^*/\partial\delta < 0$ and $\partial\omega_I^*/\partial\gamma > 0$ imply that, for any initial distribution of types, the emergence of E_1 as the cultural-institutional equilibrium of the economy is more likely, the greater the design cost of control δ and the less effective the technologies of censoring, i.e. the lower γ.

3.3.3 Discussion

Looking at the features of the digital economy at the end of the 1969-1995 period, it is easy to see which type of cultural-institutional equilibrium the non-commercial network eventually evolved into. Several authors indeed agree in considering both the relatively low degree of control and the widespread diffusion of intrinsic motives and social norms as two peculiar features of the networked environment as of the mid-1990s (Zittrain, 2008; Lessig, 2006; Benkler, 1998, 2001, 2006; Bollier, 2008). Lessig (1996), for instance, writing in that period about the future of cyberspace, gave the following description:

> As it is just now, cyberspace is such a place of relative freedom. The technologies of control are relatively crude. Not that there is no control. Cyberspace is not anarchy. But that control is exercised through the ordinary tools of human regulation - through social norms, and social stigma; through peer pressure, and reward. How

this happens is an amazing question - how people who need never meet can establish and enforce a rich set of social norms is a question that will push theories of social norm development far. But no one who has lived any part of her life in this space as it is just now can doubt that this is a space filled with community, and with the freedom that the imperfections of community allows. (p. 1407)

In line with the content of Remark 3.2, most of this literature tends to relate the emergence of such a loosely controlled social space in the non-commercial network with the poor initial development of control-enhancing technologies. In the early days of cyberspace (1970s and 1980s), in fact, control supportive tools such as DRM[12] and DPI systems[13] were not as fully developed as they are today, and were thus easy targets of users' hacking (i.e. low γ) (Zittrain, 2008). At the same time, the low malleability of digital technologies (i.e. high δ) made it relatively costly for platform designers to use code as an effective instrument of regulation. The combination of these two factors created a technical environment that was highly conductive to the emergence of an E_1-type of equilibrium (i.e. it increased the latter's basin of attraction), which was indeed the final state to which the economy converged.

With respect to this interpretation, the above model adds two important points. First of all, the model makes clear that the emergence of a social space characterized by relatively little control was only one of the possible ways in which the public Internet could have evolved. During the 1970s and 1980s there are indeed several examples of proprietary networks that evolved along completely different dynamic paths, becoming in the end highly controlled social environments (e.g. CompuServe, The Source, America Online, Prodigy) (Lessig, 2006). According to Zittrain (2008, 2006), and in line with the results of the model, these networks were relatively inefficient as compared to the public Internet, because they were unable to mobilize a sufficiently high degree of users' participation. As as a result they almost disappeared from the landscape of digital communication. Nonetheless, they do represent clear examples of what

[12]Digital rights management (DRM) systems are an example of access control technology that adds code to digital content that disables the simple ability to copy or distribute that content - at least without the technical permission of the DRM system itself (Lessig, 2006). Presently, DRM is in common use by the entertainment industry (e.g. audio and video publisher). Many on-line music stores, such as Apple Inc.'s iTunes Store, as well as many e-book publisher also use DRM, as do cable and satellite service operators to prevent unauthorized use of content or services.

[13]Deep packet inspection (DPI) systems are a form of computer network packet filtering that read and classify Internet traffic as it passes through a network, enabling the identification, analysis, blockage and even alteration of information (MacKinnon, 2012). Initially, DPI were used mainly to secure private internal networks. Recently, Internet service providers (ISPs) have also started to apply this technology on the public network provided to consumers. Common uses of DPI by ISPs are lawful intercetp, policy definition and enforcement, targeted advertising, quality service and copyright enforcement.

alternative systems based on tight forms of control could eventually look like, and thus provide a direct benchmark against which future developments can be compared.

In addition to this, the model suggests that the emergence of a loosely controlled social space in the public Internet was neither the result of pure chance, nor the unavoidable consequence of the high cost of digital control. Rather, it has deep roots in the specific set of norms and values that formed the early culture of the networked environment. As reported in many analyses on the history of the Internet, in fact, the original population of on-line users consisted for the most part of academics and amateurs who looked at the emerging Internet infrastructure more as an instrument to enhance the human capabilities to communicate and share knowledge, rather than as a tool for running business (Leiner et al., 2001; Berners-Lee, 1999; Abbate, 1999; Wu, 2010). Most of these users exhibited strong intrinsic motives for their on-line actions, and behaved according to a well defined set of ethical norms (Zittrain, 2008; Himanen, 2001; Sterling, 2002). This contributed to generate a cultural environment (i.e. an initial distribution of behavioral types) in which designers employing week forms of control tended to perform far better than those exercising high control, because they were better capable of taking advantage of users' motivation while at the same time saving on the costs of control. Overtime, the dynamic adaptation of digital designs to the cultural features of surrounding environment led to the convergence towards an E_1-type of equilibrium, with low control practices becoming largely predominant. In this sense, both the evidence and the model suggest that the public Internet bore from the very beginning the "cultural seeds" that were necessary for a loosely controlled social space to actually emerge. Quite interestingly, it is exactly the composition of such cultural seeds that got completely overturned as soon as the network was opened to commerce.

3.4 Opening the network to commerce

The opening of the network to commercial uses occurring in 1995 brought two main changes. First of all, it dramatically increased the size of the populations of both on-line users and designers. Secondly, it brought an upsurge in the number of security incidents associated with attacks to Internet-connected systems (e.g. diffusion of viruses, worms and spams). These two effects are well captured by the data reported in Figures 3.3 and 3.4. Figure 3.3 shows ISC's data[14]

[14]Internet Systems Consortium (ISC) is a non-profit public benefit corporation dedicated to supporting the infrastructure of the universal connected self-organizing Internet - and the autonomy of its participants - by developing and maintaining core production quality software, protocols, and operations. For more detail on ISC and the data reported in Figure 3.3 see `http://www.isc.org` (last time checked: April 30, 2012).

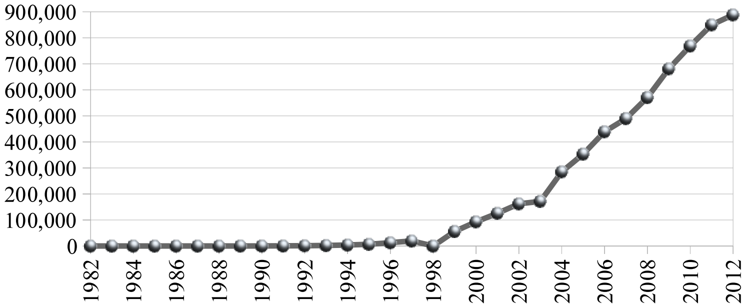

Figure 3.3: Thousands of Internet hosts, 1982-2012. Source: The Internet System Consortium Domain Survey - Internet host count history, 1981-present.

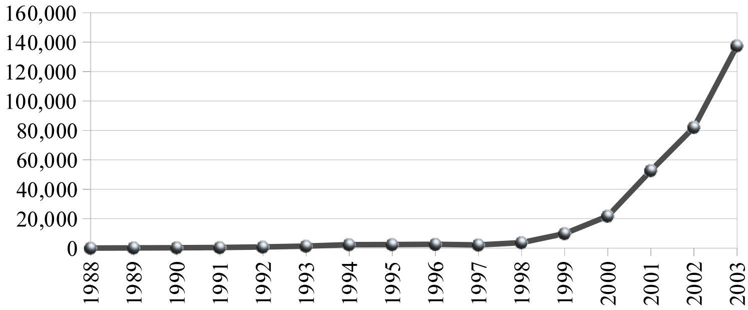

Figure 3.4: Number of security incidents reported to CERT, 1988-2003. Source: CERT Coordination Center, CERT/CC Statistics 1988-2005.

on the evolution in the number of Internet hosts during the period 1982-2012. Figure 3.4 presents figures on the trend of security incidents reported to the US Department of Defense's CERT Coordination Center for the sub-period 1988-2003.[15] The two graphs show that, starting in 1998, there has indeed been a dramatic increase in the number of both hosts and incidents, with the latter roughly doubling each year through 2003. The two trends, at least for the overlapping time window that I consider, look surprisingly aligned, and there are reasons to believe that a similar tendency extended well beyond 2003. Other informative sources report in fact a constant increase in the rate of Internet vulnerabilities all the way up until the most recent years (see Zittrain, 2008).

The remarkable growth in security incidents that followed the advent of commerce on the Internet has been the subject of several studies. Zittrain

[15] The Computer Emergency Response Team (CERT) Coordination Center is a research center located at Carnegie Mellon University's Software Engineering Institute with the aim of studying Internet security vulnerabilities. The same data were originally reported by Zittrain (2006). The data are available only for the period 1988-2003 because in 2004 CERT announced it would no longer keep track of security incidents, since attacks had become so commonplace to be indistinguishable from one another.

(2006, 2008), in particular, links it to the massive increase in the number of unskilled and inexpert users/designers, who became easy targets of malware developers and spammers.[16] What is certainly true is that the reduced security of Internet connections is a symptom of a deep cultural change that took place in cyberspace starting in 1995. As the network became so ubiquitous, in fact, the Net-wide set of ethics that worked so well in sustaining the quality of on-line transactions under the loosely controlled environment of the pre-commercial era began to waver. A large number of new users (and designers) who were relatively unused to ethics of cyberspace started to enter in the digital space, causing a significant change in the distribution of behavioral types. Purely extrinsic motives became an important driver behind users' on-line actions (e.g. diffusion of e-commerce), to an extent that ethical values started to be quite often subdued to the possibility of earning monetary rewards. In this sense, the rising business model backing the diffusion of viruses and malware can be seen as a direct consequence of this type of change (Zittrain, 2008).

In order to formally investigate the effect of such change on the equilibrium selection dynamics presented in the previous section, I follows two steps. First of all, I assume the existence of an outside population of users and designers that each period are randomly selected in subsamples to enter the digital economy. Secondly, I study how the distribution of types in these subsamples influences the probability that a transition to a different type of cultural-institutional equilibrium occurs. The key assumption that I introduce is that, for any τ, the distribution types in the outside population is independent of the distribution of types in the inside population. This allows me to transform the economy in a stochastic environment, with the distribution of types changing over time for both endogenous and exogenous reasons. Given this framework, I am interested in identifying the conditions under which each of the two cultural-institutional equilibria qualifies as the stochastically stable state of the economy.

From the technical point of view I proceed as follows. I call $s_u^\tau = s_I^\tau + s_E^\tau$ (> 0) and $s_d^\tau = s_L^\tau + s_H^\tau$ (> 0) the subsample of users and designers that in each period τ may be selected to enter the economy, with s_i (for $i = \{I, E, L, H\}$) being the number of agents (users and designers) of type i. On this basis, I define:

$$\nu_I^\tau = \frac{s_I^\tau}{s_I^\tau + s_E^\tau} \quad \nu_L^\tau = \frac{s_L^\tau}{s_H^\tau + s_L^\tau} \tag{3.16}$$

as the fractions of I-users and L-designers existing in this subsample. As previously stated, I assume the value of ν_I^τ and ν_L^τ to be independent of ω_I^τ and ω_L^τ at any τ. In particular, I assume the former to be random draws from the probability distributions $f_I(\nu)$ and $f_L(\nu)$, with $f(x)$ continuous over the inter-

[16] Software designed to infiltrate and damage a computer system (Zittrain, 2006).

val $x \in [0,1]$. I call $\overline{\nu}_I = \int_{-\infty}^{+\infty} \nu f_I(\nu)\mathrm{d}\nu$ and $\overline{\nu}_L = \int_{-\infty}^{+\infty} \nu f_L(\nu)\mathrm{d}\nu$ the expected fractions of I-users and L-designers in the selected subsample. The latter can be indeed seen as indexes of how homogeneous the distribution of types is in the outside population.

The timing of entrance is modeled as follows. At the beginning of any period τ, users and designers update their type following the process described in the previous section. This process takes as a reference the distribution of preferences and designs that exist in the economy at the beginning of that period. Once such updating is completed, Nature makes two moves. First, she determines with probability $\epsilon d\tau$ (> 0) whether a new set of s_u users and s_d designers enter the economy. Second, she selects the value of ν_I^τ and ν_L^τ to be associated to that set. For the sake of simplicity I assume that both populations of users and designers grow at the same constant rate so that, for any τ, we have $s_u^\tau = \rho\, n_u^\tau$ and $s_d^\tau = \rho\, n_d^\tau$ with $\rho > 0$.

The effective possibility of external entrance transforms the dynamical system into an ergodic process, with transitions between the basins of attraction of the two equilibria E_1 and E_0 that now becomes possible. Whenever a new entrance occurs, in fact, the distribution of types at any given τ reflects both the endogenous updating undertaken by the inside population and the exogenous variation due to the new entrants. When the effect of the latter is sufficiently strong, the population can be drifted away from the status-quo convention, and eventually converge towards a new equilibrium. In order to see why, let us suppose that the population is in equilibrium E_1 and entrance occurs. Once the individual updating is completed, the fraction of I-users and L-designers at the beginning of next period can be written as follows:

$$\omega_I^{\tau+1} = \frac{1+\rho\nu_I^\tau}{1+\rho} \qquad \omega_L^{\tau+1} = \frac{1+\rho\nu_L^\tau}{1+\rho} \tag{3.17}$$

where I used the fact that $\omega_I^\tau = 1$, $\omega_L^\tau = 1$, $s_u^\tau = \rho\ n_u^\tau$ and $s_d^\tau = \rho\ n_d^\tau$. A transition from E_1 to E_0's basin of attraction will occur whenever $1 - \omega_I^{\tau+1} \leq 1 - \omega_I^*$ and/or $1 - \omega_L^{\tau+1} \leq 1 - \omega_L^*$, which is the case if

$$\nu_I^\tau \leq \frac{\omega_I^*(1+\rho)-1}{\rho} \qquad \mathit{and} \qquad \nu_L^\tau \leq \frac{\omega_L^*(1+\rho)-1}{\rho} \tag{3.18}$$

Depending on the value of ρ and the shape of $f(\nu)$, therefore, the "tipping" of the population from one basin of attraction to the other is more or less likely to occur.

Figure 3.5 offers a graphical representation of the way in which motivation (upper panel) and control (lower panel) may co-evolve in this stochastic environment (for the derivation of the underlying dynamical system see Appendix

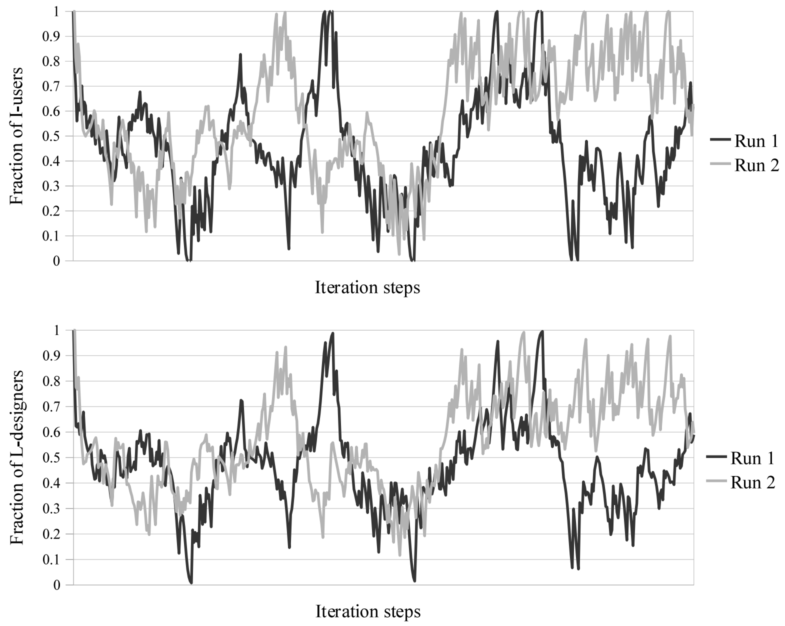

Figure 3.5: Evolution of motivation and control in a stochastic environment. Note: $\phi = 2.4$, $\lambda = 1$, $q = 1$, $\gamma = 1$, $\eta = 0.33$, $k = 2.41$, $\mu = 2.91$, $\delta = 2.21$, $\alpha\beta = 0.4$, ν_I^τ and ν_I^τ are random draws from the uniform distribution $[0.3, 0.7]$.

3.2). The black and gray lines represent two distinct runs of 500 iterations, with starting point at $\{1, 1\}$. The system is calibrated using the parameters reported the Figure's caption. In particular, I assume $f_I(\nu)$ and $f_L(\nu)$ to be a uniform distribution over the interval $[0.3, 0.7]$, with $\overline{\nu}_I = \overline{\nu}_L = 0.5$. As it is easy to see the evolution of individual types in the two populations follows a closely related path. In Run 1 such path oscillates between the two basins of attraction for all 500 iterations. In Run 2 the dynamics oscillates too for nearly half of the iterations, and then it tends stabilize in the orbit of equilibrium E_1. In the two cases, starting from the same initial conditions, the population follows two completely different dynamic paths with transitions between the two stable equilibria being relatively frequent.

Among the several factors that may explain both the speed and frequency of transitions, one that appears to be of major relevance for the present discussion concerns the distribution of types in the population of new entrants. The more such distribution is biased towards the predominance of one particular type, in fact, the more the exogenous variation will tend to keep the economy close to one specific equilibrium and make transition in the opposite direction unlikely to occur. Quite interestingly, this is true also when such bias concerns only one of the two populations of new entrants, being either users and designers.

On this respect, Figure 3.6 shows the evolution of control when the distri-

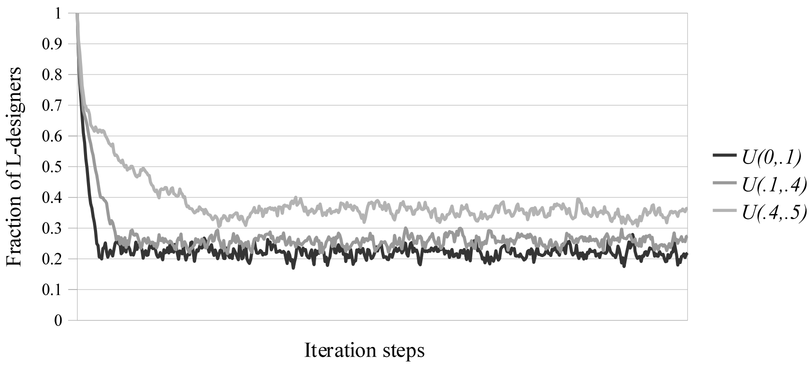

Figure 3.6: Emergence of control for different distribution of behavioral types in the outside population. Note: each curve is the average of 40 runs under the indicated uniform distribution; all other parameters are as in Figure 3.5.

bution of behavioral types in the population of new users is biased in favor of E-type (motivation obviously follows a closely related path). Each curve represents the average of 40 runs under the indicated uniform distribution. All the other parameters are kept the same as in Figure 3.5. As it is easy to observe, small variations in the distribution of behavioral types significantly change the evolution of control. In all cases, the fraction of H-designers tends to increase over time and become largely predominant. The more the distribution is biased in favor of E-type (from the lightest to darkest curve), the faster the convergence towards a high-control-type of equilibrium and the greater the fraction of H-designers in the stable path.

In addition to the distribution of individual types, another factor that plays a crucial role in influencing the shape of the overall dynamics concerns the two critical values ω_I^* and ω_L^*. As reported in equation (3.18), in fact, the latter contribute to the definition of the threshold values against which a transition between the two basins of attraction is made possible, and therefore affect the amount of exogenous variation that is actually necessary for such a switch to occurs. Intuition suggests that the cultural-institutional equilibrium that requires more exogenous variation to dislodge, and less exogenous variation to access will tend to persist longer than the other. At the same time, if dislodged, it will tend to reemerge readily. This, at least for a sufficiently homogeneous distribution of types in the outside population, is the cultural-institutional equilibrium that is most likely to be observed in the long-run.

In order to formalize the above intuition consider the following definitions - both adaptations from Young (1998) and Bowles (2006):

Definition 3.3. *Let r_{jk}, the reduced resistance on the path from E_j to E_k, be the minimal fraction of agents (users and designers) that, should the population's type frequencies after entrance be greater or equal r_{jk}, would induce the best-responding partners to switch their types. Then, $r_{01} = \min\{\omega_I^*, \omega_L^*\}$ and $r_{10} = \min\{1 - \omega_I^*, 1 - \omega_L^*\}$.*

Definition 3.4. *The stochastically stable equilibrium (SSE) is the one that occurs with non-negligible probability when the rate of exogenous variation is arbitrarily small. In a 2×2 coordination game with two asymptotically stable equilibria E_j and E_k, E_j is SSE if and only if $r_{kj} < r_{jk}$.*

Definitions 3.3 and 3.4 can be used in order to find the conditions under which each of the two asymptotically stable cultural-institutional equilibria identified in Proposition 3.3 qualifies as SSE. This turns out to be of particular interest especially if related to the efficiency properties of the two equilibria (see Proposition 3.2). In particular, I obtain the following result :

Proposition 3.4. *Suppose $\epsilon > 0$. Then, in the dynamic system with exogenous variation there exist a $k^* = [\psi(2q\lambda + \delta) + 2\mu\delta]/2\gamma(2\mu + \eta\psi)$ where $\psi = \lambda(\lambda + 2\phi)$ such that if $k > k^*$ E_0 is SSE. This is true even if E_0 is Pareto inefficient.*

The intuition behind Proposition 3.4 is straightforward. When the cost associated with the realization of a noisy tasks k is sufficiently high, L-designers suffer a big loss whenever they are matched with an E-users (see payoffs in Table 3.1). This implies that when there is uncertainty concerning the distribution of types among users - because for instance there is a positive rate of exogenous variation, a H-type design will tend to have a selection advantage over an L-type, because it ensures a greater expected payoff. This amounts to say that offering a H-type design is risk-dominant in the standard sense that if one believes that users are either I-type or E-type with equal probability, then the best response is to offer a H-type design.[17] Over time, H-designers will tend therefore to increase in number causing a contemporaneous reduction in the number of I-agents. The greater the average degree of control in the economy (i.e. the larger the fraction of H-designers), in fact, the stronger the crowding out effect on motivation, and thus the larger the number of agents who become purely extrinsically motivated. The combination of these effects make equilibrium E_0 stochastically stable.

The content of Proposition 3.4 has interesting implications for what concerns

[17] On the relationship between risk-dominance and stochastic stability see Foster and Peyton Young (1990).

the evolution of digital control. In spite of the efficiency advantage of equilibrium E_1, in fact, I find that there exist a whole range of values in the parameter space which makes equilibrium E_0 persistent over time. Whether the economy is actually in (or is likely to converge to) this state is impossible to say theoretically, and becomes mainly an empirical question. What the model shows is just the possibility that such Pareto inefficient state may become the long-run cultural-institutional equilibrium of the digital space. This in turn calls for a serious analysis of the policy regime that is currently governing cyberspace, with particular attention on some recent proposals on Internet regulation.

3.5 Policy implications

The results of the previous sections depict the possibility of a coordination failure in the evolution of digital control. When cost k is sufficiently high, tight forms of control and extrinsic motivation tend to become predominant in the economy, leading to the persistence of equilibrium E_0. In some cases this outcome is suboptimal from the social point of view, because both users and designers would be better-off if they could only coordinate their actions in favor of equilibrium E_1. When this happens, the economy is trapped in a low efficiency equilibrium and some forms of government intervention can be justified.

Although it is probably too early to say whether such a coordination failure will effectively emerge, it is still possible to analyze the effect of different forms of government intervention in increasing and/or reducing the likelihood of its occurrence. On this respect, several policy proposals that have been recently discussed at both the national and international level seem to be of relevance. Three, in particular, have attracted the attention of most international commentators, and include ACTA, the SOPA and PIPA bills in the U.S., and the Google-Verizon's proposal on network neutrality. Although none of these proposals is directly concerned with the implementation of control *per se*, they all impact on the latter's effectiveness and appropriateness. As a result, they all directly affect the probability that a coordination failure of the type described above may effectively occur.

ACTA is a proposed multinational treaty that aims at establishing international standards for intellectual property rights enforcement. According to the original proposing parties, the main objective of ACTA is to help fight the proliferation of counterfeit and pirated goods in international trade, which have by now become one major source of profit for illegal and criminal activities, especially in developing countries (McManis, 2008). If finally approved, ACTA would apply 'new, stricter legal and enforcement standards to the trade in informational goods', and introduce 'sweeping provisions to criminalize information use practices currently allowed under U.S., European and international law' (Shaw, 2008, p.1). With specific reference to trade in digital goods, ACTA aims at 'reinforcing so-called "Digital Rights Management" (DRM) technologies that currently prevent the personal, legal reproduction of optical discs like DVDs and trample on "fair use" rights'. In addition, it proposes to 'undermine legal safeguards that protect Internet Service Providers (ISPs) from the liability of the actions of their subscribers' (Shaw, 2008, p.3). In the language of the above model, the implementation of these provisions would at the same time improve the effectiveness of control - via the strengthening of DRM systems, i.e. increase in γ, and rise the state-enforced costs for copyright infringement - via the increased liability of ISPs, i.e. increase in k. The combination of these two effects would make digital control increasingly convenient as a design option, thus favoring the convergence towards equilibrium E_0. If that happens, the undeniable benefit that is associated with a reduction of illegal and criminal activities, would be then counterbalanced by the increased risk of altering the cultural-institutional features of the digital space in a socially inconvenient way. This would in turn question the effective appropriateness and applicability of the treaty itself.

A very similar interpretation holds also for another set of legal provisions that explicitly aim at fighting the problem of on-line piracy, such as the SOPA and PIPA bills under scrutiny in the U.S. Congress. The two bills, introduced respectively in the House and the Senate, are the most recent iteration of the long list of acts aimed at strengthening the rights of the U.S. copyright industries, such as the Digital Millennium Copyright Act of 1998, the Prioritizing Resources and Organization for Intellectual Priority Act of 2008, the Higher Education Opportunity Act of 2008, and the Combating On-line Infringement and Counterfeits Act of 2010. In their current version, the bills' provisions aims at further extending the involvement of criminal enforcement authorities in what was traditionally an area of private commercial law, and at using the state leverage to harness private platform providers to enforce the interests of copyright holders (Benkler, 2012b). Similarly to ACTA, the SOPA and PIPA bills intend to curb criminal and illegal on-line practices, while at the same ensuring the defense of individual rights. In doing so, however, they create an environment in which control becomes at the same time easy to implement (low γ) and costly to avoid (high k), thus making equilibrium E_0 likely to emerge. Whether the cost of this relatively inefficient outcome is compensated by the benefit associated with a reduced degree of on-line piracy is difficult to say, and requires an in-depth empirical investigation. What is certainly true is that the simple possibility of such trade-off suggests the need of a partial rethinking of the bills' content, with particular attention on the role played by the Internet's traditional openness.

Finally, a third type of intervention that can directly affect the evolution of digital control is the Google-Verizon's proposal on network neutrality. The proposal, presented to the U.S. Federal Communication Commission on August 2010, introduces the possibility to exempt wireless communication and other on-line services from applying the principle of net neutrality, that is the set of embedded rules which impose that all like Internet content must be treated alike and move at the same speed over the network (Wu, 2003a). The proposal finds its rationale in the conviction that by allowing ISPs to (at least partially) discriminate on some Internet applications, new economic resources could be generated, which could be in turn invested in the creation of new, more efficient broadband and information technology services.[18] Some commentators, however, urges that a similar provision would at the same time increase the discretionary power of ISPs, making it possible to tailor specific types of code-based restrictions on Internet applications.[19] With reference to the model, this would imply a substantial reduction in the design cost of digital control (i.e. δ), and thus an increase in the persistence of equilibrium E_0. Whenever the latter is Pareto inefficient, this would in turn generate a trade-off between the provision of incentives to invest in innovation and the distortion of the cultural-institutional features of the digital space. Once again, a sound balance between these types of costs and benefits is effectively difficult to strike.

Overall, the analysis of three of the most recent policy proposals on Internet regulation reveals a relatively complex scenario. If on one hand the proposed interventions pursue fairly legitimate policy objectives, on the other they all introduce provisions that tend to increase the chances that the economy gets stuck in a low efficiency equilibrium. The reason is essentially related to the fact that, while being concerned with the enforcement of particular rights and the creation of specific incentives, these laws tend to neglects the economy-wide effects that an increased viability of digital control may have on both the culture and institutions of the networked environment. Whenever these effects are worse than the benefits the laws are aimed at generating, the policy prescriptions should be revised, and the preservation of the cultural-institutional features of cyberspace should become an integral part of policy design.

[18]See Google-Verizon Proposal for a legislative framework for network neutrality, available at: `http://static.googleusercontent.com/external_content/untrusted_dlcp/www.google.com/it//googleblogs/pdfs/verizon_google_legislative_framework_proposal_081010.pdf` (last time checked: May 3, 2012).

[19]See Cain Miller and Helft, supra note 5.

3.6 Conclusion

On August 2011, while speaking with The Associated Press on the sidelines of the 7th Wikipedia's annual conference, Jimmy Wales (the website's founder) said the on-line encyclopedia was struggling to find contributors. After many years of constant growth, the non-profit organization reported that contributors leaving the website had outnumbered new users, leaving the community in short supply. Although Wales linked this poor result to the website's complex editing procedures,[20] it can be interpreted as the first sign of a deeper change. In a highly competitive environment that is increasingly populated by control-intensive platforms (e.g. social networks), in fact, open and commons-based websites like Wikipedia finds it increasingly difficult to attract deeply motivated users. Whether this implies that such kind of platforms are effectively doomed to disappear it is difficult to say; but this evidence certainly suggests that something is changing in the way in which on-line participation is being experienced.

Starting from this evidence, this chapter has presented a behavioral economic model that micro-founds the cultural-institutional evolution of the digital space. The chapter focused on the interaction between individual motivation and digital control, with the aim of modeling the latter's historical evolution. The crucial assumption of the model was that control is not neutral with respect to the nature of individual motivation, and some crowding out effect on intrinsic motives exists. On this basis, the chapter has derived three main results: a) in the long-run there exist two stable cultural-institutional equilibria in the digital economy: one with intrinsically motivated users and low control; and the other with purely extrinsically motivated users and high control; b) under a closed economy - i.e. before the opening of the network to commerce, the initial emergence of a low-control-intrinsic-motivation equilibrium can be explained by the specific set of norms and values that formed the early culture of the networked environment; and c) the opening of the network to commerce can indeed cause a transition to a high-control-extrinsic-motivation equilibrium, even if the latter is Pareto inferior. Although it is too early to say whether such a transition is actually taking place, these results call for a great deal of attention in evaluating policy proposals on Internet regulation. This chapter, in particular, has focused on three of them, such as ACTA, the SOPA and PIPA bills, and the Google-Verizon's proposal on network neutrality. All of them are deemed to have controversial effects on the cultural-institutional nature of cyberspace.

[20]See Zack Whittacker, *Wikipedia losing contributors: Fatal flaw, the community editors?*, ZDNet, Augist 4, 2011, available at: `http://www.zdnet.com/blog/btl/wikipedia-losing-contributors-fatal-flaw-the-community-editors/54144` (last time checked: May 3, 2012)

3.7 Appendix 3.1

3.7.1 Proof of Lemma 3.1.

The derivative of equation (3.4) with respect to a gives us the following best-response function for I- and E-users when paired with a generic designer j: $a_{I,j} = \phi + \lambda(1-t)$ and $a_{E,j} = \phi$. By substituting away for t we obtain the best-response level of a reported in the lemma.

3.7.2 Proof of Proposition 3.1

$\{I, L\}$ is proven to be Nash equilibrium as long as: (a) $(\phi + \lambda)^2/2 > \phi^2/2$, and (b) $q(\phi + \lambda) - \gamma\eta k > q\phi - \delta/$. Condition (a) is self-explained. Condition (b) reduces to $\delta > 2(\gamma\eta k - q\lambda) = \underline{\delta}$. Similarly, $\{E, H\}$ is a Nash equilibrium as long as: (c) $\phi^2/2 > \phi^2/2 - \mu$ and (d) $q\phi - \gamma k < q\phi - \delta/2$. Condition (c) is self-explained. Condition (d) reduces to $\delta < 2\gamma k = \overline{\delta}$. For $0 < \eta < 1$, $\underline{\delta} < \overline{\delta}$ is always true. It follows that: *(i)* when $\delta > \overline{\delta}$ condition (b) is satisfied but not condition (d), hence $\{I, L\}$ is the only Nash equilibrium; *(ii)* when $\delta < \underline{\delta}$ condition (d) is satisfied but not condition (b), hence $\{E, H\}$ is the only Nash equilibrium; and (iii) when $underline\delta < \delta < \overline{\delta}$ conditions (b) and (d) are simultaneously satisfied, hence both $\{I, L\}$ and $\{E, H\}$ are Nash equilibria. Corollary 3.1.1 follows from the fact that two necessary conditions for $\{E, L\}$ and $\{I, H\}$ to be Nash equilibria are that E is a best-response to L and I is a best response to H, but this is impossible because it would violate conditions (a) and (c) above. Corollary 3.1.2 follows directly from points (i), (ii) and (iii) above.

3.7.3 Proof of Proposition 3.2.

For any $\lambda > 0$, a necessary and sufficient condition for $\{E, H\}$ to be Pareto efficient is that $q(\phi + \lambda) - \gamma\eta k < q\phi - \delta/$, which reduces to $\delta < \overline{\delta}$. Otherwise, $\{I, L\}$ Pareto dominates $\{E, H\}$. This, together with the results of Proposition 3.1, implies that: (i) if $\delta < \overline{\delta}$, then $\{E, H\}$ is Pareto efficient and it is also the only Nash equilibrium of the game; (ii) if $\delta > \overline{\delta}$, then $\{I, L\}$ is Pareto dominant and it is also a Nash equilibrium. Points (i) and (ii), together with the fact that for $\underline{\delta} < \delta < \overline{\delta}$ both $\{I, L\}$ and $\{E, H\}$ are Nash equilibria, prove the proposition.

3.7.4 Proof of Proposition 3.3.

The five cultural-institutional equilibria are derived by simply solving the system (3.13)-(3.14) for $\dot{\omega_\tau} = 0$ and $\dot{\rho_\tau} = 0$. The proof in this case is omitted. The asymptotic properties of each equilibrium are derived by analyzing the Jacobean Matrix $J(\omega_I, \omega_L)$ associated to system (3.13)-(3.14), which takes the following form:

$$J = \begin{pmatrix} (1-2\omega_I)\left[\omega_L\left(\frac{\lambda^2}{2}+\phi\lambda+\mu\right)-\mu\right] & (\omega_I-\omega_I^2)\left(\frac{\lambda^2}{2}+\phi\lambda+\mu\right) \\ (\omega_L-\omega_L^2)\left[q\lambda+\gamma k(1-\eta)\right] & (1-2\omega_L)\left\{\omega_I\left[q\lambda+\gamma k(1-\eta)\right]+\frac{\delta}{2}-\gamma k\right\} \end{pmatrix}$$

At $\{0,0\}$, we have

$$J = \begin{pmatrix} -\mu & 0 \\ 0 & \frac{\delta}{2}-\gamma k \end{pmatrix}$$

from which it follows that

$$Tr(J) = -\mu+\frac{\delta}{2}-\gamma k \qquad and \qquad Det(J) = -\mu\left(\frac{\delta}{2}-\gamma k\right) \tag{3.19}$$

Since $\mathrm{Tr}(J) < 0$ and $\mathrm{Det}(J) > 0$ for any $\delta < 2\gamma k$, $\{0,0\}$ is asymptotically stable.

At $\{1,0\}$, we have

$$J = \begin{pmatrix} \mu & 0 \\ 0 & q\lambda-\gamma\eta k+\frac{\delta}{2} \end{pmatrix}$$

from which it follows that

$$Tr(J) = \mu+q\lambda-\gamma\eta k+\frac{\delta}{2} \qquad and \qquad Det(J) = \mu\left(q\lambda-\gamma\eta k+\frac{\delta}{2}\right) \tag{3.20}$$

Since $\mathrm{Tr}(J) > 0$ and $\mathrm{Det}(J) > 0$ for any $\delta > 2(\gamma\eta k - q\lambda)$, $\{1,0\}$ is unstable.

At $\{0,1\}$, we have

$$J = \begin{pmatrix} \frac{\lambda^2}{2}+\phi\lambda & 0 \\ 0 & -\frac{\delta}{2}+\gamma k \end{pmatrix}$$

from which it follows that

$$Tr(J) = \frac{\lambda^2}{2}+\phi\lambda-\frac{\delta}{2}+\gamma k \qquad and \qquad Det(J) = \left(\frac{\lambda^2}{2}+\phi\lambda\right)\left(\gamma k-\frac{\delta}{2}\right) \tag{3.21}$$

Since $\mathrm{Tr}(J) > 0$ and $\mathrm{Det}(J) > 0$ for any $\delta < 2\gamma k$, $\{0,1\}$ is unstable.

At $\{1,1\}$, we have

$$J = \begin{pmatrix} -\frac{\lambda^2}{2} - \phi\lambda & 0 \\ 0 & -q\lambda + \gamma\eta k - \frac{\delta}{2} \end{pmatrix}$$

from which it follows that

$$\begin{aligned} Tr(J) &= -\frac{\lambda^2}{2} - \phi\lambda - q\lambda + \gamma\eta k - \frac{\delta}{2} \qquad and \\ Det(J) &= -\left(\frac{\lambda^2}{2} + \phi\lambda\right)\left(\gamma\eta k - q\lambda - \frac{\delta}{2}\right) \end{aligned} \tag{3.22}$$

Since Tr(J) < 0 and Det(J) > 0 for any $\delta > 2(\gamma\eta k - q\lambda)$, $\{1, 1\}$ is asymptotically stable.

At $\{\omega_I^*, \omega_L^*\}$, we have

$$J = \begin{pmatrix} 0 & \frac{(2\gamma k - \delta)[2q\lambda - 2\gamma\eta k + \delta]}{4[q\lambda + \gamma k(1-\eta)]^2}\left(\frac{\lambda^2}{2} + \phi\lambda + \mu\right) \\ \frac{2\mu\lambda(\lambda + 2\phi)}{[\lambda(\lambda + 2\phi) + 2\mu]^2}[q\lambda + \gamma k(1-\eta)] & 0 \end{pmatrix}$$

from which it follows that

$$\begin{aligned} Det(J) = -\frac{(2\gamma k - \delta)[2q\lambda - 2\gamma\eta k + \delta]}{4[q\lambda + \gamma k(1-\eta)]^2}\left(\frac{\lambda^2}{2} + \phi\lambda + \mu\right) \cdot \\ \cdot \frac{2\mu\lambda(\lambda + 2\phi)}{[\lambda(\lambda + 2\phi) + 2\mu]^2}[q\lambda + \gamma k(1-\eta)] \end{aligned} \tag{3.23}$$

Since Det(J) < 0 for any $\delta > 2(\gamma\eta k - q\lambda)$, $\{\omega_I^*, \omega_L^*\}$ is a saddle.

3.7.5 Proof of Proposition 3.4.

From Definition 3.3 and the value of ω_I^* and ω_L^* reported in Proposition 3.3 it follows that:

- $\mu \geq \psi(2\gamma k - \delta)/2\,[\delta + 2(q\lambda - \gamma k\eta] \quad \Longleftrightarrow$

$$r_{01} = \omega_I^* = \frac{2\gamma k - \delta}{2[q\lambda + \gamma k(1-\eta)]} \quad and \quad r_{10} = 1 - \omega_L^* = \frac{\psi}{\psi + 2\mu} \tag{3.24}$$

- $\mu < \psi(2\gamma k - \delta)/2\,[\delta + 2(q\lambda - \gamma k\eta] \quad \Longleftrightarrow$

$$r_{01} = \omega_L^* = \frac{2\mu}{\psi + 2\mu} \quad and \quad r_{10} = 1 - \omega_I^* = \frac{\delta + 2(q\lambda - \gamma k\eta)}{2[q\lambda + \gamma k(1-\eta)]} \tag{3.25}$$

where $\psi = \lambda(\lambda + 2\phi)$. According to Definition 3.5, E_0 is SSE if and only if $r_{10} < r_{01}$. Simple algebra shows that, given equations (3.24) and (3.25), the latter condition holds if and only if $k > [\psi(2q\lambda + \delta) + 2\mu\delta]/2\gamma(2\mu + \eta\psi) = k^*$. The second part of the proposition follows directly from Proposition 3.2.

3.8 Appendix 3.2

3.8.1 Payoffs in Table 3.1

Let us indicate with $U_{i,j}$ the utility of an i-type user when matched with a j-type designer, and with $\pi_{j,i}$ the return to an j-type designer when matched with a i-type user. Moreover let us write $a_{i,j}$ as the best-response level of a for an i-type user when matched with a j-type designer. Given equations (3.1), (3.2) and the functional forms defined in Section 3.3.1, we have:

$$U_{I,j} = [\phi + \lambda(1-t)]a_{I,j} - \frac{a_{I,j}^2}{2} - \mu t \quad , \quad U_{E,j} = \phi a_{E,j} - \frac{a_{E,j}^2}{2} \tag{3.26}$$

$$\pi_{L,i} = qa_{i,L} - \gamma\eta(\lambda)k \quad , \quad \pi_{H,i} = qa_{i,H} - \frac{\delta}{2} \tag{3.27}$$

where $\eta(\lambda)$ takes the following form:

$$\eta(\lambda) = \begin{cases} 1, & \text{if } i = E \\ \\ \eta, & \text{if } i = I \end{cases} \tag{3.28}$$

By replacing into equations (3.26) and (3.27) the value for $a_{i,j}$ reported in Lemma 3.1, and substituting away for t (i.e. replacing $t = 0$ and $t = 1$ for a match with an L- and a H-type designer respectively), we obtain the following results:

$$U_{I,L} = \frac{(\phi+\lambda)^2}{2} \quad , \quad U_{I,H} = \frac{\phi^2}{2} - \mu \quad , \quad U_{E,L} = U_{E,H} = \frac{\phi^2}{2} \tag{3.29}$$

$$\pi_{L,I} = q(\phi+\lambda) - \gamma\eta k \quad , \quad \pi_{L,E} = q\phi - \gamma k \quad , \quad \pi_{H,I} = \pi_{H,E} = q\phi - \frac{\delta}{2} \tag{3.30}$$

3.8.2 Stochastic dynamical system

In the stochastic environment described in Section 3.4 the expected fraction of I-users in period $\tau + d\tau$ is given by

$$\begin{aligned} \omega_I^{\tau+d\tau} = [\omega_I^\tau - \omega_I^\tau(1-\omega_I^\tau)\alpha d\tau\sigma_E\beta(V_E^\tau - V_I^\tau) + \\ +(1-\omega_I^\tau)\omega_I^\tau\alpha d\tau\sigma_I\beta(V_I^\tau - V_E^\tau)]\chi_u^\tau + \nu_I^\tau(1-\chi_u^\tau) \end{aligned} \tag{3.31}$$

where

$$\chi_u^\tau = \frac{n_u^\tau}{n_u^\tau + \varepsilon d\tau s_u^\tau} \tag{3.32}$$

is a normalizing factor that varies according to the number of new users that enter into the economy. The part of equation (3.31) inside the square brackets is the same as equation (3.11) and represents the updating process undertaken by the users that are already part of the economy at the beginning of period τ. Once such updating process is completed, s_u^τ new users enter the economy with probability $\varepsilon d\tau$. The fraction of I-users at the beginning of next period is thus given by the updated fraction of I-users normalized by the new size of the users' population (i.e. multiplication by χ_u^τ), plus the fraction of I-users that are included in the set of new entrants (i.e. $\nu_I^\tau(1-\chi_u^\tau)$). Similarly, the expected fractions of L-designers in period $\tau + d\tau$ is given by:

$$\begin{aligned}\omega_L^{\tau+d\tau} = [\omega_L^\tau - \omega_L^\tau(1-\omega_L^\tau)\alpha d\tau\sigma_H\beta(V_H^\tau - V_L^\tau)+ \\ +(1-\omega_L^\tau)\omega_L^\tau\alpha d\tau\sigma_L\beta(V_L^\tau - V_H^\tau)]\chi_d^\tau + \nu_L^\tau(1-\chi_d^\tau)\end{aligned} \tag{3.33}$$

where

$$\chi_d^\tau = \frac{n_d^\tau}{n_d^\tau + \varepsilon d\tau s_d^\tau} \tag{3.34}$$

Subtracting ω_I^τ and ω_L^τ from both sides of equations (3.31) and (3.33) respectively, dividing both equations by $d\tau$, and taking the limit as $d\tau \to 0$, we get:

$$\dot{\omega}_I^\tau = \omega_I^\tau(1-\omega_I^\tau)(V_I^\tau(\omega_L^\tau) - V_E^\tau(\omega_L^\tau)) + \varepsilon\rho_u(\nu_I^\tau - \omega_I^\tau) \tag{3.35}$$

$$\dot{\omega}_L^\tau = \omega_L^\tau(1-\omega_L^\tau)(V_L^\tau(\omega_I^\tau) - V_H^\tau(\omega_I^\tau)) + \varepsilon\rho_d(\nu_L^\tau - \omega_L^\tau) \tag{3.36}$$

where $\rho_u = s_u/n_u$, $\rho_d = s_d/n_d$, and I assumed $\alpha\beta = 1$. Equations (3.35) and (3.36) represent a system of differential equations which describes how the distribution of types $\{\omega_I^\tau, \omega_L^\tau\}$ evolve over time. The main difference with the system composed of equations (3.13) and (3.14) is that this time there are also two stochastic components represented by variables ν_I^τ and ν_L^τ. The latter are the sources of exogenous variation that make a transition between the basins of attraction of the two stable equilibria E_0 and E_1 possible.

Chapter 4

Intangible Assets and Firm Heterogeneity: Evidence from Italy

with A. Arrighetti and A. Lasagni[1]

Abstract: The positive impact of intangible assets on several measures of economic performance is well documented in the literature. Less clear is what initially leads firms to invest in intangible assets. The latter is particularly important because, at least for the Italian manufacturing sector, firms exhibit strong heterogeneity in their investments in intangible assets. In line with the capability-based theory of the firm, we argue that the firms propensity to invest in intangible assets can be explained by factors that are internal and specific to the firm. Making use of a rich dataset, we test and provide support for our hypotheses. In particular, we find that the propensity to invest in intangible assets increases with the firms size, human capital, organizational complexity, and historical intangible asset base. This points towards the existence of a cumulative process of intangible asset accumulation, which may account for most of the heterogeneity observed in the data. The chapter adds to the previous literature in two ways: first, it highlights the existence of strong intra-industry heterogeneity in intangible asset investments, and second, it offers an explanation for such heterogeneity.

JEL: D22; L21; L25; O32.
Keywords: intangibles, firm heterogeneity, organizational capabilities

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4.1 Introduction

Intangible assets consist of the stock of immaterial resources that enter the production process and are necessary for the creation and sale of new or improved products and processes. They include both internally produced assets - e.g., designs, blueprints, brand equity, in-house software, and construction projects - and assets acquired externally - e.g., technology licenses, patents and copyrights, and the economic competencies acquired through purchases of management and consulting services (Corrado et al., 2006). A large and growing body of empirical literature has shown intangible assets to play a major role in the modern knowledge economy. Corrado et al. (2005), for instance, estimate that the total value of intangible assets in the US was already near 3.4 trillion by the early 2000s, suggesting that intangible assets accounted for over 75% of US output growth during that period. Similarly, Nakamura (2001) shows that in the last 40 years, intangible assets as a proportion of US GDP have more than doubled, increasing from 4.4% to 10%, and in the year 2000, intangible assets represented almost one-third of US corporate assets. At the firm level, Hulten and Hao (2008) show that for US firms, the value of total assets increases by 57% when R&D expenditure and intangible capital are considered in addition to conventional financial accounts. Similar trends have been shown to exist in other countries, such as Japan (Miyagawa and Kim, 2008), UK (Marrano and Haskel, 2006), Finland (Jalava et al., 2007), the Netherlands (van Rooijen-Horsten et al., 2008) and Italy (Bontempi and Mairesse, 2008).

In addition to the quantitative dimension of intangible assets, various works have also stressed a link between intangible assets and firm performance. Marrocu et al. (2012), Oliner et al. (2007) and O'Mahony and Vecchi (2009), for example, find a positive contribution of intangible assets to both firm- and industry-level productivity. Hall et al. (2005), Greenhalgh and Rogers (2006) and Sandner and Block (2011) show intangible assets to significantly contribute to market value. Denekamp (1995), Braunerhjelm (1996), and Delgado-Gómez and Ramirez-Alesón (2004) provide evidence for a positive relationship between intangible assets and internationalization.

In spite of this extensive, growing literature, however, little research has been so far conducted on the determinants of firms' investments in intangible assets. Although it is widely accepted that intangible assets are becoming a critical source of competitive advantage (Barney, 1991), few empirical studies have actually investigated the factors that may lead firms to undertake this type of technological investment in the first place. In the majority of cases, on the contrary, the level of intangible assets has been taken as given and treated more as an explanatory variable rather than as a variable to be explained.

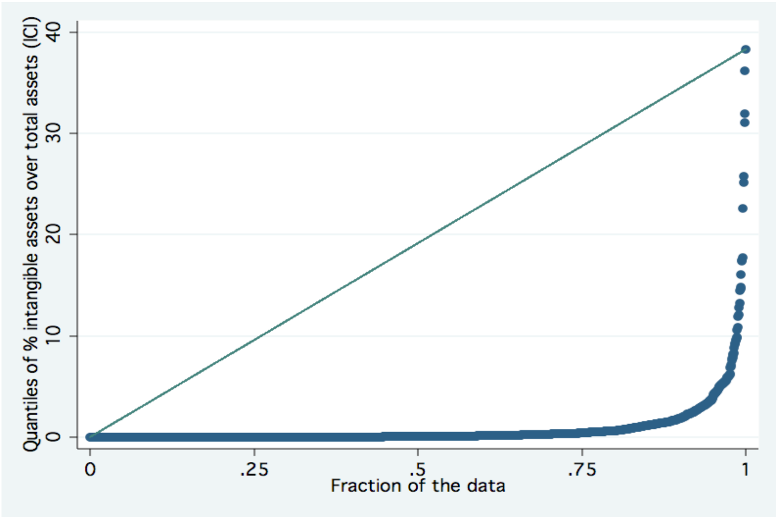
From the point of view of both managers and policy makers, however, gaining a clear understanding of what determines firms' propensity to invest in intangible assets can be of crucial importance, especially if it helps to identify the variables that discriminate between high- and low-performing firms. Moreover, such a perspective is interesting for research in that it may offer a test for alternative theories of the firm. For these reasons, this chapter will take some first steps in filling such a gap.

The first striking evidence that emerges from the data is that, at least for the Italian manufacturing sector, intangible asset investments appear to vary considerably across firms. On this subject, Panel A of Figure 4.1 reports the quantile distribution of intangible assets as a proportion of total assets in 2008 for the sample of Italian manufacturing firms included in our dataset. The value of both intangible and total assets is derived from the firms' disaggregated balance sheets (see Section 4.3). On average, intangible assets account for only 0.8% of total assets. A more detailed analysis, however, reveals that there exists high heterogeneity in the population of firms. The median of this ratio, in fact, is barely above 0%, and for over 75% of the firms, intangible assets count for less than 1% of total assets. Meanwhile, the top decile of firms invests significantly in intangible assets, which represent 2% to 38% of total assets among these firms.

The evidence resulting from Panel A of Figure 4.1 is even more interesting if one considers that the observed heterogeneity in intangible asset investments remains high even within industries. To this end, Panel B reports the quantile distribution of the same variable reported in Panel A after normalizing the ratio by the sample (right) and the industry mean (left). In particular, the Eurostat NACE Rev. 1 classification (NACE) has been used for the industry. The shape of the distribution clearly remains practically unchanged between the two cases, with the top decile of firms investing in intangible assets 3 to 60 times more than their industry average. Such a distribution clearly reveals that there exists a degree of heterogeneity that extends well beyond what could be reasonably explained by inter-industry structural differences alone. The main aim of the present chapter is thus to investigate the factors that, in addition to industry differences, can effectively explain this heterogeneity.

In line with the capability-based view of the firm, we argue that the heterogeneity in intangible asset investments ought to be studied by focusing on firm-specific traits, such as size, organizational structure, human capital, and the historical intangible asset base. In this sense, we see the firm's propensity to invest in intangible assets more as a product of the unique bundle of resources and capabilities that the firm has evolved over time than as a consequence of exogenous technological contingencies. Intangible assets, in fact, represent a form

Panel A: Non-normalized ratio intangible assets over total assets



Panel B: Normalized ratio intangible assets over total assets, sample and industry mean

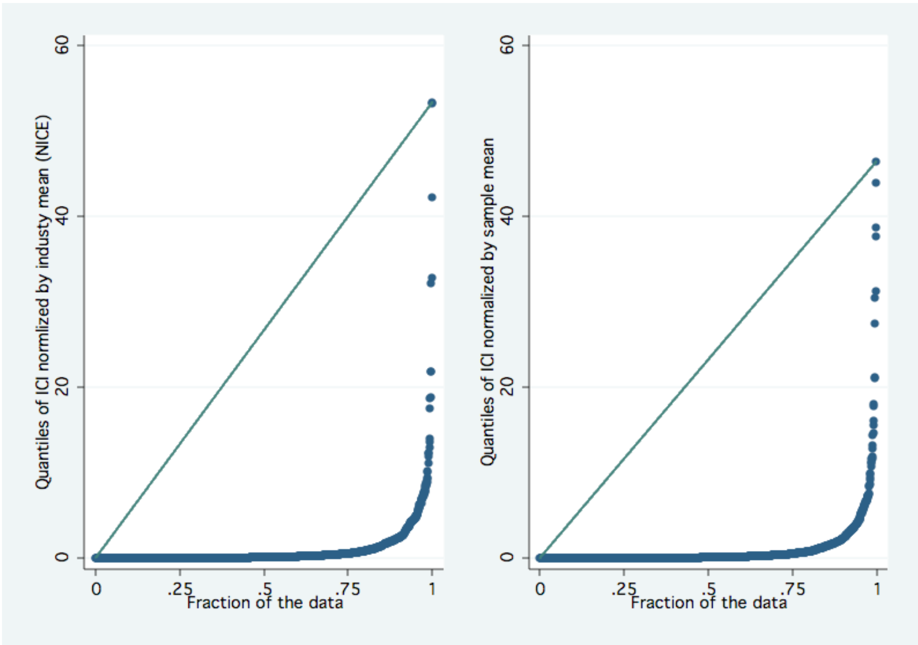


Figure 4.1: Quantile distribution of the ratio intangible assets over total assets. Panel A reports the quantile distribution of the ratio intangible assets over total assets for the sample of firms included in our dataset. Panel B reports the quantile distribution of the same variable after normalizing the ratio by the sample (right) and industry (left) mean. Notice: the shape of the distribution does not change.

of technological investment that (a) requires a certain set of internal resources to be carefully identified, planned, and managed and (b) may be made to address needs that are purely organizational in nature (e.g., to facilitate the management of a complex organization). Among firms that lack such internal resources or have internal structures that do not require this type of specific investment, intangible assets are less likely to be included in the firm's business strategy and thus are less likely to be accumulated. Moreover, for a given distribution of intangible assets in the population of firms, the existence of complementarities among different components of the intangible stock may generate a sustained process of accumulation, leading to the permanence of heterogeneity over time. Making use of a rich dataset in terms of firm-specific characteristics, we test and provide support for our hypotheses.

Overall, the chapter contributes to the previous literature on intangible assets and industrial dynamics in two ways. First, it highlights the existence of great heterogeneity in intangible asset investments. This dimension of the problem has so far received little attention in the literature, and it has certainly not been documented with respect to the Italian manufacturing sector. Second, the chapter utilizes the capability-based view to suggest an explanation for the firm's propensity to invest in intangible assets and provides an empirical test of this hypothesis. In this way, the chapter can make sense of the observed heterogeneity and offer some insights for managerial policy design as well. Overall, the results of the chapter can open new and interesting lines of research.

The structure of the chapter is as follows. Section 4.2 presents a brief overview of the literature on firm heterogeneity and intangible assets and introduces our hypotheses. Section 4.3 describes the dataset and the variables included in our models. Section 4.4 discusses the empirical strategy employed in the estimation. Section 4.5 presents and discusses the results. Section 4.6 lists several robustness checks. Finally, Section 4.7 concludes.

4.2 Literature review and hypotheses

On this topic, the business and management literature has largely focused on the relative effect of intangible assets on economic performance (Bontempi and Mairesse, 2008; Marrocu et al., 2012; Corrado et al., 2006; Oliner et al., 2007). Meanwhile, contributions concerning the factors influencing the level of intangible assets accumulated by the firm are relatively rare.

Among organizational and business scholars, the factor that has received the widest attention for its effect on the firm's propensity to invest in intangible resources is surely the firm's industry. Because the intensity and appropriability of innovation differ significantly across industries (Cockburn and Griliches, 1988), firms face different incentives for the development and formalization of intangible assets. Given a different market structure, use of technology or regulatory environment, firms may consider it appropriate to invest different amounts of resources in innovation and in its protection. On this basis, industry-related variables are expected to explain most of the variability of intangible asset accumulation (Daley, 2001; Villalonga, 2004). Gu and Lev (2001), for instance, show that the level and growth rate of intangible assets differ across industries, with the highest levels found in insurance, drugs, and telecommunications and the lowest in trucking and wholesale trade. Similarly, Klock and Megna (2000) show that in more innovative industries, the market value of the firm, capturing the importance of intangible assets, is markedly higher than book value, whereas in traditional industries, the difference between the two variables turns out to be modest. Similar findings are discussed in Gleason and Klock (2006), Ballardini et al. (2005) and Abowd et al. (2005). In addition, Vergauwen et al. (2007) maintain that non-traditional industries have a greater incentive to disclose more information about intangibles because investors expect continuous investments in R&D and intangible projects. In contrast, firms in traditional industries tend to invest less and more randomly in immaterial assets and are less prone to reveal their investments because such expenditures may signal to competitors that these firms are pursuing innovative strategies.

As previously underlined and shown in Figure 4.1, however, the available evidence for Italy suggests that industries can explain only a small proportion of the distribution of intangible asset investments. Even at the industry level, in fact, manufacturing firms tend to be largely heterogeneous in their level of accumulated intangible assets. In this sense, factors other than the industry must play important roles. Our main aim is thus to identify these other factors.

A stream of literature that has placed particular attention on the sources of inter-firms heterogeneity is the one associated with the so-called capability-based theory of the firm (Dosi et al., 2000). Such an approach, which significantly overlaps with another well-known theory among management scholars, the resource-based view (Barney, 1991, 2001), defines capabilities as firm's specific "ways of doing" and stresses heterogeneity as the distinctive feature of business organizations (Dosi et al., 2006). Although a thoughtful discussion of this theory goes beyond the scope of this chapter (for this we refer to Dosi et al., 2000), it suffices to note that according to this view, the firm's decisions are determined mainly by the capabilities that the firm has evolved over time and only marginally by exogenous technological contingencies. On this basis, the explanation of a given firm's behavioral path must rely on the interaction between firm-specific and system-specific (e.g., industry-related) factors and admit an explicit dynamics of capability accumulation (Dosi et al., 2006).

The adoption of a capability-based approach in the study of intangible asset investments prompts us to focus on a set of firm-specific traits that, in interaction with external factors, can explain the firm's propensity to undertake this type of technological investment. On this basis, we choose to focus on four variables in particular: size, human capital, organizational complexity, and accumulated intangible asset base. These variables' role in the firm's decision to invest in intangible assets will be analyzed separately.

4.2.1 Size

Size is a trait that, regardless of the industry in which the firm operates, is likely to have a positive impact on the propensity to invest in intangible assets. In the first place, large firms are better able than small ones to exploit economies of scale in intangible asset accumulation (Dierickx and Cool, 1989). Secondly, large firms can be more effective in protecting their intangible stock than small ones and thus have a greater incentive to invest. Thirdly, it may be argued that large firms are also capable of supporting a greater share of the uncertainty that is associated with intangible asset investments compared to small firms (Ghosal and Loungani, 2000). On this basis, the first hypothesis that we put forward is the following:

Hypothesis 1 - *A larger firm has a greater probability of investing in intangible assets.*

4.2.2 Human capital

In addition to size, another trait that is likely to affect the propensity to invest in intangible assets is the firm's human capital. Several authors have indeed suggested that the quality of the human resources employed by firms is a basic condition both for generating intangible assets and their economic exploitation (Abramovitz and David, 2000; Galor and Moav, 2004). In this framework, human capital is made up of not only the formal education received by the workforce before hiring but also formal and informal on-the-job training (Barney, 1991; Nerdrum and Erikson, 2001). It represents the collection of skills and abilities that are embedded in the members of the organization (Bontis and Fitz-enz, 2002) and can be leveraged to expand intangible resources at the firm level. In this sense, therefore, we should expect a firm that is endowed with a highly educated workforce to have the managerial and innovative capabilities necessary to extend its intangible asset base.

As noticed by Abowd et al. (2005), however, human capital in the form of workforce education is not the only driver of the accumulation of intangible resources. Instead, it is how human capital is organized that explains the variance of productivity and the endowment of intangible assets. The way workers are organized, together with the quality of human resources, yield complementarities that may facilitate the generation of innovation and in turn create incentives for the accumulation of intangible assets. An example of an organizational variable that could reflect such complementarities is the amount of human resources effectively employed in direct R&D activities (Liu et al., 2000). In the language of the capability-based view, the latter is synonymous with the adoption of routines and procedures that facilitate the exploitation of external sources of knowledge (Cohen and Levinthal, 1990; Dosi, 1988) and thus support the process of intangible asset accumulation. In this respect, some supporting evidence comes from Lu et al. (2010), who find R&D expenses to positively impact the firm's intangible assets with predictably positive effects on future cash flow and firm value.

Based on the above arguments, and considering workforce education and R&D activities as different proxies of a firm's human capital, we formulate our second hypothesis as follows:

Hypothesis 2 - *A firm with more human capital has a greater probability of investing in intangible assets.*

4.2.3 Organizational complexity

Like human capital and size, the degree of organizational complexity is another firm-specific trait that can affect the process of intangible assets accumulation.[2] According to some authors, the firm's intangible stock includes assets that directly increase what has come to be known as the firm's organization capital - see Kaplan and Norton (2004), Lev and Radhakrishnan (2003) and Bontis (2001), among others. Organizational capital, in the seminal contribution by Prescott and Visscher (1980), is defined as the set of information assets that the firm uses to coordinate the material factors of production, namely, physical capital and labor. Additional managerial definitions have recently been formulated, such as those by Lev and Radhakrishnan (2003), Hsu (2007) and Atkeson and Kehoe (2005). Under all the alternative specifications, a direct link between the complexity of the firm's internal organization and the accumulation of organization capital - and thus intangible assets - seems to emerge. Piekkola (2009), for instance, argues that globalized firms use more organiza-

[2] Organizational complexity has been defined and measured in different ways. In this chapter, we will follow Damanpour (1996) and define it as the degree of variety in the organization's spatial, occupational, hierarchical and functional dimensions (Hall, 1977; Miller and Contay, 1980).

tion capital. A higher number of employees in the firm that are working abroad entails a greater amount of organization capital that is needed to monitor the relationships between different production units and markets. A similar relationship has been identified by Denekamp (1995) and Braunerhjelm (1996) with respect to the need to manage a variety of foreign direct investments (FDI) and by Bartel (2007) and Brynjolfsson et al. (2002) with respect to the need to complement the enhancement of ICT with parallel extensions of organizational resources. Concerning the dynamics of vertical integration, the results obtained by González-Díaz et al. (2000) suggest the existence of a positive relationship between the degree of vertical disintegration and the amount of organizational capital accumulated by subcontractors as a way to cope with increasingly complex market transactions.

From a slightly different perspective, other authors have stressed the role that competition and the pace of technological progress play in shaping the firm's internal complexity and thus the accumulation of intangible resources. The sharpening of competition in the markets, in fact, leads firms to consolidate resources focused on protecting against imitation and updating the most firm-specific internal assets. This entails the extension of managerial resources and an increase in their complexity. Petrick and Scherer (1999), for instance, show that as the speed of comparable tangible asset acquisition and the pace of imitation accelerate, firms resort to less imitable intangible assets to enhance their distinctive know-how and product differentiation. Therefore, a firm that has a complex relationship with the market is likely to invest more in intangibles.

From the association between intangible assets and organization capital and by relying on the above arguments on the relationship between complexity and organizational resources, we deduce the following:

Hypothesis 3 - *A firm with more organizational complexity has a greater probability of investing in intangible assets.*

4.2.4 Cumulative dynamics

Finally, considering the issue of intangible asset investments from a dynamic perspective, a crucial role may also be played by the previously accumulated stock of intangible assets. In this respect, several features of the process of intangible asset accumulation can be important.

First of all, intangible assets consist of knowledge, which is cumulative by nature. Within the context of the resource-based view, for instance, Dierickx and Cool (1989) define two main features that seem to distinguish intangible asset accumulation from physical capital accumulation: asset mass efficiency, i.e., economies of scale in the generation of the intangible asset base from the existing asset stock, and time compression diseconomies, i.e., diminishing returns to current-period investments in intangible assets. As argued by Knott et al. (2003), asset mass efficiency implies that a greater level of intangible assets is associated with a lower marginal cost of investing in the further extension of the asset stock. The reason could be the existence of what Teece (1986) calls the interconnectedness of asset stocks, i.e., complementarities among the different components of the knowledge stock. Time compression diseconomies imply instead that intangible asset accumulation cannot be rushed. 'Even if an entrant invests in one year the total sum of the incumbent investments made over several years, it won't achieve the same resource position' (Knott et al., 2003, p.192). The combination of these two factors leads to the inevitable emergence of divergent paths of intangible assets accumulation, where firms investing more (less) in the past tend to invest more (less) in the future.

Moving from the structural characteristics of intangible assets to the specific features of the firm's behavior, a similar argument for the existence of a cumulative dynamics can be formulated by relying on the idea of organizational learning (see Dosi et al., 2006). In a nutshell, the idea of organizational learning suggests that when a firm adjusts its internal organization to (a) search the knowledge landscape and (b) invest in a particular type of asset, the firm learns a set of capabilities. These capabilities are likely to generate a relative advantage in pursuing investments in similar and related assets compared to competitors that did not invest in the first place. As a result, the set of intangible resources accumulated in the firm at any given point in time largely becomes a function of the previously accumulated set of resources. Highly persistent intangible asset accumulation is then the most likely consequence.

Based on these arguments and independently of the factors that have the strongest power in explaining the cumulative path, our fourth and final hypothesis is thus the following:

Hypothesis 4 - *A firm with a larger intangible asset base has a greater probability of investing in intangible assets.*

4.3 Data, variables and descriptive statistics

To test the hypotheses defined in the previous section, we use a joint dataset retrieved from two main sources. The first source is the IX wave of Capitalia's Survey on Manufacturing Firms, which covers the period 2001-2003. The dataset contains qualitative and quantitative information for a large stratified sample of Italian firms. In particular, it gathers a wealth of information on the structure of the workforce and on governance; information on innovation, distinguishing between product, process and organizational innovation; and information on investments and R&D expenditures. The second source is the AIDA-Bureau van Dick database, which contains all Italian firms' disaggregated balance sheet information for the period 2001-2008. After combining these two sources, the final dataset contains nearly 1,500 observations. The representativeness of the original sample is maintained in terms of firm size and industry.

In the literature, there are several possible ways of measuring intangible assets. In particular, two main approaches have been pursued: the first is based on estimates derived from firm expenditures on "intangibles" such as R&D, training and innovation, and the second uses direct measures based on stocks originally reported as assets on companies' balance sheets. For a discussion on the relative suitability of these two approaches within the framework of Italian legislation, we refer to Bontempi and Mairesse (2008). In this chapter, we choose to adopt a balance sheet-type of measure and to consider, in particular, a subset of the costs usually reported under the item "intangible fixed assets", i.e., the "costs for research and advertisement", the "costs of patents" and the "costs of licensing". In doing so, we differ from some previous contributions based on similar data (e.g., Marrocu et al., 2012) that instead consider the aggregate value "intangible fixed assets". We make this choice because the item "intangible fixed assets" also includes expenditures such as start-up/goodwill costs, whose capitalization is highly subject to managers' discretion and thus is difficult to interpret. On the contrary, the items that we consider in our measure should be objective expenses incurred by the firms.

Based on this measure of intangible assets, we define a firm's intangible capital intensity (ICI) as the percentage of intangible assets over total assets. At any given point in time, ICI_i represents the amount of intangible assets accumulated by firm i and can be considered a proxy of is propensity to invest in intangible assets. ICI is the crucial variable of our analysis. In particular, for the firms in our sample, we want to understand which factors can explain the probability of being an intangible-capital-intensive firm ($ICIF$), where the latter is defined as a firm that belongs to the top decile of the ICI distribution.

Following the discussion presented in Section 4.2, we focus our attention on two main types of explanatory variables. First, we consider systemic variables, such as the industry in which the firm operates. The main classification that we adopt is the NACE (see Appendix). In the empirical strategy, to fully capture the observed heterogeneity, we choose to control for industry-related effects through a normalization of the dependent variable by the industry mean (see Section 4.4).

The second type of explanatory variables that we consider includes firm-specific characteristics, with particular attention being paid to size, human capital, organizational complexity and the degree of intangible capital accumulated in the past. A set of proxies is chosen for each of these dimensions.

As a proxy for size, we consider the total number of employees ($SIZE$). In particular, to control for non-linearities, we classified firms as small ($SIZE \leq 50$), medium ($50 < SIZE \leq 100$) and medium-large / large ($SIZE > 100$) according to their size. For each of these groups, we then consider an apposite set of dummy variables (D_SIZE_S, D_SIZE_M, D_SIZE_L).

We consider as a proxy for human capital a combination of two distinct variables: the first is a synthetic index elaborated with a factorial analysis (FCT_EDU) using as inputs the ratio between "white collars" and "blue collars" ($STAFFRATIO$), the workforce's average number of years of education ($AVEDU$) and the percentage of employees holding a university degree ($UNIDEG$); the second variable measures the percentage of employees engaged in R&D (*R&D*). The rationale behind this specification is that in our view, FCT_EDU and *R&D* capture two distinct effects of human capital.[3] On the one hand, FCT_EDU is a proxy for a firm's capability to manage knowledge-intensive assets. On the other hand, *R&D* captures the firm's propensity to engage its human resources in intangible stock-expanding activities, including the evaluation, assimilation and application of new knowledge. As argued in Section 4.2, the literature has treated each of these dimensions of human capital as a relevant component of the process of intangible asset accumulation.

For the degree of organizational complexity, we create a synthetic index based on a scale going from 0 for minimum complexity to 4 for maximum complexity ($COMPLEX$). The index captures two distinct features of the firm: the extent to which the firm does business as a subcontractor and the degree of the firm's internationalization. The idea in this case is that a firm that is more internationalized and operates more as a subcontractor will have a more diversified and flexible structure and thus have a more complex organization. In particular, the index is built on four distinct variables: the percentage of turnover due to subcontracting ($SUBCT$), the portion of turnover due to subcontracting that is earned abroad ($SUBCT\_ABD$), a dummy taking the value 1 if the firm faces international competitors ($D\_INTCOMP$), and a dummy taking the value 1 if the firm has made investments abroad (D_FDI).[4]

Finally, for a proxy for the degree of accumulated intangible capital, we consider a dummy taking the value 1 if the firm belongs to the fourth quartile of the 5-year lagged value of ICI (ICI_PAST) and zero otherwise (D_ICI_PAST).

[3] Our view is also confirmed by the empirical evidence. In fact, the factorial analysis that we conducted to compute FCT_EDU revealed *R&D* to contain a different set of information with respect to $STAFFRATIO$, $AVEDU$ and $UNIDEG$.

[4] For a complete description of how the index is constructed see Appendix 4.

	All firms			ICIFs			non-ICIF		
	N.	Mean	StDv.	N.	Mean	StDv.	N.	Mean	StDv.
ICI:	1343	0.8	2.8	135	6.2	6.6	1208	0.2	0.4
ICI_PAST	1343	0.7	2.0	135	3.1	4.7	1208	0.4	1.1
UNIDEG	1343	0.1	0.1	135	0.1	0.1	1208	0.1	0.1
STAFFRATIO	1331	0.7	2.2	133	0.9	2.0	1198	0.7	2.3
AVEDU	1343	10.4	1.4	135	10.8	1.4	1208	10.3	1.4
R&D (employm.)	1343	0.0	0.1	135	0.1	0.1	1208	0.0	0.1
AGE	1343	36.4	19.3	135	37.6	19.6	1208	36.3	19.3
SIZE (employm.)	1343	108.9	392.0	135	222.7	1037.3	1208	96.2	223.1
COMPLEX (index)	1343	0.5	0.8	135	0.7	0.9	1208	0.5	0.7
ICT_INV	1343	3.0	9.8	135	4.1	6.8	1208	2.9	10.0
LAB_PRDTY	1343	55.9	28.4	135	54.8	28.2	1208	56.0	28.4
PROFIT	1343	0.1	0.1	135	0.1	0.1	1208	0.1	0.1
ACID	1343	0.1	0.1	135	0.1	0.1	1208	0.1	0.1

Table 4.1: Descriptive statistics. For a complete list and description of the variables see Appendix 4.

In this case, because we are interested in the impact of the past level of intangible assets in absolute terms, the non-normalized value of ICI is considered.

Table 4.1 reports some descriptive statistics relative to our dataset. Indexes are differentiated between $ICIF$s and the whole sample. Apart from ICI, which is evaluated at 2008, all of the other variables are evaluated over the three-year period of 2001-2003. When looking at the whole sample, it is interesting to notice the high standard deviation associated with variables such as $SIZE$, the various proxies of human capital ($UNIDEG$, $STAFFRATIO$, $AVEDU$) and intangible capital intensity (ICI, ICI_PAST). This is symptom of a high degree of heterogeneity in the population along several firm-specific demographic dimensions. Regarding the sub-sample of $ICIF$s, we can observe that compared to non-$ICIF$s, they are larger and more complex on average and have a greater endowment of human capital. In addition, $ICIF$s have a level of previously accumulated intangible assets that is nearly eight times that of non-$ICIF$s. This points towards persistence in intangible asset investments.

The propensity of firms to maintain a level of intangible asset investments that is closely related to the level realized in the past is also confirmed by Table 4.2. In this case, we reported in Panel A the distribution of firms across four classes of ICI - *null* ($= 0$), *low* (> 0 and $< 1\%$), *medium* ($\leq 1\%$ and $< 5\%$) and *high* ($> 5\%$) - for the year 2008 (columns) and the average 2001-2003 (rows).

Panel A: distribution of firms across classes

		Classes 2008				
		Null	**Low**	**Medium**	**High**	**Total**
Classes	**Null**	197	75	11	2	285
2001-2003	**Low**	128	638	81	19	866
	Medium	9	68	63	11	151
	High	6	2	13	20	41
	Total	340	783	168	52	1343

Panel B: transition probabilities across classes

		Classes 2008				
		Null	**Low**	**Medium**	**High**	**Total**
Classes	**Null**	0.69	0.26	0.04	0.01	1.00
2001-2003	**Low**	0.15	0.74	0.09	0.02	1.00
	Medium	0.06	0.45	0.42	0.07	1.00
	High	0.15	0.05	0.32	0.49	1.00

Table 4.2: Intangible assets persistence. We consider four distinct classes of the ratio intangible assets over total assets: null (= 0), low (> 0 and < 1%), medium (>= 1% and < 5%) and high (> 5%). Panel A reports the number of firms who were in the jth class in period 2001-2003 (rows), and in the ith class in 2008 (columns). Panel B reports the transition probabilities across classes.

On this basis, we computed in Panel B the transition probabilities by simply averaging the content of each cell over the total of the row. The result, for instance, reads that a firm belonging to the null class in 2001-2003 had a 69% chance of belonging to the same class in 2008. We notice that those with the highest probabilities are the ones on the main diagonal. Moreover, the average probability below the main diagonal is greater than the average probability above it, which in turn implies that if a process of movement across classes had existed it tended to take place from high to low classes and not the reverse. Coupled with the general increase in the level of intangible capital intensity from 2001-2003 to 2008 (as shown in Table 4.1), the latter result indicates that heterogeneity not only was present among the population of firms from the very beginning but also has polarized over the past decade. The identification of the factors that could explain this increased polarization is the main objective of our empirical investigation.

4.4 Empirical strategy

The model that we want to estimate takes the following form:

$$ICI_i = f(IND_i, XF_i, XC_i, \epsilon_i), \epsilon_i \sim N(0, \sigma^2), \tag{4.1}$$

where IND_i stands for the industry in which firm i operates; XF_i is a vector of firm-specific characteristics, including $SIZE_i$, FCT_EDU_i, $R\&D_i$, $COMPLEX_i$ and $D\_ICI\_PAST_i$; XC_i is the vector of control variables; and ϵ_i is the vector of errors.

The key issue affecting the estimation of model (4.1) is the censored nature of ICI. As argued above, this occurs because a large proportion of the firms included in our sample do not invest in intangible assets at all. In such a context, the application of standard OLS would generate biased estimates, with the magnitude of the bias being linked to the proportion of non-censored observations in the sample. To avoid this problem, we use an alternative estimation technique based on a probit specification. Moreover, to investigate the role that different variables may play at different points of the distribution of ICI, we also estimate the same model through a set of quantile regressions (Koenker and Basset, 1978). The combination of these two techniques should give us sufficient confidence in interpreting the results.

In the probit specification, we follow three steps. First, for each firm, we normalize the value of ICI by the mean value of the industry in which the firm operates. In this way, we can eliminate all sorts of industry-related effects from the distribution of ICI. We call this new industry-normalized variable $\underline{ICI}$.

Secondly, we classified as $\underline{ICIF}$ all of the firms belonging to the 10th decile of $\underline{ICI}$. Finally, we transformed our dependent variable into a dichotomic variable that takes the value 1 if the firm is $\underline{ICIF}$ and zero otherwise ($\underline{ICIF}_i$). All of the other variables remain the same as in model (1), with the exception of IND_i, which will obviously disappear from the right-hand side of the equation. The idea in this case is to estimate the probability of a firm being intangible-capital intensive relative to the industry mean, given a set of firm-specific characteristics. The baseline equation to be estimated thus becomes

$$Pr\left[\underline{ICIF} = 1\right] = \Phi(XF_i'\beta_F + XC_i'\beta_C), \tag{4.2}$$

where $\Phi(.)$ is the cumulative distribution function for the standard normal, and β_F and β_C are the vectors of parameters to be estimated. The parameters of model (4.2) are estimated via maximum likelihood (ML) estimation.

We also conjecture that the different variables included in our baseline model may play different roles as determinants of ICI depending on the point of the distribution that we consider. For instance, it could be the case that firms at the very top of the distribution (i.e., the highly intangible-capital-intensive firms) are following a strategic pattern according to which the stock of intangible assets must be constantly renewed and updated (e.g., because its accumulation requires highly specific investments by the firms). On the contrary, firms at the bottom may simply be engaging in intermittent investment, where intangible assets are accumulated for limited periods of time and bought directly on the market. If this is the case, we should then expect the different components of human capital - i.e., R&D and workforce education, to change their relative impact along the distribution, with R&D being more relevant at the top (as a source of intangible asset extension) and workforce education at the bottom (as a source of intangible asset application).

To test for these different types of effects, we estimate a set of quantile regressions. An important advantage of this method is that it reveals differences in the relationship between the dependent and independent variables at different points of the conditional distribution of the dependent variable (see Koenker and Basset, 1978). Additionally, we control here for the industry through the normalization of ICI by the industry mean. The quantile regression model that we estimate can thus be written as follows (see Coad and Rao, 2008):

$$\underline{ICI}_i = X_i'\beta_\theta + u_{\theta i} \quad with \quad Quant_\theta(\overline{ICI}_i|X_i) = X_i'\beta_\theta, \tag{4.3}$$

where $X_i = (XF_i, XC_i)$ is the vector of regressors, $\beta = (\beta_F, \beta_C)$ is the vector of parameters to be estimated, and u is a vector of residuals. $Quant_\theta(.)$ denotes the θ^{th} conditional quantile of $\underline{ICI}_i$ given X_i. The θ^{th} regression quantile, $0 < \theta < 1$, solves the following problem:

$$\min_{\beta} \frac{1}{n} \left\{ \sum_{i:\overline{ICI}_i \geq X_i'\beta} \theta|\overline{ICI}_i - X_i'\beta| + \sum_{i:\overline{ICI}_i < X_i'\beta} (1-\theta)|\overline{ICI}_i - X_i'\beta| \right\} =$$
$$= \min_{\beta} \frac{1}{n} \sum_{i=1}^{n} \rho_\theta(u_{\theta i}), \tag{4.4}$$

where $\rho_\theta(.)$, which is known as the 'check function', is defined as

$$\rho_\theta(u_{\theta i}) = \begin{cases} \theta u_{\theta i}, & \text{if } u_{\theta i} \geq 0 \\ (\theta - 1)\theta u_{\theta i}, & \text{if } u_{\theta i} < 0 \end{cases} \tag{4.5}$$

The solution of this minimization problem gives OLS estimates that approximate the θ^{th} conditional quantile of the dependent variable rather than the conditional mean. The model coefficients are therefore allowed to vary across quantiles of the conditional distribution of ICI, giving us the possibility to test the performance of our explanatory variables at different points of ICI.

In each of these estimation methods, there are two additional issues we need to tackle: multicollinearity and endogeneity. With the former, it is interesting to notice that in spite of what one would expect, the degree of correlations among most of our regressors is relatively low. Table 4.3 reports the correlation matrix for all of the variables included in XF and for some of the controls. With the exclusion of the three variables that we use to compute the synthetic index for human capital ($UNIDEG$, $STAFFRATIO$, $AVEDU$), all other significant correlations have a coefficient smaller than 0.30. Interestingly, $SIZE$ seems to be correlated only with AGE and with a very low coefficient in that case (0.06). On this basis, we can conclude that although some degree of multicollinearity exists, the latter does not represent a severe issue in our estimates.

The issue of endogeneity is more complicated. Given our specification of XF_i, in fact, a certain degree of correlation between some of the regressors and the error term could emerge for two main reasons: simultaneity, e.g., the amount of human capital available in the firm is jointly determined with the investments in intangible assets; and omitted variables, where, e.g., human capital affects investments in intangible assets through some unobservable effect that we have not included in the model. Both reasons are stringent and need to be dealt with directly.

The first option that we could exploit is to rely on an instrumental variables

	UNIDEG	STAFF RATIO	AVEDU	R&D	AGE	SIZE	COMPLEX	ICI_ PAST
UNIDEG	1.00							
STAFFRATIO	0.32*	1.00						
AVEDU	0.60*	0.32*	1.00					
R&D	0.18*	0.06*	0.18*	1.00				
AGE	0.00	-0.04	-0.07*	0.00	1.00			
SIZE	0.05	0.00	0.01	0.01	0.06*	1.00		
COMPLEX	-0.05	-0.04	-0.04	0.04	-0.04	-0.02	1.00	
ICI_PAST	0.13*	0.03	0.10*	0.08*	-0.01	0.03	-0.01	1.00

Table 4.3: Correlation matrix. Legend: *= sig. 5%.

approach. In our case, however, this approach is difficult to implement because of the correlations that exist among many of the regressors that are most likely to be effectively endogenous with respect to ICI, e.g., FCT_EDU and $R\&D$. Given the lack of a clear understanding of how decisions are made within each individual firm, in fact, the likelihood of finding a viable instrument is low.

As an alternative solution - and this is the key methodological feature of our empirical strategy - we choose to exploit what is likely to be the main strength of our dataset: the detailed information it offers for a relatively large number of firms and years. In particular, we adopt two strategies. First, to deal with simultaneity, we evaluate the dependent variable of each model at 2008 and the independent variable at 2003 (for some of the latter, we also consider the average for the three-year period 2001-2003) so that there exists a lag of at least five years between them and the regressors. This duration makes it difficult (at least in principle) for the dependent variables and the regressors to be simultaneously determined and thus reduces the risk of inconsistent estimates.

To address the omitted variable issue, the second strategy that we adopt is to saturate the third group of regressors (XC_i) with as many variables as we can in order to control for any kind of firm-specific fixed effects. Because our concern is especially related to FCT_EDU and $R\&D$, we focus our attention on variables that could be correlated with human capital and the propensity to invest in $R\&D$, including age (AGE), investments in ICT (ICT_INV), and labor productivity, measured in terms of added value per employee (LAB_PRDTY). In addition, we included a series of firm-specific accounting indexes such as the $ACID$ test (short-term liquidities / total assets) and the profitability or gross earnings over total turnover ($PROFIT$). Finally, we additionally controlled for geography-related effects with the introduction of regional dummies. This solution, together with the rather detailed specification of vector XF_i, should reduce the likelihood of omitted variable bias, even though some care must be taken in interpreting the coefficients, especially for the proxies of human capital.

	Probit_1	Probit_2	Probit_3	Probit_4
	b/se	b/se	b/se	b/se
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Regional Dummies	*Yes*	*Yes*	*Yes*	*Yes*
D_SIZE_M (d)	0.058**	0.039**	0.040**	0.037*
	-0.020	-0.020	-0.020	-0.020
D_SIZE_L (d)	0.061**	0.021	0.022	0.021
	-0.020	-0.020	-0.020	-0.020
D_ICI_PAST (d)		0.214***	0.198***	0.198***
		-0.030	-0.030	-0.030
FCT_EDU (index)			0.013	0.013
			-0.010	-0.010
R&D (employm.)			0.207***	0.195**
			-0.080	-0.080
COMPLEX (index)				0.015*
				-0.010
Obs	1331	1331	1331	1331
LogL	-412.891	-357.812	-352.585	-350.891
Chi2	39.149**	149.307***	159.761***	163.150***

Table 4.4: Determinants of intangible assets: Probit regressions, dependent variable $\underline{ICIF}$. Legend: ***= sig. 1%; **= sig. 5%; and *= sig. 10%; standard errors in parentheses; marginal effects are reported

4.5 Results and discussion

Table 4.4 reports the probit estimates for our model, translated into marginal and impact effects for the continuous and dummy variables, respectively. We add the regressors included in XF_i one at a time, estimating a total of four models (Probit_1 - Probit_4).

The first interesting result in the probit estimates concerns the two dummies for firm's size (D_SIZE_M and D_SIZE_L). Being a medium or large firm positively and significantly contributes to the probability of being $ICIF$ in the first model, when the two dummies are considered alone (i.e., Probit_1). However, as soon as the dummy associated with the past level of intangible capital intensity is included (D_ICI_PAST), only the dummy for medium-sized firms continues to be positive and significant. This result seems to suggest that although size matters on average, the positive effect of being large is overwhelmed beyond a threshold of firm size by the effect associated with previously accumulated intangible assets. From a theoretical point of view, this finding is interesting in that it suggests that for large firms, the existence of complementarities and/or learning dynamics in the process of intangible assets accumulation plays a more powerful role than size alone in explaining the propensity to invest.

For what concerns human capital the dimension that seems to be the best predictor of the probability of being $ICIF$ is the amount of human resources employed in direct R&D activities (*R&D*). The effect of R&D investments, in fact, is positive and significant in all the models in which the variable has been included (Probit_3 - Probit_4). On the contrary, no significant effect seems to be associated with the level of workforce education (FCT_EDU). However, as previously argued, this effect may depend on the particular segment of the overall distribution of ICI that the probit approximates (i.e., the top decile of firms).

In addition to size and R&D activities, the probability of being $ICIF$ in 2008 is also positively associated with the presence of high intangible capital intensity in 2001-2003 (D_ICI_PAST). The coefficient in this case is positive and significant in all the models. Interestingly, the size of the coefficient in the most complete model (Probit_4) is even greater than the one associated with R&D investment. Overall, this effect seems to confirm the evidence reported in Table 4.2 on the persistence of intangible asset investments.

Finally, in the last model (Probit_4), we also find a positive and significant effect of organizational complexity ($COMPLEX$). Although such an effect does not seem to be particularly strong in terms of significance level (10% confidence) and marginal impact, it is important to note that the effect holds after controlling for all the other independent variables included in our baseline model, such as human capital, size and historical ICI. This result lends credibility to our hypothesis, which posits that organizational complexity plays an independent role as a determinant of a firm's intangible capital intensity.

Similar results are obtained from the estimates of the quantile regressions. For the sake of simplicity, we report in Table 4.5 only the results for the 25^{th}, 75^{th} and 95^{th} percentiles, together with the median (50^{th} percentile). In this case, the impact of each variable can be investigated in greater detail.

First, we find that, even after controlling for the past level of intangible assets (D_ICI_PAST), the two dummies for medium-sized and large firms (D_SIZE_M and D_SIZE_L) are positive and significant for the entire distribution of $\underline{ICI}$, except for the 95^{th} percentile. This result provides further evidence that size actually matters. However, it also confirms the evidence from the probit that for firms with high investments in intangible assets, the scale effects associated with size are of fairly low importance.

Secondly, we obtain that, in line with size, the effect of human capital also changes according to the quantile considered. In particular, whereas the coefficient of the R&D component (*R&D*) is positive and significant in the central part and right tail of the distribution (median, 75^{th} and 95^{th} percentiles), the educational component (FCT_EDU) is positive and significant in the central

	Qreg_25	Qreg_50	Qreg_75	Qreg_95
	b/se	b/se	b/se	b/se
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Regional Dummies	*Yes*	*Yes*	*Yes*	*Yes*
D_SIZE_M (d)	0.0011**	0.0390***	0.1610***	0.144
	-0.001	-0.009	-0.050	-0.964
D_SIZE_L (d)	0.0058***	0.0597***	0.1645***	0.045
	-0.001	-0.010	-0.054	-1.030
D_ICI_PAST	0.1615***	0.6779***	2.1551***	6.3827***
	-0.001	-0.009	-0.049	-0.943
FCT_EDU (index)	0.0013***	0.0292***	0.0843***	0.628
	0.000	-0.006	-0.030	-0.637
R&D (employm.)	0.004	0.1285**	1.0090***	12.5485**
	-0.004	-0.055	-0.314	-5.350
COMPLEX (index)	0.000	0.006	0.039	0.445
	0.000	-0.005	-0.029	-0.533
Costant	-0.001	0.022	0.2076**	1.333
	-0.001	-0.016	-0.092	-1.736
Obs	1331	1331	1331	1331

Table 4.5: Quantile regressions, dependent variable $\underline{ICI}$. Legend: ***= sig. 1%; **= sig. 5%; and *= sig. 10%; standard errors in parentheses.

part and left tail (median, 25^{th} and 75^{th} percentiles). When compared to the probit, this result is interesting in that it confirms our hypothesis stating that the two components of human capital can play a different role for firms with different levels of intangible capital intensity.

The third result that we obtain from quantile regressions is a fairly strong effect of the dummy for the past level of intangible capital intensity (D_ICI_PAST). The coefficient associated with the latter is, in fact, always positive and significant, independently of the quantile that we approximate. This suggests, once again, that there exists path dependence in the process of accumulating intangible assets. If we also consider the outcomes of the probit estimates, this is certainly the most robust effect that we observe.

Finally, we find that for all proxies of size, human capital and historical intangible capital intensity, the marginal effects tend to increase further up the conditional distribution of $\underline{ICI}$. This seems to suggest the existence of increasing returns to scale in intangible asset investments. Moreover, it supports the idea that there is a general tendency towards increased polarization in the level of intangible capital intensity.

For the sake of completeness, it is also important to note that in the quantile regression, we do not find any significant effect associated with organizational complexity ($COMPLEX$).

Bringing together the results obtained from the probit and quantile regressions, we derive a fairly encouraging picture concerning the test of our theoretical hypotheses. First, in accordance with HP1, we find size to be a significant predictor of the firm's level of intangible capital intensity. The dummy for medium-sized firms is positive and significant in all of the estimated models, with the only exception of the quantile regression approximating the 95^{th} percentile. The dummy for large firms, on the contrary, is significant in the quantile regressions but not in the Probit. Overall, this result is due to the importance of scale effects in the process of accumulating intangible assets for the large majority of firms in our sample and the relative lack of importance of size for a set of highly intangible-capital-intensive firms. The latter represents a group of firms that, independently of the size and the industry in which they operate, have deliberately adopted a business strategy that entails a substantial investment in intangible assets.

With reference to HP2, i.e., the role of human capital, our main finding is that the different dimensions of human capital - i.e., workforce education and R&D - affect the propensity to invest in intangible assets in different ways, depending on the point that we consider in the conditional distribution of $\underline{ICI}$. This result could reflect the tendency of firms with different levels of intangible capital intensity to accumulate different types of intangible assets and thus rely on different components of human capital to procure them. In relative terms, both the Probit and the quantile regression estimates suggest that the strongest effect is the one associated with the amount of human resources involved in active R&D. Such a finding supports the importance of not only the quality of human resources but also their organization in accumulating intangible assets.

It is important to note that in all the estimated models, the different proxies of human capital are positive and significant when controlling for both industry and firm size. This finding confirms our view that human capital explains by itself part of the propensity to invest in intangible assets. In particular, the role of human capital seems to be particularly robust for firms for which size has no explanatory power, i.e., the sub-sample of firms in the 95^{th} percentile of ICI. For the latter, in fact, the amount of human resources involved in R&D is the regressor with the strongest marginal impact on the level of intangible capital intensity.

However, relatively weak empirical evidence is found in support of the third explanatory variable that we consider in our hypotheses, organizational complexity (HP3). Our proxy for organizational complexity turns out to be only weakly significant in the Probit and not at all significant in the quantile regression estimates. One of the reasons for this could be that with our index of complexity, we are capturing only two dimensions of the firm's organizational structure, i.e., history as a subcontractor and the degree of internationalization. The latter dimensions are likely to require relatively specific investments in organizational capital and thus are unable to offer a complete proxy for the firm's managerial needs. However, because our index turns out to be significant in some of the estimates, even in spite of such specificity, we do not reject HP3. In any case, further analysis is required on this issue.

Finally, for HP4, we find clear supporting evidence in favor of the existence of path dependency in the dynamics of intangible asset accumulation. The most robust finding that we obtain across all estimates is that the coefficient associated with the past level of intangible assets is positive and significant. This implies that firms with high intangible capital intensity at a given point in time tend to remain on the same technological trajectory, while others tend to diverge towards less knowledge-intensive types of production. The size of the coefficient, moreover, suggests that such divergent dynamics in technological trajectories are fairly strong and strengthen as we move up in the conditional distribution of $\underline{ICI}$. The latter result confirms the existence of an increased polarization in the level of intangible capital intensity. As argued in Section 4.2, the causal mechanisms underlying this trend could be related to (a) the existence of complementarities among knowledge assets and (b) a process of organizational learning. Although both factors could theoretically play a role, we are unable to distinguish between them based on our data.

4.6 Robustness checks

To increase the reliability of our results, we conduct a series of robustness checks (we report the results for the Probit only). First of all, in normalizing the dependent variable, we test alternative taxonomies for the industries, including the OECD (2009) and Pavitt (1984) classifications. In both cases, the results do not change (see columns (1) and (2) in Table 4.6). In fact, independently of the taxonomy that we adopt, firms remain highly heterogeneous so far as their level of intangible asset investments is concerned. Moreover, for all industry classifications, the proxies of size, human capital, organizational complexity and past levels of intangible capital intensity turn out to be the most significant regressors.

Secondly, as a further test of the role of the firm's industry, we also try a different empirical strategy in which we control for industry-related effects by adding an apposite set of dummy variables ($d\_s01 - d\_s12$)rather than normalizing. In this case, the results are also in line with our hypotheses. In all the

	(1) Pavitt	(2) OCSE	(3) d_Ind	(4) Size	(5) TFP	(6) Heck
	b/se	b/se	b/se	b/se	b/se	b/se
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Regional Dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
D_SIZE_MEDIUM (d)	0.035*	0.038**	0.034*		0.038**	0.043**
	(0.02)	(0.02)	(0.02)		(0.02)	(0.02)
D_SIZE_LARGE (d)	0.010	0.005	0.020		0.031	0.026
	(0.02)	(0.02)	(0.02)		(0.02)	(0.02)
L_SIZE (employm.)				0.008		
				(0.01)		
D_ICI_PAST (d)	0.209***	0.215***	0.197***	0.198***	0.196***	0.180***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
FCT_EDU (index)	0.014	0.013	0.018*	0.013	0.014	0.014
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R&D (employm.)	0.169**	0.158**	0.187**	0.202**	0.200***	0.137**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)
ORGCOMPLEX (index)	0.016*	0.017**	0.016**	0.016**	0.014*	0.012*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
d_s01 (d)			0.104			
			(0.11)			
d_s02 (d)			0.046			
			(0.08)			
d_s03 (d)			0.025			
			(0.08)			
d_s04 (d)			0.013			
			(0.07)			
d_s05 (d)			0.002			
			(0.07)			
d_s06 (d)			0.005			
			(0.06)			
d_s07 (d)			0.107			
			(0.11)			
d_s08 (d)			0.063			
			(0.11)			
d_s09 (d)			-0.008			
			(0.06)			
d_s10 (d)			0.223			
			(0.19)			
d_s11 (d)			0.110			
			(0.13)			
Obs	1331	1331	1331	1331	1325	1476
LogL	-349.89	-347.62	-332.18	-352.54	-344	-759.03
Chi2	165.147***	169.688***	200.564***	159.849***	171.266***	147.815***

Table 4.6: Robustness checks. Legend: ***= sig. 1%; **= sig. 5%; and *= sig. 10%; standard errors in parentheses.

estimated models, in fact, the type of industry - whether a macro category as in OECD (2009) and Pavitt (1984) or a micro sector as in NACE - does not significantly predict the firms' intangible capital intensity. On the contrary, size, human capital, organizational complexity and past levels of intangible capital intensity remain highly significant (see column (3) in Table 4.6).

Given the relevance that scale effects play in the literature on industrial dynamics, we also tested how our results react to a different specification of size. In particular, we estimated both the probit and the quantile regressions by substituting the dummy variables for medium-sized and large firms with the continuous measure. The results are in line with those reported in Table 4.4 and 4.5 with the effect of size that, in the Probit, tends to disappear when the model is fully specified (see column (4) in Table 4.6). This test lends further credibility to our interpretation.

Because several contributions have found a relatively strong effect of intangible assets on productivity (e.g., Marrocu et al., 2012; Oliner et al., 2007), we also try different measures of productivity in our vector of control variables. In particular, apart from the value added per employee, which we use in the estimates reported in Table 4.4 and 4.5, we estimate total factor productivity using the method developed by Levinsohn and Petrin (2003). However, the results do not change in this case (see column (5) in Table 4.6).

A final robustness check is related to possible sample selection bias. As discussed in Section 4.3, after combining the data retrieved the IX wave of the Capitalia's Survey and the AIDA-Bureau van Dick database, we obtain a final dataset of nearly 1,500 observations. However, it is only possible to obtain data on intangible assets for 1,331 firms that have a detailed balance sheet report. In fact, in this case, the item "intangible fixed assets" is actually detailed in sub-items, such as "costs for research and advertisement", the "costs of patents", and "costs of licensing." We attempted to control for this possible selection bias by applying a two-step Heckman procedure. First, a Probit estimate of selection from the whole sample (all firms in the original combined dataset) is made; second, a Probit estimate (in the case of the Probit_4 specification) for the selected sample of firms using the Inverse Mill's ratio obtained from the first step is used as a correction factor (Heckman, 1976). We do not find evidence of selection bias in our results (see column (6) in Table 4.6)

4.7 Conclusion

The results of our estimates tend to confirm our initial hypotheses. In particular, we find that size, human capital and the past level of intangible capital intensity significantly increase the probability of being $ICIF$. A similar outcome is obtained for the proxy of organizational complexity, although the evidence concerning the latter is weaker. All these results are obtained after controlling for industry-related effects.

Overall, these results suggest three main conclusions. First, it seems clear that firm-specific traits are important determinants of intangible asset investments. In our sample, what makes the difference between $ICIF$s and the other firms is the presence of a composite mix of internal resources (e.g., high human capital and accumulated intangible stock) that enable a firm to effectively absorb, manage and accumulate intangible resources. Secondly, there seems to exist a rather specific although weak relationship between the dynamics of intangible asset investment and the need to manage complex market transactions. In this sense, and as a way to complement the most standard interpretation, which is focused on the link with innovations, the choice of investing in intangible assets also appears to have a connection with the firm's organization. Finally, there is evidence of a strong cumulative effect among the determinants of intangible capital accumulation. Such an effect can be found to be responsible for generating a divergent dynamics in intangible asset investments and may thus explain a relevant part of the observed heterogeneity.

These conclusions open new, interesting research questions. First, it would be interesting to investigate how the propensity to invest in intangible assets evolves over time. In this respect, we believe that some of the variables included in our baseline model may still play an important role. Secondly, an analysis aimed at testing how firms with different degrees of intangible capital intensity react to exogenous shocks would be of value. In this sense, the recent economic crises may represent an interesting application.

4.8 Appendix 4

ICI:% Intangible Assets over Total Assets in 2008;
ICI_PAST:% Intangible Assets over Total Assets in the three-years period 2001-2003;
$UNIDEG$: Graduated Employees / Tot. Employees in 2003;
$STAFFRATIO$: "White Collars" / "Blue Collars" in the three-years period 2001-2003;
$AVEDU$: Workforce Average Education in the three-years period 2001-2003;
$R\&D$ (employm.): R&D Employees / Tot. Employees in 2003;
AGE: 2010 less the year of foundation; $SIZE$ (employm.): number of employees in 2003;
$COMPLEX$ (index): composite index based on the three-years period 2001-2003 taking the following values: 4 if the firm generates 100% of her turnover through subcontracting out of which more than 50% abroad, invests abroad and faces international competitors; 3 if the firm generates 100% of her turnover through subcontracting out of which more than 50% abroad and either invests abroad or faces international competitors; 2 if the firm generates 100% of her turnover through subcontracting out of which more than 50% abroad and neither invests abroad nor face international competitors; 1 if the firm generates 100% of her turnover through subcontracting out of which less than 50% abroad; 0 if the firm generates less than 100% of her turnover through subcontracting;
$ICT\_INVESTM$: Euro Invested in ICT / Tot. Turnover in the three-years period 2001-2003;
LAB_PRDTY: Added Value per Employee in 2003;
$PROFIT$: Gross Earnings / Tot. Turnover in 2003;
$ACID$: Short-term Liquidity / Tot. Assets 2001.

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