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SCIENCE VS. PROFIT IN RESEARCH
LESSONS FROM THE HUMAN GENOME PROJECT*

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SCIENCE VS. PROFIT IN RESEARCH LESSONS FROM THE HUMAN GENOME PROJECT

Abstract

This paper elaborates on the recent race to sequence the human genome. Starting from the debate on public vs. private research arising from the genome case, the paper shows that in some fundamental research areas, where knowledge externalities play an important role, market and non-market allocation mechanisms do coexist and should coexist in order to ensure socially desirable achievements. A game-theoretic model makes it possible to demonstrate the above results and to characterise some features of an optimal research policy.

Keywords: Science; technology; allocation mechanisms; intellectual property rights; welfare.

JEL Classification: D78, H4, H23, O32, O38.

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SCIENCE vs. PROFIT IN RESEARCH

Lessons from the human genome project

1. Introduction

This paper deals with Science and Technology in research policy, trying to draw some lessons from a recent and "hot" case, the race to sequence the human genome. Following some recent literature on the economics of knowledge (i.e. Dasgupta-David, 1987; Barba-Dasgupta-Maler-Siniscalco, 1996, 1998), Science and Technology are not defined according to the types of knowledge they produce, nor on the methods of inquiry they adopt; rather, they are defined as distinct institutional arrangements, broadly corresponding to non-market and market allocation mechanisms. The aim of the paper is to show that in some crucial research areas where demand and knowledge externalities are important, Science and Technology do coexist and must coexist, even in the same research segment.

The paper is divided into six sections. Following the Introduction, Section 2 recalls the race between public and private researchers to sequence the human genome. Section 3 introduces the main definitions and concepts, discussing Science and Technology as distinct resource-allocation institutional mechanisms. Section 4 presents a formal framework that shows why (even identical) researchers may divide themselves into two groups, corresponding to Science and Technology as described above. Section 5 discusses the social desirability of the coexistence of Science and Technology. The concluding section summarises the main argument and mentions some scope for further work.

With reference to the standard economic literature on research policy, R&D, and intellectual property rights, the paper innovates in several areas. Firstly, it shows the importance of a unified framework where Science and Technology (as distinct resource allocation mechanisms) are discussed together, on positive and normative grounds, even with reference to individual research fields. Secondly, it provides a model to formally characterise the issues under review, highlighting the key variables which influence researchers' behaviour as well as social welfare. The proposed model makes it possible to discuss a welfare maximising research policy where Science and Technology interact. Finally, the paper shows that the proposed framework may capture many features of modern research.

2. Public vs. Private Research: The Race to Sequence the Human Genome

If one drives on Interstate 270 in Maryland, from Bethesda to Gaithersburgh near Washington D.C., one enters the world's largest collection of genomic firms and research centres, the so-called "DNA-Alley". In the early days, this 24 km stretch hosted the Food and Drug Administration (FDA), as well as the National Institute of Health (NIH)[1], the Institute for Genomic Research, and the Johns Hopkins University, leaders in research on the genome. But Interstate 270 now hosts some of the hottest and most brilliant biotech private companies such as Celera Genomics, founded in 1998 by Craig Venter; Gene Logic founded in 1994 and led by Mark Gessler; Human Genome Sciences, a company that patents genes and gene-based drugs; and some promising start-ups all founded in the year 2000. On the same highway you can find Genomics fund.com and Fbr Emerging Tech Partners, two venture capital funds that went public in 2000 and invest exclusively in genomics. Therefore, in a sort of DNA-district, public research centres, universities, laboratories, and private corporations now live in the same area and interact in one of the world's hottest industries (Buia, 2001).

The DNA-Alley developed in stages. When the publicly funded Human Genome Project (HGP) was first launched in 1986 it implied an effort so complex and so broad in scope that only governments had the financial and bureaucratic resources to pull it off. The US$3 billion project was originally designed to be international and supported by all major countries of the developed world (Watson, 2001). Indeed the HGP introduced, for the first time in biological science, a new research method which required large-scale facilities for genome-wide analysis, including DNA sequencing, gene expression measurements, and proteomics. As it generates data on scales of complexity and volume unprecedented in biological sciences, the project depends on the integration of computational tools to store, model and disseminate such huge cascades of information.

In 1986, at the time of HGP's kick-off meetings, federally funded genome-project scientists figured they could move at their own pace and finish up in 2005 or thereabouts. But they figured wrong. A new force quickly emerged to accelerate their pace: the profit motive. The private sector quickly discovered it could make billions of dollars by turning genome research into new drugs and treatments for a large number of diseases. And the companies that manage to get the information

[1] Founded in 1887, the NIH or National Institute of Health, presently with 16,000 employees, conducts and funds medical research for the U.S. government. It consists of 26 institutes and centres, including the Genome Institute led by Francis Collins.

first - and lock up what they find with appropriate patents - will profit most (Lemonick-Thompson, 1999).

It is no surprise, therefore, that private firms have plunged into human-genome projects of their own. Nor is it surprising, given the potential payoff, that their researchers have found ways to speed up the decoding process. The most famous of these companies is Celera Genomics, led by scientist J. Craig Venter (formerly working at NIH and then at the Institute for Genomic Research)[2] which decided to attack the problem with an innovative approach using the most sophisticated computer technology available, and to further drive the effort with the full force of Venter's personality.

Celera's initial announcement in 1998 described plans to sequence the human genome more rapidly and much more efficiently than the public HGP. The differences were astonishing: Celera's budget was US$300 million versus HGP's budget of US$3 billion; and completion of the project was set for the year 2001, four years earlier than HGP's deadline.

Celera's challenge to the academic research community provoked a new sense of urgency and reality in public researchers and eventually gave rise to a boost in HGP. Venter forced HGP to double and redouble its effort to both remain competitive and to guarantee public access to the large information databases generated. HGP was also forced to adopt some of Venter's ideas to avoid being left behind (Lemonick, 2001). In the subsequent months, thanks to many innovations in the sequencing process, the productivity of sequencing grew significantly to a turnover of 12,000 bases every minute. Francis Collins, the newly appointed head of the agency's genome project, had been under pressure to work out his differences with Celera's Craig Venter. Differences over who should receive the credit for this scientific milestone; over whose genome sequence was more complete, more accurate, more useful; over the free exchange of what may be mankind's most

[2] Celera's founder and CEO, Venter, was coming from NIH where he was trying to locate and decode a gene that governs production of a brain-cell protein. The work was agonisingly slow. When he heard about a computerised machine that used lasers to automatically identify the chemical letters in DNA, he bought a prototype, even though his NIH bosses would not pay for it. If that purchase became a symbol of Venter's disdain for authority, the new technique for finding genes, the so-called "expressed-sequence tags", he developed with that purchase demonstrated his brilliance and enabled him to start identifying genes at a hitherto unimaginable pace of 25 or so a day. Despite the success, Venter's project was denied federal funding. Venter became increasingly unhappy within NIH, with its bureaucracy, limited funds and intramural sniping. So he started talking with investors. Backed by venture capitalist Wallace Steinberg, Venter founded the Institute for Genomic Research, where in 1994 he upped the gene-sequencing to a new level. Within a year he had been transformed from a government scientist with a $2,000 savings account to a millionaire. And that money proved to be very useful to attract many young talents from public research into his project. Meanwhile, he continued to pour money into genomics. Using his own technique, Venter sequenced the entire genome of living organisms, such as the genome of *Haemophilus influenzae bacterium* (a bug which causes ear and respiratory infections). Following this path, he then founded a new company called Celera Genomics (Golden and Lemonick, 2001).

important data versus the exploitation of what may also be highly valuable. The dispute had become downright nasty at times.

In June 2000, U.S. President Bill Clinton and British Prime Minister Tony Blair, together with C. Venter and F. Collins, held a press conference to mark what was correctly presented as one of the most important scientific breakthroughs of the modern era - the complete mapping of the human genetic code (Golden-Lemonick, 2001). During the press conference, both Clinton and Blair stressed the importance of full disclosure of the results. Finally, in February 2001, Celera and the HGP simultaneously published their results on the web-sites of two leading scientific magazines, Science[3] and Nature[4] respectively. Typically a major scientific milestone has been achieved, for the most part, in an atmosphere of fierce competition between the public and private sectors involved[5]. Moreover, while the above-mentioned announcement was expressly made by Clinton and Blair to make the two scientists look like equals, most of the press considered Venter's studies much further along.

The financial dimension involved in genome sequencing is not trivial. The HGP was funded with US$ 3 billion by taxpayers and philanthropists. Celera was funded with US$330 million by private investors and the company created huge value for shareholders. During the process Celera announced that it had filed provisional patent applications on thousands of newly discovered genes, charging millions of dollars a year to wade through its data and computer services. HGP, by contrast, was publishing its results on the Web, which were free to all. One of the biggest users of HGP data, incidentally, was Celera itself (Thompson, 1999, 2000).

The scientific, medical and commercial development of the genome mapping still requires assessment. But many economists and scientists are already commenting on the research policy that should follow the genome race, as the genetic research environment will hardly remain unchanged after this story.For many observers, mainly in the U.S., the government funded research in biotech, as in other key areas, is now redundant on the basis of efficiency considerations; they argue that the private sector knows (and performs) better. Other observers, mainly in Europe, believe that private research is intrinsically risky because it is driven by profit rather than by the general interest. In the next sections we will argue that each project contributed to the other in a competitive environment,

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[3] http://www.sciencemag.org/feature/data/genomes/landmark.shl

[4] http://www.nature.com/genomics/human

[5] This is particularly disappointing since the collaboration between C. Venter of Celera Genomics and G. Rubin at the University of California at Berkeley proved, in the past, that the two sectors could work fruitfully together, yielding the sequence of *Drosophila* in only a few months (Nature Biotechnology, 2001).

showing that their coexistence is beneficial. If Science and Technology (as precisely described below) coexist, Technology works with higher effort, sometimes higher productivity, and constantly provides a competitive stimulus to researchers working in Science. On the other hand, Science provides positive externalities, through human capital, knowledge spillovers, peer-review and transparency.

Indeed, the vision that launched the publicly funded HGP in 1986 reflected, and now rewards, the confidence of those who believe that the pursuit of large-scale fundamental problems in the life sciences is in the general interest. And the technical innovation and the drive of Craig Venter and his colleagues made it possible to celebrate this accomplishment far sooner than expected. Moreover, there are excellent scientific reasons such as the opportunity for comparison, for applauding an outcome that has given two sequences of the human genome. In the following sections we shall formally address this issue and provide a unifying game-theoretic framework to discuss public versus private research.

3. Science vs. Technology

The race between public and private research in genome sequencing, briefly recalled in the previous section, fits remarkably with a recent economic theory of knowledge, developed by Partha Dasgupta, Paul David and others, where Science and Technology are defined as distinct institutions for the creation and transmission of knowledge.

In economics there is substantial literature describing and explaining the dynamics of both technological change and scientific progress, although it has been uncommon to relate the two, analysing them at once in a unified framework. In a series of papers, Dasgupta-David (1987) and Barba-Dasgupta-Maler-Siniscalco (1996, 1998) start from the idea that knowledge can be produced through different institutions or allocation mechanisms: Science and Technology, as well as Arts and Crafts. Science and Technology, in this framework, are not defined according to the types of knowledge they produce (i.e. general principles vs. applied knowledge) nor on the methods of inquiry they adopt (focused vs. broader perspective). Rather, Science and Technology are defined according to the differences in the institutional arrangements involving the allocation of resources and efforts in the production of knowledge.

To elaborate the proposed viewpoint, the obvious starting point is to study the distinctive characteristics of the commodity that both scientists and technologists are engaged in producing, namely knowledge.

Knowledge is not a homogeneous, but a differentiated good (even in the same field). There are no natural units in which knowledge can be measured. Nevertheless, it is possible to appeal to economic theory and seek an account of the forces that influence its production, dissemination, and use.

Knowledge, if properly codified through a common language, can be effectively communicated. This characteristic makes it a non-rival good. It follows that knowledge has one of the two characteristics of a public good, that it can be used jointly by many agents[6]. The other attribute of a public good -- that once it is produced, it is not possible to exclude anyone from using it -- is not an inevitable feature of knowledge; for patents, copyrights, and secrecy are ways by which people can be effectively excluded. Such arrangements (that economists call institutions) are not intrinsic to knowledge and must be introduced on legal grounds.

We also note that the use of knowledge is subject to certain indivisibilities, in that the same piece of information can be used over and over again, at no extra cost, and does not need to be produced twice. Even more, the value of knowledge tends to increase with use.

Another characteristic of knowledge is the existence of externalities (or spillovers), i.e. actions which directly affect the production possibilities by other agents. By "directly" we mean to exclude any effect which is mediated by prices. Knowledge externalities are positive (knowledge produced by one agent directly helps the production of knowledge by all the other agents) and typically are a source of increasing returns. They take place *inter alia* through human capital mobility and education; through the nature of knowledge spillovers (knowledge proceeds in incremental steps, building on other researchers' results; no project eventually can be entirely secret) and through the peer-review process (which, by validating other people's research, often improves it[7]).

A final characteristic is that the production of knowledge is a risky process *per se,* since investment or effort often does not grant attaining the desired results. The probability of success,

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[6] This observation was the starting point of Kenneth Arrow's classic analysis of the economics of inventions. See Arrow (1962, 1971).

[7] See Merton (1938, 1965).

among other things, depends on the size of the research community, on effort, and on externalities. Disappointing outcomes are always possible.

Summing up, knowledge is a partially public good, with non-rivalry in consumption, partial excludability and indivisibility. Its production takes place with important positive externalities and some degree of risk. For such reasons, the creation and transmission of knowledge imply market failures (for a general discussion, see Mas Colell-Whinston-Green, 1995).

Given this background, economists discuss the resource allocation mechanisms that can be relied upon, in principle, to produce and disseminate knowledge. In particular, they are interested in comparing different resource allocation mechanisms that can sustain an efficient production and diffusion of knowledge. In the real world there is a multiplicity of such institutions. To our aim it may be useful to investigate two limiting cases of non-market and market mechanisms, that are conventionally defined as Science and Technology.

Consider first *Science* (S). In the proposed approach, Science is a non-market allocation mechanism, where knowledge is treated as a pure public good and where fixed compensation, together with research grants and the rule of priority, gives scientists an incentive to work and disclose their results. In this scheme, intentionally, there are no property rights on knowledge, the disclosure of results is complete and positive externalities are maximum. In such a mechanism, knowledge cannot be "owned", but financial resources must come from outside (usually general taxation, but also philanthropy). This is at the heart of Samuelson's analysis of the efficient production of public goods (Samuelson and Stiglitz, 1954) and is the case of the government financing the HGP, as discussed in section 2. It is also important to note that in this scheme the volume of public expenditure in the production of knowledge (and the allocation of expenditure for the production of different kinds of knowledge) are public decisions implemented through some sort of government planning.

Consider now *Technology* (T). In the proposed scheme, which recalls Lindahl's (1919) and Coase's (1960) solution to the problem of public goods and externalities, there are intellectual property rights on knowledge which can be sold to users on the market for a profit (provided there is demand for it)[8]. In this scheme, knowledge can be owned and researchers are compensated with profits related to revenues and costs. Given the patent mechanism, revenues depend on success in the research activity.

Both Science (through priority) and Technology (through patents) reward discovery since "winners take all". In case of success, the reward in T is usually higher than in S, yet in case of failure, the reward is always positive in S, while it may be negative in T.

Unfortunately both Science and Technology are institutional arrangements with their own shortcomings. Science, as an effort allocation mechanism, ensures full disclosure and positive externalities, but implies well-known agency problems (moral hazard, free riding, low effort). Technology, by nature, is a highly motivating allocation mechanism, but seizes the main results of research and prevents many positive spillovers related to the nature of knowledge.[9]

Conventional wisdom usually treats Science and Technology as alternative mechanisms, each with its own benefits and shortcomings, and analyses them separately. The referred theory of knowledge, proposed by Dasgupta, David and others, suggests that Science and Technology do coexist and should coexist in the society as a whole. The genome sequencing race recalled in section 2 tells an important story where Science and Technology coexist even in the same research field.

Starting from the portrayed story, therefore, we ask a few fundamental questions: (i) why do researchers with similar backgrounds and education choose to do research in the same field but in different institutions (Science and Technology)? (ii) Is the co-existence of Science and Technology in similar research areas a transitory or permanent state of affairs? And finally, (iii) is the coexistence between Science and Technology socially desirable?

Such questions, which are relevant in any research field, become particularly important in the Science vs. Technology controversy in genomics.

[8] The demand for knowledge, as usual, is related to the specific product of research: for example the demand for mathematical theorems is low, while the demand for gene mapping or gene related drugs can be very high. This can be rationalised considering fundamentals, such as consumers' preferences and production technology.

[9] In addition to the above referred shortcomings, markets for knowledge are usually thin, with few transactions, and non competitive players. We do not consider this case in our analysis.

4. Choosing between Science and Technology: A Positive Analysis

Consider N individuals – researchers – who have identical attributes (i.e. they are symmetric players), work in the same scientific environment, and have absolute specialisation (i.e. work only as researchers in a given field). Of course, researchers can decide not to work if their expected compensation is lower than their reservation wage. However, in the sequel we will assume this not to be the case. Hence, all N researchers work and the supply of researchers is perfectly inelastic.

Researchers produce knowledge, which is a partially public good with positive externalities. More precisely, as described in the previous section, knowledge is a differentiated good, with non-rivalry, partial excludability and indivisibility in consumption, and positive externalities (or spillovers) in production which depend on intrinsic and institutional factors. The intrinsic characteristics of knowledge which generate positive externalities are education, human capital mobility and leakages. The institutional features which can internalise externalities are patents and copyright; at the opposite end, the peer review process. Given the existence of knowledge externalities, each researcher $i=1,2\ldots N$ produces knowledge by means of his/her own effort x_i and the other researchers effort X_{-i} which spills over his/her own production. Effort x_i, is, of course, costly.

Imagine that researchers face two distinct institutions that govern the production and diffusion of knowledge: Science (S) and Technology (T). Assume, by now, that S and T are exogenously received institutions.

In S, knowledge is intentionally treated as a pure public good, with no property rights and full disclosure of results. In this institutional context, positive externalities are as large as possible. To deal with the incentive problem related to the production of public goods with externalities, researchers in S are compensated through a complex remuneration structure: a fixed component F_i, unrelated to effort or to success, plus a "prize" component k related to the discovery.[10] F and K

[10] The "prize" component k, which is meant to summarise a priority-based compensation system, includes monetary and non monetary rewards directly and indirectly related to discovery.

(respectively, the sum of F_i and k which are payed to the whole scientific community) are usually provided by the government.

In T, the existence of intellectual property rights limits positive externalities to create a private incentive mechanism. Thanks to patents and copyrights, knowledge can be sold. Thanks to human capital mobility, leakages, etc., some positive externalities still exist (smaller than in S). The compensation mechanism of researchers in T is quite standard. Researchers in T produce knowledge and sell their product on the market. Their reward is the profit from selling their product.

In both S and T, the production of knowledge is a risky activity with a probability of success. Only winners get a prize (in S) or a patent (in T). But knowledge, even in the same field, is a differentiated good so that more than one prize and/or one patent are available even in the same field. Accordingly, this model can be considered a Dasgupta-Stiglitz type model with more than one winner of the race towards invention (see Dasgupta and Stiglitz, 1980). To sum up, in any field the probability of success for researchers, both in S and in T, depends on several elements: own effort, the effort by all other researchers in S and T (with different externalities, greater from S than from T), the number of researchers N. Notice that the probability of success does not affect the fixed component of compensation of researchers in S, while it affects the revenues of researchers in T.

Given the above hypotheses, it is possible to write the payoff functions for researchers that work in S and T respectively. Let

$$\Pi_i^S = F_i(n) + P_r^S(N, x_i^S, X_{-i}^S, X^T)\, k - c_i^S(x_i^S) \qquad [1]$$

be the expected payoff of researchers in S, where n is the number of researchers working in T, and

$$\Pi_i^T = P_r^T(N, x_i^T, X^S, X_{-i}^T)\, p_i^T\, \gamma_i(x_i^T) - c_i^T(x_i^T) \qquad [2]$$

be the expected payoff of researchers in T, where $p_i^T = D[\gamma_i(x_i^T)]$ is the inverse demand function and $\gamma_i(x_i^T)$ denotes total output. Hence $\gamma(.)$ is the production function of knowledge in Technology. Let $\beta(.)$ be the production function of knowledge in Science. As usual, $\gamma(.)$ and $\beta(.)$ are increasing and concave, with $\gamma(0) = 0$, $\beta(0) = 0$.

In equation [1], the expected payoff Π_i^S of a researcher i working in Science is equal to a fixed component F_i (n), plus the prize k multiplied by the probability of success $P_r^S(.)$ minus the cost of the research effort $c_i^S(x_i^S)$. As usual, the cost function $c_i^S(.)$ is assumed to be convex with $c_i^S(0) =$

0. The fixed component $F_i(n)$ positively depends on n, which is the number of researchers working in T; for example, $F_i(n)$ does not depend on effort, but is positively related to the condition of the labour market (given N, the higher the competition for researchers from T, the higher F_i, i.e. $\partial F_i(n)/\partial n > 0$).

The probability of success $P_r^S(.)$ positively depends on own effort x_i and on the effort X_{-i}^S by the other researchers in Science (because of positive spillovers across researchers in S). It negatively depends on the size of the research community N and on the total effort X^T undertaken by the n researchers working in T. Hence, N and X^T capture a competition or race effect (the more competitors in the overall field and in T, the lower the probability of being a winner, despite the own effort and the positive externalities flowing from the other researchers in S. In addition, increased competition may reduce the accuracy of research thus further decreasing the probability of success). Therefore:

$$\partial P_r^S/\partial N < 0 \qquad \partial P_r^S/\partial x_i^S > 0 \qquad \partial P_r^S/\partial X^S_{-i} > 0 \qquad \partial P_r^S/\partial X^T < 0$$

Notice that, if $F_i(n)$ is larger than $c_i^S(x_i^S)$ for all $n \in [0,N-1]$ and all equilibrium effort levels, then Π_i^S is always greater than zero. In addition, whatever $F_i(n) > 0$, researchers working in S can always get a positive payoff if their effort is zero, because $c_i^S(0) = 0$. For this reason, some free-riding effects may occur. Indeed, at no effort, $\Pi_i^S = F_i(n) > 0$ for all $n \in [0,N-1]$.

Finally, let us assume decreasing returns from research efforts, i.e. $\partial^2 P_r^S/\partial(x_i^S)^2 < 0$, $\partial^2 P_r^S/\partial(X^S_{-i})^2 < 0$ but increasing effects of competition $\partial^2 P_r^S/\partial(X^T)^2 < 0$.

In equation [2], the expected payoff Π_i^T of a researcher i working in Technology is equal to the revenue $p_i^T\gamma_i(x_i^T)$ from the knowledge product sold on the market thanks to patents, multiplied by the probability of success $P_r^T(.)$, minus the cost of own effort $c_i^T(x_i^T)$. Again, the cost function $c_i^T(.)$ is assumed convex with $c_i^T(0) = 0$.

The probability of success (only winners get a patent) positively depends on own effort x_i^T and on the externality flowing from the total effort X^S of the researchers working in Science. It negatively depends on N and X_{-i}^T, which capture again a competition or race effect. Therefore:

$$\partial P_r^T/\partial N < 0 \qquad \partial P_r^T/\partial x_i^T > 0 \qquad \partial P_r^T/\partial X^S > 0 \qquad \partial P_r^T/\partial X^T_{-i} < 0$$

Notice that, since the whole revenue depends on $P_r^T(.)$, the payoff, Π_i^T may be negative. At no effort, $\Pi_i^T = 0$. Again, let us assume decreasing returns from research efforts, i.e. $\partial^2 P_r^T/\partial(x_i^T)^2 < 0$, $\partial^2 P_r^T/\partial(X^S)^2 < 0$ but increasing effects of competition $\partial^2 P_r^T/\partial(X^T_{-i})^2 < 0$.

As said above, absolute specialisation prevails. Therefore, all N researchers decide to work in this research field, because their reservation wage is assumed to be smaller than max[Π_i^S, Π_i^T]. This condition is feasible because at worst researchers get $F_i(n)$ when they set their effort equal to zero.

It is worth noting that for both groups of researchers in S and T, the sign of knowledge externalities depends on the institutional arrangements (partial excludability vs. non-excludability). With knowledge as a public good in S, the effect of X^S on both Π_i^S and Π_i^T is positive, as the positive spillover effect dominates the negative competition effect. On the contrary, with knowledge as a private good in T, the effect of X^T is negative as the competition effect dominates the positive spillover effect, which is smaller than in S but still existing.

The following two important assumptions concern spillovers:

Assumption 1*: A marginal change of own effort has an impact on the probability of success larger than the one of a marginal change of the total effort undertaken by the other researchers (both internal and external).*

Assumption 2*: A marginal change of internal spillovers has an impact on the probability of success larger than the one of a marginal change of external spillovers.*

These two assumptions define a hierarchy of knowledge spillovers. A researcher's own effort has a larger impact on its own probability of success than the total effort of the other researchers in his/her group, which is larger than the impact of the total effort of the researchers in the other group.

The emergence of the two institutions, S and T, is modelled as a two-stage, non-cooperative game. In the first stage, symmetric researchers choose to work either in S or T. This is a group formation game, where N researchers can all join T or S or divide themselves into two groups. In the second stage, researchers choose their optimal effort level, either x_i^S or x_i^T.

Let us solve the game backward. The optimal effort level is obtained by maximising the payoff functions [1] and [2] with respect to x_i^S and x_i^T respectively. This yields:

[3] $$\frac{\partial \Pi_i^S}{\partial x_i^S} = k \frac{\partial P_r^S(N, x_i^S, X_{-i}^S, X^T)}{\partial x_i^S} - \frac{\partial c_i^S}{\partial x_i^S} = 0$$

[4] $$\frac{\partial \Pi_i^T}{\partial \mathrm{x}_i^T} = \mathrm{P}_\mathrm{r}^\mathrm{T}(N, \mathrm{x}_i^T, X_{-i}^T, X^S)\left[\frac{\partial \mathrm{P}_\mathrm{i}^\mathrm{T}}{\partial \mathrm{x}_\mathrm{i}^\mathrm{T}}\gamma_\mathrm{i}(\mathrm{x}_i^T) + \mathrm{p}_\mathrm{i}^\mathrm{T}\frac{\partial \gamma_i(\mathrm{x}_i^T)}{\partial \mathrm{x}_i^T}\right] + \mathrm{p}_\mathrm{i}^\mathrm{T}\gamma_i(\mathrm{x}_i^T)\frac{\partial \mathrm{P}_\mathrm{r}^\mathrm{T}(N, \mathrm{x}_i^T, X^S, X_{-i}^T)}{\partial \mathrm{x}_i^T} - \frac{\partial \mathrm{c}_\mathrm{i}^\mathrm{T}}{\partial \mathrm{x}_\mathrm{i}^\mathrm{T}} = 0$$

These first order conditions can be re-written as:

[5] $$\mathrm{k}\frac{\partial \mathrm{P}_\mathrm{r}^\mathrm{S}(\mathrm{N}, \mathrm{x}_\mathrm{i}^\mathrm{S}, \mathrm{X}_{-\mathrm{i}}^\mathrm{S}, \mathrm{X}^\mathrm{T})}{\partial \mathrm{x}_\mathrm{i}^\mathrm{S}} = \frac{\partial \mathrm{c}_\mathrm{i}^\mathrm{S}}{\partial \mathrm{x}_\mathrm{i}^\mathrm{S}} \qquad \mathrm{i} = \mathrm{n}+1,\ldots\mathrm{N}$$

[6] $$\mathrm{P}_r^T(N, \mathrm{x}_i^T, X^S, X_{-i}^T)[1-\varepsilon]\mathrm{p}_\mathrm{i}^\mathrm{T}\frac{\partial \gamma_\mathrm{i}(\mathrm{x}_i^T)}{\partial \mathrm{x}_i^T} + \mathrm{p}_\mathrm{i}^\mathrm{T}\gamma_i(\mathrm{x}_i^T)\frac{\partial \mathrm{P}_r^T(N, \mathrm{x}_i^T, X^S, X_{-i}^T)}{\partial \mathrm{x}_i^T} = \frac{\partial \mathrm{c}_\mathrm{i}^\mathrm{T}}{\partial \mathrm{x}_\mathrm{i}^\mathrm{T}} \qquad \mathrm{i} = 1,\ldots\mathrm{n}$$

where, without loss of generality, we have assumed that the first n researchers work in T and where $\varepsilon < 1$ is the inverse of demand elasticity.

The equilibrium conditions for the research effort can be interpreted as follows. Equation [5] says that in Science the marginal cost of the research effort must be equal to the marginal benefit yielded by this effort, where the marginal benefit is equal to the reward k multiplied by the change of the probability of success induced by a marginal change of the research effort. Hence, research effort in Science can be increased by:

- increasing the reward k (through more prizes, public recognition of the value of research, sabbatical years, publications in journals, etc.)
- reducing the cost of carrying out research (i.e. less bureaucracy in Universities).

However, research effort does not depend on the fixed remuneration $F_i(n)$. Therefore, a researcher in S who believes that his/her own effort has a very small probability of success provides a very small research effort.

Equation [6] states that also in Technology the marginal cost of the research effort must be equal to its marginal benefit. Now the marginal benefit is equal to the change of the probability of success multiplied by the reward for researchers working in Technology, which is the revenue from selling to the market the output of the research effort, plus the change of revenue induced by the marginal change of effort multiplied by the probability of success. Notice that demand elasticity has an impact on the marginal benefit of effort. An elastic demand ($\varepsilon < 1$) implies that a positive change of effort increases the revenue for researchers in Technology. An increased effort in Technology can be induced by giving researchers the possibility to patent their discoveries thus creating a demand for the output of their research.

By solving [5] and [6] with respect to x_i^S and x_i^T, we obtain the system of reaction functions:

[7]

$$x_i^S = R_i^S\,(x^S_{-i}\,,\, X^T, N, k) \qquad i = n+1,\ldots.N$$

$$x_i^T = R_i^T\,(x^T_{-i}\,,\, X^S, N, \varepsilon) \qquad i = 1,\ldots.n$$

which can be written, at the Nash equilibrium $\hat{x}_i^S$, i = n+1,….N, and $\hat{x}_i^T$, i = 1,….n, as:

[8]

$$\hat{x}_i^S = R_i^S\left[(N - n - 1)\,\hat{x}_i^S, n\,\hat{x}_i^T, N, k\right] \qquad i = n+1,\ldots.N$$

$$\hat{x}_i^T = R_i^T\left[(N - n)\,\hat{x}_i^S, (n-1)\,\hat{x}_i^T, N, \varepsilon\right] \qquad i = 1,\ldots.n$$

because of symmetry. Notice that, from here on, the index i could be dropped. We prefer to preserve it in order to emphasise the individual nature of the choice between the two institutions.

Assuming a unique and interior solution, the N equations [8] yields the equilibrium values of the researchers' effort levels:

[9] $$\hat{x}_i^S(n) = x_i^S(n, N, k, \varepsilon) \qquad \frac{\partial \hat{x}_i^S}{\partial n} > 0 \qquad i = n+1,\ldots.N$$

and

[10] $\hat{x}_i^T(n) = x_i^T(n, N, k, \varepsilon)$ $\frac{\partial \hat{x}_i^T}{\partial n} < 0$ i = 1,….n

where N, k and ε < 1 are given and n is determined in the first stage of the game. Total research effort is then (N-n) $\hat{x}_i^S(n)$ in Science and n $\hat{x}_i^T(n)$ in Technology.

Assumption 3*: The effect of a positive change of the group size on the total research effort produced by the group is positive, i.e. the positive size effect dominates the negative effort effect.*

By replacing the equilibrium values [9] and [10] into [1]and [2], we obtain the values of the payoff functions in the first stage of the game.

[11] $\Pi_i^S(n) = F_i(n) + P_r^S\left[\hat{x}_i^S(n),\ (N-n-1)\,\hat{x}_i^S(n),\ n\,\hat{x}_i^T(n)\right]k - c_i^S\left[\hat{x}_i^S(n)\right]$ i = n+1,….N

[12] $\Pi_i^T(n) = P_r^T\left[\hat{x}_i^S(n), (N-n)\hat{x}_i^S(n), (n-1)\hat{x}_i^T(n)\right]D\left[\gamma\left(\hat{x}_i^T(n)\right)\right]\gamma_i\left(\hat{x}_i^T(n)\right) - c_i^T\left[\hat{x}_i^T(n)\right]$ i = 1,….n

Notice that, in the first stage, expected payoffs depend only on the number of researchers in each group, i.e. on n, because the size of the other group is given by N-n. In the first stage, the strategy space of each researcher is binary – [S,T] – because he/she decides which institution to choose to carry out his/her own research activity.

The equilibrium of the first stage is again a non-cooperative Nash equilibrium. Following a widely accepted standard in coalition formation theory (Cf. D'Aspremont et al., 1983, Carraro and Siniscalco, 1993, Barrett, 1994, Yi, 1997), the Nash equilibrium is defined as follows: n* researchers choose Technology at the equilibrium, and consequently N-n* researchers choose science, iff:

[13] $\Pi_i^S(n^*) \geq 0$ and $\Pi_i^T(n^*) \geq 0$ $0 \leq n^* \leq N$

and

[14] $\Pi_i^T(n^*) \geq \Pi_i^S(n^*-1)$ and $\Pi_i^T(n^*+1) \leq \Pi_i^S(n^*)$ $0 < n^* < N$

Conditions [13] define the usual profitability of the equilibrium group size n*. Conditions [14] define the stability of the equilibrium group size. At the equilibrium, no researcher wants to leave Technology to join Science and no researcher wants to leave Science to join Technology. Assuming N sufficiently large, [14] can be approximated by the following equilibrium condition:

[15] $$\Pi_i^S(n^*) = \Pi_i^T(n^*)$$

In order to determine the equilibria of the first stage of the game, i.e. the size of the group of researchers choosing Technology, we make use of a geometric representation of the payoff functions $\Pi_i^S(n)$ and $\Pi_i^T(n)$ that will help understanding under which conditions either an interior solution exists or one of the two corner solutions ($n^* = 0$ or $n^* = N$) emerge at the equilibrium.

Differentiating the payoff functions $\Pi_i^S(n)$ and $\Pi_i^T(n)$ with respect to n, we obtain:

$$\frac{d\Pi_i^S}{dn} = \left\{ \frac{\partial P_r^S}{\partial x_i^S}\frac{\partial \hat{x}_i^S}{\partial n} + \frac{\partial P_r^S}{\partial X_{-i}^S}\left[(N-n-1)\frac{\partial \hat{x}_i^S}{\partial n} - \hat{x}_i^S\right] + \frac{\partial P_r^S}{\partial X^T}\left[n\frac{\partial \hat{x}_i^T}{\partial n} + \hat{x}_i^T\right]\right\} k - \frac{\partial c_i^S}{\partial x_i^S}\frac{\partial \hat{x}_i^S}{\partial n} + \frac{\partial F_i}{\partial n}$$

$$\frac{d\Pi_i^T}{dn} = \left\{ \frac{\partial P_r^T}{\partial x_i^T}\frac{\partial \hat{x}_i^T}{\partial n} + \frac{\partial P_r^T}{\partial x_{-i}^T}\left[(n-1)\frac{\partial \hat{x}_i^T}{\partial n} + \hat{x}_i^T\right] + \frac{\partial P_r^T}{\partial X^s}\left[(N-n)\frac{\partial \hat{x}_i^S}{\partial n} - \hat{x}_i^S\right]\right\} p_i^T \gamma_i(\hat{x}_i^T) +$$

$$+ \; P_r^T(\,)\, p_i^T \frac{\partial \gamma_i}{\partial x_i^T}\frac{\partial \hat{x}_i^T}{\partial n} + P_r^T(\,)\gamma_i(\hat{x}_i^T)\frac{\partial p_i^T}{\partial x_i^T}\frac{\partial \hat{x}_i^T}{\partial n} - \frac{\partial c_i^T}{\partial x_i^T}\frac{\partial \hat{x}_i^T}{\partial n}$$

Let $\delta_i^S = -[\partial \hat{x}_i^S/\partial(N-n)][(N-n)/\hat{x}_i^S]$ and $\delta_i^T = -(\partial \hat{x}_i^T/\partial n)(n/\hat{x}_i^T)$ be the elasticities of the optimal effort with respect to the size of the group of researchers in S and in T respectively. Using Assumption 3, $\delta_i^S < 1$ and $\delta_i^T < 1$, i.e. the size effect dominates the effort effect. Then, the derivatives of the payoff functions with respect to n can be written as:

[16] $$\frac{d\Pi_i^S}{dn} = \left[\frac{\partial P_r^S}{\partial x_i^S} - \frac{\partial P_r^S}{\partial X_{-i}^S}\right]\frac{\partial \hat{x}_i^S}{\partial n} k + \frac{\partial F_i(n)}{\partial n} + $$
$$- \left[\frac{\partial P_r^S}{\partial X_{-i}^S}(1-\delta_i^S)\,\hat{x}_i^S\, k + \left(-\frac{\partial P_r^S}{\partial X_i^T}\right)(1-\delta_i^T)\,\hat{x}_i^T k + \frac{\partial c_i^S}{\partial x_i^S}\frac{\partial x_i^S}{\partial n}\right]$$

[17]

$$\frac{d\Pi_i^T}{dn} = \left[\frac{\partial P_r^T}{\partial x_i^T} - \frac{\partial P_r^T}{\partial x_{-i}^T}\right]\frac{\partial \hat{x}_i^T}{\partial n} R_i^T - \frac{\partial P_r^T}{\partial X^S}(1-\delta_i^S)\,\hat{x}_i^S R_i^T - \left(-\frac{\partial P_r^T}{\partial x_{-i}^T}\right)(1-\delta_i^T)\,\hat{x}_i^T R_i^T + $$

$$- P_r^T(\,)\,(1-\varepsilon)\,p_i^T \frac{\partial \gamma_i}{\partial x_i^T}\left(-\frac{\partial \hat{x}_i^T}{\partial n}\right) + \frac{\partial c_i^T}{\partial x_i^T}\left(-\frac{\partial \hat{x}_i^T}{\partial n}\right)$$

where $R_i^T = p_i^T \gamma_i(x_i^T)$ is the revenue obtained by a winner in Technology. Given what said in sections 2 and 3, it should be obvious to assume:

Assumption 4*: A winner in Technology receives a reward larger than the one of a winner in Science, i.e.* $R_i^T > k$ *for all* $0 < n \leq N$.

Using Assumption 1, namely that own effort has a larger impact on the probability of success than internal spillovers, then $\left[\frac{\partial P_r^S}{\partial x_i^S} - \frac{\partial P_r^S}{\partial X_{-i}^S}\right]$ is positive and consequently:

$$A(n) \equiv \left[\frac{\partial P_r^S}{\partial x_i^S} - \frac{\partial P_r^S}{\partial X_{-i}^S}\right]\frac{\partial \hat{x}_i^S}{\partial n} k + \frac{\partial F_i(n)}{\partial n} > 0;$$

Moreover,

$$B(n) \equiv \left[\frac{\partial P_r^S}{\partial X_{-i}^S}(1-\delta_i^S)\,\hat{x}_i^S\, k + \left(-\frac{\partial P_r^S}{\partial X_i^T}\right)(1-\delta_i^T)\,\hat{x}_i^T k + \frac{\partial c_i^S}{\partial x_i^S}\frac{\partial x_i^S}{\partial n}\right] > 0$$

because $\delta_i^S < 1$ and $\delta_i^T < 1$ by Assumption 3. Hence, $\frac{d\Pi_i^S}{dn}$ can be positive or negative in the interval [0,N-1].

By contrast $\frac{d\Pi_i^T}{dn}$ is negative for all $n \in [1,N]$. Indeed, by Assumption 1, $\left[\frac{\partial P_r^T}{\partial x_i^T} - \frac{\partial P_r^T}{\partial x_{-i}^T}\right]$ is positive, which implies $\left[\frac{\partial P_r^T}{\partial x_i^T} - \frac{\partial P_r^T}{\partial x_{-i}^T}\right]\frac{\partial \hat{x}_i^T}{\partial n} R_i^T < 0$. All the other terms of [17] are also negative by Assumption 3, with the exception of the last one, $\frac{\partial c_i^T}{\partial x_i^T}\left(-\frac{\partial \hat{x}_i^T}{\partial n}\right)$, which is positive. It is however sufficient to assume that the effect of a change of the group size on revenue is larger than the effect on costs, namely $P_r^T(\,)\,(1-\varepsilon)\,p_i^T \frac{\partial \gamma_i}{\partial x_i^T} - \frac{\partial c_i^T}{\partial x_i^T} > 0$, to conclude that $\frac{d\Pi_i^T}{dn}$ is negative for all $n \in [1,N]$. As a consequence, $\Pi_i^T(n)$ is monotonic and decreasing in the interval [1,N].

In order to simplify the analysis and to reduce the number of cases to be analysed, let us assume that $\Pi_i^S(n)$ is also monotonic in the interval [0,N-1]. Hence, we have two cases:

Case A: $A(n) \geq B(n)$ for $n \in [0,N-1]$ for which $\Pi_i^S(n)$ is monotonically increasing.

Case B: $A(n) \leq B(n)$ for $n \in [0,N-1]$ for which $\Pi_i^S(n)$ is monotonically decreasing.

Moreover, the difference between $\frac{d\Pi_i^S}{dn}$ and $\frac{d\Pi_i^T}{dn}$ is equal to:

$$\left[\frac{\partial P_r^S}{\partial x_i^S} - \frac{\partial P_r^S}{\partial X_{-i}^S}\right]\frac{\partial \hat{x}_i^S}{\partial n}\,k + \left[\frac{\partial P_r^T}{\partial x_i^T} - \frac{\partial P_r^T}{\partial X_{-i}^T}\right]\left(-\frac{\partial \hat{x}_i^T}{\partial n}\right)R_i^T + \frac{\partial F_i(n)}{\partial n} - \left[\frac{\partial P_r^S}{\partial X_{-i}^S}\,k - \frac{\partial P_r^T}{\partial X^S}\,R_i^T\right](1-\delta_i^S)\hat{x}_i^S +$$

$$-\left[\left(-\frac{\partial P_r^S}{\partial X_i^T}\right)k - \left(-\frac{\partial P_r^T}{\partial X_{-i}^T}\right)R_i^T\right](1-\delta_i^T)\,\hat{x}_i^T + \left[P_r^T(\,)\,(1-\varepsilon)\,p_i^T\,\frac{\partial \gamma_i}{\partial x_i^T}\left(-\frac{\partial \hat{x}_i^T}{\partial n}\right)\right] - \left[\frac{\partial c_i^S}{\partial n} - \frac{\partial c_i^T}{\partial n}\right]$$

where the first three terms are positive by Assumption 1 and because $\partial F_i(n)/\partial n > 0$. The fifth term,

$$-\left[\left(-\frac{\partial P_r^S}{\partial X_i^T}\right)k - \left(-\frac{\partial P_r^T}{\partial X_{-i}^T}\right)R_i^T\right](1-\delta_i^T)\,\hat{x}_i^T$$

is also positive by Assumption 2, namely that internal spillovers are larger than external ones, by Assumption 3, which implies $\delta_i^T < 1$ and by Assumption 4.

The fourth term $-\left[\frac{\partial P_r^S}{\partial X_{-i}^S}\,k - \frac{\partial P_r^T}{\partial X^S}\,R_i^T\right](1-\delta_i^S)\hat{x}_i^S$ is ambiguous because $\left[\frac{\partial P_r^S}{\partial X_{-i}^S} - \frac{\partial P_r^T}{\partial X^S}\right] > 0$ by Assumption 2, but $k < R_i^T$ by Assumption 4.

Finally, $\left[P_r^T(\,)\,(1-\varepsilon)\,p_i^T\,\frac{\partial \gamma_i}{\partial x_i^T}\left(-\frac{\partial \hat{x}_i^T}{\partial n}\right)\right] > 0$ and $-\left[\frac{\partial c_i^S}{\partial n} - \frac{\partial c_i^T}{\partial n}\right] < 0$.

Assuming that the difference between R_i^T and k is sufficiently large to induce $\left[\frac{\partial P_r^S}{\partial X_{-i}^S} k - \frac{\partial P_r^T}{\partial X^S} R_i^T\right] < 0$ and that $\partial F_i(n)/\partial n \geq \partial c_i^S/\partial n$, then:

[18] $$\frac{d\Pi_i^S}{dn} - \frac{d\Pi_i^T}{dn} > 0 \qquad \text{for all } 1 < n < N\text{-}1$$

i.e. the slope of $\Pi_i^S(n)$ is always larger than the slope of $\Pi_i^T(n)$, even when $\Pi_i^S(n)$ is decreasing.

Finally, when n* = 0, all researchers are in Science and:

[19] $$\Pi_i^S(0) = F_i(0) + P_r^S\left[\hat{x}_i^S(0),\ (N-1)\,\hat{x}_i^S(0)\right]k - c_i^S\left[\hat{x}_i^S(0)\right]$$

When n* = N, all researchers are in Technology and:

[20] $$\Pi_i^T(N) = P_r^T\left[\hat{x}_i^T(N), (N-1)\hat{x}_i^T(N)\right] D\left[\gamma\left(\hat{x}_i^T(N)\right)\right] \gamma_i\left(x_i^T(N)\right) - c_i^T\left[x_i^T(N)\right]$$

By normalising the reservation wage to zero, we have $\Pi_i^S(0) \geq 0$, $\Pi_i^T(N) \geq 0$. Of course, $\Pi_i^T(0)$ and $\Pi_i^S(N)$ are not defined. From the above analysis, three main conclusions can be derived:

(i) The equilibrium payoff in T is a negative function of n. Indeed, more researchers in T induce less spillovers from S and more competition in T.

(ii) The slope of $\Pi_i^T(n)$ is always smaller than the slope of $\Pi_i^S(n)$. As a consequence, if $\Pi_i^S(1) > \Pi_i^T(1)$, then $\Pi_i^S(n)$ is above $\Pi_i^T(n)$ for all $n \in [1,N-1]$ which implies that all N researchers are in Science.

(iii) In all other cases, the two institutions co-exist unless the equilibrium payoff in T is larger than in S even when almost all researchers are in T [$\Pi_i^T(N-1) > \Pi_i^S(N-1)$].

From these conclusions, three types of equilibria of the above two-stage game may emerge:

(a) Science only.

If $\Pi_i^S(1) > \Pi_i^T(1)$, then the payoff from choosing Science is higher than the payoff from choosing Technology for all group sizes in the interval [1,N-1]. Hence, all researchers choose Science which is the only institution which emerges at the equilibrium (see Figure 1). This is the case when property rights in T are weak or ill-defined and hence researchers in T cannot market their discoveries; or when there is no demand for the output of research in T, e.g. because the research field focuses mostly on basic research (e.g. mathematical theorems). Hence, there is no incentive to move from S to T.

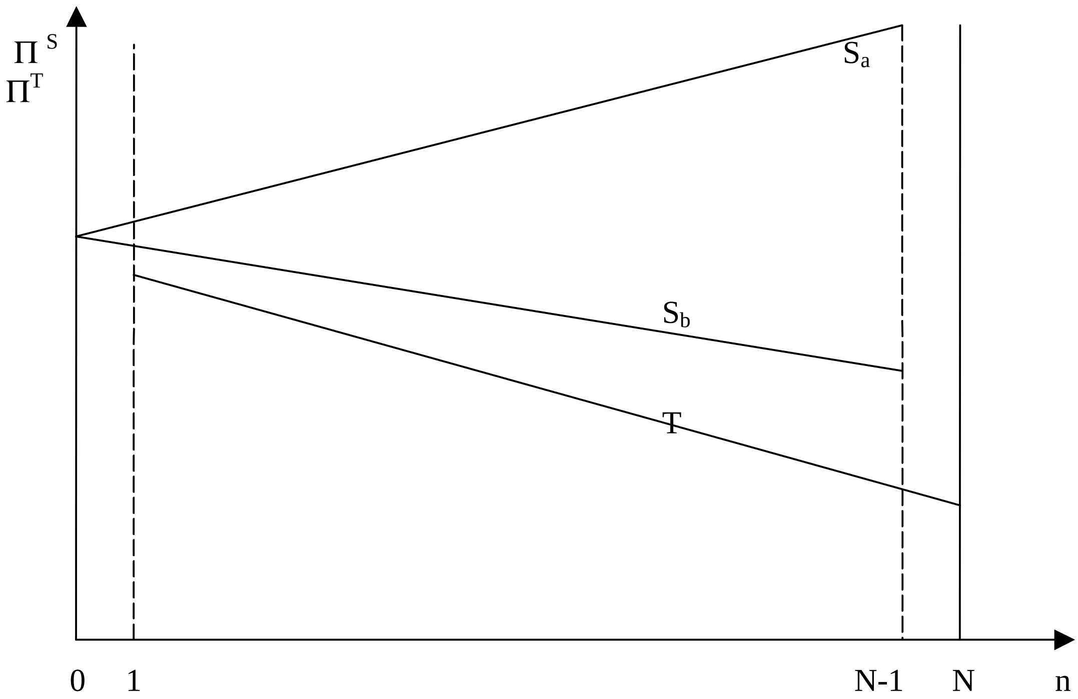

Figure 1. Science only

(b) Technology only.

If $\Pi_i^S(1) < \Pi_i^T(1)$ and $\Pi_i^S(N\text{-}1) < \Pi_i^T(N\text{-}1)$, then the payoff from choosing Technology is higher than the payoff from choosing Science for all group sizes in the interval [1,N-1]. Hence, all researchers choose Technology, which is the only institution which emerges at the equilibrium (see Figure 2). This is the case when researchers in S are badly paid, or when discoveries in T are highly demanded and innovations can adequately be patented.

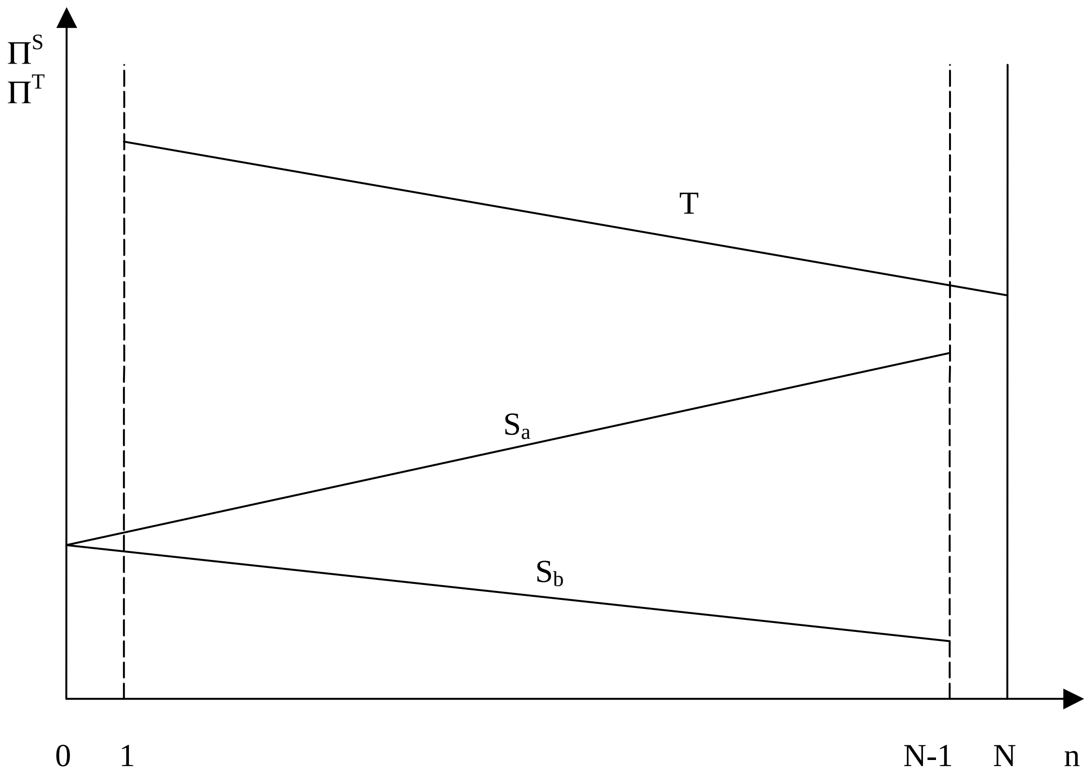

Figure 2. Technology only

(c) Science and Technology.

If $\Pi_i^S(1) < \Pi_i^T(1)$ and $\Pi_i^S(N\text{-}1) > \Pi_i^T(N\text{-}1)$, then there exists a value of n*, with $0 < n^* < N$, such that $\Pi_i^S(n^*) = \Pi_i^T(n^*)$. Hence n* defines the number of researchers who choose Technology. The remaning N-n* researchers choose Science (see Figure 3) Hence, even identical researchers divide themselves into two groups. Consequently, S and T permanently coexist even in the same field. In this case, Technology is more profitable than Science when there are few producers in T who benefit from spillovers from S and from reduced competition in T. However, as the number of researchers in T increases, competition also increases and spillovers from S decrease, thus creating an incentive to belong to S.

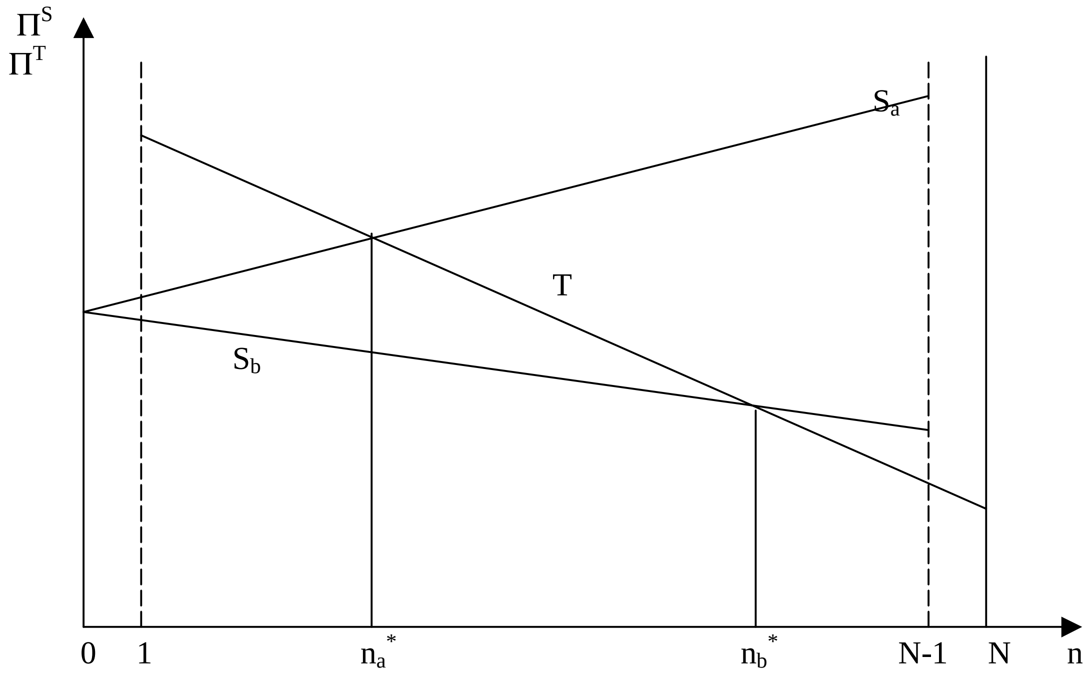

Figure 3. Science and Technology

To sum up, looking at the structure of the model, n* and N – n* depend on spillovers, property rights and market demand for knowledge. The model also explains why some research fields are commonly defined as science or technology, respectively. Science is usually associated to subjects where market does not play any role; technology is usually referred to research subjects where the market does play a role. The difference, we argue does not depend on the subject per se, but rather on the resource allocation mechanism intrinsically associated to it.

5. Welfare Analysis

The situation characterised in Section 4 shows that, on positive grounds, identical researchers may divide themselves into two groups, corresponding to Science and Technology as institutions. The obvious question at this point is whether (or not) such state of affairs is socially desirable, or welfare maximising.

Assume for simplicity that the social cost of tax revenue collection is zero or negligible (i.e. there are no distortionary effects of taxation). Then, the aggregate revenue of researchers in Science $F_i(n)(N-n) + K$ (where K is the total amount of prizes k paid to scientists) is equal to the cost born by the taxpayers.

Given the above assumption, the social welfare function W(n) is:

[21] $$W(n) = n\Pi_i^T(n) + CS(n) + E[Y(n)]$$

where $n\Pi_i^T(n)$ is the aggregate profit of the researchers in T, CS(n) is the consumers' surplus, and E[Y(n)] is the expected monetary social value of Y(n), which is the flow of produced knowledge. Hence, E(Y) is the value of knowledge as a public good, whereas $n\Pi_i^T(n) + CS(n)$ is the market value of knowledge. [21] is the welfare function usually adopted in the literature on industry regulation (see, for example, Laffont and Tirole, 1993) in which the positive public good value of knowledge has been added. In a similar vein, the negative value of environmental externalities is added to the welfare function in environmental economics (see, for example, Xepapadeas, 1995)

The total production of knowledge is

$$Y(n) = (N-n)\, P_r^S(N, x_i^s, X^S_{-i}, X^T)\beta_i(x_i^S) + nP_r^T(N, x_i^T, X^S, X^T_{-i})\gamma_i(x_i^T),$$

which, by substituting equilibrium values, becomes

[22] $$\begin{aligned} Y(n) &= (N - n)\, P_r^S[\hat{x}_i^S(n), (N-n-1)\hat{x}_i^S(n), n\hat{x}_i^T(n)]\, \beta_i(\hat{x}_i^S(n)) \\ &+ nP_r^T[\hat{x}_i^T(n), (N-n)\hat{x}_i^S(n), (n-1)\hat{x}_i^T(n)]\gamma_i(\hat{x}_i^T(n)) \end{aligned}$$

In order to analyse the shape of the welfare function W(n), let us focus on its components. The consumers' surplus CS(n) is, as usual, an increasing function of the number of researchers in Technology. More competition induces lower prices and higher quantities, thus increasing surplus.

The total profit $n\Pi_i^T(n)$ is by contrast a decreasing function of n. By differentiating $n\Pi_i^T(n)$ with respect to n, we have:

[23] $$\frac{\partial[n\Pi_i^T(n)]}{\partial n} = \Pi_i^T(n) + n\frac{\partial \Pi_i^T}{\partial n} < 0$$

Without externalities and spillovers, $n\Pi_i^T(n)$ would be a decreasing function of n because the negative effect on revenue is larger than the increase of total profits induced by an additional producer. In our model, this implies:

[24] $$P_r^T(\,)\,(1-\varepsilon)\,p_i^T\,\frac{\partial\gamma_i(x_i^T)}{\partial x_i^T}\;\frac{\partial\hat{x}_i^T}{\partial n}<0$$

a condition already used when comparing the slope of $\Pi_i^S(n)$ and $\Pi_i^T(n)$.

Moreover, due to externalities and spillovers, there are three additional effects that further reduce aggregate profits of researchers in T when n increases. The first one is a race effect:

[25] $$\frac{\partial P_r^T}{\partial X_{-i}^T}\,(1-\delta_i^T)\,\hat{X}_i^T\;R_i^T<0$$

i.e. an increased number of producers in T increases competition and reduces the probability of success. The second one is a knowledge spillover effect:

[26] $$-\frac{\partial P_r^T}{\partial X^s}(1-\delta_i^S)\,\hat{x}_i^S\;R_i^T<0$$

because less researchers in S produce smaller spillovers to T (given Assumption 3 in Section 4). Finally, there is a negative effort effect:

[27] $$\left[\frac{\partial P_r^T}{\partial x_i^T}-\frac{\partial P_r^T}{\partial X_{-i}^T}\right]\frac{\partial\hat{x}_i^T}{\partial n}\,R_i^T$$

because more researchers in T reduce the individual effort in T (see equation [10]). As a consequence, total profits $n\Pi_i^T(n)$ are a decreasing function of n.

By differentiating the total production of knowledge Y(n) with respect to n, we obtain:

[28]
$$\begin{aligned}\frac{\partial Y(n)}{\partial n} &= -P_r^S(\,)\,\beta_i(\hat{x}_i^S(n))+(N-n)\,P_r^S(\,)\,\frac{\partial\beta_i(x_i^S)}{\partial x_i^S}\;\frac{\partial\hat{x}_i^S(n)}{\partial n}+\\ &+\;(N-n)\,\beta_i(\hat{x}_i^S(n))\left\{\left[\frac{\partial P_r^S(\,)}{\partial x_i^S}-\frac{\partial P_r^S(\,)}{\partial X_{-i}^S}\right]\frac{\partial\hat{x}_i^S}{\partial n}-\frac{\partial P_r^S(\,)}{\partial X_{-i}^S}(1-\delta_i^S)\,\hat{x}_i^S(n)+\frac{\partial P_r^S(\,)}{\partial X_i^T}(1-\delta_i^T)\,\hat{x}_i^T(n)\right\}+\\ &+P_r^T(\,)\,\gamma_i(\hat{x}_i^T(n))+nP_r^T(\,)\,\frac{\partial\gamma_i(x_i^T)}{\partial x_i^T}\,\frac{\partial\hat{x}_i^T(n)}{\partial n}+\\ &+n\gamma_i(\hat{x}_i^T(n))\left\{\left[\frac{\partial P_r^T(\,)}{\partial x_i^T}-\frac{\partial P_r^T(\,)}{\partial X_{-i}^T}\right]\frac{\partial\hat{x}_i^T}{\partial n}-\frac{\partial P_r^T(\,)}{\partial X^S}(1-\delta_i^S)\,x_i^S(n)+\frac{\partial P_r^T(\,)}{\partial X_{-i}^T}(1-\delta_i^T)\,\hat{x}_i^T(n)\right\}\end{aligned}$$

which can be decomposed into the sum of five effects:

(a) a productivity effect

[29] $$\left[P_r^T(\,)\,\gamma_{\mathrm{i}}(\hat{x}_i^T(n)) - P_r^S(\,)\,\beta_{\mathrm{i}}(\hat{x}_i^S(n))\right]$$

which is positive if productivity in Technology is sufficiently higher than productivity in Science.

(b) a direct effort effect

[30] $$\left[(\mathrm{N - n})\mathrm{P_r^S}(\,)\,\frac{\partial\beta_{\mathrm{i}}(x_i^S)}{\partial x_i^S}\,\frac{\partial\hat{\mathrm{x}}_{\mathrm{i}}^{\mathrm{S}}(n)}{\partial n} - nP_r^T(\,)\,\frac{\partial\gamma_{\mathrm{i}}(x_i^T)}{\partial x_i^T}\left(\frac{\partial\hat{\mathrm{x}}_{\mathrm{i}}^{\mathrm{T}}(n)}{\partial n}\right)\right]$$

which is positive for low values of n/N and becomes negative as n tends to N. This humped-shape depends on equations [9] and [10]. At the equilibrium, effort in S increases with n, whereas effort in T decreases with n. When n/N is small, the increase in effort in S dominates the decrease of effort in T. Vice versa when n is close to N.

(c) a spillover effect

[31] $$-\left[(\mathrm{N - n})\;\beta_{\mathrm{i}}(\,)\;\frac{\partial\mathrm{P_r^S}(\,)}{\partial\mathrm{X_{-i}^S}} + n\gamma_i(\,)\,\frac{\partial\mathrm{P_r^T}(\,)}{\partial\mathrm{X^S}}\right](1 - \delta_{\mathrm{i}}^{\mathrm{S}})\hat{x}_i^S(n)$$

which is negative for all n∈[1,N-1], because a smaller number of researchers in S reduces the positive knowledge spillovers both within S and towards T. This reduces the probability of success for researchers in S and T and thus the production of knowledge Y.

(d) a race effect

[32] $$\left[(\mathrm{N - n})\,\beta_{\mathrm{i}}(\,)\,\frac{\partial\mathrm{P_r^S}(\,)}{\partial\mathrm{X_i^T}} + n\gamma_i(\,)\,\frac{\partial\mathrm{P_r^T}(\,)}{\partial\mathrm{X_{-i}^T}}\right](1 - \delta_{\mathrm{i}}^{\mathrm{T}})\hat{x}_i^T(n)$$

which is also negative for all n∈[1,N-1], because an increasing number of researchers in T increases competition and reduces the individual probability of success both in S and in T.

(e) an indirect effort effect via externalities

[33]
$$\left[(N - n)\ \beta_i(\,)\left[\frac{\partial P_r^S(\,)}{\partial x_i^S} - \frac{\partial P_r^S(\,)}{\partial X_{-i}^S}\right]\frac{\partial \hat{x}_i^S}{\partial n} - n\gamma_i(\,)\left[\frac{\partial P_r^T(\,)}{\partial x_i^T} - \frac{\partial P_r^T(\,)}{\partial X_{-i}^T}\right]\left(-\frac{\partial \hat{x}_i^T}{\partial n}\right)\right]$$

which is positive for low values of n/N and becomes negative as n tends to N. The reason is the same as for the direct effort effect explained above.

In order to strengthen our results, let us assume that researchers are identical also in terms of productivity, namely γ (.) = β(.). As a consequence, the productivity effect [29] is likely to be negligible. Let us also recall that we assumed decreasing returns of research effort. This implies that the effect of total effort undertaken in Science shows decreasing returns both within S and from S to T (mainly because of indivisibilities). By contrast, the marginal effect of total effort undertaken in Technology, where the race component dominates, was assumed to be increasing ($\partial^2 P_r^S/\partial(X^T_{-i})^2 < 0$ and $\partial^2 P_r^T/\partial(X^T_{-i})^2 < 0$).

Using these assumptions, when n/N is close to zero, i.e. most researchers work in Science, the four effects [30]-[33] are either positive, or negative but small. The reason is that, when n/N is small, an increase of producers in Technology fosters individual effort in Science, whereas the negative effects on the probability of success of an increase of n are still small. When n is close to N, all four effects become negative or, if already negative, they further decrease. The reason is that when most researchers work in Technology, research spillovers are low, the negative effects on the probability of success of excess competition are high, and individual effort decreases in T.

The above results lead to the following conclusions:

(a) If N is sufficiently large, the function Y(n) is first increasing and then decreasing in the interval [1,N-1]. The first derivative of Y(n) is indeed positive for small value of n/N (unless positive knowledge spillovers and negative race externalities are very large), whereas it becomes negative for n/N which approaches one (unless the probability of success in T is much larger than in S).

(b) If N is sufficiently large and Y(n) is humped shaped, then Y(n) is also slightly skewed to the left, because when n/N is small, positive components of the first derivative of W(n) are partly offset by negative components, whereas when n tends to N all components but one become negative.

As a consequence, the three components of the welfare function are as follows: CS(n) is an increasing function of n; $n\Pi_i^T(n)$ is a decreasing function of n; E[Y(n)] is typically first increasing and then decreasing with respect to n in the interval [1,N-1]. The total derivative $\partial W(n)/\partial n = \partial CS(n)/\partial n + [\Pi_i^T(n) + \partial \Pi_i^T(n)/\partial n] + E[\partial Y(n)/\partial n]$ is therefore positive if:

$$[34] \qquad \partial CS(n)/\partial n + E[\partial Y(n)/\partial n] > - [\Pi_i^T(n) + \partial \Pi_i^T(n)/\partial n]$$

whereas it becomes negative if:

$$[35] \qquad \partial CS(n)/\partial n < - [\Pi_i^T(n) + \partial \Pi_i^T(n)/\partial n] - E[\partial Y(n)/\partial n]$$

From the above discussion, [34] is very likely to hold for small values of n/N, whereas [35] is very likely to be true for values of n/N approaching 1. Indeed, when n is sufficiently close to N, $E[\partial Y(n)/\partial n]$ is most likely to become negative. As a consequence, the welfare function W(n) is first increasing and then decreasing with respect to n in the interval [1,N-1]. Of course, there may be cases in which W(n) is increasing for all $n \in [1,N-1]$. For example, when the probability of success in T is much larger than in S, or when demand in T and therefore the consumers' surplus are very high. And there may be cases in which W(n) is decreasing for all $n \in [1,N-1]$. For example, when knowledge spillovers within S and from S to T are very large, or when the negative race effects are very strong. However, if N is sufficiently large (as it is the case because our model is a micro model of individual choices), then the most likely case is the one in which W(n) is first increasing and then decreasing with respect to n. In this case, the above effects simply move the maximand of n either to the right or to the left in the interval [1,N-1].

Figure 4 shows the welfare function [21] resulting from the sum of the above described effects. Total welfare W(n) increases and then decreases with the number n of researchers in Technology. This implies that the co-existence of Science and Technology as resource allocation mechanisms maximises social welfare even within the same research field and even if researchers are identical. This is true even when the production functions $\gamma_i(.)$ and $\beta_i(.)$ of Technology and Science are the same. The above conclusion means that Science and Technology as different allocation mechanisms should be part of a single consistent research policy.

Let n** be the maximand of W(n), i.e. n** is the socially optimal number of researchers that should work in Technology. As a consequence, N-n** researchers should work in Science. The above conclusions implies 0 < n** < N. Depending on the whole set of parameters, the socially optimal value n** may be larger or smaller than the equilibrium value n* (see Figures 5 and 6). Hence, there is a scope for a research policy which should reconcile individual behaviour and social optimum.

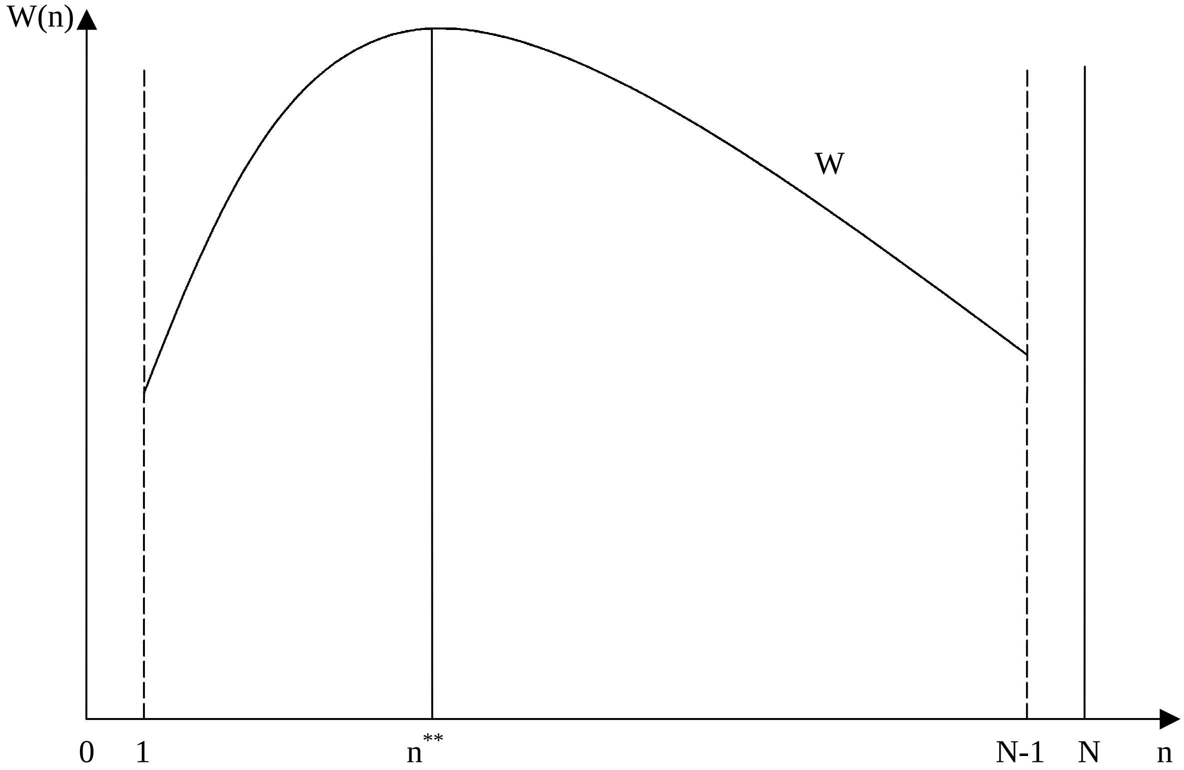

Figure 4. The welfare function W(n)

Suppose that, given N, n* > n** (too many researchers in T vis a vis the social optimum). Research policy can induce a decrease of n* by increasing $\Pi_i^S(.)$, i.e. by increasing the fixed compensation of scientists, or their success related prize k, or by inducing higher spillovers among scientists through better cooperation or more intense peer-review (in Figure 5, the function S moves upward). Alternatively, policy could decrease the payoff $\Pi_i^T(.)$ in Technology, but this would reduce total welfare. The reason is that $\Pi_i^S(s)$ does not enter social welfare directly, whereas $\Pi_i^T(.)$ does (see equation [21]).

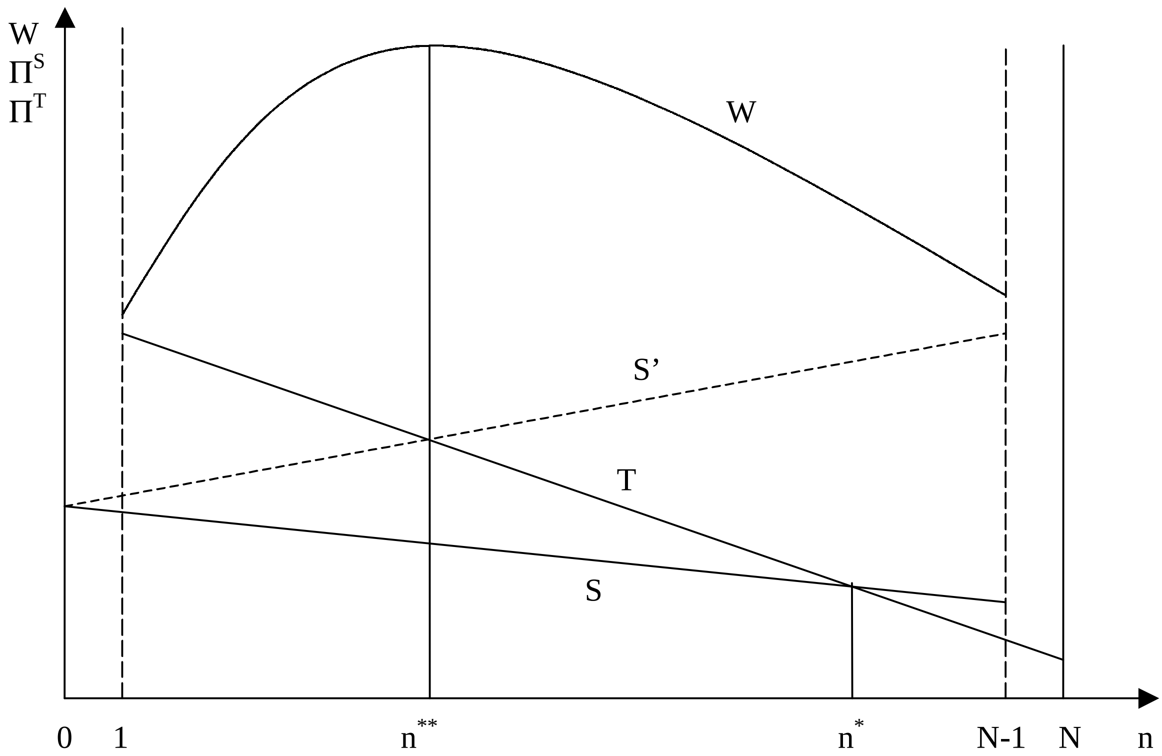

Figure 5. Too many researchers in Technology (W and Πs on different scales)

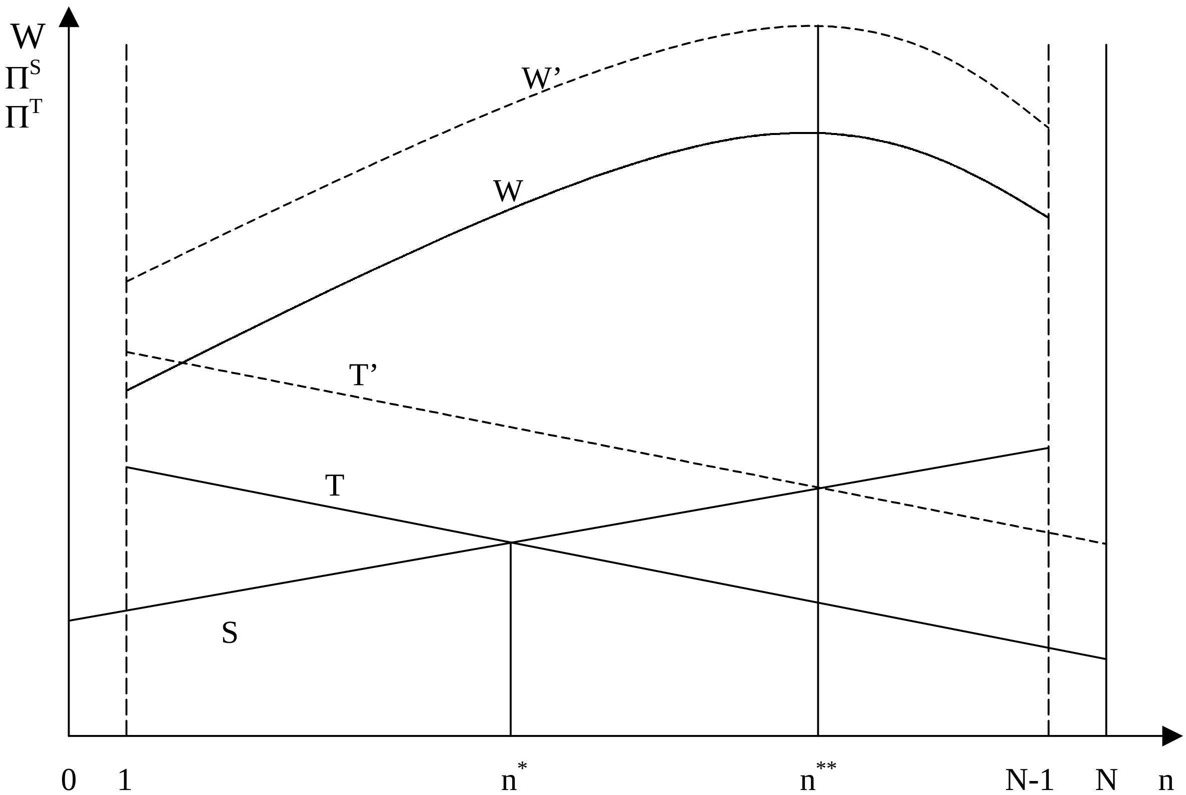

Figure 6. Too few researchers in Technology (W and Πs on different scales)

Suppose now that, given N, $n^* < n^{**}$ (too many researchers in S vis a vis the social optimum). Research policy can increase the number of researchers in T either by reducing the payoff of researchers in S or by increasing the one in T. The second policy option is to be preferred because it shifts upward the welfare function. Hence, total welfare increases both because n^* becomes equal to n^{**} and because W(n) moves upward (see Figure 6). Examples of this type of policy can be a reinforcement of intellectual property rights on knowledge produced by T, an enhancement of spillovers from S to T, an increased demand in T induced by public spending (the government buys products of researchers in T like in the case of vaccines), and tax exemptions for researchers in T.

At this point it is worth noting that, given N, the move from n^* to the social optimum n^{**} can also be Pareto improving for all researchers in S and T. Both in Figures 5 and 6, the payoff of both types of researchers increase when the social optimum is achieved by increasing the payoff of the group of researchers which is relatively too small.

Research policy can also induce a positive change of the consumers' surplus when it increases the number of researchers in T up to n^{**}. If, however, it is socially desirable to reduce n^*, consumers' surplus may decrease. This latter conclusion depends on the fact that, for simplicity, in our model the demand for knowledge-products does not depend on the total amount of knowledge embodied in such products. It is reasonable to imagine that demand does positively depend on such knowledge content (consumers are prepared to buy excellent products, shifting upwards their demand curve). If we consider the latter effect, consumers too may be better off whenever the total production of knowledge increases even through a reduction in n^*.

The proposed research policy may also be applied to correct cases where, for institutional reasons, researchers are all in S or in T. For example, if all researchers are in S, public demand for researchers in T may create the incentives for researchers to move from S to T. Vice versa, if all researchers are in T, weaker property rights may induce some researchers to move from T to S.

6. Conclusions

The paper makes it possible to reconsider the race to sequencing the human genome, as well as other cases, and to argue in favour of the coexistence of Science and Technology. In particular, under fairly reasonable assumptions, the model shows why similar, even identical, researchers choose to work in two different institutions (S,T) and why this state of affairs can be welfare maximising.

The analytical framework, admittedly, provides a highly simplified picture. However, some simplifications make the results stronger. For example, with asymmetric researchers (i.e. in terms of risk aversion and/or productivity) the separation of researchers into two groups, Science and Technology, would be easier but trivial to obtain.

Some other simplifications make the results clearer. For example, Science and Technology are intentionally characterised as limiting cases, with no blend among the two institutions (in the real world, in many countries there are intermediate models where, for example, universities can patent their research or where researchers can work both in S and in T).

Additionally, other simplifications are there for analytical convenience. For example, in our model one researcher in T is one firm, and the organisational dimension is ruled out both in S and in T. Researchers in Science and Technology compete, and we do not consider forms of cooperation between S and T, which exist in the real world and can create further spillovers. Science and Technology are exogenously given institutions, chosen in a static two-stage game, and there are no dynamics whatsoever. Finally, the demand for knowledge products does not depend on their knowledge content (more and better knowledge could increase the demand for knowledge related products).

Even at this stage, however, we believe that the fundamental structure of our argument should be clear and that the proposed analysis can help discussing what common sense cannot often grasp. In a nutshell, (i) we recognise that the production of knowledge involves several market failures and (ii) we argue that the two approaches to solve such market failure problems, namely Science and Technology, tend to coexist and should coexist on social welfare grounds. Science, which is a non-market allocation mechanism where knowledge is treated as a public good, maximises positive externalities, but involves agency problems (moral hazard, free-riding, etc.) which hamper both effort and productivity. Technology solves the agency problem, but limits severely the positive externalities. The interaction between Science and Technology, even within the same field, can mix optimally the two institutions combining somehow the best of both worlds.

If you believe this argument, in the race for human genome sequencing neither Celera nor NIH won the race. The real winners were research and social welfare.

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