# KNOWLEDGE IN MARKETS WITH IMPERFECT INFORMATION

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# Contents

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# Introduction

According to basic information theory, data are the original representation of a phenomenon, while information is the result of interpreting, filtering, and organizing data. Finally, abstraction and information processing provide knowledge. Knowledge is thus the result of sorting, processing, evaluating, and making sense of data and signals, screening between reliable and false signals, and on aggregating them to the existing stock of information.[1]

Causes and consequences of information asymmetry have been largely explored in many markets. However, the way in which imperfect information affects the production and dissemination of knowledge needs to receive more emphasis. Therefore, this *Thesis* aims to study the role and consequences of imperfect information in different knowledge markets and how policymaker can achieve certain outcomes in these markets. Specifically, the work is structured into five chapters.

Chapter 1, *Science in the mist: A model of asymmetric information for the research market*,[2] discusses how information asymmetry influences the publication process of high-quality papers in top journals. The model reveals many insights of modern publishing systems. On the one hand, imperfect information is beneficial for innovation as groundbreaking papers, which are more risky in terms on how likely they will be acknowledged by the scientific community, are more likely to be published than with perfect information. On the other, the rejection rate received by many worthy researchers is higher than what they would expect if journals were perfectly able to evaluate their papers. Scientific systems based on signaling through researchers' reputation are strongly biased

[1] Antonelli, C. (2018). From the economics of information to the economics of knowledge. In Antonelli, C. (Ed.), Recent developments in the economics of information. The International Library of Critical Writings in Economics series, Edward Elgar, Cheltenham.

[2] Pernagallo, G. (2023). Science in the mist: A model of asymmetric information for the research market. Metroeconomica, 74 (2), pp. 390–415.

as young and worthy researcher would be penalized. Moreover, with imperfect information a unique rejection rate is charged to all researchers, with the unpleasant consequence of all the papers being submitted.

Chapter 2, *Too much science*, starts from this last consideration. Science production is growing at unprecedented rates, and this risks to crowd the market with negative effects on society. The model shows on which conditions the scientific system produces too many papers, or the undesirable effect of expected costs exceeding expected research returns. This happens because editors cannot perfectly evaluate the submitted papers, hence they end up publishing papers that wastes society resources. The severity of this problem depends on the distribution of papers returns. In fact, if this is skewed to the right, there is a greater likelihood of publishing undeserving articles. The paper also shows that while the publication of scientific articles is certainly (socially) inefficient, the production of science in general could be efficient depending on the amount of knowledge produced by the lowest impact article published. Oligopolies and non-meritocratic systems tend to exacerbate the problem, while a simple solution for policymakers is to employ 'inefficient' researchers in activities other than research, such as a tenure track for teaching only.

Chapter 3, *Academic treasure hunt: Incentive policies to attract research talent*, is the last paper in the triptych on science and discusses why innovation is slowing down by resorting to the traditional adverse selection effect. In fact, research institutions that offer one-size-fits-all salaries to candidates for the same positions may push talented researchers out of the market. This situation is sub-optimal for academia, as total academic welfare would be greater when even highly talented researchers accept the contract. A simple solution relies on incentive policies: by rewarding the best researchers, the policymaker can also satisfy the participation constraint of highly talented individuals.

Chapter 4, *The student funding dilemma*, shifts attention to another category of knowledge producers and consumers: students. In particular, the paper studies the thorny problem of how to finance needy students in their higher studies. The existence of information asymmetry makes choosing the optimal scheme a daunting task for the policymaker. The model shows that grants and scholarships outperform student loans because they can be cost-effective and socially efficient. Therefore, investing so many resources in the debt instrument poses problems of financial stability without playing the important role of ensuring access to adequate education for many deserving students.

The final chapter, *Overcoming asymmetric information: A data-driven approach*,[3] represents the paper linking the old standard approach of theoretic models in information economics with recent advances in artificial intelligence and statistics. The paper aims to take stock of the state of the art of how data-driven methods can be used to address information asymmetry and what new problems these methods may bring.

[3] Pernagallo, G. (2024). Overcoming asymmetric information: A data-driven approach. In Włodarczyk, J., Raban. D. (Eds.), *Elgar Companion to Information Economics*. Edward Elgar Publishing.

# Science in the mist: A model of asymmetric information for the research market

Giuseppe Pernagallo*

**Abstract**

This paper aims to describe the process underlying the submission and acceptance of high quality papers to top journals via a model of asymmetric information. Researchers have the relevant information, namely the probability that the research paper will be recognised by the scientific community. The model predicts many empirical facts of modern publishing systems: top journals receive too many submissions; few published papers are recognised by the scientific community; risky papers benefit from imperfect information, and groundbreaking papers are more likely to be published than in the case of perfect information; the distribution of papers can be skewed to the right. An extension of the model that considers the reputation of researchers shows that researchers with low reputation may be precluded from publishing in top journals, so the scientific system may be against innovation fostered by young scholars. Monte Carlo simulations and real data are used to substantiate the paper's findings. Policy implications and Pareto efficiency are also discussed.

*Keywords*: Economics of Science; Information Economics; Innovation; Information Asymmetry; Knowledge; Research Policy JEL Codes: C46; D7; D8; I23; O3.

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# 1 Introduction

Scientific production is a formidable channel of innovation (Price & Bass, 1969; Carayol & Matt, 2006). Nonetheless, this paper shows that the publication process presents a problem of asymmetric information. The research market investigated in this paper is a stylised representation of reality, where two categories of agents interact: editors and researchers. The idea of this paper is that researchers have the relevant information, which is the 'riskiness' of the paper submitted to journals, whereas editors do not have this information. The model shows a seemingly unexpected result: with information asymmetry, innovative papers have higher chances of being published than in the case of perfect information. Hence, information asymmetry fosters, potentially, more innovation. I argue that this is the inevitable result of turning science into a business. This does not mean that the current publishing system is unable to publish influential research, but simply that if information were symmetrical, editors would limit the amount of risky papers published. The model shows that the publishing system can be biased towards incremental development of existing methods and against innovation (Fölster, 1995), and that limitations of the publishing system can serve a function (Tiokhin et al., 2021).

This paper has several merits. Although there is some literature on the topic (Ellison, 2002; Leslie, 2005; McCabe & Snyder, 2005; Heintzelman & Nocetti, 2009; Jeon & Rochet, 2010; Cotton, 2013; Azar, 2015; Besancenot & Vranceanu, 2017; Tiokhin et al., 2021), the use of theoretical models to study the research market has not yet received much attention, especially compared to empirical studies. This paper departs from the existing literature that relies on the idea of signalling (Leslie, 2005; Heintzelman & Nocetti, 2009; Azar, 2015; Besancenot & Vranceanu, 2017), proposing a model of information asymmetry that focuses on the innovative potential of the research market.

Besides the innovative theoretical framework, the paper is relevant also in the fields of research policy, since several policies are discussed to deal with the problem, and of epistemology, for obvious reasons. Economists should be interested in this topic for several reasons. First, publishing is pivotal to the career of academics, and the entire market relies on the interactions between researchers and academic journals. Second, many works have discussed the existence of relationships between the research market and industry (e.g., Mansfield, 1991; Mansfield & Lee, 1996; Boehm & Hogan, 2013). Indeed, the exchange between science and industry is a trigger for innovation (e.g., Mansfield, 1995; Mansfield & Lee, 1996; Grossman et al., 2001; Kaufmann & Tödtling, 2001; Pittaway et al., 2004; Kang & Motohashi, 2020). Third, innovation fosters economic growth (e.g., Schumpeter, 1911, 1912; Romer, 1990; Grossman & Helpman, 1991; Segerstrom, 1991; Aghion & Howitt, 1992; King & Levine, 1993; Aghion et al., 2005). Fourth, there is a strand of economic literature on the study of knowledge as an economic good (e.g., Arrow, 1962; Stiglitz, 1999; Antonelli, 2019), and its relationship with growth (Gans, 1989; Metcalfe, 2002). Finally, it is well-known that the presence of information asymmetries can generate market failures. Hence, the issue is important also for policy makers.

The mathematical model presented in this paper can reproduce many empirical facts of modern publishing systems. One important result is the fact that, with imperfect information, only one rejection rate is charged to all the research papers, and all the papers are submitted. This feature of the model explains why journals receive so many submissions (see the data in Section 5). In fact, risky papers are encouraged to be submitted with imperfect information because the unique rejection rate is lower than it would have been with perfect information. So, groundbreaking research papers, which are risky, have higher chances of being published with information asymmetry. However, if the proportion of risky papers is much higher than that of safe papers, then the rejection rate charged to all papers will be very high and, as a consequence, many worthy researches will not be published. This also explains why rejection rates charged by top journals are so high nowadays (see Section 5). Finally, the presence of many risky papers also explains why, among the published papers, very few are acknowledged by the scientific community (e.g., Lotka, 1926; Seglen, 1992; Tahamtan et al., 2016; Bornmann & Leydesdorff, 2017).

The remainder of the paper discusses a range of possible policies to regulate the research market. Besides traditional reform proposals, such as reforming the review process (e.g. Berns, 1981 or Kovanis et al., 2017) or changing the reward scheme (e.g. Strevens, 2003), I discuss policies to regulate the market in both information regimes. Under conditions of information asymmetry, the introduction of collateral favours editors. The intuition is to consider the publication of a paper as a 'loan.' This loan will be repaid only if the paper is acknowledged by the scientific community. The result of this policy approaches the perfect information situation, but the price to pay is high: science under perfect information conditions, and in its current entrepreneurial structure, penalises innovative papers, while information asymmetry potentially leads to more innovation.

On the other hand, under conditions of perfect information, innovative papers are discouraged by high rejection rates. To mitigate this problem, I propose the introduction of a premium to reward published papers based on their scientific output.

The paper is structured as follows. Section 2 presents the mathematical model. In Section 3 the results of the model are validated via Monte Carlo simulations. Section 4 presents some policy proposals. Section 5 discusses the results of the model using real data and concludes the paper.

# 2 The model

## 2.1 Setup

We have a continuum of researchers, each of whom is endowed with a research paper, and many competitive top journals that potentially could publish these papers.[1] Papers are all of the same high quality (a discussion on this assumption and a possible extension of the model with different papers are provided in Appendix B). Journals can potentially publish all the papers.[2] Journals and research papers are broad terms for editors and researchers, respectively, that is, the agents that populate the model. Agents are assumed to be risk neutral. For the sake of simplicity we neglect the role of reviewers in this model (this choice is discussed in Section 5). If accepted, each research paper has a probability of success $p$ of being recognised by the scientific community, in which case the research paper will yield an output $y$ (scientific impact of the research, such as citations), and a probability of failure $1 - p$, in which case the research paper will produce nothing (like in an example in Stiglitz & Weiss, 1981). The latter is a strong assumption because even unrecognised papers contribute to scientific progress. However, their contribution is marginal and can be approximated to zero when compared with relevant papers.

Research papers are indexed by their probability of success, $p_i \in (0, 1)$, with $i \in \mathcal{I}$, the index set of all types of papers in the continuum. Different papers can have the same probability of success, so we write the distribution

[1] The competition hypothesis is motivated in Section 5, while the model focuses on the top journals because we assume that the papers are all of high quality and we are interested in the most innovative contributions, which are generally placed in the best journals. The reader interested in a model with journals of different quality is referred to Tiokhin et al., 2021

[2] We ignore the fact that journals have in reality limited space in each issue for two reasons. First, we are studying the research market as a whole and without modelling time. Then, we do not need to consider the effective space in each journal's issue. Second, journals are slowly moving towards electronic issues, which makes this model closer to the evolution of the publishing system.

of papers as $G(p_i)$ and the density function as $g(p_i)$. Papers differ not only in their probability of success, but also in the $y$ output they will produce in case of recognition by the scientific community (e.g., papers with probability $p_i$ will produce $y_i$, papers with probability $p_k$ will produce $y_k$, and so on). The output $y$, for simplicity citations, cannot be considered a good measure of the quality of a paper (Seglen, 1997, 1998; Tahamtan et al., 2016; Sochacki et al., 2018; Liskiewicz et al., 2021), so for the purposes of the analysis it should be interpreted simply as a measure of the scientific impact, such as the number of citations a paper can potentially generate. It is limiting to assume that researchers and publishers only care about $y$; however, for an economic analysis it is the most important variable, since journals and researchers can only exist if they get a return from their activity. More importantly, since $y$ is not a measure of the quality of a paper, papers with low $y$ should not be considered low quality papers, but simply papers with low citation potential.

We assume that all research papers have the same mean return, $\bar{y} = p_i y_i, \forall i$. In order for this to be possible, we have to assume that papers with higher probability of success have a lower output, while papers with lower probability of success have a higher output. This assumption serves to reproduce two empirical facts. First, this introduces the trade-off between risk and return in the model, where the word 'risk' is used because journals invest resources in published papers in the possibility of obtaining a return ($y$). Groundbreaking research papers are risky, for example, because they can be thwarted by the dominant theories (on the issue, see Fölster, 1995), and in general we are seeing a flattening or decrease in the level of innovation (Gold, 2021). The idea that innovation is risky is certainly not new in the literature (e.g., Gourville, 2006; Fernandes & Paunov, 2015; Hyytinen et al., 2015; Guzzini & Iacobucci, 2017). Nonetheless, groundbreaking papers are very important for scientific progress, so if the research has success, its scientific output $y$ will be high. On the other hand, mainstream research papers are more likely to be recognised, but it is unlikely that they can produce a shift in the scientific paradigm. This assumption is also made in credit markets by Stiglitz and Weiss (Stiglitz & Weiss, 1981). Think of heliocentrism as a theory that invalidated the dominant paradigm of geocentrism. The proponents of the heliocentric theory had a low chance of getting their theory accepted by the scientific community (very low $p$), but once it was accepted, it produced a shift in the scientific paradigm (very high $y$).

Second, it is established in the literature that only few papers are highly cited (e.g., Seglen, 1992; Tahamtan et al., 2016; Bornmann & Leydesdorff, 2017). This fact can still be modelled through $p$, which is the probability of producing a given scientific output $y$. Evidently, since the data suggest that papers with a high number of citations are limited, high values of $y$ must be associated with low values of $p$, otherwise we might have many highly cited papers among the published papers, which is unrealistic.

Certainly, we actually observe even incremental innovation papers with a high number of citations. In this case, the high number of citations may be due to the reputation or network of the author(s), or the topic of the paper. Appendix C, following the referees' suggestions, shows an extension of the model to account for reputation and its effects.

Editors only know the distribution of types in the population. However, they do not observe the riskiness of each paper, whereas researchers know the riskiness of their papers. This introduces a source of information asymmetry in the model. This happens because editors do not have all the necessary skills or knowledge of all the topics to perfectly evaluate the research papers they receive, whereas researchers should be aware of the potential of their research. A similar assumption is thoroughly motivated in Azar's model (Azar, 2015).

## 2.2 Case with perfect information

Editors in this scenario know the probability of success of each paper and the resulting output in case of success, so they know the exact share of research papers with the same probability of success. In this way editors can operate a proper segmentation of the potential papers and, consequently, there is a rejection rate $r_i$ for each paper of type $i$. The rejection rate is, *de facto*, the probability of being published for researchers. This means that only a share of papers of type $i$ will be accepted, and this share is determined by $r_i$. Researchers can present their paper by paying a fixed submission fee $F$ (this assumption is motivated in Appendix A, which provides a partial list of renowned journals charging a submission fee, and is generally adopted in similar papers, like in McCabe & Snyder, 2005, Heintzelman & Nocetti, 2009, or Cotton, 2013). The expected utility of a researcher deriving from presenting the paper of type $i$ is

$$E[u_i] = (1 - r_i)p_i(y_i - F) + (1 - r_i)(1 - p_i)(-F) - r_iF = (1 - r_i)p_iy_i - F \quad (1)$$

We could make the form of (1) more complex, but this would needlessly complicate the model.

Editors, besides their decision to accept or reject the $i$-th paper, will always get the submission fee $F$ if a paper is submitted, but depending on the success of the research paper, they can earn a share $\alpha$ of the scientific recognition of the published paper[3] with probability $p_i$, whereas if the research has no impact, they lose with probability $1 - p_i$ the opportunity of publishing deserving papers, a loss quantified by $C(p_i)$. This loss depends only on $p_i$ such that it will

[3] This share $\alpha$ models the fact that albeit researchers gain most of the fame, also journals benefit in part of the success of published research in the form of increased impact factor, reputation, and so on. The magnitude of $\alpha$ determines how much of the output the journal gains.

be higher for riskier papers, or $\partial C(p_i)/\partial p_i < 0$. The sign of the partial derivative finds the following explanation: if journals decide to accept risky papers, they are sacrificing safer papers that might have been more likely to produce some output. Consequently, the riskier the paper, the higher the opportunity cost of publishing that paper instead of a safer one. Even though many other factors may affect $C$, they can be assumed constant, which is mathematically convenient. Furthermore, if the paper is published, editors bear a fixed publishing cost equal to $K$ (McCabe & Snyder, 2005; Armstrong, 2015). Note that the opportunity cost does not result from the fact that journals have limited space to publish papers (we assume they can potentially publish all papers, see footnote 2), but from the fact that publishing a paper has a cost in terms of resources needed for publication that is wasted if a paper is not acknowledged.

Here we also assume that $C(p_i)(1 - p_i) + K > \alpha\bar{y}$, which means that the average share obtained by the journal on a published paper is not sufficient to fully cover its cost. This assumption serves to justify the introduction of the fee. Moreover, without this assumption, journals would find it optimal to accept all submissions, which would be a useless result. We also assume that the average return on a paper covers the fee, i.e. $F \leq \bar{y}$. Reasonably, on average, high quality papers are worth the fee.

Hence, the expected return for journals on the $i$-th paper is

$$E[\pi] = (1 - r_i)[p_i\alpha y_i - (1 - p_i)C(p_i) - K] + F \tag{2}$$

Competition among journals will drive expected returns to zero

$$E[\pi] = 0 \implies$$

$$p_i\alpha y_i - (1 - p_i)C(p_i) - K - r_ip_i\alpha y_i + r_i(1 - p_i)C(p_i) + r_iK + F = 0 \implies$$

$$r_i = 1 - \frac{F}{(1-p_i)C(p_i) + K - p_i\alpha y_i} \tag{3}$$

Journals cannot deviate from this rate in a competitive market, otherwise if they offer a lower level of $r$ they would register a negative expected return, while with higher levels of $r$ papers would be submitted to the other journals. From (3) we get the mechanism behind the determination of the rejection rate. We can make some considerations:

1. The higher the fee, the lower the rejection rate. This depends from the fact that a higher $F$ will impose an higher cost to researchers; consequently, the number of submitted papers will decrease and, at the same time, journals expected return increases (given the higher fee).

2. The higher the probability of success, the lower the rejection rate. Papers that are more likely to have some impact will be less exposed to rejection.

3. The higher the costs, the higher the rejection rate.

Nonetheless, for the end of our analysis, the variables $F$, $K$, and $\alpha$ are given, whereas $C$ depends only on $p_i$, so the determination of the rejection rate depends only on $p_i$. Under conditions of perfect information, journals can screen the submitted papers because they know the relevant information. In particular, risky papers (low $p$ and high $y$) of the same type will face higher rejection rates or, in other words, $r_{risky} > r_{safe}$. This can be seen by rewriting (3) as follows

$$r_i = 1 - \frac{F}{(1-p_i)C(p_i) + K - \alpha\bar{y}} \tag{4}$$

where $\bar{y} = p_i y_i$ as assumed in Section 2.1. Given that $\bar{y}$, $F$, $K$, and $\alpha$ do not change, the only difference between a risky paper and a safe paper in (4) is given by $p_i$. In this case each research paper of the same type receives a rejection rate computed on the basis of its riskiness. Of course, in this scenario it may be the case that not all types of papers are submitted, but only the safer ones, since for risky papers the expected utility of researchers may be negative.

For editors, the decision variable in (2) is the rejection rate, through which they can determine the potential citations produced by published papers. This is realistic because, as one of the referees noted, publishers are concerned about the scientific impact (citations) that each new accepted paper will produce, which has a monetary value. In fact, the greater the scientific impact of a paper, the higher the impact factor and the greater the number of journal subscriptions, especially institutional library subscriptions.

## 2.3 Case with information asymmetry

In this scenario editors cannot distinguish papers based on riskiness. Given an average probability of success $\bar{p}$, which implies that $C(\bar{p}) = C$, editors know that the expected output is equal to $\bar{y}$ for each type of paper. The expected profit of journals should be now constructed using $\bar{p}$, which yields the following expression for the rejection rate

$$\bar{r} = 1 - \frac{F}{(1-\bar{p})C + K - \alpha\bar{y}} \tag{5}$$

where $\bar{p} = E[p] = \int_0^1 p_i g(p_i) dp_i$, $(1-\bar{p})C + K > \alpha\bar{y}$, and $F \leq \bar{y}$ (coherently with Section 2.2).

There is a unique rejection rate for all papers, and the expected utility of a researcher becomes

$$E[u_i] = E[u] = (1-\bar{r})\bar{y} - F \tag{6}$$

The introduction of information asymmetry leads journals to charge only one rejection rate. We can surely assert that this rate favours a part of the risky papers, in particular all the papers for which $\bar{r} < r^*$, where $r^*$ is the rate that would have been charged in the absence of information asymmetry. So, there is a higher incentive to submit risky research papers because the positive part of the expected utility is higher in this case than in the case without information asymmetry.

We provide the following definitions before presenting the main results of the model.

**Definition 2.1** (There exists at least $n$)**.** *Given $n \in \mathbb{N}$, we define $\exists^{\geq n}$ recursively as*

$$\exists^{\geq 1} x,\ P(x) \equiv \exists x,\ P(x)$$

$$\exists^{\geq n+1} x,\ P(x) \equiv \exists x,\ P(x) \wedge (\exists^{\geq n} y,\ (P(y) \wedge y \neq x))$$

*where $P(x)$ is a true proposition.*

The meaning of Definition 2.1 is that $\exists x$ means that there exists at least one element $x$ that makes the proposition $P$ true. The symbol $\exists^{\geq 2} x$ means that there exists at least one element $x$ that makes the proposition $P$ true and also one element $y$ that makes $P$ true, but with $x$ different from $y$. By recursion we can define the general symbol $\exists^{\geq n+1} x$ which means that there exist at least $n+1$ elements, all different from each other, that make the proposition $P$ true.

**Definition 2.2** (Groundbreaking research paper)**.** *A groundbreaking research paper, $(p_{GB}, y_{GB})$, is a research paper with low probability of success and high scientific output.*[4]

**Definition 2.3** (Set of accepted papers)**.** *Let $\mathcal{A}$ be the set of accepted papers. Let $PI$ and $IA$ denote the situation of perfect information and information asymmetry, respectively, and let $\mathcal{A}|PI$ and $\mathcal{A}|IA$ be the sets of the accepted papers with $PI$ and $IA$, respectively.*

[4] For the sake of our analysis, we do not need to provide a more specific definition.

**Lemma 2.1.** *The maximum expected profit for journals is reached by setting* $r = 1 - \frac{F}{\bar{y}}$.

*Proof.* Set $L = (1-\bar{p})C + K - \alpha\bar{y}$, which is a positive constant. Then, the maximization problem is

$$max_r \; E[\pi] = -(1-r)L + F$$
$$s.t. \; E[u] = (1-r)\bar{y} - F \geq 0 \;\; ; \;\; r \in [0,1]$$

where we can omit the subscript in $E[u]$ given that the expected utility is the same for all researchers. In order to maximize $E[\pi]$, we need to minimize $1-r$ subject to the constraint $r \leq 1 - \frac{F}{\bar{y}}$. Given that $F \leq \bar{y}$, $r = 1 - \frac{F}{\bar{y}}$ maximizes $E[\pi]$.

□

**Lemma 2.2** (Existence of the research market)**.** *Under conditions of information asymmetry, if the zero-profit condition is attainable, then the research market exists.*

*Proof.* Existence of the research market under conditions of information asymmetry means that $E[u] \geq 0$ given the rejection rate $\bar{r}$. By Lemma 2.1 we know that $r = 1 - \frac{F}{\bar{y}}$ is the rate that maximises editors' profits, and that $\bar{r}$ yields $E[\pi] = 0$, then

$$1 - \frac{F}{\bar{y}} \geq 1 - \frac{F}{(1-\bar{p})C + K - \alpha\bar{y}}$$

because, by Lemma 2.1, $r \leq 1 - \frac{F}{\bar{y}}$. This means that $\bar{r}$ must also satisfy the constraint.

□

**Theorem 2.1.** *Let* $(p_i, y_i)$ *indicate the research paper of type* $i$*, with* $i \in \mathcal{I}$*, where* $\mathcal{I}$ *is the index set of all types of papers in the continuum. We call* $\Theta$ *the* *set containing all the possible papers, and $\mathcal{P}$ the set containing all the submitted papers given a sequence of rejection rates $\{r_i\}_{i\in\mathcal{I}}$ (which are all equal to $\bar{r}$ with imperfect information). To avoid trivial scenarios, we assume that under conditions of perfect information $\exists^{\geq 2} j, z \in \mathcal{I} : r_j, r_z \implies E[u_j] > 0, E[u_z] < 0$ and that the zero-profit condition is attainable. Then, we have:*

*(I) under conditions of information asymmetry, all the papers are submitted, or $\mathcal{P} = \Theta$;*

*(II) under conditions of perfect information, only a part of all available papers is submitted, or $\mathcal{P} \subseteq \Theta$;*

*(III) $\exists\, k \in \mathcal{I} : r_k \implies E[u_k] = 0$;*

*(IV) the chances of publishing groundbreaking researches are higher with information asymmetry; mathematically, if $(p_{GB}, y_{GB}) \in \mathcal{P}$, then $P[(p_{GB}, y_{GB}) \in \mathcal{A}|PI] < P[(p_{GB}, y_{GB}) \in \mathcal{A}|IA]$.*

*Proof.* The proof of (I) is straightforward. With information asymmetry $r_i = \bar{r}$ is the unique rate charged, $\forall i \in \mathcal{I}$. By Lemma 2.2 $(1-\bar{r})\bar{y} \geq F$, we have $E[u_i] \geq 0, \forall i \in \mathcal{I} \implies \mathcal{P} = \Theta$.

(II) follows tautologically from assuming that $\exists z \in \mathcal{I} : r_z \implies E[u_z] < 0$. So, since with perfect information at least one paper is not submitted, it follows immediately that $\mathcal{P} \subseteq \Theta$. We can provide motivation for this result. Having at least one paper for which $E[u_k] > 0$ is necessary to ensure the existence of the market. Having at least one paper for which $E[u_z] < 0$ is coherent with the fact that $\partial E[u_i]/\partial r_i < 0, \forall i \in \mathcal{I}$. With perfect information, as $p_i \to 0, r_i \to 1 \implies E[u_i]^{gross} \to 0$, where $E[u_i]^{gross} = (1-r_i)\bar{y}$, which means that the riskier the paper, the lower the expected utility, hence as $r_i$ increases, many risky papers are not submitted. $E[u_k] = 0$ follows immediately from the fact the there is a continuum of papers between the riskiest ones and the safest ones, so there is not a drop in $E[u]$ from paper $j$ to paper $z$ because in the middle there will be at least a paper $k$ for which $E[u_k] = 0$. This proves (III).

Finally, to prove (IV) we notice that information asymmetry has a positive effect on risky papers: by (I), more risky papers are submitted, because the rejection rate charged to a share of risky papers is lower than in the case of perfect information. Consider the riskiest papers, $(p_{risky} = min\{p_i\}_{i\in\mathcal{I}}, y_{risky} = max\{y_i\}_{i\in\mathcal{I}})$, for which, with perfect information, the highest rejection rate, $r_{max}$, is charged. Given that $\exists\, z \in \mathcal{I} : r_z \implies E[u_z] < 0$, we have that $E[u_{risky}] < 0$, so the riskiest papers are not submitted with perfect information. With information asymmetry, $r_{risky} = \bar{r} \implies E[u_{risky}] > 0$, then the riskiest papers are submitted. Moreover, given that $\bar{r} < r_{max}$, we have that $P[(p_{risky}, y_{risky}) \in \mathcal{A}|\text{PI}] = 1 - r_{max} < P[(p_{risky}, y_{risky}) \in \mathcal{A}|\text{IA}] = 1 - \bar{r}$.

The same rationale applies to papers for which $p \to p_{risky}$ and since groundbreaking researches are within the papers with lower probability of success, they are likely to be charged a lower rejection rate with information asymmetry. This contributes to increase the probability of accepting a groundbreaking research paper. □

**Theorem 2.2.** *On average, research papers are socially efficient, that is,* $\bar{y} + \alpha\bar{y} \geq (1-\bar{p})C + K$.

*Proof.* Let $\hat{r} = 1 - \frac{F}{\bar{y}}$ be the rate that maximizes the expected profits for journals and $\bar{r} = 1 - \frac{F}{(1-\bar{p})C+K-\alpha\bar{y}}$. Both $\hat{r}$ and $\bar{r}$ satisfy the constraint $E[u] \geq 0$, respectively, by Lemma 2.1 and by Lemma 2.2. Then,

$$1 - \frac{F}{\bar{y}} \geq 1 - \frac{F}{(1-\bar{p})C + K - \alpha\bar{y}}$$

This is possible only if

$$\bar{y} \geq (1-\bar{p})C + K - \alpha\bar{y} \implies$$

$$\bar{y} + \alpha\bar{y} \geq (1-\bar{p})C + K$$

$\square$

Theorem 2.2 shows that, on average, each research paper is worth publishing from the point of view of society, as it does not consume more resources than it creates. The robustness of the model and the results obtained in this section are discussed in Section 4, Section 5 and Appendix.

# 3 Monte Carlo simulations

The aim of this section is to simulate different research markets to validate the results of Section 2. Depending on the amount of risky papers that can be submitted, we can have three types of configurations (Figure 1). When the distribution of the probability of success (riskiness) is positively skewed, the density is higher for values close to zero, which is the case when the market is characterised by more risky papers. On the other hand, a distribution negatively skewed is typical of a safe market since more papers exhibit probability of success close to 1. Finally, when the distribution is symmetric, the density peaks near 0.5, which we refer to as a 'normal' research market. We show that independently from the initial configuration of the market, with information asymmetry we end up publishing more risky papers, which potentially could lead to more innovation. The empirical literature seems to support the risky market hypothesis.

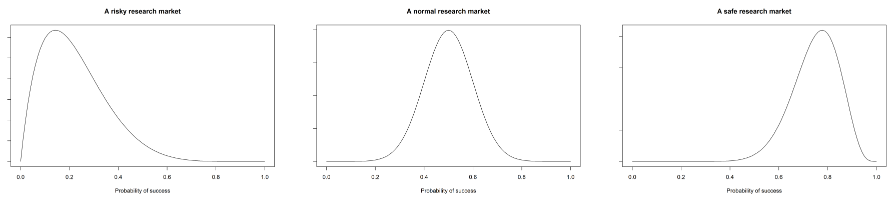


Figure 1: Depending on the amount of risky and safe papers that can be submitted, we can have three different markets. A risky research market where many risky papers can be submitted, a normal research market where the average probability of success is around 0.5, and a safe research market where many safe papers can be submitted.

### 3.1 Algorithm

We assume that $C$ under conditions of perfect information takes the form $C(p_i) = 1/p_i$, whereas under conditions of imperfect information we have $C(\bar{p}) = 1/\bar{p}$. This functional form is chosen for numerical convenience, but any $C$ satisfying $\partial C(p_i)/\partial p_i < 0$ can be used. Let $F = 0.5$, $K = 2$, $\bar{y} = 2.7$, and $\alpha = 0.5$, whereas the three types of markets (Figure 1) can be generated by using the Beta distribution. Specifically, a risky market can be generated from a Beta with parameters $\alpha = 2$ and $\beta = 4$, a normal market can be generated from a Beta with parameters $\alpha = 5$ and $\beta = 5$, and a safe market can be generated from a Beta with parameters $\alpha = 5$ and $\beta = 2$. The choice of the Beta is convenient to model probabilities since the distribution is supported on $[0, 1]$. We indicate with $N$ the number of simulations (or iterations) and with $n$ the sample size in each iteration, i.e. the number of papers that can be submitted.

The algorithm implemented with perfect information can be synthesised as follows.

1. At each iteration, a Beta distribution with $n = 10000$ is generated according to one of the three market configurations. This yields 10000 papers with different probabilities of success, which are then sorted and stored in a vector.

2. In order to make comparisons with the case of information asymmetry, we need the average of $p$, $\bar{p}$, to satisfy $(1-\bar{r})\bar{y} \geq F$, if this condition is satisfied, we can use the current distribution.

3. We compute the rejection rate for each paper and, if $E[u_i] \geq 0$, the paper is submitted to the journal, with $i = 1, ..., n$.

4. The submitted paper has a probability $(1 - r_i)$ of being accepted by the journal: this can be implemented by drawing a random number from a Bernoulli with probability of success equal to $(1 - r_i)$, where 1 represents the state 'accept' and 0 'reject'.

5. If the paper is accepted, its probability is stored in a vector to get the distribution of the accepted papers, and then several statistics of this distribution are computed at each iteration.

The algorithm with information asymmetry works in the same way, the only difference is that all the papers are submitted and receive the same rejection rate, $\bar{r}$. So, acceptance of a paper can be modelled using a Bernoulli with probability of success equal to $(1 - \bar{r})$. Since we want to compare the two scenarios using the same distributions, before starting the simulation a seed can be set to ensure that the $j$-th distribution will be the same with both perfect and imperfect information, with $j = 1, ..., N$. The seed to reproduce the results in this paper is 111, and the programming language used is `R`.

## 3.2 Results

Figures 2–4 show a computational example for each type of market under conditions of perfect information. Figure 2 is the case of a risky market, Figure 3 the case of a normal market, and Figure 4 the case of a safe market. We can see that the function $C$ decreases as $p$ increases, and so the rejection rate, whereas the expected utility increases as $p$ increases. The dashed line in the plot of the expected utility represents the case $E[u_i] = 0$, all the points above this line represent papers submitted to journals. Obviously, in a safe market more papers are submitted given that more researchers present papers with a high probability of success. Nonetheless, a risky market is a market with more innovative papers.

Via Monte Carlo simulations 1000 risky markets, 1000 normal markets, and 1000 safe markets are generated, and for each simulation some statistics are computed and reported in Table 1. The following details can help the reader to interpret Table 1.

- Mean of means: at each iteration the probabilities of success of the accepted papers ($p$) are stored into a vector, then the mean probability of success of the accepted papers is computed. The value reported in the table is the mean of all the means.
- Min: this is the minimum probability of success of the accepted papers in the simulations; then, it represents the riskiest paper accepted.
- Mean minimum: at each iteration the minimum probability of success of the accepted papers is computed and then the mean of all these values is reported.
- Max: this is the maximum probability of success of the accepted papers in the simulations; then, it represents the safest paper accepted.
- Mean maximum: at each iteration the maximum probability of success of the accepted papers is computed and then the mean of all these values is reported.
- Mean skewness: at each iteration the skewness of the probabilities of success of the accepted papers is computed, and then the mean of all these

values is reported. This is useful to assess the shape of the distribution of accepted papers.

- Mean rejection rate: it is the mean rejection rate in the 1000 simulations. This value is reported only for the case of information asymmetry, since with perfect information each paper receives a different rejection rate based on its probability of success.

- SD of rejection rate: it is the standard deviation of the rejection rate in the 1000 simulations.

Table 1: Results of 1000 Monte Carlo simulations for each market type. Each simulation is executed according to the algorithm of Section 3.1. PI stands for 'perfect information' and IA stands for 'information asymmetry.'

| | Risky market | | Normal market | | Safe market | |
|---|---|---|---|---|---|---|
| | PI | IA | PI | IA | PI | IA |
| Mean of means | 0.5251 | 0.3333 | 0.5734 | 0.5000 | 0.7620 | 0.7143 |
| Min | 0.3279 | 0.0001 | 0.3279 | 0.0220 | 0.3278 | 0.0365 |
| Mean minimum | 0.3282 | 0.0067 | 0.3282 | 0.0740 | 0.3301 | 0.1208 |
| Max | 0.9861 | 0.9788 | 0.9844 | 0.9881 | 0.9999 | 0.9999 |
| Mean maximum | 0.9330 | 0.9058 | 0.9383 | 0.9263 | 0.9974 | 0.9966 |
| Mean skewness | 0.5406 | 0.4662 | 0.1645 | -0.0016 | -0.6332 | -0.5955 |
| Mean rejection rate | . | 0.8113 | . | 0.6970 | . | 0.5237 |
| SD of rejection rate | . | 0.0011 | . | 0.0011 | . | 0.0014 |

The results of the simulations validate Theorem 2.1; indeed, information asymmetry fosters (potentially) more innovation. The first reason is a obvious consequence of $(1-\bar{r})\bar{y} \geq F$; the second reason is that many risky papers receive a lower rejection rate under conditions of information asymmetry. The positive aspect of information asymmetry is that highly innovative papers are accepted (lower minimum values than in the case of perfect information) and also safe papers can be accepted (maximum values similar to perfect information). The negative aspect is that safe papers are charged with a higher rejection rate

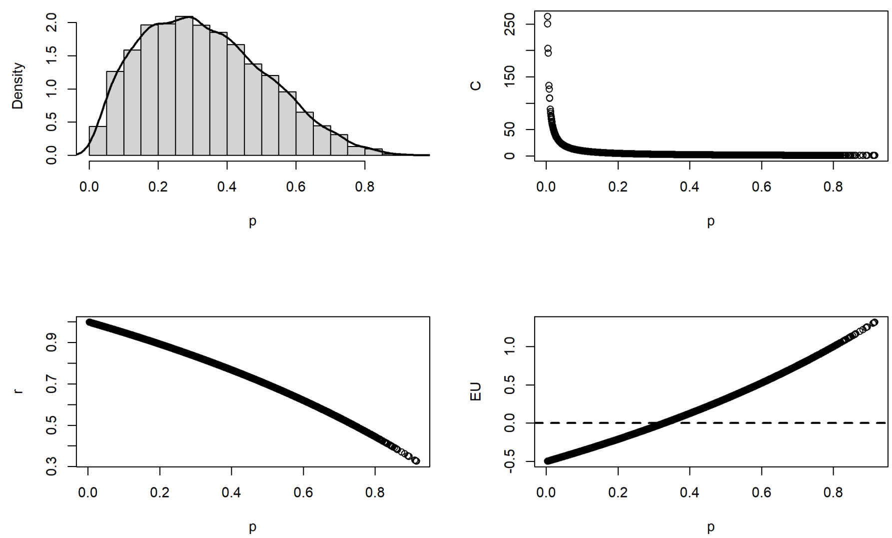


Figure 2: Example of a risky research market. A Beta distribution with parameters $\alpha = 2$ and $\beta = 4$ is generated and then, based on these probabilities, $C(p_i)$, $r_i$, and $E[u_i]$ are computed. The numerical values are chosen as discussed in Section 3.1. The black line in the histogram is the kernel density estimate.

with imperfect information and that (potentially) less papers are likely to be acknowledged by the scientific community, as shown by the lower mean values. These results are consistent regardless of the initial market configuration (risky, normal or safe).

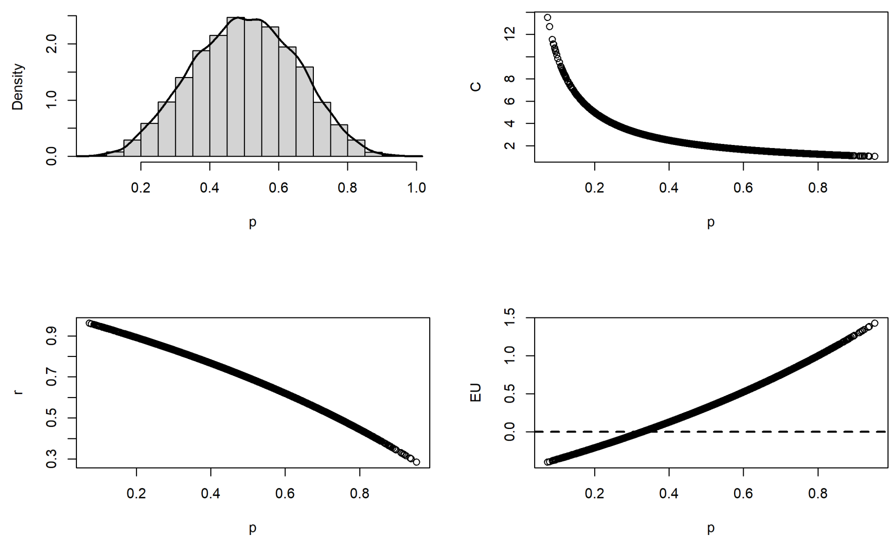


Figure 3: Example of a normal research market. A Beta distribution with parameters $\alpha = 5$ and $\beta = 5$ is generated and then, based on these probabilities, $C(p_i)$, $r_i$, and $E[u_i]$ are computed. The numerical values are chosen as discussed in Section 3.1. The black line in the histogram is the kernel density estimate.

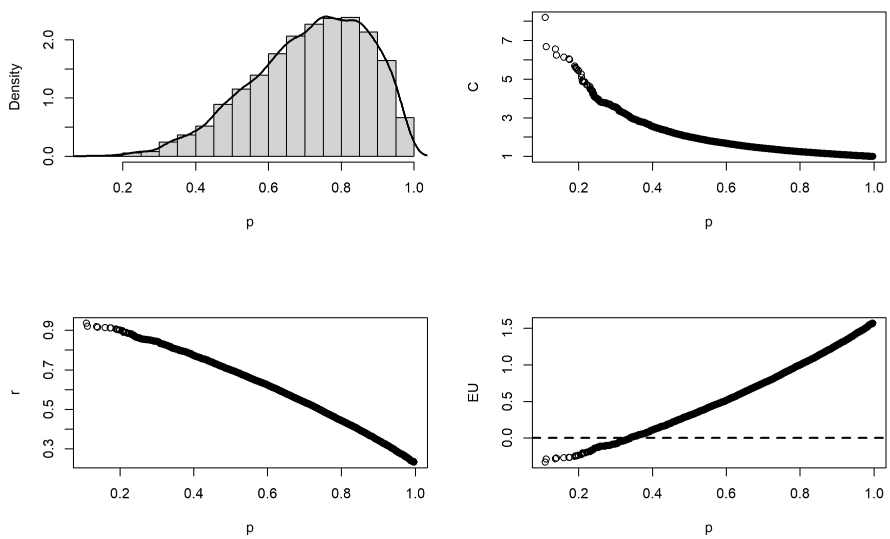


Figure 4: Example of a safe research market. A Beta distribution with parameters $\alpha = 5$ and $\beta = 2$ is generated and then, based on these probabilities, $C(p_i)$, $r_i$, and $E[u_i]$ are computed. The numerical values are chosen as discussed in Section 3.1. The black line in the histogram is the kernel density estimate.

### 3.3 Robustness check

To show that the results are not due to the choice of the statistical distribution, we repeat the simulations changing the underlying data generating process. Instead of considering a Beta distribution, we use in this section the triangular distribution. The triangular distribution is another convenient distribution to model the riskiness of papers. Indeed, it is supported on an interval $[a, b]$, with $a$ and $b$ real numbers and $a < b$. The configuration of the market can be determined by setting properly the maximum $c$, with $c \in [a, b]$.

To generate a risky research market using a triangular distribution, one can choose $c = 0$, whereas setting $c = 0.5$ generates a normal research market and $c = 1$ a safe research market. An example of these markets using the triangular distribution is illustrated in Figure 5. The plots of $C(p_i)$, $r_i$ and $E[u_i]$ are omitted as they are similar to the case of the Beta distribution. The values of the model, the algorithm, and the seed are the same as for the simulations in Section 3.2.

The results of these simulations are reported in Table 2. We can see that, as expected, the results are similar to the simulations with the Beta distribution.

Table 2: Results of 1000 Monte Carlo simulations for each type of market. Each simulation is executed according to the algorithm of Section 3.1 but using a triangular distribution instead of a Beta. PI stands for 'perfect information' and IA stands for 'information asymmetry.'

| | Risky market | | Normal market | | Safe market | |
|---|---|---|---|---|---|---|
| | PI | IA | PI | IA | PI | IA |
| Mean of means | 0.6098 | 0.3337 | 0.6295 | 0.5001 | 0.7818 | 0.6667 |
| Min | 0.3279 | $\approx$ 0.0000 | 0.3279 | 0.0009 | 0.3279 | 0.0011 |
| Mean minimum | 0.3283 | 0.0003 | 0.3283 | 0.0114 | 0.3287 | 0.0134 |
| Max | 0.9997 | 0.9989 | 0.9999 | 0.9998 | 1 | 1 |
| Mean maximum | 0.9899 | 0.9792 | 0.9930 | 0.9885 | 0.9999 | 0.9999 |
| Mean skewness | 0.1921 | 0.5623 | 0.1283 | -0.0017 | -0.7332 | -0.5663 |
| Mean rejection rate | . | 0.8114 | . | 0.6970 | . | 0.5652 |
| SD of rejection rate | . | 0.0015 | . | 0.0015 | . | 0.0020 |

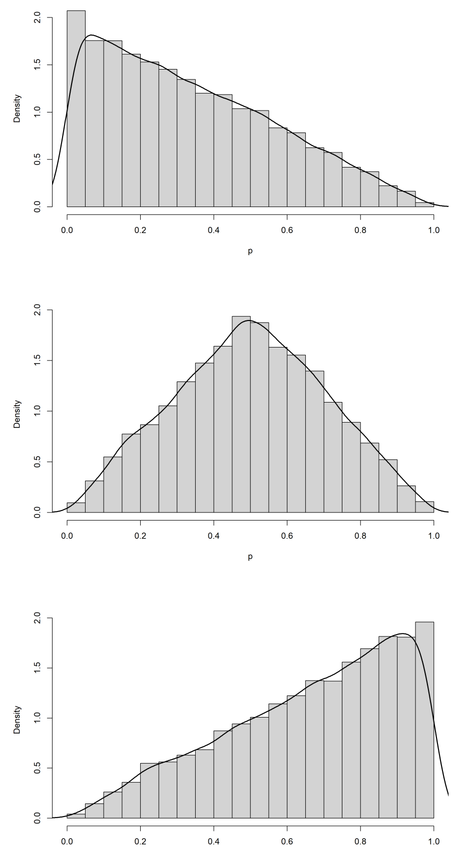


Figure 5: Example of a risky (upper panel), normal (middle panel), and safe (bottom panel) research market using the triangular distribution. The distributions are generated using a triangular distribution with $a = 0$ and $b = 1$, and by setting $c = 0$ for the risky market, $c = 0.5$ for the normal market, and $c = 1$ for the safe market. The black line in the histograms is the kernel density estimate.

# 4 Policy proposals and Pareto efficiency

In this section we discuss possible policies based on the results of the model. As enlightened by the model and simulations, we have negative results with both perfect and imperfect information. Indeed, with perfect information we can have less innovation since risky papers are penalized, whereas with information asymmetry, many deserving papers are not published because of the high rejection rate. However, Theorem 2.2 shows that on average all research papers are worthy of publication. Furthermore, we can show that the information asymmetry equilibrium is Pareto efficient.

**Proposition 4.1.** *Information asymmetry with rate $r = \bar{r}$ is Pareto efficient.*

*Proof.* Take the riskiest paper, $(p_{risky} = min\{p_i\}_{i \in \mathcal{I}}, y_{risky} = max\{y_i\}_{i \in \mathcal{I}})$, for which under conditions of perfect information the highest rejection rate, $r_{max}$, is charged. Let $E[u_{risky}]$ be the expected utility of the riskiest paper with perfect information, and $E[u]$ the expected utility with information asymmetry. Then $E[u_{risky}] = (1 - r_{max})\bar{y} - F < (1 - \bar{r})\bar{y} - F$, so it is not possible to make at least one individual better off without making anyone worse off, from information asymmetry to perfect information. □

Since Pareto efficiency is not a problem under conditions of imperfect information, policies are then aimed only at directing the research market towards more innovation or less risk.[5] Then, we discuss several policies. One aims to reduce the risk (and the rejection rate) in an asymmetric market, while a second one aims to make more innovative a research market with perfect information. Finally, I also propose a policy to reward properly safe papers with information asymmetry. These policies do not change the publication system, but only seek

[5] The idea that information asymmetry in the research market may have a function has already been glimpsed in other work (e.g. Tiokhin et al., 2021). However, as far as I know, it has not been formalised mathematically.

to mitigate some effects in both information regimes. The reader can find a discussion on a reform of the research market in Section 5.

### 4.1 Policy 1: Less risky papers with imperfect information

This policy is inspired by works on the credit market. In such markets, it is quite common to pledge properties of the borrower to the lender, to secure the repayment of a loan (e.g., the model of Bester, 1994). The idea here is to relate journals to lenders and researchers to borrowers. The loan is represented by the fact that editors publish in their journals researchers' accepted papers. This loan will be returned to the journal only if the paper is acknowledged by the scientific community. Unfortunately for editors, once researches are published, they bear all the risk of this loan. Albeit I strongly discourage such a solution for the reason explained below, I show it in this paper for completeness and to stimulate a debate.

Using our mathematical model, by introducing a fixed collateral, say $D$, we are changing the expected utility of researchers and the expected profit of editors under conditions of imperfect information as follows

$$E[u_i] = (1 - \bar{r})[\bar{y} - (1 - p_i)D] - F \tag{7}$$

$$E[\pi] = (1 - \bar{r})[\alpha\bar{y} - (1 - p_i)C(p_i) - K + (1 - p_i)D] + F \tag{8}$$

The nature of the collateral needs a separate discussion and can be investigated in future research. With the introduction of the collateral, researchers may not be willing to submit risky papers even with imperfect information, because the riskier the paper, the lower the expected utility. This partly solves the problem for editors; however, such a solution damages researchers by reducing their expected utility and, most importantly, discourages the submission of innovative papers, a very bad outcome for society. On the other hand, since the number of risky papers submitted decreases, the rejection rate by (5) decreases. Such a policy can be used to discourage very risky papers. They are a source of great innovation if acknowledged by the scientific community, but their probability of success is so low that it might be better to 'finance' innovative papers with a greater chance of success.

## 4.2 Policy 2: A premium for successful papers with imperfect information

Under conditions of information asymmetry the expected utility of many safe papers is lower than under conditions of perfect information. This happens because the unique rejection rate charged is higher than the rate that a safe paper would receive if information was symmetric. It is like researchers with safe papers pay the price of having a more innovative research market. There are also consequences for journals, given that safe papers are more likely to produce their scientific output given the higher probability of success.

The policy maker can make the situation more 'fair.' A policy that rewards successful papers with an amount $W$ in case of success would indeed favour safe papers, which are more likely to receive the premium given their higher probability of success. The form of the expected utility with this policy becomes

$$E[u_i] = (1 - \bar{r})\bar{y} - F + (1 - \bar{r})p_i W \tag{9}$$

while nothing changes for journals. Notice that the policy maker needs to pay $W$ to everyone since the riskiness of the paper is not an available information in this scenario.

### 4.3 Policy 3: More innovation with perfect information

Assume that we can make the relevant information in the research market available to everyone (we do not discuss whether this is possible or not). In this hypothetical scenario, the fact that with perfect information less innovative papers are submitted can be assessed by a simple policy. The policy maker should intervene by encouraging the submission of more risky (innovative) papers via a premium, say $Z$, paid to successful papers. This premium should be higher for risky papers that produce more innovation, so that (1) can be rewritten as

$$E[u_i] = (1 - r_i)\bar{y} - F + (1 - r_i)p_i Z(y_i) \tag{10}$$

where one can assume $\partial Z(y_i)/\partial y_i > 0$. In this way, the expected return for journals does not change, but many new risky papers are submitted because, even though they are charged with a higher rejection rate, in case of success they will be payed an additional amount $Z(y_i)$ by the policy maker, which is higher for higher levels of $y_i$. This partly mitigates the exodus of innovative papers from the market depending on the magnitude of the premium.

## 5 Discussion and conclusions

The model introduced in this paper delivers many empirical facts of modern publication systems.

1. *Journals receive too many submissions.* The model predicts that with information asymmetry all the papers are submitted (for a similar conclusion see Tiokhin et al., 2021). This is consistent with the fact that top journals receive a massive amount of submissions, and even papers with low probability of success are submitted because the average rejection rate is lower than the rate that they would have been charged with

perfect information.

2. *Few published papers are acknowledged by the scientific community.* Information asymmetry favours risky papers. This fact increases also the chances of publishing papers that are unlikely to be recognised by the scientific community. This may explain why only a part of the published papers leaves an imprint in science (Lotka, 1926; Seglen, 1992; Tahamtan et al., 2016; Bornmann & Leydesdorff, 2017).

3. *Groundbreaking research papers have higher chances of being published with imperfect information.* On the other hand, the chances of publishing groundbreaking papers are higher with information asymmetry. The model can reproduce the fact that the publishing system can be biased towards incremental development of existing methods and against innovation (Fölster, 1995), and that limitations of the publishing system can serve a function (Tiokhin et al., 2021).

The model also unveils that under both information regimes we have negative results. Under conditions of perfect information, innovative papers are penalised, whereas imperfect information fosters, potentially, more innovation, but many deserving papers are not published because of the high rejection rate. This does not mean that top journals are against innovation or that they do not publish innovative papers, but simply that they would produce less innovation under conditions of perfect information. The results of this model are in line with empirical evidence and other theoretical models that, although using a different framework, arrive at similar conclusions (e.g., Tiokhin et al., 2021).

An important result of the model is that on average papers are worth publishing because they produce more than the resources they consume, and that information asymmetry is Pareto efficient. Thus, unlike other markets (Rothschild & Stiglitz, 1976), the externality that high-risk individuals exert on low-risk individuals is negative but not completely dissipative. This may explain why the current publishing system has become so consolidated over time and only a minority is in favour of drastic changes.

In this model, unlike models with similar assumptions (e.g., Stiglitz & Weiss, 1981), adverse selection does not occur. In this framework, adverse selection would mean that if the rejection rate increases, safe papers leave the market while risky papers remain. This does not happen because each researcher incurs a fixed cost $F$ that is not related to the probability of success.

The problem of asymmetry in the research market has been historically assessed using peer-review. Having one or more experts in the field reviewing the quality of a research paper should screen risky papers from safe papers. The problem with the research market is that the rejection rate fails in its role as a screening device. For example, in the credit market, the interest rate has the role of screening good projects from bad ones (Stiglitz & Weiss, 1981). As shown in this model, the average rejection rate does not discourage risky papers to be submitted. This happens because researchers, at most, will lose the submission fee, so they are willing to submit their papers because the expected return exceeds the fixed cost.

Nonetheless, peer-review cannot solve the problem of asymmetry and presents many shortcomings (see, for example, Smith, 1988, 2006, or recently Heesen & Bright, 2020). We could embed reviewers in the model, but this would simply complicate the framework without adding further insights. Indeed, in many other works the role of referees is neglected (for example, McCabe & Snyder, 2005, or Tiokhin et al., 2021, do not explicitly model referees but only journals). The reader interested in models with reviewers is referred to other works (Laband, 1990; Leslie, 2005; Azar, 2015; Heintzelman & Nocetti, 2009). Reviewers are experts in their field, but they have less information on a paper than the authors, and their judgement, albeit useful, many times reveals to be wrong (think of how many Nobel prize winning researches were rejected before finding place in some journal). The assumption of 'omniscient' reviewers, able to know the riskiness of each paper, is unrealistic. The idea that authors are more informed than referees is also assumed by Azar (Azar, 2015). In any case, in future work the model could be modified to account for reviewers, whose role could be, in line with the literature, to signal the riskiness of a paper to editors.

The fact that in many fields (such as economics) researchers are forced to constantly publish to get a promotion is one of the principal factors that have led to an increased number of submissions over the years (Grimes et al., 2018). This is clearly shown in Figure 6 (upper panels) using data over 21 years of three top economic journals (Quarterly Journal of Economics, American Economic Review and Econometrica) and Nature.[6] These four journals are in research areas where promotion depends on publication in top journals.

Moreover, since information asymmetry creates better conditions for risky papers than in the case of perfect information, this could lead to a right-skewed distribution of papers as in Figure 1-left panel. Such a distribution would present a low $\bar{p}$, and by (5) a high $\bar{r}$. Then, all the papers are charged with a high rejection rate, which in turn reduces the proportion of worthy papers published. This hypothesis is warranted by the low acceptance rates shown in Figure 6 (bottom panels). The acceptance rates in Figure 6 are computed using the rough estimate of Card and DellaVigna (Card & DellaVigna, 2013), i.e. the ratio of the number of papers published in a year divided by the average number of submissions in previous two years.

I argue that trying to disclose the relevant information is not a convenient solution, mainly because it requires time and resources that both editors and

[6] Data sources: Nature, and Update to 'Nine Facts about Top Journals in Economics' (4/2018) David Card, UC Berkeley and Stefano DellaVigna, UC Berkeley.

researchers are not willing to invest. Moreover, no one can know a work better than its author, so information asymmetry appears to be an inherent feature of the research market. We have already discussed in Section 4 policies to regulate the market in the case of asymmetry and in the (unrealistic) case of perfect information. However, policy makers should aim to reform the publication system.

First, the incentive system should base career promotions on new parameters. Strevens (Strevens, 2003) discusses the aspects of several possible reward schemes and their impact on scientific progress. Changing the current reward scheme may have many positive effects on the research market, such as limiting the 'winner-takes-all race.'

Second, we could change the evaluation process, substituting or integrating peer-review (on the topic, among the others, see Berns, 1981 or Kovanis et al., 2017). Furthermore, abolishing the 'publish or perish' system appears necessary to achieve a reduction in submissions.

Third, we need more heterogeneity. The fact that promotions in important schools can be achieved only via publication in top journals leads to an increased supply of papers in these journals, and given the high rejection rates, only a small share of these deserving papers is published. A simple solution to this problem would be to link career promotions to the impact of the research rather than the journals in which it is published. Is it better to have three publications in top-level journals with zero citations and ignored by the scientific community, or three publications in lower-level journals with thousands of citations and recognised by the scientific community? This raises serious concerns, becuase as noted by many authors (e.g., Fölster, 1995; Hodgson & Rothman, 1999), the publishing process can discourage the creation of innovation in many disciplines, and it may be the case that the oligopolistic dominance of a few journals decreases the likelihood of accepting innovative papers (Hodgson & Rothman, 1999). This concern seems confirmed by the present model with the assumption of competition, things may be even worse if we assume that journals operate in a regime of oligopoly. It is important to note that the competition hypothesis made in this article is based on the fact that we are not making a distinction between scientific areas, so that the research market is studied as a whole and consists of many top journals and many research papers with the same average return. In future research we can study non-competitive markets.

The discussed solutions are neither exhaustive nor mutually exclusive. However, a productive discussion on the issue requires to meditate on how science has become just another product of the modern capitalistic society. The model of this paper shows that information asymmetry produces a positive effect as it fosters, potentially, innovation. This outcome may appear surprising to economists, but it is the inevitable result of the commodification of science (on the topic, see Radder, 2010). Modern academic journals are enterprises and they care about their return. Consequently, with perfect information, they would discourage the submission of too many risky papers. Nevertheless, innovation is the fuel of scientific progress (Ness, 2015), so it is evident that academic journals, in their current enterprise form, cannot adequately fulfill this role. Information asymmetry, by shuffling the cards, provides new opportunities for innovative thinkers, but the price to pay is a unique and high rejection rate.

The problem of information asymmetry in the research market is an economic problem. This is a peculiar market since the society loses something under any information regime. In the light of the results presented, the intervention of the policy maker is essential to make the research market an effective engine of innovation.

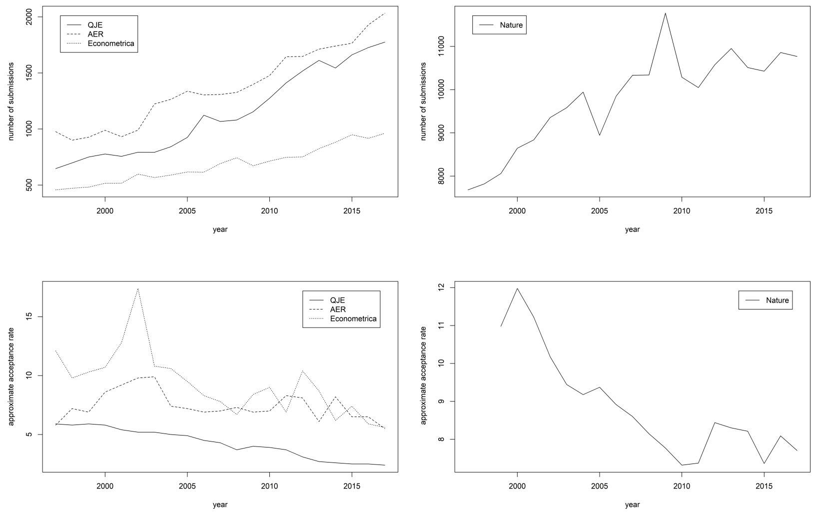


Figure 6: Submitted papers (upper panels) and approximate acceptance rate (bottom panels) in the years 1997-2017 for Quarterly Journal of Economics (QJE), American Economic Review (AER), Econometrica and Nature.

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# Appendix A – Partial list of renowned journals charging a submission fee

The following table shows a partial list of important scientific journals with submission fee. The fee considered is the basic fee for non-members, further details can be found on the websites of these journals.

However, in many branches of sciences we are seeing a slow transition from submission fees to article processing charges. This is a different story that will be investigated in a future paper.

| Journals | Field | Submission fee ($) |
|---|---|---|
| American Economic Journal(s) | Economics | 300 |
| American Economic Review | Economics | 300 |
| American Journal of Sociology | Sociology | 30 |
| American Sociological Review | Sociology | 25 |
| Blood | Medicine | 75 |
| Cerebral Cortex | Neuroscience | 75 |
| Econometrica | Economics | 50 |
| Journal of Accounting Research | Accounting | 500 |
| Journal of Banking & Finance | Finance | 300 |
| Journal of Clinical Oncology | Medicine | 60 |
| Journal of Econometrics | Econometrics | 75 |
| Journal of Empirical Finance | Finance | 175 |
| Journal of Finance | Finance | 300 |
| Journal of Financial Economics | Finance | 750 |
| Journal of Financial Intermediation | Finance | 400 |
| Journal of Financial Markets | Finance | 170 |
| Journal of Immunology | Medicine | 50 |
| Journal of Investigative Dermatology | Medicine | 50 |
| Journal of Money, Credit and Banking | Economics | 200 |
| Journal of Pharmacology and Experimental Therapeutics | Medicine | 75 |
| Review of Economic Studies | Economics | 150 |
| Review of Finance | Finance | 300 |
| Stem Cells | Biology | 90 |
| The FASEB Journal | Biology | 50 |
| The Journal of Economic History | History | 60 |

## Appendix B – Modelling quality

Assuming that all the papers are of the same high quality is not only convenient but also realistic given that we are considering top journals. Indeed, a common assumption in theoretical models is that editors perfectly observe the quality of papers during the review process or that editors can perfectly identify good papers as good (Azar, 2015; McCabe & Snyder, 2005). In this case, thinking about papers of different quality would be meaningless because editors would immediately identify low quality papers, and the model presented in the previous sections for high quality papers would not change. This idea is reasonable since editors of top journals should be able to assess the quality of the papers they receive.

If we drop this assumption, we can let $q$ be a dummy variable equal to $q_L$ if the paper is of low quality, and $q_H$ if the paper is of high quality (McCabe & Snyder, 2005; Cotton, 2013; Tiokhin et al., 2021). Since quality is generally assumed to be uniformly distributed between 0 and 1 (Azar, 2015), then in our case $q_H = 1$ and $q_L \in [0, 1)$.

Editors in this scenario cannot observe both the quality and riskiness of papers, even though they know that papers can be $q_L$ or $q_H$. If we assume that quality affects the probability of being acknowledged by the scientific community, then we would have $p_i(q_L) < p_i(q_H)$. A simple functional form could be $p_i(q) = qp_i \implies q_L p_i < q_H p_i$. Then with perfect information the rejection rate would depend on the quality of the paper as usual in other models. Obviously, editors wish to receive only high quality papers because they yield higher expected returns. With information asymmetry the expected utility of research project $i$ would be

$$E[u_i] = \begin{cases} (1-r)q_L p_i y_i - F = (1-r)q_L \bar{y} - F & \text{if} \quad q = q_L \\ (1-r)q_H p_i y_i - F = (1-r)\bar{y} - F & \text{if} \quad q = q_H = 1 \end{cases} \tag{11}$$

Given that $E[u_i^{q_L}] < E[u_i^{q_H}]$ is common knowledge, if $r = \bar{r}$ and $E[u_i^{q_L}] < 0$ only high quality papers would remain on the market. This assumption seems to be justified by the low acceptance rates observed in top journals (see Section 5), so that the expected utility of low-quality papers is likely to be lower than the cost of submission.

If the rate charged to high quality papers with information asymmetry $\bar{r}$ does not discourage submission of low quality papers, i.e. $E[u_i^{q_L}] \geq 0$, the journal would register an expected loss on low-quality papers. In this case, we should change the model accordingly to create a screening mechanism. The simplest thing to do is to let the editors decide $F$ before setting $r$ (as in Cotton, 2013). Editors should simply set $q_L \bar{y} < F \leq \bar{y}$ (a similar result is obtained in Tiokhin et al., 2021). In this way, editors can ensure that only high quality papers are submitted. The interested reader is referred to the work of Tiokhin et al. (Tiokhin et al., 2021) which shows in detail how submission costs provide the existence of a separating equilibrium.

Another way in which quality could enter the model is through the scientific output $y$ of papers. The reasoning adopted above for $p$ can also be transposed to $y$, and in that case the baseline model of Section 2 simply becomes the case $y_i(q) = y_i(q_H) = y_i, \forall i$. However, assuming that the quality of a paper influences its citations is not in line with the empirical literature, which suggests that high citations are not necessarily associated with high quality papers, as citations can be driven by different factors (Seglen, 1997, 1998; Tahamtan et al., 2016; Sochacki et al., 2018; Liskiewicz et al., 2021). For example, it is well known that researchers do not necessarily read all the papers they cite. This is because they are usually more interested in the idea and result of a scientific work. Consequently, a paper may have an impact on the scientific community because the idea and results are worthy of being cited, not necessarily because of the quality of the paper.

The comment in this Appendix shows that assuming all papers to be of high quality is not limiting to the results presented, as the assumption is reasonable and the model easily amendable. Adding papers of different quality does not affect the main predictions of the model, but would complicate the theoretical framework considerably. The model could also be extended to take into account the quality of journals, for example by modelling top and lower tier journals. In this case, it would be easy to demonstrate (and it has already been demonstrated in the literature) that top journals can screen high quality papers. Although in future work the model may be modified, the reader may look to Tiokhin et al. (Tiokhin et al., 2021) who already provide insights into this aspect.

# Appendix C – Some extensions of the original model

In this section, we consider extensions of the model according to the referees' suggestions and discuss the results of the model under different assumptions.

## Same scientific impact

We keep all assumptions, but instead of assuming the same average return for all papers, we assume that all papers produce the same $y$ but with different probabilities of success, as was done in credit markets by De Meza and Webb (De Meza & Webb, 1987). One motivation behind these different probabilities of success may be the reputation of the author (as illustrated in the next section). This changes the research market, as now all papers can potentially produce the same scientific output (number of citations). The resulting new expected utility of researchers with information asymmetry is

$$E[u_i] = (1 - \bar{r})p_i y - F \tag{12}$$

In this case, unlike the original model, some risky paper may not be submitted with information asymmetry, since for risky papers the positive part of $E[u_i]$ would be lower at the same $\bar{r}$. This assumption is unrealistic because it is evident from the data that papers in the top journals produce different numbers of citations; in addition, we are also eliminating the trade off between risk and innovativeness of the original model. We also lose the useful results of too many papers submitted to the top journals. For this reason, the hypothesis of the original model seems more appropriate.

**Reputation**

As noted by one of the referees, authors with high reputation are much more likely to be cited, according to the typical Matthew effect. Since the quality of the papers is the same, editors may be inclined to publish papers submitted by famous authors. We assume that the probability of success depends on the reputation of the $i$-th author, $R$, so we have $p(R_i)$, with $i \in \mathcal{I}$ and $\partial p(R_i)/\partial R_i > 0$. Again, the lower $p(R_i)$, the riskier the paper. To maintain information asymmetry, we must assume that even if editors observe $R_i$, they do not know exactly $p(R_i)$, even though they know that $p(R_i) > p(R_j)$ if $R_i > R_j$. As predicted by one of the referees, we now show that by changing the model in this way, reputation can produce perverse effects on the scientific market.

If we keep the original model assumption with the trade-off between risk and innovativeness, the result does not change, so we study this scenario under the assumption of $y$ equal for all papers, as done in the previous section. We focus only on the imperfect information case. The expected utility of researchers in this case is

$$E[u_i] = (1 - \bar{r})p(R_i)y - F \tag{13}$$

Unlike equation (6), now the expected utility is different for each researcher even in the presence of asymmetric information and depends on the reputation of the researcher. It is clear that researchers with higher reputation have higher expected utility. Knowing this, editors can now exclude risky work by simply increasing $\bar{r}$. In fact, as $\bar{r}$ increases, more and more risky papers are not submitted, while authors with high reputation will remain in the market as long as $E[u_i] = 0$. It follows that, even if all papers are of the same quality and have the potential to produce the same scientific impact, editors will be biased toward authors with high reputation and will have a mechanism for screening papers.

This produces two undesirable effects. First, science becomes reputation-based and not merit-based. Second, a kind of *cold-start* problem. This problem occurs when new buyers or sellers who do not have a track record in an e-commerce platform are marginalised because users do not trust them because of their lack of reputation (Milgrom & Tadelis, 2019). In this model, young scientists with low reputation will find it difficult to publish in top journals despite the fact that their work is meritorious (same $y$ for all papers). This alternative model deserves to be explored in more detail in a future paper.

# Too much science

Giuseppe Pernagallo*

**Abstract**

Scientific production is growing at an unprecedented rate, but how many of the published articles are really useful to society? With an asymmetric information model, I show on what conditions scientific journals might publish more articles than would be socially efficient. Moreover, publishing all science would certainly be inefficient. These results apply to both submission fee and free submission scientific publication systems. To avoid this social inefficiency, policymakers should keep inefficient researchers out of the market by offering, for example, a subsidy or alternative employment in the public sector. In this sense, the division of academic labor between research and teaching would be helpful in streamlining the research market. The paper also discusses the effects of meritocracy and market power on the phenomenon of excess science, showing that paying all researchers the same salary or tolerating academic oligopolies can have negative consequences on scientific production.

*Keywords*: Economics of Science; Epistemology; Information Economics; Innovation; Information Asymmetry; Knowledge JEL Codes: D7; D8; I23; O3.

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# 1 Introduction

It is estimated that more than 50 million academic articles were published until 2010, while in 2014 researchers estimated the number of English-language academic articles accessible on the Web at 114 million (Jinha, 2010; Khabsa & Giles, 2014). These numbers are expected to grow further, as research has shown that the number of articles published has increased by about 8-9 percent per year in recent decades (Landhuis, 2016). The increase in scientific production stems mainly from the *publish-or-perish* philosophy and produces many negative consequences, such as skewness of scientific impact, decay of attention in science, high rejection rates with the loss of much innovative research, and loss of trustworthiness of science (Ruiz-Castillo & Costans, 2014; Grimes et al., 2018; Pernagallo, 2023).

This paper addresses the important philosophical and economic question of whether the current scientific system is really producing too much science. If all published articles were beneficial to society, in the sense that they produced more resources than they consumed, then producing too much science would not be a problem. To test this, we need to focus on the three main agents involved. On the one hand, researchers invest time and money in their research to be published in academic journals and get salary, funding, fame and so on in return, while editors manage academic journals to publish meritorious articles and earn from institutional or private subscriptions. On the other hand, academic researchers are mainly employed in public institutions and are paid with public money in exchange for knowledge that will spark innovation and economic growth (on the role of knowledge for growth, see Antonelli, 2019).

The problem of excess science can be studied as a problem of scientific publication or as a problem of scientific production. Scientific publication mainly concerns academic journals, which have the key role of validating research work by accepting articles for publication. When considering publication, the main actors involved are researchers, who submit their papers, and editors, who can accept or reject research papers. In this scenario, efficiency means that the expected return to researchers and editors offsets or exceeds their expected cost. The model introduced in this paper shows that publication is certainly (socially) inefficient, with obvious repercussions for the broader problem of scientific production.

Science production involves society as a whole, affecting not only researchers and editors but also taxpayers. In this case, efficiency is achieved if the expected returns from the three agents offset or exceed their expected costs. The model shows that in this case efficiency depends closely on the distribution of articles and the knowledge produced by the lowest impact article published.

The source of this inefficiency comes from asymmetric information. Scientific systems, as argued by some research (e.g., Azar, 2015; Pernagallo, 2023), have a significant asymmetric information problem. Editors cannot perfectly ascertain the quality of a submitted article, whereas the author of the article generally has a better idea of its potential for the scientific community. Reviewers, while providing a useful signal to the editor, cannot solve the problem (for a discussion of this issue, see Pernagallo, 2023). The existence of information asymmetry, in that editors do not know whether or not a published article will have an impact on science, has two important consequences. On the one hand, it is possible for articles with less impact to be published; on the other hand, articles with greater impact face a higher rejection rate than would be the case with perfect information.

The approach in this article draws on mathematical tools, such as probability theory, which have also been used in epistemology to study knowledge (e.g., Levi, 1980). In particular, using a simple model with asymmetric information, this paper shows that under realistic assumptions, we face a problem of excess science. In other words, information asymmetry leads to the undesirable result of publishing many socially inefficient papers. The severity of this problem depends closely on the structure of the research market. If scientific impact is measured as a variable between zero and one (as hypothesized in Section 2), then the density of this variable can have three forms.

Figure 1 shows the possible densities for the research market. In a 'risky' research market (top panel), there is a high percentage of low-impact articles, so there is a higher probability for journals to publish less-than-worthy scientific work. This type of distribution is called skewed to the right. On the other hand, a distribution skewed to the left (bottom panel) has the mode close to one, which means that journals have a higher probability of publishing worthy work, which is why the market is said to be 'safe.' Finally, a 'normal' market has a symmetric distribution with mode at 0.5, which represents an intermediate situation.

Previous literature has amply demonstrated that the research market is skewed to the right (e.g., Seglen, 1992; Ruiz-Castillo & Costans, 2014), which means that most published papers are low impact. Whether or not this distribution follows a power law is still a subject of scientometric research (see, for example, Brzezinski, 2015 or Siudem et al., 2022). If we rely on scientific impact, generally measured through citations, as a measure of a research paper's usefulness, this means that only a few researchers contribute significantly to scientific progress (e.g., Lotka, 1926; Bornmann & Leydesdorff, 2017). This aspect plays a key role in our discussion, because if the knowledge created by researchers depends on the scientific importance of the article, most published articles generate little knowledge for society. It is therefore reasonable to think that much of the science funded today is socially inefficient, because the return

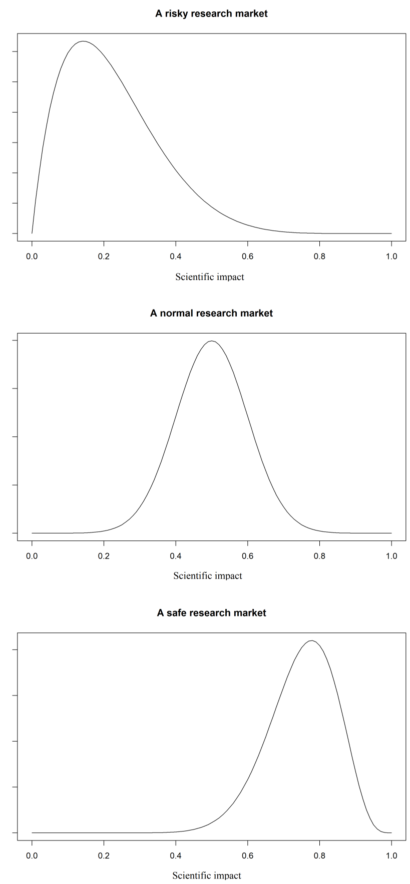


Figure 1: Example of risky (top panel), normal (middle panel), and safe (bottom panel) research market. The horizontal axis represents the scientific impact measured by a variable between zero and one, while the vertical axis represents the density of the distribution.

to society (knowledge) does not offset the cost to society (mainly, researchers' salaries and journal publication costs). This clearly shows a major contradiction in the research market, which is inherently inefficient in that the success of a few scientists is sustained by the multitudes of inefficient articles that cite them, a process that feeds on the mechanisms of the Matthew effect (Merton, 1968).

The model in this paper allows us to formulate policy proposals to improve the scientific system. In the tradition of incentive policies (on incentives in science see Strevens, 2003), the problem of scientific overload can be solved by keeping inefficient researchers out of the research market, for example, by offering a subsidy or alternative employment in the public sector. In fact, currently a common practice in some business schools (cost-effective organizations) is to divide academic staff into two tracks, one for 'research' and one for 'teaching.' In this way, researchers with low-impact work are not forced to publish their work, as they can earn their salary in another way without congesting the research market. This allows the scientific system to publish more work with high knowledge potential, which compensates for or even exceeds its cost to society.

The problem under consideration is the inevitable consequence of the transformation of the scientific system into a business and the over-reliance on inaccurate indicators of the importance of articles, such as citations or metrics like the $H$ index (Radder, 2010; Dorogovtsev & Mendes, 2015; Siudem et al., 2022). Therefore, this article questions the reliability of current indicators of scientific impact and the central role that publication has assumed in the careers of researchers with respect to the advancement of human knowledge.

The model also shows that if science is oligopolistic (Hodgson & Rothman, 1999; Larivière et al., 2015), meaning that a few journals have high market power and thus their expected profits are positive, journals end up publishing more low-impact articles than in the case of perfect competition (zero expected profits). This makes it more likely to publish papers for which the knowledge produced for society does not cover their costs.

Finally, the model also shows that, in the absence of a meritocratic system that rewards researchers with high-impact work, scientific overload would worsen, as the scientific system could also potentially publish articles without impact, which are only costly to society without generating any knowledge in return.

## 2 The model

### 2.1 Setup

We have a continuum of researchers, each of whom is endowed with a research paper, and many competitive journals (editors) that potentially could publish these papers. The hypothesis of perfect competition has been discussed extensively in other works (Pernagallo, 2023); however, in Section 3 we abandon it to show that we obtain an even stronger result in terms of scientific overload. Agents are assumed to be risk neutral.

Research papers are different because of their scientific impact,[1] $y_i \in [0, 1]$, with $i \in \mathcal{I}$, the index set of all types of papers in the continuum. Given two papers $i$ and $j$, we say that paper $i$ is better than paper $j$ if $y_i > y_j$. The distribution of papers is indicated with $G(y_i)$ and the density function with $g(y_i)$.

The scientific impact of research has economic value for both researchers and editors, as researchers gain, for example, tenure or funding, while journals increase their impact factor, which translates into increased subscriptions, prestige, and so on. So we have a function $T(y_i)$ that transforms the scientific impact of the published paper into a salary for the researcher, and a function $IF(y_i)$ that transforms scientific impact into revenue for the journal. We have that $\frac{\partial T(y_i)}{\partial y_i} > 0$ and $\frac{\partial IF(y_i)}{\partial y_i} > 0$, because the better the article, the greater the return for researchers and editors.

Here we assume that $T(y_i)$ is strictly positive, so that $T(0) \neq 0$. This is easy to justify, since in many scientific fields researchers gain tenure simply by publishing articles regardless of their impact on the scientific community (this is

[1] There is no unambiguous way to measure the scientific impact of research; for simplicity, we assume that this measure takes values in the unit interval. This has been done in previous work as well, just to mention, McCabe & Snyder, 2005 model quality of papers in the unit interval. Choosing different intervals does not change the result of the mathematical model.

common, for example, in many areas of the social sciences), so that even articles without impact have economic value for researchers. However, the system is still meritocratic, as researchers who produce higher quality articles receive a greater return (more funding, work at a better institution, and so on). Abandoning this assumption produces undesirable effects for science, as discussed in Section 3. On the other hand, the assumption of $IF(0) = 0$ is derived from the usual formulas for measuring scientometric journal indices.[2]

Moreover, once published, a paper produces knowledge for society. The knowledge function, $K(y_i)$, is increasing in $y_i$ as $T$ and $IF$. We assume that $K(0) = 0$ since papers without scientific impact do not increase knowledge for society because they are not recognized by the scientific community. This is a strong assumption, but one that is consistent with the current scientific system, which generally considers only works with an impact (e.g., citations). We could also assume that the knowledge function is concave, since the increase in knowledge by going from a very important article to a slightly more important one is less than the increase in knowledge by going from an unimportant article to an important one. But for the purposes of this model this is not relevant.

Editors and policy makers only know the distribution of types in the population. However, they do not observe the scientific potential of each article, whereas researchers have this information. It is clear that editors do not have all the necessary skills or knowledge of all the topics to perfectly evaluate the research papers they receive, while researchers should be aware of the potential of their research. The policy maker must rely on the evaluation done by journals to determine which papers are worthy of publication. For simplicity, we neglect reviewers, as is the case in many models and since they cannot solve the asymmetry problem (see, for example, McCabe & Snyder, 2005; Tiokhin et al.,

[2] For example, the *Impact Factor* (IF) is generally measured as a ratio, where the numerator is the number of citations. If an article has zero scientific impact, it will produce zero citations and a zero IF for the journal.

2021; Pernagallo, 2023).

We consider the two most recurring publishing systems to show that the results of this work are robust. We consider the case of journals with a submission fee and free submission. The rejection rate is denoted by $r$ and the editors incur a fixed cost of $C$ to support editorial services (McCabe & Snyder , 2005; Armstrong , 2015; Pernagallo, 2023), while researchers in each case incur a cost of $E$ to produce the article (think of the funds used to collect the data, hire the assistants, purchase the software, etc.).

Finally, we know that in most cases (excluding totally private institutions) academic researchers are generally paid with public money, which means that the expected utility to taxpayers on the $i$th paper can be defined as

$$E[U_i] = (1-r)[K(y_i) - T(y_i)]$$

which means that if the article is accepted, it yields the difference between the knowledge produced and the cost represented by the publicly funded salary.

## 2.2 Submission fee

In this publishing system, the researcher must pay a fixed submission fee, $F$, to submit the paper. We focus on this case first because the free system is the special case of the submission fee system when $F = 0$.

The expected utility for the researcher on the $i$th paper is

$$E[u_i] = (1-r)T(y_i) - F - E \tag{1}$$

**Definition 2.1** (Marginal paper)**.** *A research paper with $y_m$, $m \in \mathcal{I}$, for which (1) is equal to zero.*

Journals receive a fixed submission fee, $F$, for each paper submitted. As with credit markets (Stiglitz & Weiss, 1981; De Meza & Webb, 1987), we can focus our attention directly on the pooling equilibrium case. The expected profit function for journals is given by

$$E[\pi] = (1 - r)IF(\bar{y}) + F - C \tag{2}$$

where

$$E[y] = \bar{y} = \frac{\int_{y_m(r)}^{1} y_i g(y_i) dy_i}{\int_{y_m(r)}^{1} g(y_i) dy_i} = \int_{y_m(r)}^{1} y_i \hat{g}(y_i) dy_i \tag{3}$$

Journals maximize with respect to $r$, and we can show that, analogous to credit markets (Stiglitz & Weiss, 1981), the expected profit function may not be monotonically increasing in rejection rate and that the equilibrium is not market clearing, which means that in equilibrium there are researchers who submit the article but whose research is not published. However, we can show that, unlike in credit markets, there is no adverse selection effect, as an increased rejection rate makes it less convenient to submit lower-impact papers. Thus, a higher rejection rate increases the average quality of submitted papers.

**Proposition 2.1.** *As the rejection rate increases, the scientific impact of the marginal article, below which researchers do not submit the article, increases, or*

$$\frac{\partial y_m(r)}{\partial r} > 0 \tag{4}$$

*Proof.* This follows upon differentiating $E[u_m]$. Indeed, $\partial E[u_m]/\partial r < 0$. So, since $E[u_m] = 0$ for a given $r_1$, if a new rate $r_2$ is charged, such that $r_2 > r_1$, we have that $E[u_m] < 0 \implies \exists\, y_k > y_m \ :\ E[u_k] = 0, k \in \mathcal{I}$.

□

**Proposition 2.2.** *The expected profit function of journals may not be monoton-*

*ically increasing in $r$, and there is a rejection rate that maximizes the expected return of the journal.*

*Proof.* If we look at the partial derivative of (2) with respect to $r$, we see that an increase in $r$ produces two effects:

- a negative effect on $E[\pi]$ given that $(1 - r)$ decreases;
- a positive effect on $E[\pi]$ given that $\int_{y_m(r)}^{1} y_i \hat{g}(y_i) dy_i$ increases.

Furthermore, since $E[\pi]$ is continuous on the closed interval $[0, 1]$, the extreme value theorem guarantees that a maximum is reached.

$\square$

**Proposition 2.3.** *In equilibrium, there is no market clearing.*

*Proof.* To prove this, it is sufficient to note that, given an equilibrium rejection rate $r^*$, the number of papers submitted is equal to

$$\int_{y_m(r^*)}^{1} g(y_i) dy_i$$

while journals accept $(1 - r^*) \int_{y_m(r^*)}^{1} g(y_i) dy_i$ papers. Any $r^* \neq 0$ will not clear the market because, despite submitting the paper with the current rejection rate (and paying the fee), some researchers' papers are not published. $\square$

The current scientific system is unable to publish all the papers submitted, which is not necessarily a bad thing, since it can be shown that among the research papers published by journals, some may be socially inefficient, in the sense that they consume more resources than they create.

**Proposition 2.4.** *In the competitive equilibrium, journals may publish socially inefficient papers.*

*Proof.* To be socially efficient, a paper must satisfy the following

$$(1-r)[T(y_i)+IF(y_i)+K(y_i)] \geq C+E+(1-r)T(y_i) \tag{5}$$

The left-hand side of (5) represents the expected return to society if the $i$th paper is published, while the right-hand side is the expected cost.

Competition will bring journals' expected profits to zero. Let $\bar{r}$ be the rejection rate of the competitive equilibrium. At this rate, between $y_m$ and 1 there are researchers for whom $y_i < E[y]$, researchers for whom $y_i = E[y]$, and researchers for whom $y_i > E[y]$. Moreover, we know that for any $y \in [y_m, 1]$, the researcher submits the paper, which means

$$E[u_m] = 0 \iff (1-\bar{r})T(y_m) - E = F \tag{6}$$

Obviously, $y_m < E[y]$, then

$$E[\pi_m] = (1-\bar{r})IF(y_m) + F - C < 0 \implies$$

$$(1-\bar{r})IF(y_m) + F < C \overset{by\ (6)}{\implies}$$

$$(1-\bar{r})IF(y_m) + (1-\bar{r})T(y_m) - E < C \implies$$

$$(1-\bar{r})[T(y_m)+IF(y_m)] < C+E \tag{7}$$

We can have three situations. If $E[U_m]=0$, we have that socially inefficient papers can be published as

$$E[U_m] = (1-\bar{r})K(y_m) - (1-\bar{r})T(y_m) = 0 \implies (1-\bar{r})K(y_m) = (1-\bar{r})T(y_m)$$

Then we can rewrite (7) as

$$(1-\bar{r})[T(y_m)+IF(y_m)]+(1-\bar{r})K(y_m) < K+E+(1-\bar{r})T(y_m) \implies$$

$$(1-\bar{r})[T(y_m)+IF(y_m)+K(y_m)] < K+E+(1-\bar{r})T(y_m)$$

which proves that papers of type $m$ can be published even if they are socially inefficient. If $E[U_m] < 0$, *a fortitiori*, the same result holds.

If $E[U_m] > 0$, then $(1-\bar{r})K(y_m) > (1-\bar{r})T(y_m)$. This means that $(1-\bar{r})K(y_m) = (1-\bar{r})T(y_m)+\epsilon$, with $\epsilon > 0$. We can rewrite (7) as follows

$$(1-\bar{r})[T(y_m)+IF(y_m)]+(1-\bar{r})K(y_m) < K+E+(1-\bar{r})T(y_m)+\epsilon$$

$$(1-\bar{r})[T(y_m)+IF(y_m)+K(y_m)] < K+E+(1-\bar{r})T(y_m)+\epsilon$$

as $\epsilon \to 0$, we have that the paper of type $m$ is socially inefficient.

□

Proposition 2.4 shows that the only case in which the scientific system can be socially efficient is when the marginal article produces sufficient knowledge and returns for editors and researchers to offset the total cost to society. Whether this is true depends strictly on the distributions of $y_i$ and the explicit form of the functions. Since the distribution of scientific impact is strongly skewed to the right as discussed in the introduction of this paper, with a large majority of low-impact articles published, it is realistic to assume that the current publishing system publishes socially inefficient papers.

If we focus our attention simply on the problem of science publication, it is easy to show that the result would certainly be (socially) inefficient, since journals end up publishing at least one category of socially inefficient papers, the marginal papers. The proof for this claim is given in Appendix A.

### 2.3 Free submission

This scenario is the special case of Section 2.2 when $F = 0$. The results obtained in the previous section are the same, except that more articles are submitted in a free system, which potentially worsens the problem of excessive science. This is due to the lower cost to researchers and lower rejection rate (journals need to publish more papers to achieve zero expected profit, since they now do not earn $F$ on each paper submitted). The problem can be formalized as follows.

**Proposition 2.5.** *As $F \to 0$, the rejection rate decreases.*

*Proof.* The competitive equilibrium is reached for

$$E[\pi] = 0 \implies r = 1 - \frac{C - F}{IF(\bar{y})} \tag{8}$$

A decrease in $F$ has two effects on the rejection rate of the competitive equilibrium. First, the numerator of (8) increases, making $r$ smaller. Second, when $r$ decreases, $IF(\bar{y})$ also decreases, because the lower rejection rate attracts lower-impact papers, making the average scientific impact $\bar{y}$ smaller and thus the rejection rate decreases more.

□

## 3 Policy implications

In this section we limit ourselves to examples in the case of the submission fee system, since the free system is only the special case for $F = 0$.

## 3.1 Why should we not publish all the science?

It is clear that if the scientific system produces too much science, it wastes valuable resources. It can be shown that a world in which all scientific production is published would certainly be inefficient for society. Imagine that policy makers make an agreement with journals to cover any loss from publishing all work, so that the expected profits for editors are zero, as expected in perfect competition. In other words, if $r = 0$, the expected utility for the journals becomes

$$E[\pi] = IF(\bar{y}) + F - C + TR = 0 \tag{9}$$

where $TR$ is a transfer made by the government to ensure that journals remain in the market and, in principle, could also be a tax in case $IF(\bar{y}) + F - C > 0$. Of course, this is a transfer of wealth between taxpayers and editors, so it does not affect the social welfare function. In fact, the government knows exactly the magnitude of $TR$ to fix, since all the variables in (9) are common knowledge for the agents. Note that in the case where all papers are published, we have that

$$E[y] = \bar{y} = \int_0^1 y_i g(y_i) dy_i \tag{10}$$

**Proposition 3.1.** *If all papers are published, the scientific system is socially inefficient.*

*Proof.* Social efficiency in this scenario requires that

$$T(y_i) + IF(y_i) + K(y_i) \geq C + E + T(y_i)$$

Since all papers are published, we know that papers with $y_0 = 0$ are also published. For these papers, we have that $IF(0) = 0$ and $K(0) = 0$, which means that

$$T(y_0) + IF(y_0) + K(y_0) < C + E + T(y_0) \iff T(y_0) < C + E + T(y_0)$$

So the scientific system is certainly publishing at least one category of socially inefficient articles. If scientific output is skewed to the right (thus, many 0-type articles), this means that a large percentage of inefficient articles are published.

□

## 3.2 How to solve the problem of excessive science?

To solve the problem of excess science, one possible solution would be to prevent inefficient work from being submitted. This can be accomplished through various mechanisms.

One solution is to offer researchers an alternative to producing and submitting articles. For example, imagine a subsidy or public work that produces $W = C - F$ (for example, the creation of two tenure tracks, one for research and one for teaching). In this case, the expected utility of researchers must include this opportunity cost

$$E[u_i] = (1-r)T(y_i) - F - E - W = (1-r)T(y_i) - E - C \tag{11}$$

Equation (13) implies that researchers who submit articles are only those for whom $E[u_i] \geq 0$ or $(1-r)T(y_i) \geq C + E$, so only researchers with socially efficient papers will find it convenient to give up $W$ to enter the research market. This can be formalized as follows.

**Proposition 3.2.** *Introducing an opportunity cost $W = C - F$ for researchers can make the scientific system socially efficient.*

*Proof.* Given the expected utility (13), researchers submit their papers only if

$$(1-r)T(y_i) \geq C + E \implies$$

$$(1-r)T(y_i) + (1-r)IF(y_i) > C + E$$

which shows that the publication of science is efficient. As for scientific production, if $E[U_i] \geq 0$, we have that $(1-r)K(y_i) \geq (1-r)T(y_i)$, then

$$(1-r)T(y_i) + (1-r)IF(y_i) + (1-r)K(y_i) > C + E + (1-r)T(y_i)$$

and the proof is complete.

If $E[U_i] < 0$, then $K(y_i) < T(y_i)$, which means that $K(y_i) = T(y_i) - \epsilon$, with $\epsilon > 0$. So we have

$$(1-r)T(y_i) + (1-r)IF(y_i) + (1-r)K(y_i) \geq C + E + (1-r)T(y_i) - \epsilon$$

and as $\epsilon \to 0$, we have the result.

□

## 3.3 Why is it a bad idea to pay all researchers the same salary?

In many countries, especially in public institutions, researchers receive a fixed salary independent of the quality of published articles. The model presented in this paper allows us to show why this causes excessive scientific production.

Mathematically, this means that each researcher receives $T$, which is independent of the impact of the paper $y_i$. Thus, publication produces the same salary for all, and the expected utility for the $i$th researcher is

$$E[u_i] = E[u] = (1-r)T - F - E \tag{12}$$

This means that if the rejection rate is such that at least one article is submitted, then all articles are submitted. The existence of the research market is thus based on satisfying the researcher constraint $E[u] \geq 0$, which means that journals solve the following maximization problem

$$max_r \;\; E[\pi] = (1-r)IF(\bar{y}) + F - C \tag{13}$$

$$\text{s.t.} \;\; (1-r)T \geq F + E$$

where

$$E[y] = \bar{y} = \int_0^1 y_i g(y_i) dy_i \tag{14}$$

If there is a rejection rate that satisfies the constraint of (13), it means that the lowest impact article submitted in this case is the article of type 0, for which $y_0 = 0$, and an increase in the rejection rate, unlike in Proposition 2.1, does not increase the impact of the marginal article but can make the research market disappear. Recalling that the article of type 0 is socially inefficient as shown in Proposition 3.1, we have that for the same salary a socially inefficient article of type 0 has a $1-r$ probability of being published, while in the meritocratic system it is not even submitted.

This clearly shows that a unique salary in the research market has the negative consequence of producing a socially inefficient scientific system. It can be shown (and will be done in a forthcoming paper) that a single salary can also have the negative effect of pushing good or innovative science out of the market, just as it does in the lemons market (Akerlof, 1970).

### 3.4 Should we tolerate oligopolies in science?

One strand of the literature argues that scientific publishing can be described by an oligopoly rather than a perfectly competitive market. There are several reasons why this is bad for science, such as bias or discouragement of innovative work (Hodgson & Rothman , 1999). Moreover, journals with market power could use their position to strengthen their control over the scientific community (Larivière et al., 2015). How does this relate to the problem of excess science? The model presented here shows that market power could exacerbate the problem of scientific overload.

To demonstrate this, we abandon our competition hypothesis in this section. In this case, we have that the expected profit for the journals is

$$E[\pi] > 0 \implies r < 1 - \frac{C - F}{IF(\bar{y})} = \bar{r} \tag{15}$$

where $\bar{r}$ is the rejection rate of perfect competition. In other words, if there is market concentration, more articles are published because the rejection rate is lower than in the competitive case. Thus, the marginal article with market concentration will be a lower impact article than the competitive case, according to Proposition 2.1. In other words, if the goal of policy makers is to publish articles that can generate at least as much knowledge as they cost, oligopolies or other forms of market power should not be tolerated.

# 4 Discussion and conclusions

The model presented in this paper raises serious questions about the sustainability of the current publishing and scientific system. From a purely economic point of view, excessive science simply means that the expected return on a published article does not cover its expected cost. The model shows that we can be one *epsilon* away from publishing many inefficient articles, while if we focus our attention simply on the publication process neglecting the spillovers for taxpayers, we can conclude that the system is certainly inefficient.

Analysis of historical data (Fortunato et al., 2018; Fire & Guestrin, 2019) showed an exponential growth in the number of articles published over the years. The main reason stems from linking career and financial incentives to the publication of articles. Scientific production is how academics signal their value to the scientific community (Grimes et al., 2018), so it is reasonable to assume that researchers do not maximize the social knowledge function, but their expected utility, as in the Smithian *self-love* tradition. Consequently, although there may be a motivation related to active participation in the scientific community, publication is primarily functional for career promotion and funding needs.

Innovation in the research market has also radically changed the way researchers produce science. Advances in computation and statistics have made it easier for researchers to formulate research questions, access relevant data sources, and process them. In other words, the $E$ factor that we have referred to as the cost for the researcher to produce an article has decreased over the years and is expected to decrease further. Whereas in the past even running a simple regression represented a cost to researchers, today even simple free software can perform advanced statistical tasks, making scientific production easier and faster, with obvious repercussions on the ability of systems to efficiently process all the new science produced. In other words, as the cost to the researcher decreases, more and more papers will be submitted.

But the problem is not only about supply of papers. In fact, scientific journals have become a lucrative business (Larivière et al., 2015), which has also led to a huge increase in the number of potential outlets for papers. In other words, journals support the system simply because they do not maximize the knowledge function, but their expected profits. This is perfectly rational from an economic point of view, but it is certainly questionable from an ethical and philosophical point of view. It is legitimate to ask whether journals, in their current corporate organization, can play the delicate role in science for which they were originally conceived.

This paper also presents an inherent contradiction in the scientific system. If we stick to the convention of measuring the impact and usefulness of research using common (but debatable) metrics such as citations, the data have clearly shown that only a few researchers contribute substantially to science and that most of the work goes unrecognized (very low citations). But this huge number of unrecognized papers is functional in making the few highly recognized research papers relevant. The scientific system thus feeds on its inefficiency.

The model in this paper is static, but the results would not change in a dynamic model. Given time, researchers would have a great incentive to publish as many articles as possible, to take advantage of the cumulative benefits of a growing productive *corpus*, as predicted by the Mertonian and Bourdieusian theory of scientific capital accumulation (Merton, 1968; Bourdieu, 2004). In other words, the more an author publishes and, consequently, accumulates citations, the more this capital will produce additional articles and citations. In addition, authors with a lot of scientific capital could contribute more to papers through more opportunities for collaboration or funding.

The solution to the problem is quite simple: policy makers should simply offer alternatives to inefficient researchers. It is inevitable that if we rely on scientific impact as a measure of an article's usefulness to society, policy makers should prevent all research from being submitted and published. For example, by allowing academics to choose between a teaching salary and a research salary, it would be possible to skim socially efficient researchers from inefficient ones, exploiting the human capital of academics in two different ways.

This would alleviate the problem of excess science, but in principle it would not solve the issue of bad incentives for science. As long as financial incentives are tied to production, there will be no slowdown in science production in the future. Even assuming that all this production is useful to society, we will reach a point where we may simply be unable to process all this science, in the same way that too much information produces overload (Pernagallo & Torrisi, 2022). A serious debate should therefore seriously consider redesigning the figures of researchers and editors, making central again what should only matter in science: advancing human knowledge.

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# Appendix A – Science publication is socially inefficient

In this appendix we focus our attention on the problem of scientific publication. Here we consider the subset of society represented by the agent categories of editors, who publish research articles, and researchers who submit articles. It is easy to show that the publication of scientific articles in the competitive equilibrium is socially inefficient, because to be socially efficient, an article must meet the following condition

$$(1-r)[T(y_i)+IF(y_i)] \geq C+E \tag{16}$$

Obviously, the cost of scientific publication is the sum of the editorial cost of editors, represented by $C$, and the cost to researchers, represented by $E$. Science is published only if researchers get something from the submission of their articles and editors from their publication, which is given by the left-hand side of (16).

Competition will bring journals' expected profits to zero. Let $\bar{r}$ be the rejection rate of the competitive equilibrium. At this rate, between $y_m$ and 1 there are researchers for whom $y_i < E[y]$, researchers for whom $y_i = E[y]$, and researchers for whom $y_i > E[y]$. Moreover, we know that for any $y \in [y_m, 1]$, the researcher submits the paper, which means

$$E[u_m] = 0 \iff (1-\bar{r})T(y_m) - E = F \tag{17}$$

Obviously, $y_m < E[y]$, then

$$E[\pi_m] = (1-\bar{r})IF(y_m) + F - C < 0 \implies$$

$$(1-\bar{r})IF(y_m) + F < C \overset{by\ (6)}{\Longrightarrow}$$

$$(1-\bar{r})IF(y_m) + (1-\bar{r})T(y_m) - E < C \implies$$

$$(1-\bar{r})[T(y_m) + IF(y_m)] < C + E \tag{18}$$

Then the marginal article can be published even if it is socially inefficient.

# Academic treasure hunt: Incentive policies to attract research talent

Giuseppe Pernagallo*

**Abstract**

What causes the slowdown of innovation in academia? In addition to established explanations, this paper proposes an imperfect information argument. Universities that offer the same salary to scholars in the same position may trigger an adverse selection effect that pushes the best talent out of the market. This model shows that multiple equilibria can exist under perfect competition. In particular, the equilibrium in which even highly talented researchers accept the contract Pareto dominates the one in which only low-talent researchers accept the contract. Incentive-based policies are proposed as a solution to the problem.

*Keywords*: Economics of Science; Information Economics; Innovation; Knowledge; Research Policy JEL Codes: D8; O3.

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# 1 Introduction

It is well documented in the literature that innovation is slowing down (Gold, 2021). Explanations for this phenomenon generally refer to the *low-hanging fruit* argument or the exponential growth of ideas (Bloom et al., 2020; Park et al., 2023). These two arguments are very effective in explaining why science is becoming less disruptive. The *low-hanging fruit* argument is the idea that revolutionary discoveries are unique and that, once made, it is much more difficult to make new ones. However, this theory is difficult to reconcile with the fact that almost all scientific fields are experiencing the same fate (as documented in Park et al., 2023), making hard to believe that all the fields shares the same (degree of) low-hanging fruits.

On the other hand, the growth of ideas offers both an explanation for the increase and decrease in innovation. If new knowledge is generated by recombining existing knowledge (Weitzman, 1996), then past innovations should help find new ones. The negative consequence of this is that researchers must master increasingly complex tools and keep up with the increased costs of acquiring and exploiting knowledge.

This paper offers a complementary justification for the phenomenon, based on information asymmetry. European universities and many others around the world choose to offer the same salaries to scholars in the same position, usually in exchange for teaching and research activities. In a framework of imperfect information, this can trigger an adverse selection effect that pushes top talent out of the market.

The model presented here shows that under perfect competition there may be multiple equilibria, some of which are better for the academia, namely those in which even highly talented researchers accept the contract, which Pareto dominate those in which only low-talent researchers accept the contract. Incentive-based policies are proposed as a solution to attract top talent. This approach is somewhat similar to the argument of scholars (e.g., Gold, 2021) who think that the decline in innovation is also due to an imbalance of incentives between the principal (universities or companies) and the agents (research groups).

The question of why an imperfect information approach is more effective today than in the past is largely due to the process of commodification of science and the conditions of access to the research market (Radder, 2010; Pernagallo, 2023; 2023b). These aspects are discussed in more detail in Section 4.

# 2 The model

## 2.1 Setup

Competitive profit-maximizing research institutions, such as universities, want to hire researchers whose job is to produce research that brings prestige to the institution, and perform a fixed teaching workload, $T$. Researchers can produce research based on their talent (determined by nature), modeled with the continuous variable $t \in [t_{min}, t_{max}] = \mathcal{T}$, in exchange for a salary $w$. Thus there is a continuum of researchers, each endowed with a different level of talent.

The university's research output, $R(t)$, is increasing in the talent of researchers. The university offers a wage scheme $w(R(t))$, with $w \in \mathcal{W}$ and $\mathcal{W}$ the space of the wage scheme. The utility of a researcher if hired by the university is $u(w) = v[w(R(t)] - T$.

We assume that researchers are risk-averse, so we have that $u_w(w) > 0$, $u_{ww}(w) < 0$, $u_w(0) = 0$, $v' > 0$ and $v'' < 0$. The researchers' risk aversion (with respect to wages) hypothesis is well supported by previous literature (e.g., Strevens, 2003; Byford, 2017). In addition, the researcher may decide to enter industry instead of academia, where she will receive a salary $S(t)$ that is the reservation utility, so that $S(t_H) > S(t_L)$ for $t_H > t_L$.[1]

Universities are risk neutral and their prestige is higher when more talented researchers are hired. The information asymmetry stems from the fact that the university is unable to observe the talent of the researcher before hiring.[2]

The expected profits for the university are

$$E[\pi] = E[R(t) - w(R(t)) + T] = R(t) - w(R(t)) + T \tag{1}$$

The university's problem is to design an optimal wage scheme that maximizes expected profit. Mathematically

$$\arg\max_{w \in \mathcal{W}} E[\pi] = \arg\max_{w \in \mathcal{W}} R(t) - w(R(t)) + T \qquad s.t. \tag{2}$$

$$v[w(R(t))] - T \geq S(t) \tag{3}$$

where (3) is the *individual participation constraint*. Finally, an equilibrium in this model is defined as follows.

**Definition 2.1.** *An equilibrium in the model is a salary scheme that must satisfy the zero (expected) profit condition and satisfies at least one individual participation constraint.*

## 2.2 Case with perfect information

If the university can perfectly observe the talent level of each researcher, then it can offer a salary to each researcher according to his or her talent level. The Lagrangian is

[1] In a model of *brain drain*, $S(t)$ may represent the abroad economic opportunity for the researcher.

[2] There are imperfect signals of talent, such as awards or previous publications, but a signal game is currently the subject of future research and beyond the scope of this article.

$$\mathcal{L} = R(t) - w(R(t)) + T + \lambda\Big[v[w(R(t))] - T - S(t)\Big] \tag{4}$$

with F.O.C.

$$\frac{\partial \mathcal{L}}{\partial w(R(t))} = 0 \iff$$

$$-1 + \lambda v'[w(R(t))] = 0 \iff$$

$$v'[w(R(t))] = \frac{1}{\lambda} \tag{5}$$

which means that, given the researcher's risk aversion, the university should offer a constant salary. The salary can be set using the individual participation constraint. Specifically, the optimal salary $w^*$ for maximizing the profits of a researcher with talent $t$ would be

$$v[w^*(R(t))] = S(t) + T \implies$$

$$w^*(R(t)) = v^{-1}[S(t) + T] \tag{6}$$

However, competition will determine a wage $w^c$ that satisfies the zero (expected) profit condition

$$E[\pi] = R(t) - w^c(R(t)) + T = 0 \implies$$

$$R(t) + T = w^c(R(t)) = w^c(t) \geq w^*(R(t)) \tag{7}$$

Obviously, the most talented researchers receive higher salaries. In this scenario, the university can hire researchers and pay them according to the prestige they will bring to the institution (in practice, there is an equilibrium salary for each talent level). From now on, we will use the simpler notation $w(t)$

to denote salaries, and in particular $w^c(t)$ will denote the wage for the talent level $t$ that satisfies the zero profit condition.

## 2.3 Case with information asymmetry

Suppose now that talent is not information available to the university, which means that the university cannot observe which researchers it is hiring before the contract is signed. We now show that a possible equilibrium is reached when the university offers a single salary based on the average level of talent in the market. Before formalizing the result, we show that given $E[t] = t^* = \int_{t_{min}}^{t_{max}} tf(t)dt$, the corresponding competitive wage $w^c(t^*)$ can trigger adverse selection. Note that, as usual in these models, the talent distribution, $F(t)$, and the density function, $f(t)$, are known to all.

**Proposition 2.1.** *Given* $E[t] = t^* = \int_{t_{min}}^{t_{max}} tf(t)dt$, $w^c(t^*)$, *which is the corresponding unique salary that satisfies the zero profit condition, can trigger adverse selection.*

*Proof.* We define the marginal researcher, $t_m$, as the researcher with the highest talent who accepts the contract $w^c(t^*)$, so that $u_m(w^c(t^*)) = v[w^c(t^*)] - T = S(t_m)$. Clearly, $\partial t_m(w)/\partial w > 0$, and for all $t > t_m$ no one will not accept the contract. Let $Pr(u_{max}(w^c(t^*)) \geq 0)$ be the probability that the most talented researchers in the continuum accept the contract. Then, if $t_m < t_{max} \implies Pr(u_{max}(w^c(t^*)) \geq 0) = 0$. $\square$

**Corollary 2.0.1.** *If* $t_m < t_{max}$, $w^c(t^*)$ *is not an equilibrium.*

In most European institutions, salaries are fixed for scholars in the same position, so talented researchers may prefer to accept contracts outside academia rather than work and produce high-quality research at low salaries.

The fact that $w^c(t^*)$ is not an equilibrium when $t_m < t_{max}$ can be shown graphically. When $t_{max}$ researchers leave the market, the average talent level decreases. The process to reach equilibrium is illustrated in Figure 1. For example, suppose that when $w^c(t^*)$ is offered, all the researchers for whom $t > t^*$ leave the market if their participation constraint is violated, then the talent will no longer be distributed over the whole set $\mathcal{T}$, but over a subset ranging from $t_{min}$ to $t^*$ (area $A \cup B \cup C$), where $t^* > t_{min}$.

At this point, the university must set a new salary wage scheme. Suppose the new average talent in the market after shrinkage is $t'$, at which the university offers $w'$. If the individual participation constraint is still violated for researchers with talent above $t'$, the market shrinks further from $A \cup B \cup C$, to $B \cup C$. The new average $t''$ will determine a new salary scheme $w''$ and the market shrinks further from $B \cup C$ to $C$. The process will continue until the fixed average salary determines a range of talent from $t_{min}$ to $t_m$.

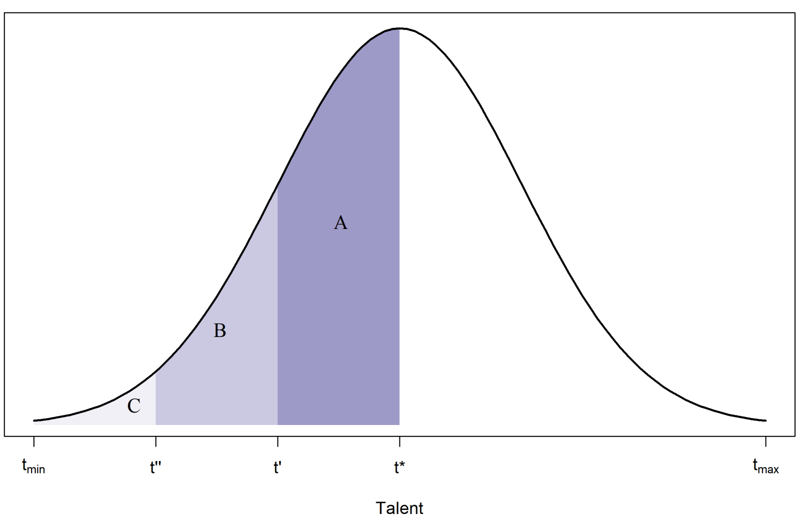


Figure 1: The shrinkage of talent.

**Proposition 2.2.** *The salary scheme* $w^c(\hat{t})$ *with* $\hat{t} = \int_{t_{min}}^{t_m} tf(t)dt$ *is a possible equilibrium.*

*Proof.* We simply note that $E[\pi(w^c(\hat{t}))] = 0$ and that all researchers with $t \in [t_{min}, t_m]$ accept the contract. $\square$

**Proposition 2.3.** *The equilibrium* $w^c(\hat{t})$ *is not unique.*

*Proof.* To prove the proposition, it is sufficient to find at least one more equilibrium. Let us take $w^c(t_{min})$, which is the expected zero-profit wage for researchers with talent $t_{min}$. The university makes $E[\pi(w^c(t_{min}))] = 0$ and $u_{min}(w^c(t_{min})) \geq 0$, so this is an equilibrium. $\square$

## 2.4 Example with two types

In this section we further explore the theory introduced in the previous sections by considering a research market with only two types of researchers, one of low talent, $t_L$, and one of high talent, $t_H$, with $t_L < t_H$. The ideas discussed here can be easily generalized to more types of researchers.

**Proposition 2.4.** *Given any* $\mathcal{T} = [\underline{t}, \bar{t}]$, $\underline{t} \neq \bar{t}$, $w^c(\bar{t})$ *cannot be an equilibrium.*

*Proof.* If the university offers $w^c(t_H)$, it will make zero profit on $t_H$, but losses on $t_L$ that accepts the $w^c(t_H)$ contract, which satisfies also the participation constraint of $L$. Thus, the total expected profits are negative, which is incompatible with the notion of equilibrium.

$\square$

**Proposition 2.5.** *There is no possible separating equilibrium, or an equilibrium in which the two researchers choose different contracts*

*Proof.* If the university offers two contracts, $w^c(t_L)$ and $w^c(t_H)$, both the agents will choose $w^c(t_H)$, with $w^c_H > w^c_L$, but in that case the university makes zero profit on $H$-type researcher but negative profits on $L$-type researchers, so this is not compatible with the notion of equilibrium. The same is true if the university offers $w^c(t_H)$ and $w^*$, where $E[t] = t^* = \frac{t_L + t_H}{2}$ and $w^* = w^c(t^*)$.

If the university offers $w^c(t_L)$ and $w^*$, then either both agents accepts $w^*$, which is again a pooling equilibrium, or $t_H$ researchers exit the market forcing the university to offer simply $w^c(t_L)$, which is an equilibrium. □

**Proposition 2.6.** *Academia is better off when both types of researchers accept the contract.*

*Proof.* The term 'academia' is used here to refer to universities and researchers. We can then construct a kind of welfare function for academia, $\mathcal{A}[w(t)]$, which is the sum of the profits and utilities of all agents involved.

If the equilibrium is one in which $w^c(t_L)$ is offered, then we know that only researchers of type $L$ accept the contract and thus

$$\mathcal{A}[w^c(t_L)] = E[\pi] + u_L(w^c(t_L)) = u_L(w^c(t_L)) \tag{8}$$

since expected profits are zero in equilibrium.

On the other hand, if $w^*$ is offered and both researchers accept the contract, we have that

$$\mathcal{A}(w^*) = E[\pi] + u_L(w^*) + u_H(w^*) = u_L(w^*) + u_H(w^*) \tag{9}$$

$$> \mathcal{A}[w^c(t_L)] = u_L(w^c(t_L))$$

□

**Corollary 2.0.2.** *If there exists two equilibria, $w^c(t_L)$ and $w^*$, $w^c(t_L)$ is not Pareto optimal.*

*Proof.* To prove this corollary we need to show that at least one agent is better off when the wage is $w^*$ and everyone else is no worse off. We know that for both $w^c(t_L)$ and $w^*$ the expected profit for universities is zero. However, when $w^*$ is the equilibrium wage, researchers of type $L$ have higher utility than $w^c(t_L)$, and if researchers of type $H$ accept the contract it means they have at least as much utility as they would have in industry. $\square$

Proposition 2.6 and its corollary must be interpreted carefully. First, despite being less talented, $L$-type researchers are still socially efficient in that they produce enough teaching and research to cover their paid salary. Second, $\mathcal{A}$ should not be confused with the total social welfare of society. Researchers can be more productive and innovative outside academia (for a discussion see Section 4). However, it would be better for academia to find a way to retain the most talented researchers. In this regard, several solutions can be proposed. Here, we focus on incentive-based policies (as in Pernagallo, 2023).

# 3 Policy

There are several policies that can be implemented to incentivize highly talented researchers to stay in academia. One effective way to address this problem is to introduce a reward system that fosters talent. Reward systems can be very effective in promoting innovation in asymmetric research markets (e.g., Pernagallo, 2023). Let us say that the government wants to achieve a level of talent in the market equal to $t^o > t_m > t_{min}$. We know that the wage scheme that satisfies the zero profit condition for $t^o$ is $w^c(t^o)$, but once $w^c(\hat{t})$ is fixed, researchers with $t^o$ leave the market. Introducing a reward, $Z(R(t))$, based on the level of research produced can mitigate the adverse selection problem. In other words, the policymaker can intervene *ex post* to ensure that the individual participation constraint of highly talented researchers is also respected.

**Proposition 3.1.** *Rewards, $Z$, can be used to mitigate (or even solve, in some cases) the adverse selection problem or* $\exists Z(R(t)) : t^o > t_m \wedge E[u_{t^o}(w^c(\hat{t}))] = 0 \implies max(t) \neq t_m$. *The reward scheme that satisfies the previous condition is not unique.*

*Proof.* We demonstrate how a fixed reward can attract highly talented researchers. Suppose the government wants researchers of type $t^o > t_m$ to enter the research market. Let then $\hat{t} = \int_{t_{min}}^{t_m} tf(t)dt$, knowing that $w^c(\hat{t})$ is the wage offered in equilibrium, it is sufficient for the government to give each researcher $Z = v[w^c(t^o)] - v[w^c(\hat{t})]$ so that universities satisfy the zero profit (expected) condition and the market has a continuum of researchers from $t_{min}$ to $t^o$.

However, this scheme is unfair because it excessively rewards researchers with little talent. Therefore, another reward scheme can link the reward amount to the level of research produced by the researcher, which is observable *ex post*. For ease of demonstration and without loss of generality, let us consider the simple discrete case of a market with only two types of researchers, $t_L = t_{min}$ and $t_H = t_{max}$. Then $E[t] = t^* = \frac{t_L + t_H}{2}$ and $w^* = w^c(t^*)$. The reward scheme for avoiding adverse selection can be structured as follows

$$Z(R(t)) = \begin{cases} 0 \quad \text{if} \quad t = t_L \\ \\ v[w_H^c] - v[w^*] \quad \text{if} \quad t = t_H \end{cases} \tag{10}$$

where $w_H^c$ denotes the wage that meets the zero profit condition for highly talented researchers. With this reward scheme we have that $t_L$ accepts the contract because $w^* > w_L^c$, and $t_H$ also accepts the contract because $E[u_H] \geq S_H$ since $E[u_H] = v[w^*] - T + Z(R(t)) = v[w^*] - T + v[w_H^c] - v[w^*] = v[w_H^c] - T \geq S_H$.

□

# 4 Discussion

This paper proposes an argument based on imperfect information to explain why innovation is flattening out. In fact, if research institutions are unable to distinguish talented researchers, it is very likely that those who are most likely to trigger innovation will end up pursuing something else. There are several counterarguments to this idea, and in this section I try to give a possible justification for these objections.

First, why should this argument be relevant today and not in the past? There is strong evidence that science has become a profitable business today (Larivière et al., 2015). Scientific journals are proliferating, and inevitably this increases the demand for research products. On the other hand, the research market has become much more accessible than in the past, for many reasons (Pernagallo, 2023b). One of the most relevant is the fact that doing research today, especially in quantitative fields, is easier than in the past, thanks to advances in computational science, statistics and access to data. The assumption of a continuum of researchers basically means 'a lot of' researchers. The more researchers there are in the market, the more expensive and difficult it is for institutions to select talent and the more likely the adverse selection effect.

Second, can research institutions really distinguish talent from the crowd? To some extent, this is certainly possible, using signals such as previous publications, awards, or letters of reference. However, the argument becomes evanescent when considering juniors. In many fields, it is not uncommon for junior researchers to lack an adequate publication track record, and more or less when they apply for the same position their resumes tend to resemble each other. Using a single article (the job market paper) to select talent seems inappropriate.

The argument can easily be extended to nonacademic research institutions as well. When institutions offer a unique salary and there are many potential candidates, the topic of imperfect information becomes relevant. If a talented researcher ends up doing something else in the industry, such as non-innovative work, society as a whole loses the opportunity to create new knowledge and growth. This should convince the reader that the argument proposed in this article is worthy of consideration and further research.

## Authors statement

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# The student funding dilemma

Giuseppe Pernagallo*

**Abstract**

Access to higher education in several countries still has many barriers, mainly represented by the high cost of tuition fees. Given the importance of higher education for innovation and economic growth, this paper analyzes the best financing scheme for needy students. Using an asymmetric information model, the paper shows that student loans involve a moral hazard problem with sub-optimal levels of effort and quality of education, and are socially inefficient and inequitable. On the other hand, merit-based scholarships and need-based grants pose no moral hazard, are socially efficient, and are no more expensive than alternative financing schemes. In particular, while scholarships may be more cost-effective than grants, the latter allow to achieve directly the first best. The paper also examines loan forgiveness policies and talent funding. The results of the model are supported by a large strand of empirical literature.

*Keywords*: Economics of Education; Human Capital; Information Economics; Information Asymmetry; Student Loans JEL Codes: D8; G2; I23.

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# 1 Introduction

Education covers, especially at the university level, a fundamental role in modern societies for innovation and economic growth. Through the dissemination of knowledge and new ideas, higher education institutions foster innovation and the accumulation of human capital, thus stimulating growth (Becker, 1962; Denison, 1962; Griliches, 1997; Krueger & Lindahl, 2001; Jones, 2005; Jones, 2009; Biasi et al., 2020; Biasi & Ma, 2022). This is even more important when it comes to talented students, who are more likely to spark innovation and growth after completing their studies. Indeed, there is a rich strand of literature demonstrating how proper talent allocation can foster growth and innovation (Murphy et al., 1991; Terviö, 2009; Acharya et al., 2016; Cubas et al., 2016; Hsieh et al., 2019; Akcigit et al., 2020).

Despite its importance to the economy, access to higher education still has many barriers, mainly represented by the high cost of tuition fees or the cost of living to afford a university far from home. In this regard, many countries, such as those in Europe, offer education almost free in terms of fees, while others, such as the United States, the United Kingdom, Australia or New Zealand, offer higher education with high fees, especially to access the best institutions. Students who cannot rely on family wealth are therefore forced to borrow from financial institutions. In many countries this form of borrowing is called 'student loans' and is governed by specific legislation. The loan can be offered by private institutions or by the government itself (through one of its departments, such as the Department of Education), and has special rules regarding interest rates, bankruptcy regulations, the amount that can be borrowed, and so on.

Policymaker intervention in the market is necessary, since under a *laissez-faire* regime the result would be both inefficient and inequitable (Long, 2019). The question is how the policymaker should intervene. Student loans have been a favorite policy (Section 5), but the debt issue has taken on enormous dimensions over time, with much criticism of the sustainability of many policies related to student loans. Just to give an idea of the magnitude of the problem, in 2010 student loan debt in the United States rose to over $800 billion, surpassing total credit card debt for the first time (Avery & Turner, 2012). In 2019, the Federal Reserve Bank of New York reported that outstanding student loans exceeded $1.5 trillion; in addition, more than half of U.S. undergraduates financed their undergraduate studies with federal student loans (Black et al., 2020). By 2022 this value has risen to nearly $2 trillion,[1] which is why many specialists speak of a 'crisis' (Looney & Yannelis, 2015).

The empirical literature has extensively analyzed this issue in recent years (Field, 2009; Beyer et al., 2015; Schmeiser et. al., 2016; Daniels & Smythe, 2019; Marx & Turner, 2019; Denning & Jones, 2021; Chakrabarti et al., 2022; Montalbàn, 2023), while in recent years no equivalent attention has been paid to the theoretical aspect (among theoretical work, see Caucutt & Kumar, 2003; Gallipoli et al., 2011; Cigno & Luporini, 2009; Chatterjee & Ionescu, 2012; or Long, 2019). Student loans can clearly be seen as a problem of imperfect information, which can be treated using information economics and many of the models explored for credit markets (e.g., Rothschild & Stiglitz, 1976; Stiglitz & Weiss, 1981; De Meza & Webb, 1987; Mas-Colell et al., 1995; Ghosh et al., 2000; Pernagallo, 2023). This paper therefore draws on this literature to contribute to the issue. In particular, the major novelty of this work is to use a simple information asymmetry framework to study the main possible funding schemes and their effect on effort, school quality choice, and talent funding, whereas other work generally focuses only on a subset of these schemes and topics.

Countries with high costs for college or university access rely heavily on the use of government-based student loans. It is very difficult to provide a

[1] https://finaid.org/loans/studentloandebtclock/

complete overview of the many types of existing contracts, but generally in these countries the state can intervene in two ways: directly or indirectly. The state can finance needy students directly; for example, the William D. Ford Federal Direct Loan Program in the United States uses funds that come directly from the U.S. Department of Education, which receives the money from the U.S. Treasury. The loans are provided by the Department of Education and backed by the federal government. There may also be indirect state involvement, as was the case with the Federal Family Education Loan Program, where the lenders were private (such as banks, credit unions, etc.), but the amount was guaranteed by the federal government, which acted as guarantor in case of default.

In these cases, government intervention creates costs for taxpayers. A viable alternative, already implemented in many countries, is the use of scholarships to support economically needy and/or deserving students. The point of this paper is that a scholarship-based system not only does not pose a moral hazard problem, but is potentially no more costly than a system based on student loans. Even a mixed system with student loans and scholarships can yield better results than one based entirely on debt. For this reason, this paper strongly suggests that more resources should be allocated to scholarships than to student loans.

Recently, forgiveness policies have occupied a central role in the policy debate. Despite some potential economic benefits (Chemmanur et al., 2022), forgiveness policies are generally regressive (Looney, 2022; Catherine & Yannelis, 2023) and can generate dissatisfaction among taxpayers. This paper shows that universal forgiveness policies can have a positive impact on students' decisions and generate greater effort and enrollment in better schools than the case of pure student loans, but do not outperform a scholarship system.

In summary, the main findings of the papers are as follows. The model explains why in a student loan financing system (i) students are less committed and choose lower-ranked schools compared to the self-funding situation, (ii) poorer students are more likely to fail, pay higher interest rates, and produce Pareto equilibria with lower social surplus, (iii) non-competitive credit markets produce equilibria with lower social surplus, (iv) lower interest rates increase enrollment in the highest-ranked schools. Moreover, the model also shows that (v) scholarships or grants are better than student loans because they do not involve a moral hazard problem and are not more expensive than government student loans. In particular, need-based grants, despite being potentially less cost-effective than merit-based scholarships, can directly achieve the first best level of effort and school choice. A variation to the original model allows us also to show that (vi) student loans are not socially efficient, while scholarships and grants are socially efficient as they allow to finance only deserving students.

Therefore, this paper contributes to several strands of literature with the main objective of providing a general framework to compare and possibly select the best funding scheme for needy students. First, it contributes to the literature on the role of financial aid in promoting equity and efficiency in the educational system (James, 1988; Edlin, 1993; Anderson, 2020); in particular, this model shows that scholarships and grants are equitable and socially efficient. Second, it follows the strand of research that supports merit- and/or need-based financial aid over student loans (Dynarski, 2004; Cigno & Luporini, 2009; Minaya et al., 2022; Montalbàn, 2023). Finally, it emphasizes the role of the policymaker in determining enrollment in top schools, the accumulation of human capital, and the exploitation of talent (Fernández and Rogerson, 1998; Arcidiacono, 2005; Hsieh et al., 2019; Égert et al., 2020).

The paper is structured as follows. Section 2 presents a moral hazard model to understand the differences between possible education financing systems. Section 3 shows an application of the model to the case of loan forgiveness policies.

Section 4 uses a variation of the original model to show that scholarships are socially efficient while student loans involve an overlending problem. Finally, Section 5 discusses the results and concludes the paper.

# 2 The model

## 2.1 Setup

A student decides to pursue tertiary education and, if she succeeds, acquires a degree that has $y$ value, while if she fails, she gets nothing. The probability of success, $p(e) \in (0, 1)$, depends on the student's level of effort $e$, and here we assume that $p'(e) > 0$ and $p''(e) < 0$ to reproduce the usual diminishing returns to effort. As is common in the lending market literature (e.g., Stiglitz & Weiss, 1981; De Meza & Webb, 1987; Ghosh et al., 2000), all agents are assumed to be risk-neutral.

To undertake these studies, students need a fixed sum $T$, which represents the cost of tuition (in principle, it could also include the cost of study materials, rent and so on). If the student is unable to self-finance her studies because she is not rich enough to cover all expenses, she will have to borrow the necessary money from a financial institution. In this case, the student borrows $T$ and, given an interest rate on loans $i$, will repay $R = (1 + i)T$ if successful. Note that success is necessary to repay the debt; in fact, without the degree, the student cannot access good jobs to repay her debt. This means that $y > R$. The nature of the financial institution can be private or governmental. For now we focus on private institutions, then when we discuss policies, we will also cover government loans.

Financial institutions demand collateral to grant the loan. Let $W$ be the value of the borrower's transferable wealth that can be used as collateral, and to make the problem interesting, we assume $W < T$. These assets serve as collateral for the financial institution and will be transferred in the event of the student's failure. In practice, these types of loans are often guaranteed by the government, in which case $W$ can be seen as the cost to the student if the debt is not repaid (such as legal fees). This will be relevant to our policy discussion, but for now we assume that the student provides the collateral.

Since we are not interested in the alternative allocation of student wealth, for simplicity, and without loss of generality, we assume that the safe interest rate is zero, so that quantities do not have to be discounted. Then, the student's problem is to choose how much effort to put into studies. More effort will produce not only a degree, but also better preparation, which will make it more likely to find a good job and thus repay the debt. At the same time, the effort is costly for students but not observed by lenders, which introduces moral hazard into this model.

Finally, there is a social planner whose main aim is to maximize the social welfare of society. The definition of social welfare is provided in the following sections and depends on the agents involved and the form of contracts.

## 2.2 Self-financing vs. borrowing

This section presents a baseline version of the model to establish some common findings with the credit market literature (from the model in Ghosh et al., 2000), then subsequent sections elaborate an extension of this model more suitable for studying the educational system.

If the student is able to pay for her studies (e.g., because her family is wealthy enough), the problem is to maximize the following expected utility, $E[u]$, or

$$\max_{e} E[u] = p(e)y - e - T \tag{1}$$

with F.O.C.

$$p'(e^*) = \frac{1}{y} \tag{2}$$

which is a maximum given the assumptions on $p(e)$. Effort $e^*$ is the first best level of effort obtainable when the student pays for her studies with her own money.

We consider now the problem of a student loan

$$\max_e E[u] = p(e)(y-R) + [1-p(e)](-W) - e \tag{3}$$

with F.O.C.

$$p'(\bar{e}) = \frac{1}{y-R+W} \tag{4}$$

The lenders' profit is

$$\pi = p(e)R + [1-p(e)]W - T \tag{5}$$

and by choosing the level of $\pi$, different equilibrium configurations can be determined by maximizing the student's expected utility, where $\pi = 0$ represents the case of perfect competition. The lender may decide not to lend, which means that $\pi \geq 0$.

The monopolistic case involves the highest possible interest rate, $i_{UB}$, above which it will not be profitable for the lender to raise interest. It is easy to show that the level of effort $\bar{e}$ is lower than the first best level of effort $e^*$, this because $\frac{1}{y-R+W} > \frac{1}{y}$ since $-R+W < 0$. The point is illustrated in Figure 1. This allows us to formulate the following proposition.

**Proposition 2.1.** *Student loans involve less effort than the first best case of* *self-financing.*

Clearly, the level of effort chosen by the student is decreasing in $R$ and increasing in $W$ and $y$. The higher the value of the degree, the higher the effort, while a higher level of collateral imposes a higher cost in the bankruptcy scenario, encouraging the student to avoid that situation. Finally, the higher the debt burden, the lower the student's effort, because higher debt reduces the payoff in the case of success, but not in the case of failure.

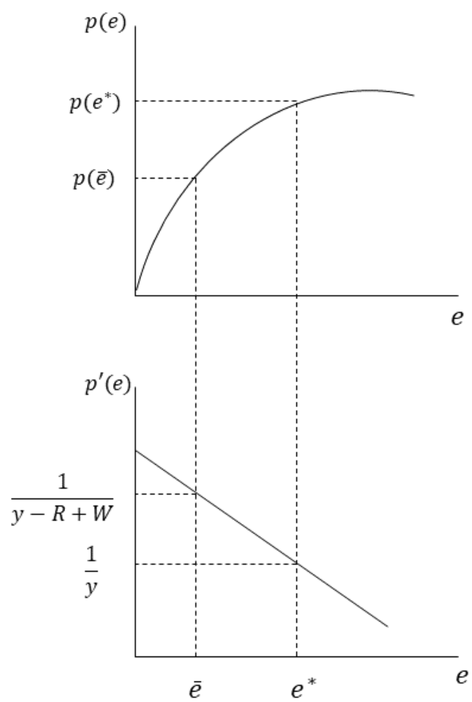


Figure 1: A graphical representation of the two situations (self-financing and borrowing) to show that the first best effort level is higher.

The equilibrium is given by the level of effort chosen by the student and the repayment chosen by the lender (through the interest rate). We can represent the possible equilibria on a plane $(e, R)$ using the isoprofit curve (equation (5)) and the incentive curve (equation (4)). Both curves have a negative slope, since effort is decreasing in $R$ and if the student tries harder, making default less likely, less repayment is required to maintain the same level of profit.

Following recurring examples in literature (Grossman & Hart, 1983; Mas-Colell et al., 1995; Ghosh et al., 2000), a few possible equilibria are illustrated in Figure 2. The dashed line represents the incentive curve, while $\pi_1$ and $\pi_2$ are two possible isoprofit curves, with the second one indicating a higher profit. The Pareto optimum is given by the lowest intersection between the two curves, provided that the incentive curve is steeper at that point than the isoprofit curve.

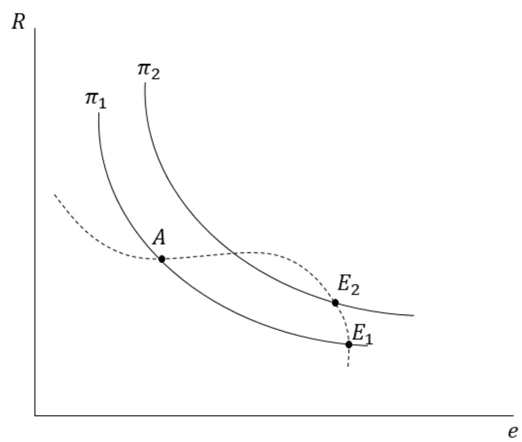


Figure 2: A possible representation of isoprofit and incentive curves. Pareto equilibria $E_1$ and $E_2$ are reached when the isoprofit curves are $\pi_1$ and $\pi_2$, respectively, while $A$ is not an equilibrium when the isoprofit curve is $\pi_1$ as it is Pareto improvable.

For example, $A$ is not an equilibrium because when the isoprofit curve is $\pi_1$, we can find a different allocation to the right of $A$ on the incentive curve where the student is better off and the lender is no worse off (e.g., the $E_1$ point). We can also see that as profit increases, the equilibrium involves lower levels of effort as shown by the equilibrium $E_2$. This means that the maximum level of effort occurs with perfect competition, while the minimum level of effort occurs with monopoly. This has important consequences for society.

**Proposition 2.2.** *Higher profits, and thus higher market concentration, produce Pareto equilibria with lower social surplus.*

*Proof.* Define social surplus as

$$SW = p(e)(y - R) + [1 - p(e)](-W) - e + p(e)R + [1 - p(e)]W - T$$

$$= p(e)y - e - T$$

then

$$\frac{\partial SW}{\partial e} = p'(e)y - 1 > 0 \tag{6}$$

because in the student loan case we know that the effort is less than first best and consequently the marginal probability of success in this scenario will be higher than in the self-financing case given by equation (2). This means that if repayment increases, and thus profits, the debt burden on the student increases, thus decreasing her effort and consequently also the social surplus.

□

Proposition 2.2 also allows us to say that with richer students we can produce equilibria with a higher social surplus. This is immediate to see since the level of effort is increasing in $W$, so the higher the collateral, the higher the cost to the student in case of failure, and this works as an incentive to succeed. From (6) we know that this increases the social surplus. In fact, more effort increases the expected profit for lenders, who consequently, if profits are held constant, can charge a lower interest rate, thus increasing the student payoff. We can then formulate the following proposition.

**Proposition 2.3.** *If profits are held constant, wealthier students produce Pareto equilibria with higher social surplus.*

If there had been students with different wealth, wealthier students would have been more likely to succeed and pay lower interest rates than poorer students. This raises serious questions about the adequacy of student loans to help poorer students achieve a degree and thus a better career (on the issue see, for example, Callender & Mason, 2017), and is consistent with the fact that student debt is concentrated mainly among high-wealth households (Looney, 2022). The social planner's action in the case of private lenders may be limited to trying to keep the interest rate as close as possible to the perfect competition interest rate, since more effort increases $SW$. The next section shows an expansion of this simple model to account for school prestige as well.

## 2.3 Modeling the prestige of schools

In this section we modify the baseline model with a new feature. We now also consider school prestige, so that the student, in addition to choosing the level of effort $e$, must also decide which school to enroll in. In this way, the student borrower chooses how much to borrow from financial institutions.

For this purpose, we assume that the tuition, $T \in (0, T_{max}]$, is a measure of school prestige. Higher tuition fees are usually associated with top schools, so the assumption, while simple, allows us to easily model this aspect of the educational system. Better schools allow the student to eventually obtain a degree of greater value in the job market. In other words, we have $y(T)$, with $y'(T) > 0$ and $y''(T) < 0$. The decreasing marginal return on tuition is easy to justify, since for the best schools the difference in output is small (e.g., the best-ranked school will not be much different from the second-best). Of course, the profit of lenders remains unchanged in its functional form from the previous section.

In this case, the expected utility for a self-funded student is

$$E[u] = p(e)y(T) - e - T \tag{7}$$

The problem of a student loan becomes in this case

$$\max_{e,T} E[u] = p(e)[y(T) - (1+i)T] + [1 - p(e)](-W) - e \tag{8}$$

with F.O.C.

$$\frac{\partial E[u]}{\partial e} = 0 \implies p'(\bar{e}) = \frac{1}{y(T) - R + W} \tag{9}$$

$$\frac{\partial E[u]}{\partial T} = 0 \implies y'(\bar{T}) = 1 + i \tag{10}$$

which shows that in the case of loans, school choice is determined according to the interest rate charged by the lender. In particular, we can see that (10) represents the usual equality between marginal benefit and marginal cost. Higher interest rates are associated with a higher $y'(\bar{T})$, which implies a lower $T$ level, so students choose a lower level school. Figure 3 shows that when lenders decrease the interest rate, the level of $T$ increases. In fact, (10) means that the maximum expected utility is reached when $y(T)$ has the same slope as the repayment function.

Note also that if students choose better schools, according to (9) the level of effort chosen increases. This is reasonable since the better the school, the better the potential outcome for the student in case of success, and thus the greater the student's effort.

**Proposition 2.4.** *When students can enroll in different ranked schools, a decrease in the interest rate determines the choice of higher ranked schools and,*

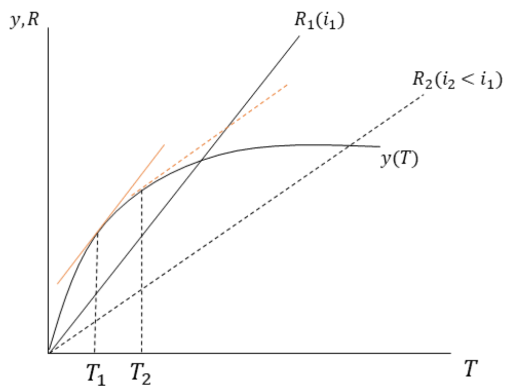


Figure 3: A decrease in the interest rate increases the level $T$ chosen by students. The red lines are used to illustrate the optimal points at which the slope of $y$ and $R$ are equal.

*consequently, higher levels of effort.*

**Proposition 2.5.** *A lower interest rate does not necessarily produce Pareto equilibria with a higher social surplus.*

*Proof.* Social surplus in this case is given by

$$SW = p(e)y(T) - e - T \tag{11}$$

then

$$\frac{\partial SW}{\partial e} = p'(e)y(T) - 1 > 0 \tag{12}$$

given that the student is debt-financed and the choice of effort is less than first best. On the other hand

$$\frac{\partial SW}{\partial T} = p(e)y'(T) - 1 = p(e)(1+i) - 1 \tag{13}$$

The sign of (13) depends on $i$. A reduction in $i$ causes an increase in $T$ by (10), and an increase in $T$ causes an increase in $e$ by (9), and this by (12) results in a larger social surplus. However, for lower levels of $i$ the sign of (13) is ambiguous as $p(e)$ increases and $1 + i$ decreases. The global effect on $SW$ depends on the size of $p(e)$ and $i$. $\square$

The economic relevance of Proposition 2.4 is worth noting, as the policy-maker in this case has a tool in the interest rate to determine not only the 'quality' of education chosen by students, but also their effort, thus approaching the first best level of effort. Higher levels of $i$ result in the choice of lower-level schools. This again shows that students in need of borrowing, who are generally the poorest, will be less likely to afford the best schools. Nevertheless, lower interest rates do not necessarily imply higher social surplus.

The loan system is not equitable, as the model shows that poorer students would be less likely to afford the best schools and, in general, to pay lower interest rates. If we drop the limited liability assumption, we can show that $\bar{T} < T^*$ (see Appendix A).

Moreover, in the next section we show that financial aid can be used to promote enrollment in top schools, thus achieving higher levels of human capital and a better positioning for the students in the job market (on the importance of financial aid in determining enrollment in the best schools for disadvantaged students see, among the others, Arcidiacono, 2005).

## 2.4 Scholarships and hybrid systems

In this section we use again the baseline model to compare the equilibrium in the case of self-financing with the equilibrium in the case of scholarships. In other words, in this scenario a student can finance her studies using state or private scholarships. Suppose the government pays a scholarship $S > 0$ used by students to pay their expenses. Generally, scholarships are disbursed gradually as students progress in their careers and are based on merit criteria.[2] In our static model this can be introduced by awarding the scholarship in case of success.

It is easy to show that with scholarships we can attain a level of effort higher than the first best case as

$$\max_{e} E[u] = p(e)(y+S) - e - T \tag{14}$$

yields the F.O.C.

$$p'(\tilde{e}) = \frac{1}{y+S} \tag{15}$$

This is not necessarily a good thing from the social planner perspective, since students now put more effort than in the first best case, and it can be shown that the social surplus with scholarships is decreasing in $e$.

**Proposition 2.6.** *Higher scholarships, and thus higher effort, produce Pareto equilibria with lower social surplus.*

*Proof.* The social surplus in this case is defined by students and taxpayers. Taxpayers pay an expected cost of $p(e)S$, then

$$SW = p(e)(y+S) - e - T - p(e)S = p(e)y - e - T \implies$$

$$\frac{\partial SW}{\partial e} = p'(e)y - 1 < 0$$

because we know that the effort with scholarships is greater than the self-financing case, we have that $p(e^*) < p(e) \implies p'(e^*) = \frac{1}{y} > p'(e)$. □

[2] In this paper we adopt the convention of referring to scholarships when the eligibility criteria are merit-based, while grants are need-based. In reality, the distinction is not always so clear-cut, and scholarships can also be based in part on financial need.

Nonetheless, previous literature has shown that a first or second best can always be implemented using a scholarship system funded by a graduate tax (e.g., Cigno & Luporini, 2009). This paper adds to this literature by showing that the first best is easily achieved also by combining a scholarship with a loan system.

In fact, students can finance their studies for one part with a loan and for the remaining part by benefiting from scholarships provided by the government. With this scheme, we can assume that the student borrows (or the lender grants) only the amount that she cannot finance with the scholarship.

**Proposition 2.7.** *A system with student loans and scholarships allows the government to achieve the first best level of effort.*

*Proof.* In this case the student's problem is

$$\max_e E[u] = p(e)[y - R^* + S] + [1 - p(e)](-W) - e \tag{16}$$

where $R^* = (1 + i)(T - S)$ and $S < T$, with F.O.C.

$$\frac{\partial E[u]}{\partial e} = 0 \implies p'(\bar{e}) = \frac{1}{y - R^* + W + S} \tag{17}$$

if the government sets $S = R^* - W$, we have that $\bar{e} = e^*$. □

From the perspective of equity, by choosing $S$ appropriately, the policymaker can allow students to choose higher levels of $T$ than in the first best case. In other words, in this scenario, even poor students can enroll in the best schools. This would, of course, cause some degree of inefficiency because students may overinvest in education.

**Proposition 2.8.** *A scholarship system allows students to choose higher-ranked schools than the first best case.*

*Proof.* Say that $S = T$, so that the policymaker offers the student the possibility to enroll in any school. The problem of the student becomes

$$\max_T E[u] = p(e)[y(T) + T] - e - T$$

with F.O.C.

$$p(e) = \frac{1}{y'(T) + 1}$$

Knowing that effort level is higher than in the first best case, we get

$$p(e) > p(e^*) \implies$$

$$\frac{1}{y'(T) + 1} > \frac{1}{y'(T^*)} \implies$$

$$y'(T^*) > y'(T) + 1 \implies$$

$$y'(T^*) > y'(T) \implies$$

$$T^* < T$$

□

The fact that scholarships increase the probability of success (given greater effort level) and enrollment in better schools is well documented in the empirical literature (e.g., Scott-Clayton & Zafar, 2019; Cosentino et al., 2019). Consequently, an education system without student loans but with scholarships, still allows for poorer students to afford high quality education without causing moral hazard problems or without making students debtors. Access to merit-based scholarships can also be based on financial need criteria to avoid excessive spending, which we do not consider here so as not to over-complicate the model.

Despite being equitable, we have seen that scholarships introduce a form of inefficiency into the system (specifically, over-investment and suboptimality for the social planner compared to the first best case). So, the question to ask is whether there are concrete economic reasons to prefer a pure scholarship system to a pure loan system, and using the model it turns out that there is a cost-related advantage with scholarships. If we focus on which policy imposes the highest cost on taxpayers, we must then estimate the cost to taxpayers under different schemes. The expected cost with a scholarship-based system is $p(e)S$, while with a federal loan the contract takes the same form as studied in Section 2.2, so the expected cost to taxpayers would be $T$.

A separate argument must be made for government-backed loans. In this case, the government decides to guarantee part or all of the student loan amount from a private lender. Without any loss of generality, suppose the government backs the entire loan, then the problem for the student becomes

$$\underset{e,T}{max}\ E[u] = p(e)[y(T) - R)] - e \tag{18}$$

with F.O.C.

$$p'(\hat{e}) = \frac{1}{y(T) - R} \tag{19}$$

$$y'(\hat{T}) = 1 + i \tag{20}$$

It is clear that in this case the moral hazard will lead the student to commit less than in the first best case, in other words $\hat{e} < e^*$, but also less than in the case of federal loans (see Appendix B). In this scenario the social surplus is lower than in the pure federal student loan case with collateral (see Appendix B), and the expected cost to taxpayers is given by $[1 - p(\hat{e})]R$.[3]

Comparing these expected costs with the expected cost of a scholarship, we find that to be indifferent to taxpayers, the expected cost per student of a scholarship must equal the expected cost per student of loans. Thus, for example, this equality implies that for a government-backed private loan

$$[1 - p(e)]R = p(e)S \tag{21}$$

while for a federal loan

$$T = p(e)S \tag{22}$$

It is important to note that the right-hand side can be changed by the government, which has control over the $S$ instrument and consequently over the level of commitment chosen by students. In conclusion, a system with scholarships is not necessarily more expensive than one with government-backed student loans or federal loans.

**Proposition 2.9.** *A scholarship system in general is no more expensive than a student loan system, whether federal or government-guaranteed.*

## 2.5 Grants

Grants are generally different from scholarships because they are need-based, so the student's wealth determines whether or not he or she is eligible for a grant. In our model this means that the grant amount $G$ is given to the student in

[3] This probably explains why government-guaranteed loans are now rarer in several countries.

any case if her wealth, $W$, is below a certain threshold, $W_T$. The grant can be decreasing in wealth, so that higher levels of wealth give access to lower grant amounts. We consider here the simple case of a fixed grant for all eligible students. The problem for the student in this case is

$$\max_{e} E[u] = p(e)y + G(W) - e - T \tag{23}$$

with F.O.C.

$$p'(e^*) = \frac{1}{y(T)} \tag{24}$$

As can be seen from (24), the introduction of grants does not change the F.O.C. for the student compared to the case of self-funding, which means that grants do not involve a moral hazard problem. Moreover, grants can be used to incentivize enrollment in the best schools. However, despite their efficiency, grants can be more expensive for taxpayers than scholarships.

**Proposition 2.10.** *A grant system does not cause moral hazard and produces the first best.*

**Proposition 2.11.** *Grants can be used to incentivize enrollment in top schools.*

*Proof.* If the policymaker sets $G(W) = T - W$, then the student's problem becomes

$$\max_{e,T} E[u] = p(e)y(T) - W - e \tag{25}$$

with F.O.C.

$$p'(e^*) = \frac{1}{y(T)} \tag{26}$$

$$y'(T_{max}) = 0 \tag{27}$$

$\square$

**Proposition 2.12.** *Consider a grant-eligible student. If the policymaker allocated the same amount of funds to grants and scholarships, meaning that* $G(W) = S$*, then a grant is expected to be more costly than a scholarships*

*Proof.* It suffices to note that $G(W) > p(e)S$. $\square$

# 3 The model at work: the case of student loan forgiveness

A much-discussed policy in recent years is the possibility of writing off a portion of student debt, a practice that generally goes by the name of 'loan forgiveness.' In the United States, for example, President Biden has launched a plan to forgive loans of up to \$20,000,[4] and in general, student loan forgiveness plans are quite widespread in the United States.[5] The model developed in this paper can be used to study the potential effects of such policies.

The policymaker can forgive up to $\lambda$ percent of the original debt if the student is successful. Students also know the frequency with which such policies occur, say $\alpha \in [0, 1]$, which is common knowledge, and for simplicity, let $W = 0$. This means that the student only has to repay $(1 - \lambda)R$ in case of success. The student loan problem becomes

$$\max_{e,T} E[u] = p(e)[y(T) - \alpha(1 - \lambda)R - (1 - \alpha)R] - e \tag{28}$$

with F.O.C.

$$\frac{\partial E[u]}{\partial e} = 0 \implies p'(\bar{e}) = \frac{1}{y(T) + [\alpha(1 - \lambda) + (1 - \alpha)](-R)} \tag{29}$$

[4] https://studentaid.gov/debt-relief-announcement
[5] https://www.investopedia.com/student-loan-debt-by-state-5198562

$$\frac{\partial E[u]}{\partial T} = 0 \implies y'(\bar{T}) = [\alpha(1-\lambda) + (1-\alpha)](1+i) \tag{30}$$

From the equilibrium, it can be seen that loan forgiveness acts as an incentive for students to commit more, since (29) is lower than (9) when $W = 0$. In addition, students will choose higher ranked schools, since (30) is also lower than (10).

**Proposition 3.1.** *The implementation of a loan forgiveness policy induces students to commit more and enroll in higher-level schools.*

**Proposition 3.2.** *More generous and more likely loan forgiveness policies allow policymakers to approach the first best effort level and incentivize students to enroll in the best schools.*

*Proof.* To prove this proposition, we simply take

$$\lim_{\lambda,\alpha \to 1} p'(e^*) = \frac{1}{y(T)} \tag{31}$$

$$\lim_{\lambda,\alpha \to 1} y'(T_{max}) = 0 \tag{32}$$

□

Although attractive, there are at least three arguments that can be made against loan forgiveness policies. First, the higher the percentage of debt forgiven, the lower the profit for the government, which in the case of federal loans is the lender. This means that an increase in $\lambda$ or $\alpha$ results in a transfer of wealth from the lender (the government in this case) to the student. If we are under perfect competition, this implies that a forgiveness policy causes a loss for the lender, which could be an unpopular policy for taxpayers.

Second, recent literature has shown that universal loan forgiveness policies, which are the most recurring, are highly regressive, since the vast majority of benefits would go to high-income individuals (Looney, 2022; Catherine & Yannelis, 2023). This makes this policy unfair to low-income students, who should be the privileged recipients of such policies.

Third, more frequent and more generous forgiveness policies may lead to overinvestment in education by students. In other words, students would be incentivized to borrow more than they would need in the first best scenario.

Despite these aspects, forgiveness policies have a positive impact on students' decisions, as a higher $\lambda$ (and/or $\alpha$) also increases the commitment and rank of the schools chosen by students. This result is in line with a recent literature discussing the potential benefits of loan forgiveness policies despite their cost to taxpayers (Chemmanur et al., 2022). Nonetheless, we must again emphasize the superiority of scholarship/grant systems even over forgiveness policies in that they can be efficient and are not expected to be more expensive.

# 4 Talent and the overlending problem

In this section we introduce heterogeneity in the original model to study which students are granted loans. To introduce the role of talent in determining student success into the model, we assume that for the same $e$, talented students can achieve higher $p(e)$. Note that this introduces heterogeneity into the model, since if we have a talented student $H$ and a normal student $L$, we have that for the same level of effort $e$, $p_H(e) > p_L(e)$.

Assuming for simplicity that all needy students share the same level of wealth $W = 0$ and fixing $e$ (since we already know the chosen amount of effort from previous sections), we have that any difference in $p$ is the result of talent. Say that there is a continuum of students such that $p_j \in (0, 1)$, with $j \in \mathcal{I}$, where $\mathcal{I}$ is the index set. We denote the distribution of these probabilities as $G(p_j)$ and the density function as $g(p_j)$. The asymmetry in this case stems from the fact that talented students, *ex ante*, cannot be recognized, so the government does not know whether a loan is given to a talented student or not.

The expected utility for the $j$th student is

$$u_j = p_j(y - R) - e \tag{33}$$

and obviously $\frac{\partial u_j}{\partial p_j} > 0$. Clearly, given the continuum of students, not everyone will accept the loan contract depending on the interest rate $i$.

**Definition 4.1** (Marginal student)**.** *A student with probability $p_m$, with $m \in \mathcal{I}$, is a marginal student if all students for whom $p_j \geq p_m$ accept the contract, while all students for whom $p_j < p_m$ do not accept the contract.*

**Proposition 4.1.** *As the interest rate increases, the marginal student's probability of success $p_m$, below which students do not accept the contract, increases, or*

$$\frac{\partial p_m(i)}{\partial i} > 0 \tag{34}$$

*Proof.* This follows immediately upon differentiating $u_m$. Indeed, $\partial u_m / \partial i < 0$. So, since $u_m = 0$ for a given $i_1$, if a new rate $i_2$ is charged, such that $i_2 > i_1$, we have that $u_m < 0 \implies \exists\, p_k > p_m \;:\; u_k = 0, k \in \mathcal{I}$.

□

The intuition behind Proposition 4.1 is that as $i$ increases, the expected cost to students will be higher and, consequently, only students with higher $p$ maintain non-negative expected utility. This means that with higher interest rates, loans are given to more talented students, while less talented students leave the market. Hence, for equity purposes student loans are generally given at lower interest rates. Although student loans do not involve a problem of talent recognition (talented students can get the loan), they do involve a problem of excessive borrowing compared to what should be socially desirable.

To show this we need to define the expected profit function of the lender. As well-known for credit markets (Stiglitz & Weiss, 1981; De Meza & Webb, 1987), given that agents are price takers, and given risk neutrality and the fixed principal, we focus our attention on the pooling equilibrium case. The profit function is given by

$$\pi = R \int_{p_m(i)}^{1} p_j \hat{g}(p_j) dp_j - T \tag{35}$$

where

$$E[p] = \frac{\int_{p_m(i)}^{1} p_j g(p_j) dp_j}{\int_{p_m(i)}^{1} g(p_j) dp_j} = \int_{p_m(i)}^{1} p_j \hat{g}(p_j) dp_j \tag{36}$$

is the average probability of success among students who accept the contract. From (35) we clearly see that profits increase with the interest rate, since an increase in $i$ increases both repayment and the average probability of success.[6]

If federal loans are made at the interest rate of competition (we can safely assume that the government does not charge higher rates), it can be shown that some contracts are not socially efficient because they consume more resources than they create.

**Theorem 4.1.** *Student loans with competitive interest rates are not socially efficient.*

*Proof.* To be socially efficient, a contract must satisfy the following

$$p_j y \geq T + e \tag{37}$$

The competitive interest rate $i^*$ is such that $\pi = 0$. At this rate, between $p_m$

[6] The absence of credit rationing in these markets has already been demonstrated in De Meza & Webb,1987.

and 1 there are students for whom $p_j < E[p]$, students for whom $p_j = E[p]$, and students for whom $p_j > E[p]$. Moreover, we know that for any probability between $p_m$ and 1 the contract is signed, which means

$$u_m = 0 \iff p_m(y - R) = e \tag{38}$$

Obviously, $p_m < E[p]$, then

$$\pi_m = p_m R - T < 0 \implies$$

$$p_m R < T \implies$$

$$p_m R + p_m y < T + p_m y \implies$$

$$p_m y < T + p_m(y - R) \overset{by\ (38)}{\implies}$$

$$p_m y < T + e$$

□

Theorem 4.1 shows that in equilibrium even students who should not deserve the loan (from the point of view of social efficiency), receive it. The superiority of scholarships can also be demonstrated in this variant of the model.

**Theorem 4.2.** *Scholarships are socially efficient.*

*Proof.* A needy student will undertake studies if

$$p_j(y + S) - e - T \geq 0 \implies$$

$$p_j(y + S) \geq T + e \tag{39}$$

this means that the only students who undertake studies are those for whom (39) is satisfied.

□

Theorem 4.2 shows that the policymaker can use scholarships to allocate taxpayers' money to the most deserving students. In fact, by lowering $S$, only the most talented students will find it worthwhile to undertake studies. We have shown in previous sections that scholarships are more equitable in that, unlike student loans, they do not penalize poorer students. This extension of the original model also shows that they can be more efficient. The same proof (omitted here for brevity) can also be applied to grants.

## 5 Discussion and conclusions

The way education is financed has major consequences for a country's economy. From a macroeconomic perspective, facilitating access to education and stimulating student effort contributes to innovation and growth by increasing human capital accumulation (Becker, 1962; Denison, 1962; Griliches, 1997; Krueger & Lindahl, 2001; Jones, 2005). Education can be regarded as a measure of human capital, so when students put a lot of effort into their studies, they contribute to human capital growth for at least two reasons. First, by increasing the probability of success, there will be more students graduating; second, effort can be seen as a measure of the quality and results of education (Douzenis, 1996; De Fraja et al., 2010; Dunlosky et al., 2020), in that the more effort students put in, the better their knowledge and the higher their potential in the economy. For this reason, access to higher education can be considered an engine for economic growth and is at the center of policy debate.

However, the heavy use of student loans made in several countries is questionable on both a macroeconomic and microeconomic basis. Access to higher education through debt has at least one important negative macroeconomic implication, namely financial stability. Unlike most commercial loans, student loans cannot be directly secured by the asset for which the loan is made, which is the reason for government intervention. The debate over whether this causes excessive student debt is an old one, and while past research had shown that the problem was not that severe (Hansen & Rhodes, 1988), today the scenario has changed dramatically. Empirical research has highlighted that student debt is likely associated with less household financial stability, specially for students who borrows but do not complete a bachelor's degree (Gicheva & Thompson, 2015). In other words, the positive effect on human capital caused by student debt may be offset by the negative effect of financial distress; therefore, relying too much on student loans may not be an optimal policy.

From a microeconomic perspective, for example, an in-depth analysis conducted in 2018 (de Gayardon et al., 2018) showed that the relationship between student loan debt and career choices is mostly negative. These negative effects are particularly relevant with regard to participation in entrepreneurial ventures, home ownership, family formation for women, and health or financial well-being over a lifetime.

This paper's emphasis on scholarship and grants is particularly important to the policy perspectives of many countries. Data show that the United States, for example, still relies too heavily on student loans and, in general, too little on merit- or need-based financial aid. Figure 4 shows trends in federal loans, federal grants, and non-federal loans. It is clear that federal loans are an important component of the student financing system and a preferred policy choice over scholarships and grants (Gross et al., 2009). These numbers are coherent with the analysis presented in Section 4, and may explain why there may be a problem of excessive lending in the student loan market. The use of loans for access to higher education continues to monopolize the policy debate, despite the fact that empirical and theoretical work has demonstrated the superiority of scholarships and grants. This is likely due to the fact that loans pays an interest if the student is able to repay the debt.

On the issue of merit-based scholarships, it is well known that in the United States federal aid has generally been need-based (Caucutt & Kumar, 2003; Dynarski, 2004). Empirical work has found that merit-based programs can be effective in promoting higher education and increasing various dimensions of aid recipient performance (Dynarski, 2004; Minaya et al., 2022), and that even need-based grants are more effective when coupled with more demanding academic standards (Montalbàn, 2023). In general, scholarships can increase the probability of success and enrollment in better schools, as shown by this model and previous empirical work (e.g., Scott-Clayton & Zafar, 2019; Cosentino et al., 2019). However, as shown by this model, scholarships can lead to an over-investment problem, as the level of effort would be higher than first best, while grants do not lead to this problem.

Theoretical work has shown that a first or second best can always be implemented using a scholarship system financed by a graduate tax and that this system cannot be outperformed by a loan system (Cigno & Luporini, 2009). The model presented here confirms these results.

A scholarship or grant system is not necessarily more expensive than a loan system. A hybrid system (scholarships plus loans) may also be more efficient, as it can achieve the first best. We have already mentioned that an effective way to finance the scholarship system could be a graduate tax. Moreover, scholarships and grants are socially efficient, while student loans are not. The choice of which instrument should be preferred by the policymaker seems clear. If the policymaker maximizes social welfare, need-based scholarships, since they achieve the first best, should be preferred. However, scholarships have a significant advantage over grants in that if the policymaker allocates the same amount of funds to scholarships and grants, the expected cost to taxpayers is higher in the grant system.

The use of forgiveness policies, while having merits (Chemmanur et al., 2022), is difficult for taxpayers to tolerate because if the interest rate was competitively determined, it would impose a loss on the government. Moreover, universal forgiveness policies are regressive (Looney, 2022; Catherine & Yannelis, 2023), and may cause students to overinvest in education. The model shows that forgiveness policies can achieve higher levels of commitment and incentivize enrollment in better schools (for obvious reasons), but there is no compelling reason why this should become established practice, given the superiority of the scholarships/grants system.

A natural extension of this framework would be a dynamic model to analyze the process in three stages (before enrollment, during studies, after school). It can also be hypothesized that scholarships would be variable and grow with student accomplishments to achieve greater commitment and reward more talented students. In addition, variable scholarships could also be used to create an incentive for top schools to improve the talent selection process. These ideas will be presented in future research.

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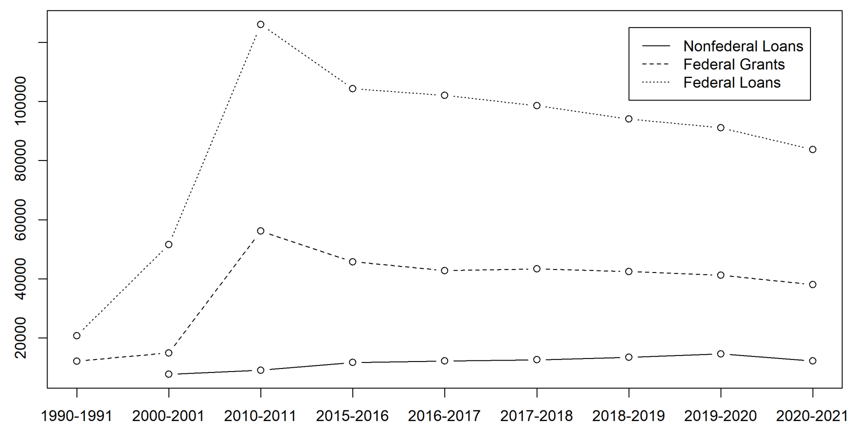


Figure 4: Time series of U.S. federal grants and non-federal/federal loans in millions of dollars (base year: 2020). Grants considered are Pell Grants, FSEOG, LEAP, Academic Competitiveness Grants, SMART Grants, and Veteran's Benefits, while loans considered are Perkins, subsidized, unsubsidized, Parent PLUS, and Grad PLUS. *Data Source: Trends in Student Aid 2021, CollegeBoard.*

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# Appendix A – Sub-optimal school choice

Using the model of Section 2.3 and abandoning the limited liability assumption, we can also show that the loan system provides sub-optimal school choice, in the sense that students would have enrolled in better schools without the information asymmetry. To achieve this result, we can focus on the loan contract,

$$L = p(e)y(T) - (1+i)T \tag{40}$$

the student maximizes with respect to $T$, so we get

$$p(e) = \frac{(1+i)}{y'(T)} \tag{41}$$

**Proposition 5.1.** *Given a loan contract $L$, the student will choose a lower-ranked school with the loan scheme than the self-financing scheme.*

*Proof.* Effort $e$ under debt will be less than first best $e^*$

$$p(e) < p(e^*) \implies$$

$$\frac{(1+i)}{y'(T)} < \frac{1}{y'(T^*)} \implies$$

$$y'(T^*) < y'(T) \implies$$

$$T^* > T$$

□

# Appendix B – Government-backed loan

We show that the social surplus for the fully government-backed loan is lower than that for federal student loans. For federal loans, we know that the social surplus is

$$SW = p(e)y(T) - e - T$$

while for government-backed loans we have that

$$SW = p(e)[y(T) - R] - e - [1 - p(e)]R = p(e)y(T) - e - R$$

We also know that in both cases $y'(T) = 1 + i$, while for federal loans $p'(e) = \frac{1}{y(T)-R+W}$ and for government-backed loans $p'(e) = \frac{1}{y(T)-R}$, which means that the level of effort is higher in the federal loan system. To compare the two situations, let $W = 0$, so that the effort level is the same in both scenarios. From this and the fact that $R > T$ we get the result

$$p(e)y(T) - e - R < p(e)y(T) - e - T$$

# Overcoming asymmetric information: A data-driven approach

Giuseppe Pernagallo*

**Abstract**

The rise of artificial intelligence and information technology is changing the branches of the economics of information and knowledge, making it easier to access, screen and process massive amounts of data. Thus, technology provides formidable new tools against asymmetric information in 'traditional' markets such as credit, labour, or insurance. However, there are many instances where technology itself is creating new sources of asymmetry. In many cases, data-driven approaches can mitigate the information asymmetry problem, in others it is not sufficient. I propose that the distinction between these two situations can be made by resorting to the idea of monopolies of knowledge. The purpose of this chapter is to discuss old and new problems of information asymmetry and to propose data-driven solutions, mainly based on artificial intelligence, highlighting their advantages over traditional approaches and in which cases they may not be sufficient.

*Keywords*: Economics of Science; Artificial Intelligence; Economics of Information; Economics of Knowledge; Information Asymmetry; Machine Learning; Philosophy of Economics JEL Codes: B4; C1; D8.

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# 1 Introduction

Asymmetric information is a long-standing theme in the economic literature, with many of the most influential works in economics published in this field (e.g., Akerlof, 1970; Spence, 1973; Rothschild & Stiglitz, 1976; Stiglitz & Weiss, 1981). Before the massive spread of information technology, obtaining information was difficult and asymmetries could undermine market functioning. In this scenario, information was a valuable commodity, and its cost of acquisition and processing was not negligible. With the advent of the 'data revolution,' the amount of information available has grown exponentially, to the point that today we are no longer faced with a problem of scarce and costly information, but of managing huge amounts of data. Innovation, especially in information technology, is radically changing the way we approach this problem. In particular, the rise of artificial intelligence is changing the branches of the economics of information and knowledge, making it easier to access, screen and process massive amounts of data. It is inevitable that this will change the way information is accessed and exploited, so it is very likely that soon in many markets where asymmetric information was considered an inherent feature, the problem will be solved through technology. However, there are many other situations where technological innovation itself generates new asymmetries as, for example, in personal data markets. Artificial intelligence is the key to better understanding our current limitations and possibilities for making relevant information accessible to all.

The contribution of this chapter is twofold. First, I show that, in many cases, the problem of asymmetries can become marginal, thanks to the advancement of data collection systems and artificial intelligence tools that can handle huge streams of data. In these situations, traditional approaches based on mere theoretical models should be replaced or supplemented by data-driven approaches such as machine learning. Second, I provide a demarcation criterion that allows us to distinguish in which cases artificial intelligence and machine learning can really solve the problem and in which they cannot. This demarcation criterion is based on the idea of *monopolies of knowledge*, which is the content of Section 4. The rest of the chapter is structured as follows. Section 2 introduces concepts useful for understanding the argumentation of this chapter, while Section 3 presents old and new asymmetric information problems and applications of machine learning and artificial intelligence to solve them. The last section concludes the chapter.

# 2 Basic concepts

## 2.1 Information asymmetry

Information asymmetry (also referred to as 'imperfect information') occurs when some agents are endowed with 'more' or 'better' information than the others, which is associated with undesirable situations such as *moral hazard* or *adverse selection*. The issue is so important because it affects many important markets, such as the credit market (e.g., Stiglitz & Weiss, 1981; Bester, 1994), the labour market (e.g., Spence, 1973), or the insurance market (Rothschild & Stiglitz, 1976). In undergraduate courses, the recurring example is the market for used cars ('lemons'), which was target of Akerlof's famous paper (Akerlof, 1970) and a prime example of adverse selection. In this market, the fact that the potential buyer cannot observe the quality of the car puts the seller in a privileged position. Consequently, bad cars and good cars are sold at the same price, pushing good cars out of the market since they are valued by their sellers more than the market price.

A typical example of moral hazard involves agency relationships. An agency relationship is '*a contract under which one or more persons (the principal(s)) engage another person (the agent) to perform some service on their behalf which involves delegating some decision making authority to the agent*' (Jensen & Meckling, 1976, p. 308). The agency problem (or principal-agent problem) revolves around the fact that the principal wants to induce the agent to behave as if she is maximizing the principal's welfare. In this case, we may have *hidden information* or *hidden actions* problems (Mas-Colell et al., 1995), the latter known as *moral hazard* since the principal cannot observe the agent's effort after signing the contract. Indeed, the timing of when the asymmetry occurs is another useful demarcation criterion between adverse selection and moral hazard, since in adverse selection the asymmetry exists at the time the contract is made, whereas in moral hazard it is after the contract is signed.

## 2.2 Artificial intelligence and machine learning

The term *machine learning* generally indicates the automated detection of relevant patterns in data (Shalev-Shwartz & Ben-David, 2014). In simple terms, machine learning aims to allow the machine itself to perform tasks decided by the programmer. The meaning of the word 'learning' can be illustrated with an example from the animal world. When some animal species are baited with unfamiliar types of food, they first taste a little bit of the new food and then, based on their physiological response, decide whether it is worth eating it all. If that small amount of food causes disease, the animal learns to avoid that new food. By associating the characteristics of the new food with a dangerous or repulsive food, the animal can avoid, for example, food poisoning. With machine learning, attempts are made to reproduce this behaviour using computers, thereby automating procedures and tasks.

The main tasks of machine learning are prediction (regression) and classification, which are examples of supervised learning, and clustering (or grouping tasks), which falls under unsupervised learning (Athey, 2019). Following an established definition (James et al., 2021), in *supervised learning* we have for each observation of the independent variable(s), $x_i$, $i = 1, 2, ..., n$, an observation of the associated outcome variable, $y_i$, with $n$ being the sample size. The purpose is to fit a model that relates the outcome variable to the covariates to predict values of the response variable for future observations (prediction) or simply to study the relationship between the outcome variable and the predictors (inference). If we let $Y$ be an $n \times 1$ column vector containing all the observations of the dependent variable, and $X$ be the $n \times p$ matrix of covariates, with $p$ the number of covariates, then we want to construct an estimator of the conditional expectation, $\mu(x) = \mathbb{E}[Y|X = x]$, to make predictions as close as possible to the true values of $Y$ in an independent dataset. Observations are generally assumed to be independent, and data are split in two sets: a training and a test set.

The *training dataset* or *training set* is the set of data used to train the algorithm. Only part of the data is used to allow the algorithm to learn the relevant features of the data. Once we have obtained a learner (i.e., a machine learning algorithm), we test its performance on the other unused portion of the data, called the *test dataset* or *test set*. The test set contains elements that are not known by the model, so predictions about the validation set allow the accuracy of the model to be properly assessed. Others prefer to articulate the learning in three phases by adding a phase between the training and the test stages. The *validation set* can be used instead of the test set to evaluate the performance of the algorithm, while the test set in this subdivision has the role of applying the model to real-world data. This division is necessary to prevent the algorithm from learning and evaluating on the same data, which in turn would cause several biases. The main problem with not splitting data into sets is overfitting, which means that the model follows errors, or noise, too closely (James et al., 2021). A simple rule for dividing the data into training and test sets is the Pareto principle or 80/20 rule, which is to assign 80% of the observations to the training set, and the remaining 20% of the observations to the test set. This rule is quite common in many applied works (Koch, 1999; Pernagallo & Torrisi, 2020; Pernagallo et al., 2021; Warnat-Herresthal et al., 2021).

In the case of classification, algorithms are used to classify observations. For example, given a dataset with spam emails and ham emails (emails wanted by the recipient), we can construct an algorithm that, based on a set of features, classifies new emails into spam or ham. In this case the estimation problem is to estimate the probability $P(Y = k|X = x)$ for each $k = 1, ..., K$ possible realizations of $Y$. The best model should ideally minimize the deviations between actual and predicted outcomes, so we can use different selection criteria, such as information criteria (e.g., Akaike information criterion or Bayes information criterion) or the percentage of correct predictions. When $K = 2$, we have a classification problem with a dummy or binary dependent variable. In Section 3.3 we present many applications of this classification problem applied to information asymmetry. Famous supervised algorithms include regression, support-vector machines, or decision trees.

In *unsupervised learning*, a learning algorithm provides unlabelled data that the machine tries to define by extracting features and patterns on its own, unlike supervised learning algorithms that learn on a labelled dataset (in the sense that the data are ingested in the form of input-output pairs). Clustering, a primary example of unsupervised learning, involves dividing the data into a number of clusters within which the data are more similar to each other than those in the other clusters. Other examples of unsupervised learning are tools for dimension reduction or matrix completion (e.g., Principal Component Analysis). Thus, the word 'unsupervised' is used because hidden patterns in the data are discovered without human intervention. The demarcation between supervised and unsupervised learning is not always so clear as in the case of the so-called *semi-supervised learning* problems (see Engelen & Hoos, 2020).

Machine learning is a branch of *Artificial Intelligence* (AI), the latter defined by IBM[1] as '*the broadest term used to classify machines that mimic human intelligence.*' There are several definitions of AI, each covering different aspects (thought and reasoning processes, or behaviour), for which the interested reader can consult Russell and Norvig's book (Russell & Norvig, 2010). The goal of AI is to predict, automate, and optimize human tasks faster and, ideally, achieve higher levels of accuracy. In simple terms, AI aims to reproduce human intelligence by means of machines. The term 'data-driven approaches' used in this chapter refers primarily to AI tools and techniques.

Scientific production on AI and machine learning has increased exponentially over the past 50 years (Figure 1), and economics is no exception. Indeed, both AI and machine learning are increasingly being applied to various economic problems (Varian, 2014; Mullainathan & Spiess, 2017; Athey, 2019),[2] and in this chapter we focus on its application to asymmetric information problems.

## 2.3 Data, information, and knowledge

We need to clarify at this stage the difference between data, information, and knowledge. According to basic information theory, data are the original representation of a phenomenon, while information is the result of interpreting,

[1] Kavlakoglu, E. (2020). AI vs. Machine Learning vs. Deep Learning vs. Neural Networks: What's the Difference? IBM.

[2] See also the special issue The Economics of Artificial Intelligence and Machine Learning published in *Information Economics and Policy.*

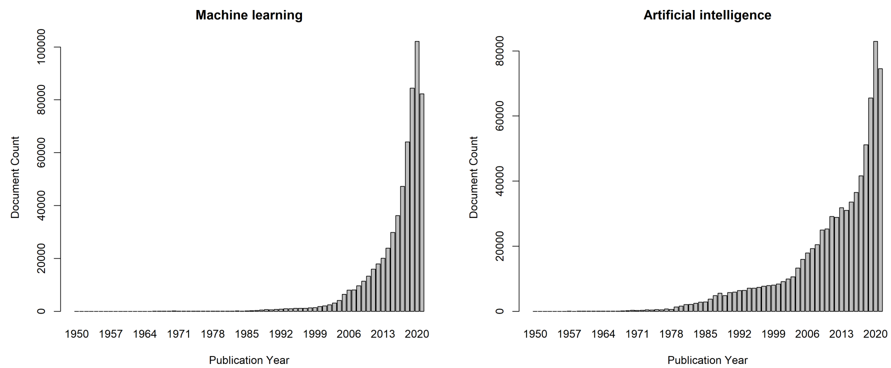


Figure 1: Count of scholarly works (e.g., papers, book chapters, etc.) on machine learning (left panel) and artificial intelligence (right panel) from 1950 to 2020. Data source: *Lens.org*.

filtering, and organising data. Finally, abstraction and information processing provide knowledge. Knowledge is thus the result of sorting, processing, evaluating, and making sense of data and signals, screening between reliable and false signals, and on aggregating them to the existing stock of information (Antonelli, 2018). According to the Bayesian approach of Arrow (Arrow, 1969; 1996), signals constitute information, they are not given, and their knowledge changes the (conditional) probability distribution of an unknown state of the world, driving the value realised by the economic agent's action.

To help the reader better understand the distinction, we can provide a simple example. Take the vector $Age = (35, 21, 23, 44, 37, 50)$, this is a clear example of data, i.e., a collection of text, numbers, or symbols in raw or unorganised form. We can then interpret these data by assigning a meaning or a context, for example, by saying that these numbers represent the age of six individuals: we now have information. Finally, we can use this information to gain knowledge, for example, by saying that the oldest individual in our dataset is 50 years old. In economics, the distinction between the three terms is sometimes very blurry. The three words are usually used without a clear demarcation in some econometric work. The difference does not seem to be of much interest to economists, yet it is crucial. On this issue, the interested reader is referred to Boisot and Canals (Boisot & Canals, 2004). For a more in-depth analysis of the three terms, the interested reader is referred to other works (e.g., Stock & Stock, 2013).

Another important distinction to make is that between knowledge, technological knowledge, and scientific knowledge. The boundary between these concepts is not easy to highlight. In simple terms, 'technological knowledge' and 'scientific knowledge' can be seen as subsets of the larger set of 'knowledge.' The two subsets sometimes intersect, but they are distinct. The key difference is related to the adjective 'technological,' which is defined by the online *Cambridge Dictionary* as '*relating to, or involving, technology.*' Instead, '*technology*' is defined by the same dictionary as '*(the study and knowledge of) the practical, especially industrial, use of scientific discoveries.*' On the other hand, '*scientific*' is about science, in the sense of knowledge provided, for example, by scholars or researchers. The adoption of information and communication technologies (ICTs) has reduced the separation between scientific and technological knowledge, reducing barriers to access to knowledge and fostering the interaction between science and technology. (Antonelli, 2017). The gap between scientific and technological knowledge has narrowed even further with the adoption of artificial intelligence. Scientific and technological knowledge producers can speak the same algorithmic language and can access and process unprecedented amounts of data through big data analytics, changing the way new knowledge is generated.

## 2.4 AI and knowledge generation

AI is hardly a new idea, as it dates back to the 1950s. The real radical innovation is the development of computational systems and skills that have made the application of AI effective and pervasive. AI is influencing the knowledge generation process by reducing its cost and increasing its spillovers.

As with information and communication technologies (Antonelli et al., 2000; Antonelli, 2017), AI allows the user to acquire massive amounts of external knowledge while reducing the cost of collecting and processing it. Unlike information and communication technologies, AI has made it possible to access new knowledge that was precluded prior to its introduction and enhancement. For example, in 2019, for the first time, astronomers were able to produce an image of a black hole.[3] The researchers developed a series of algorithms that converted the telescopic data into this historical image, a process that required the collection of about five petabytes of data.[4] Without modern computing power and advances in data analysis techniques, obtaining this knowledge would have been impossible.

The fact that AI can collect and process huge amounts of data is one of its salient features as it allows agents to make intensive use of external knowledge surpassing any other available alternative. If new knowledge is generated by recombining existing knowledge (Weitzman, 1996), then AI offers unprecedented possibilities in the knowledge generation process as the same algorithm can be implemented in countless applications. The polymorphic nature of AI algorithms can generate knowledge in a variety of fields, from finance to medicine, from biology to the arts, at no cost other than the initial creation of the mathematical and computer framework. This has tremendous repercussions on society as production, distribution and use of knowledge is the foundation for modern

[3] Castelvecchi, D. (2019). Black hole pictured for first time — in spectacular detail, Nature.
[4] Drake (2019). First-ever picture of a black hole unveiled, National Geographic.

economic growth (Geuna, 1999; Antonelli, 2019).

Section 3 shows how AI can turn data into valuable knowledge in many situations. Thus, AI can generate knowledge in financial markets from microeconomic data on borrowers and stocks to assess the riskiness of future borrowers and companies to be financed. The same mechanism can be used to evaluate candidates for a job position in the labour market, or to assess the quality and reliability of news or news creators. Electronic markets are a source of huge datasets, many times in unstructured form, which can be processed using, for instance, text mining techniques. Finally, AI also brings value to Public Administration, for instance, by making government action more transparent and citizens more informed.

# 3 A new paradigm: AI and information asymmetry

## 3.1 The data revolution

Big data processing undermines the generation of new knowledge, as humans can only process a limited amount of data (Pernagallo & Torrisi, 2022). Instead, big data makes AI applications effective, because the more data there is, the more accurate the results produced by the machines (Bag et al., 2021). Two relevant problems in applying AI algorithms in knowledge extraction are the *black box syndrome* and the interpretation of results. The first problem occurs because AI allows for standardization of procedures, in the sense that once the best algorithm has been identified, it is sufficient to feed the data to the machine to produce a result. This obviously severely penalizes the robustness of the knowledge production process, as researchers must rely on some sort of invisible action.

The second problem is more extensive as it concerns the interaction between AI and the individuals producing knowledge, such as researchers or practitioners. Turning the results of AI algorithms, the raw computer output, into valuable knowledge is a difficult process. There are two pivotal figures who play this important role. Researchers and practitioners act as interpreters of the language of AI. Researchers use and develop AI techniques to produce scientific results, which can then be converted into something practical for society (on this issue, see Chubb et al., 2022). Practitioners use and develop AI techniques to perform their tasks within a company or to earn a profit by selling algorithms and their knowledge to other individuals. The two figures many times are closely related or may even coincide. The fact that the field is very active nowadays for both figures is demonstrated by the large number of academic papers published in recent years (see Figure 1) and the high number of patents (e.g., Balland & Boschma, 2021).

The potential of AI is not limited to the extraction of data, information and knowledge from common sources or mainstream literature. Potentially, everything that can be turned into input for the machine can be sifted and processed by AI algorithms and turned into knowledge. Some examples are the so-called *grey literature* (which is less used in academic research), images, or even audio. The real problem today is not finding data mines but finding capable *data miners*. Clearly, AI can create 'public' knowledge when agents have free and unrestricted access to data, information, and existing knowledge. When this is not possible, sources of asymmetry may arise.

## 3.2 The relationship between innovation and imperfect information: old and new problems

Asymmetric information can influence innovation in many ways. The credit market is a common example of a market with asymmetric information (e.g., Stiglitz & Weiss, 1981; De Meza & Webb, 1987; Bester, 1994) where information plays a crucial role as access to credit promotes entrepreneurship and innovation (Antonelli, 2019). This market is asymmetric because a borrower usually has better information about the potential returns and risks associated with the investment projects than the lender (Mishkin & Eakins, 2018). Formally, there is a distribution of borrowers, e.g., firms or consumers, each with a given probability of success, $p$, representing the probability of being able to repay the debt. The interest rate should act as a screening mechanism to separate risky borrowers from safe ones. With perfect information, riskier borrowers with low $p$ should expect higher interest rates; unfortunately, lenders cannot observe the riskiness of borrowers, and this introduces a source of asymmetry. This lack of information can lead to credit rationing (Stiglitz & Weiss, 1981), which causes society to miss the opportunity to finance many worthy entrepreneurial projects.

On the other hand, the academic job market is a good example of how moral hazard can affect innovation. Every researcher's dream is to obtain tenure; however, the system with tenure is easily exposed to moral hazard (e.g., McDonald, 1974; Byford, 2017), pre- and post-tenure. Pre-tenure, a newly appointed researcher may decide to pursue a research agenda without significant contributions that involve high risk-taking (Byford, 2017). Post-tenure, the researcher may lose the incentive to do meaningful research since they have acquired lifetime job security. In either case, agents may produce less innovative research (for a broader model on the relationship between imperfect information and innovation in the research market, see Pernagallo, 2023).

The relationship between innovation and asymmetric information is not unidirectional, as innovation also affects asymmetric information. Technological innovation is slowly solving the asymmetry problem in many situations due to the large use of data collection systems.[5] We can provide several examples. One of the most common solutions to the problem of adverse selection in the market for used cars is the adoption of warranties, which protect the buyer in the event of fraudulent behaviour by the seller or simply if the product does not conform to the description. Nevertheless, a simple data-driven approach is enough to solve (or mitigate) the problem. The odometer reading is sufficient to provide the buyer with important information about the state of the car. The future seems to be even more transparent, as many vehicles are now equipped with an event data recorder (or black box) that collects various useful information such as speed, braking, or even location, which could be used to determine as precisely as possible the condition of the vehicle at the time of sale. Economic theory predicted that information asymmetry could lead to a collapse of the market for used cars; today, this market is more than double that of new cars, with about 39 million used cars sold in 2020 in the United States versus 14 million new cars.[6] A similar approach could be used in the insurance market, where moral hazard problems are recurrent, to ensure that the customer behave properly after signing an insurance contract.

Another interesting example comes from the monitoring systems employed by large companies. Monitoring is a possible solution to the principal-agent problem in the case of hidden actions because it encourages the agent to increase effort (e.g., Jost, 1991). However, monitoring has generally been considered costly, especially in large companies where the high number of employees makes it difficult to implement monitoring of their actions. The advent of new

[5] For a discussion on digital innovation, see Bauer & Prado, 2024.

[6] https://www.statista.com/statistics/183713/value-of-us-passenger-cas-sales-and-leases-since-1990/

technological systems, such as video cameras, has greatly reduced this problem. As documented by the *Cnbc*,[7] according to a 2018 survey by *Gartner*, 22% of organizations worldwide in various industries are using employee-motion data, 17% are monitoring work-computer-usage data, and 16% are using Microsoft Outlook- or calendar-usage data. This is the case with companies such as Walmart or UPS, which, thanks to sensors, can collect data such as scanner beeps at the checkout, chats between employers and customers, or the status of the vehicle being driven. Processing such a large amount of data requires the application of appropriate statistical techniques and has, *de facto*, reduced the prominence of traditional approaches (e.g., game theoretic models).

Unfortunately, although technological innovation is solving many old asymmetric information problems, it has simultaneously created new ones. These data gathering systems are considered an invasion of privacy, which raises serious concerns about their legitimacy. In addition, there are many other situations where our data are being collected, think of data collected by smartphones and other technological devices, or by social media platforms. This has created a marketplace for our personal data where companies sell this data to third parties without the consumer's knowledge, creating a new source of asymmetry because '*data-driven companies collect much more personal data than the consumer knows or can reasonably oversee, and data-driven companies have much more (technical) information about how this data is processed than consumers would be able to understand*' (Waerdt, 2020).

Another new source of information asymmetry is provided by the news market, which has been profoundly changed by the daily use of the Internet and social networks. In this case, the relevant information is the veracity of a news story shared by a news website, which is not revealed to consumers. Some

[7] https://www.cnbc.com/2019/04/15/employee-privacy-is-at-stake-as-surveillance-tech-monitors-workers.html

authors have shown that in this market, competition is not very effective in promoting news accuracy, and that this asymmetry can lead to the unintended effect of 'bad' news (e.g., fake news) replacing 'good' news (Mullainathan & Shleifer, 2005; Pernagallo et al., 2021).

Increasing returns triggered by economies of density and network externalities characterise both the generation and exploitation of technological knowledge and the use of the array of digital technologies. Large firms enjoy the benefits triggered by the use of the very same software to large stocks of data and information. The larger the number of data-rich interactions and transactions, the larger the amount of information that can be extracted and the larger the amount of knowledge that can be generated and exploited. Increasing returns associated with digital technologies and the generation of technological, commercial, financial, and economic data are a new source of information asymmetries: evidence from platform and grid corporations provides substantial support for this aspect (Rikap, 2022).

## 3.3 Applications of machine learning and AI with imperfect information

The creation of data-driven markets poses the need to address asymmetric information using a different paradigm. Artificial Intelligence offers a framework that can be applied to both traditional asymmetric information problems and new ones. The following is a review of some of the potential applications.

### 3.3.1 Financial markets

As discussed above, asymmetric information could cause credit rationing, limiting the innovation potential of the economic system. One device commonly used in response to asymmetric information in the credit market is the *collateral*, or the pledge of the borrower's properties to the lender, to ensure repayment of a loan (e.g., Bester, 1987; 1994). However, the introduction of a collateral would not eliminate the possibility of credit rationing (Stiglitz & Weiss, 1992).

Traditionally, research on this topic has dealt with microeconomic models, which has two major shortcomings. First, they are (for the most part) purely theoretical, which has certainly been the dominant paradigm in the past, but which reveals little appeal in the era of the data revolution. Second, the models tacitly assume that borrowers have the relevant information or, in other words, that they know, more or less, their riskiness. There are many reasons why this might not be the case. In fact, several biases may influence the borrower's judgement, such as overconfidence (e.g., Invernizzi et al., 2016), and borrowers are not always able to properly assess their projects due to a lack of adequate economic expertise, which can be a cause of over-indebtedness (e.g., Gutiérrez-Nieto et al., 2016).

Nowadays we have enough data and statistical tools to change approach and try to solve the problem of information asymmetry using data analysis. Machine learning offers a quantitative framework that allows us to compute the probability of success (or default) of borrowers without relying on theoretically rigid assumptions. The problem of estimating the probability of success is a problem of classification. These problems are extensively studied in the machine learning literature and can be easily adapted to economic contexts. These approaches can be used, among the others, by banks to estimate credit risk (Khandani et al., 2010), or by insurance companies for risk prediction (Boodhun & Jayabalan, 2018).

The usual approach is to obtain microdata on borrower default, consisting of a dummy dependent variable, *Default*, and independent variables, such as personal information about the borrower (age, income, marital status, etc.). Then the researchers use machine learning algorithms to perform the task of correctly classifying borrowers who are in default and those who are not, so that the algorithm can be used in the future to evaluate the default risk of new applicants. Famous algorithms in literature are the simple logit model (e.g., Ge et al., 2017) or more sophisticated approaches like random forests, extreme gradient boosting, and neural networks (e.g., Xu et al., 2021). Data-driven credit scoring systems are already in use. For example, *Dun & Bradstreet*, a well-known company that provides business data, analysis, and insights for companies, already offers automated solutions for credit decisions based on several variables.[8] The benefits of this approach are considerable, and the following is a partial list of them.

1. We have an accurate measure of the borrower's probability of success (or default).

2. This probability is computed 'objectively' by algorithms based on available data.

3. This method can deal with big data.

4. We do not have to make rigid theoretical assumptions (for example, agents are all risk-neutral and described by the same utility function).

5. Greater degree of flexibility. It is very difficult to move from one theoretical model (made of many assumptions) to another, because even changing one assumption can lead to different conclusions. Consider Stiglitz and Weiss (Stiglitz & Weiss, 1981) who use second-order stochastic dominance in their model and conclude that the credit market can experience credit rationing, while De Meza and Webb (De Meza & Webb, 1987) use first-order stochastic dominance and arrive at the opposite conclusion of

[8] https://www.dnb.com/resources/business-credit-scorecard.html

excessive lending. On the other hand, changing one algorithm to another requires less effort.

6. We can determine 'objectively' the best model, for example, by using information criteria or the percentage of correctly predicted cases.

One of the main flaws is that this approach can easily become a black box approach, which can lead researchers to neglect investigating the economic logic behind the observed phenomena. In addition, AI also raises some ethical issues related to problems of unjustified actions, opacity, bias, discrimination, information privacy, and moral responsibility (Mittelstadt et al., 2016). Unjustified actions can arise because highlighting causal relationships is very difficult and relying on inductive correlations can have a negative impact on humans in terms of actions taken based on algorithms. Algorithms can also be opaque because of their lack of accessibility and comprehensibility, a condition exacerbated by the need to keep the mechanism behind a method secret to preserve its profitability. The fact that AI can be biased follows from the fact that the developer can be biased; in fact, many choices are made during the process of algorithm development that can lead to certain outcomes and that can also naturally result in discrimination, for example, based on gender or ethnicity. We also pointed out how accessibility to our personal data can generate asymmetries and unregulated markets, and the use of AI algorithms contributes to this problem as it allows easier use and extraction of this data. Finally, AI poses a liability problem, since in the event of an error it is unclear who should be blamed. This is certainly not a comprehensive review of all AI-related problems, so we refer the interested reader to other works (e.g., Allen et al., 2006; Mittelstadt et al., 2016; Hagendorff & Wezel, 2020).

Asymmetric information in equity markets has also been vastly investigated in the literature (Narayanan, 1988; Dierkens, 1991; Welker, 1995; Park et al., 2021). The asymmetry arises because managers should normally have an information advantage over the market, so lenders do not know whether they are financing a worthy firm or a 'lemon.' As noted by Hubbard (Hubbard, 1990, p. 2), '*For equity finance, new shareholders demand a premium to purchase the shares of relatively good firms to offset the losses arising from funding lemons [...] This premium raises the cost of new equity finance faced by managers of relatively high-quality firms above the opportunity cost of internal finance faced by existing shareholders.*'

If there are good and bad companies issuing stocks in the equity market, machine learning can be used to choose the best stocks to invest in. The field is receiving increasing interest in recent years. For example, Gu et al. (Gu et al., 2020) provide a comparative analysis of various machine learning tools to assess the problem of measuring asset risk premiums, which is the canonical problem in empirical asset pricing. The authors show that the use of machine learning-based predictions, using decision trees and neural networks, yields great advantages over canonical methods, allowing investors to earn large economic gains.

Although data-driven approaches have the potential to mitigate asymmetry in financial markets, they are not enough to completely solve the problem. In fact, there are many other factors that machines cannot evaluate. When a bank finances an entrepreneur, elements such as talent or even luck cannot be evaluated by algorithms, so human evaluation is still a relevant component in the process. The same is true in the stock market, where private information cannot be fully disclosed, otherwise informed traders could gain huge advantages over other market participants. For this reason, there are strict rules on insider trading that highlight the key role of the policymaker in this market.

### 3.3.2 The labour market

AI is also a formidable tool for reducing information asymmetry in the labour market. As discussed in Section 3.2, companies are gathering huge streams of data through sensors and other data collection systems. It is obvious that these data are humanly impossible to manage, so AI offers appropriate tools to manage and process the data in these contexts. This kind of continuous, automated supervision would provide an appropriate incentive for the worker to behave properly.

In addition to this, machine learning could also be used to predict the skill level of job candidates when hiring (Fumagalli et al., 2022). Hiring is notoriously considered an investment under uncertainty since, in most labour markets, the employer does not know an applicant's productive skills at the time of the interview, and this information may become available to the employer after an unknown period if the applicant is hired (Spence, 1973). This is clearly an asymmetric information problem, as the candidate has more information about his or her capabilities than the employer. Following a similar approach to that described in Section 3.3.1, we assume for simplicity that there are only two types of applicants, low-skilled ($L$) and highly skilled ($H$) applicants. If we collect data on past applicants and their job performance after being hired, we have again a classification problem in which we want to predict $p$, in this case the probability of hiring a highly skilled worker, using a set of covariates, such as education, age, previous work experience, and so on. This approach is certainly feasible these days given that large (as well as mid-sized) companies are creating databases of candidates and employees. AI has the potential to profoundly change human resource management and offer companies the opportunity to gain a competitive advantage (Pan et al., 2022).

The main disadvantage of this approach is that a purely algorithmic selection process would penalize assessment elements that can only be gathered during personal exchanges with the recruiter or employer; therefore, this innovative process should be used to complement the normal assessment process. As noted in a *Forbes* article,[9] recruiting that leverages artificial intelligence with experienced human talent acquisition professionals will be a successful strategy to recruit the best candidate.

### 3.3.3 Digital marketplaces

Digital marketplaces have grown to the point where they are now perceived as a common way of doing business. In principle, in these platforms anything can be offered in exchange for money, from items that users no longer use (e.g., eBay) to hotel reservations (e.g., Booking.com), from freelance services (e.g., Fiverr) to used and vintage clothing pieces (e.g., Depop). The initial mistrust of many users for this way of trading has now been overcome, and today online platforms such as eBay have billions of visits every month.[10] Digital markets present an asymmetric information problem; in fact, strangers engaged in a transaction are reluctant to trust the counterparty. Fraud can occur on both the seller's and buyer's side. On platforms like eBay, the buyer may not receive the product or may receive a different one, while on platforms like Booking.com, fraudulent reservations made by the client can cause the hotelier lost revenue.

The introduction of feedback and reputation mechanisms changed the game. However, many studies have shown that user-generated feedback is not entirely reliable because it is often biased ('grade inflation') and can be manipulated by sellers (Milgrom & Tadelis, 2019). Fortunately, the amount of data generated by these marketplaces offers alternative solutions to address the asymmetry problem.

[9] Windley, D. (2021). Is AI The Answer To Recruiting Effectiveness? orbes Human Resources Council.
[10] https://www.statista.com/topics/2181/ebay/#dossierKeyfigures

A first application of AI to digital marketplaces comes from the huge amount of data generated by users during private chat conversations before and after the transaction. In many platforms, such as eBay or Booking.com, it is customary to contact the counterparty before finalizing the transaction to ask specific questions that are not provided in the insertion, or afterwards to provide feedback. This helps the buyer gain all the necessary information before making a choice, and the seller get feedback and design a better customer experience. Techniques such as Natural Language Processing (NLP) or other text mining tools can be used to analyse the elements that characterize successful transactions in terms of customer and seller experience. This would help generate more comprehensive feedback from users.

As a matter of fact, AI is already changing the user experience on these websites, as search engines rely on algorithms that try to come up with the most relevant results for the user as the first results. For example, eBay uses the *Best Match* method, which is '*designed to show the most relevant listings, taking into account the things our users find most important when they're deciding what to buy.*'[11] This algorithm weighs several factors, such as how closely the listing matches the buyer's search terms, the price of the item, or the seller's track record. This saves the buyer a lot of time and increases the likelihood of finding a good seller. Indeed, the disclosure provided in the listing in these markets is an effective remedy against information asymmetry (on the issue, see Lewis, 2011).

Unfortunately, a major problem of asymmetric information against new users persists. New buyers or sellers without a record of their activity in the platform could easily be marginalized as users would not trust them. This is known as the *cold-start* problem (Milgrom & Tadelis, 2019) and can be addressed in several

[11] https://www.ebay.com/help/selling/listings/listing-tips/optimising-listings-best-match?id=4166

ways. For example, NLP AI algorithms can be used to provide feedback in such situations (Milgrom & Tadelis, 2019) or deep learning can be used to overcome the item cold-start problem (Yuan et al., 2016), e.g., when items added to a catalogue have no or very few interactions.

### 3.3.4 The market for news

With the advent of social networking, news sharing and production have been revolutionized. Nowadays, we are constantly and immediately informed about what is happening in the world. The accessibility and shareability of news are immediate in the internet age; however, the fact that almost anyone can produce news poses serious problems in the process of information dissemination. For example, one of the main problems is the spread of fake news, which can be defined as unfounded information that mimics the form of reliable content in news media (Lazer et al., 2018). The presence of good and bad news, and asymmetric information, exposes this market to the same problems as Akerlof's market for used cars.

To solve the problem of asymmetry in the news market, researchers have designed online tools that provide guidelines for unaware users to recognize bad news. The purpose is to reveal to users the relevant information, i.e., the quality of the news or the reliability of the author. For example, *Botometer*[12] monitors the activity of Twitter accounts and rates them on how likely they are to be bots, while *FactCheck.org* is a website that checks the factual accuracy of what is stated by leading US politicians to the media. Pernagallo et al. (Pernagallo et al., 2021) use machine learning algorithms to assign a trustworthiness score to news websites. Logit and probit models are used to rank news websites based on a set of features, such as the presence of a 'contact us' section or a secure connection. These features are manifestations of a legitimate and editorially

[12] https://botometer.osome.iu.edu/

compliant organization. The use of algorithms to combat the spread of bad news proves to be a formidable tool for disseminating information to users quickly and easily.

### 3.3.5 Public administration

The relationship between Public Administration (PA) and citizens is also characterised by the presence of information asymmetry (Mayston, 1993; Pernagallo & Torrisi, 2020), because the 'principal' (citizens) cannot directly observe the actions of the 'agent' (PA). Then, transparency becomes crucial to make the 'action' of the agent observable. To solve this problem, it is now customary to disseminate relevant information through official PA websites, a phenomenon generally referred to as *e-government*. In this way, citizens can monitor PA actions, for example, by reading spending reports and other documents.

One of the main problems associated with such a solution is that, especially at the municipal level, websites can be poorly constructed, so their actual use by citizens is very limited (Pernagallo & Torrisi, 2020). Machine learning algorithms can be used to verify the quality of websites and their compliance with transparency regulations. Learning algorithms can assess the transparency of institutional websites based on various features available on the website.

In general, the implementation of AI can be used to improve public decision-making and increase trust in citizens, thereby decreasing the information discrepancy between citizens and administrators (Zuiderwijk et al., 2021). However, the implementation of AI in the management of *res publica* carries several risks as many citizens may lose trust in the government due to low protection of their privacy and the creation of black box systems. In addition, the use of AI creates a serious liability issue: since AI cannot be legally prosecuted, who should be blamed for mistakes? These issues will be a topic of debate in the coming years, and the literature on the subject is growing at an increasing rate (on this issue, see Pernagallo & Torrisi, 2020; de Fine Licht & de Fine Licht, 2020; Zuiderwijk et al., 2021).

# 4 AI and information asymmetries: present and future perspectives

As discussed in Section 3, there are many situations where data-driven approaches have reduced the problem of asymmetric information. However, there are many other situations where asymmetric information is still relevant. Two examples are personal data markets and the market for news. In both cases, the problem is so severe that it requires policymaker intervention to prevent misuse of private data and dissemination of misleading news. In these cases, the use of algorithms is certainly useful to inform users (Waerdt, 2020; Pernagallo et al., 2021), but insufficient without the support of laws that disincentivise misbehaviour. Thus, the question is: how can we distinguish between cases where the asymmetric problem can be addressed only with data and cases where data-driven approaches are insufficient?

My answer to this question is based on the concept of *monopolies of knowledge*. This idea was developed by historian and economist Harold Innis (Innis, 1946, 1986; Heyer, 2003) to denote situations in which a group monopolises knowledge by controlling both the information available and how it is interpreted (Comor, 2018). Innis gives the example of ancient societies, where mastery of writing systems gave priests a monopoly on knowledge (Innis, 1986). We can extend this idea to modern societies by using the Internet as our main example. In fact, the Internet resembles a complex system that allows capable users to control information and, consequently, gain a better position than naive users. Large users take advantage of the new forms of increasing returns that characterise both the use of digital technologies and the generation of an array of knowledge(s) ranging from technological, to financial, commercial, and economic knowledge. In economics, similar research into knowledge monopolies has found breeding ground in the more recent literature on intellectual capital and intellectual monopoly capitalism (Pagano & Rossi, 2009; Pagano, 2014; Rikap & Lundvall, 2022).

We can see how monopolies of knowledge play a role in data-driven markets or the market for news. In data-driven markets such as the market for personal data, the asymmetry arises because companies through the Internet can collect much more personal data than consumers think to give. This is the result of better knowledge about how private data information is processed than consumers. The problem is also broader, as it affects different types of users besides consumers, such as citizens or workers. Consider how citizens' personal information is stored online by the public administration or how private companies process the personal information of applicants and employees. This information is easily accessible via the Web and can be exploited by third parties.

In the market for news, news creators know the quality of news because they know the quality of their sources or how to look for news veracity, while users generally lack media literacy skills, attention, or more generally, relevant knowledge (Guess et al., 2020; De Paor & Heravi, 2020; Pennycook & Rand, 2021; Pennycook et al., 2021). In both examples, one party profits from its better knowledge of the Internet at the expense of the other party. The technology itself creates information asymmetries that are bound to persist if the policymaker does not intervene (e.g., through legislation) or if the monopoly on knowledge is not extinguished (e.g., by increasing user knowledge).

The use of data-driven approaches such as AI or machine learning in contexts with monopolies of knowledge may or may not extinguish the asymmetry. To

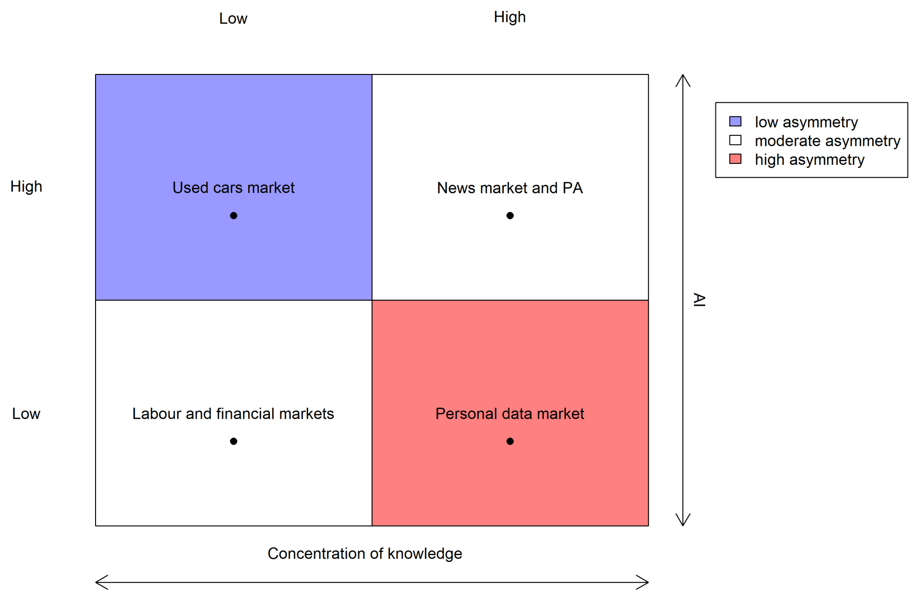


Figure 2: Markets by knowledge concentration and AI pervasiveness.

better understand this point, Figure 2 shows a matrix, where the horizontal axis represents the concentration of knowledge, and the vertical axis represents the level of pervasiveness of AI. The term 'pervasiveness' is used to indicate the effectiveness with which AI can be applied to solve a problem. Obviously, the more concentrated the knowledge, the closer we get to a monopoly of knowledge. We obtain four regions of the plane based on the level of AI pervasiveness and knowledge concentration, into which, for example, we can classify some of the markets discussed in Section 3.

Based on the discussion made in Section 3, we can say that the personal data market is an example of a market with a significant concentration of knowledge and a low level of AI pervasiveness.[13] Legislation (such as laws protecting user privacy) and user awareness are essential, so this market has a significant level of asymmetry. On the other hand, the used car market is a good example of a

[13] On this issue, Bodoff offers a discussion on the role of machine learning in data privacy (Bodoff, 2024).

market with low knowledge concentration and high AI pervasiveness, as data-driven approaches are easy to implement and can drastically reduce, or even solve, asymmetry. The labour market has a low level of knowledge concentration, but the asymmetry persists even with the application of AI tools. Indeed, machines cannot assess the talent or many skills of employees and candidates, so human intervention is still needed in the process. Finally, the news market or PA are situations with relevant knowledge concentration but high AI pervasiveness because algorithms can be used to disseminate relevant information to users and reduce information discrepancy.

This demarcation criterion seems to work well, although it is only an exemplification of reality and serves only to illustrate how the idea of monopolies of knowledge can help us distinguish precise areas in which to apply data-driven approaches. The argument also stimulates another consideration. As modern society is increasingly dependent on digital technologies, the problem of asymmetric information is likely to change and evolve over time. For example, the use of sensors in the workplace on the one hand reduces the problem of moral hazard, but on the other hand can introduce a knowledge differential between employers and employees as occurs in personal data markets. If this issue is not managed by the policymaker, this can create a monopoly of knowledge and a new source of asymmetry.

## 5 Conclusions

Innovation is changing our daily lives in many ways. Digital technologies have become an integral part of our routines and it is inevitable that this changes the way we deal with many problems. The problem of information asymmetries in many cases seems to be obsolete in the era of big data, in which decision makers struggle to process huge amounts of information (Pernagallo & Torrisi, 2022).

In fact, the use of data represents a formidable tool against asymmetric information. A first purpose of this chapter is to show how data-driven approaches are effective in dealing with information asymmetries. This is certainly true in 'traditional' markets such as credit, labour, or insurance; however, there are many instances where technology itself is creating new sources of asymmetry. In some cases, AI can mitigate the asymmetry, in others human intervention is still needed. Thus, a second purpose is to propose the idea of *monopolies of knowledge* to distinguish between these two situations.

Machine learning and AI can be used, for example, to estimate the default probability of borrowers (Ge et al., 2017; Xu et al, 2021), to predict risk in actuarial problems (Boodhun & Jayabalan, 2018), to monitor workers and in the candidate selection process (Fumagalli et al., 2022), to address the 'cold-start' problem in digital marketplaces (Yuan et al, 2016; Milgrom & Tadelis, 2019), to increase the transparency of PA action (Pernagallo & Torrisi, 2020; Zuiderwijk et al., 2021), or to reveal the quality of news or news sources to internet users (Pernagallo et al., 2021). In all these cases, data-driven approaches mitigate the asymmetry problem. However, digital technologies inevitably create monopolies of knowledge, as only a fraction of users can master these new tools and new forms of increasing returns are at work in their use. This introduces new scenarios with asymmetries, as is the case of data-driven markets. Exactly as in ancient cultures the class that dominated the writing systems exerted a form of power over other classes, the same is happening with the Internet. In these cases, algorithmic solutions, although useful, must be supported by policymaker intervention and by fostering people's information literacy to avoid digital monopolies of knowledge.

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