SIN-CHN SCIENTIFIC PRESS PTE.LTD.

*Microeconomics* 2025, 1(1), 2005.
https://doi.org/10.62617/me2005

Article

# Artificial intelligence agents and superstar effects

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**CITATION**

Lanzi D. Artificial intelligence agents and superstar effects. Microeconomics. 2025; 1(1): 2005. https://doi.org/10.62617/me2005

**ARTICLE INFO**

Received: 9 April 2025
Accepted: 26 May 2025
Available online: 4 June 2025



**Abstract:** The paper models AI-services market competition in the presence of superstar effects. By modifying the original Rosen's setup consistently with recent advancements of superstar theory, we discuss the role of scale-related technical change in the advent of superstar artificial intelligent agents and the main consequences of superstar effects on competition between AI-based systems. Furthermore, we outline how to extend the model for addressing three issues: (i) positive feedback loops from data accumulation; (ii) the co-evolution of artificial intelligence agents' capabilities and market size; and, (iii) the "winner-takes-all" dynamics triggered by superstar effects.

**Keywords:** artificial intelligence; digital innovation; superstar effects; technical change; "winner-takes-all" dynamics
**JEL:** D31; L11; O33

## 1. Introduction

Information technology allows a small number of talented individuals or firms to serve a large market and reap large rewards. In a series of papers, published in the second half of the 70s, Sattinger [1,2] and Rosen [3,4] called such a magnification "*superstar effect*". Superstars are a small number of people (or sellers) earning enormous amount of money and dominating the activity they engage in. When the superstar effect operates there is a concentration of output and income among a few agents, and the distribution of rewards exhibits high skewness. Rosen's first example [4] was that of comedians and television.

More recently, Gabaix and Landier [5] and Terviö [6] have applied the superstar theory to labor markets. Workers with heterogeneous talent and employers of varying size are matched with some superstar workers earning enormous wages and big firms very high profits. From this perspective, superstar effects increase income inequality[1].

In a recent paper, Korinek and Ng [8] emphasize that advances in information technologies and digitalization have supercharged the superstar phenomenon. Superstar firms of the digital economy have had, between 1990 and 2015, rising market shares, rising mark-ups and an explosive growth of their intangible/physical capital ratio. Furthermore, the advent of artificial intelligence (AI) and artificial intelligence agents (AIAs) will increasingly generate superstar rents and absorb them in terms of investment, hence enhancing superstar effects. In the future economy, a few self-improving AIAs will likely dominate in terms of profits, notoriety and market size. A "*winner-takes-all*" dynamics, made easier by AI-based digital innovation, which allows us to replace tasks performed by traditional labor and capital; collect and process excludable information; and, replicate a technology at negligible cost [9].

In 1981, Rosen concludes that the main driving force of superstar effects is technological change that facilitates an increase in market scale. During periods of "scale-related technical change" (SRTC), large-scale production is easier and superstar effects are amplified. A conclusion recently confirmed, for the case of the television industry, by Koening [10]. Hence, some questions seem legitimate: Can superstar theory explain the rise of global natural oligopolies powered by superstar AI systems? What is the role of SRTC on the skewness of AI-related markets in terms of AIAs' size and profitability? How can the "winner-takes-all" competition explain runaway superstar dynamics in AI markets?

In these regards, Korinek and Ng [8] argue that if patented innovation allows automating a larger fraction of production tasks, thus realizing a cost advantage for the innovator with respect to other producers, then profit margins rise with further innovation, and economies of scale create few superstar sellers. In short, superstar effects, digital innovation and SRTC interact in the creation of global AI-powered superstar firms.

For addressing the aforementioned live issues, this paper provides a simple model built by mixing elements of the superstar theory. We integrate Rosen's theory [4] with the updated set-up used in recent research on the topic to get a mature framework for the analysis of AI systems, technical change and superstar effects. We discuss the role of SRTC in the advent of superstar AIAs, and the main consequences of superstar effects on competition between AI-based systems. For doing this, we mainly use a static framework; some possible dynamic extensions of the model are sketched separately. In particular, we will focus on three dynamic issues: (*i*) positive feedback loops from data accumulation; (*ii*) the co-evolution of AIAs' capabilities and market size; and, (*iii*) the "winner-takes-all" competition triggered by superstar effects.

The remainder of this essay is organized as follows. In section 2, we briefly review the main pillars of superstar theory with reference to AI-related markets. Section 3 introduces the model. Section 4 discusses the case of SRTC, while section 5 addresses the extreme case of a public goods technology. In section 6, we outline some insightful dynamic extensions. The last section concludes.

## 2. Superstar theory and artificial intelligence

Rosen's magnification dynamics [4] has several economic reasons and yields clear market effects. On the one hand, the main reasons for superstar effects are: (*i*) imperfect substitutability between high-quality services (greater talent) and low-quality ones (lesser talent); (*ii*) the impossibility of compensating lower quality levels with larger consumed quantities of the service; (*iii*) scale economies of joint consumption. On the other hand, superstar effects involve: (*i*) the convexity of producers' revenue with respect to talent/quality; (*ii*) a "winner-takes-all" kind of market competition which reinforces the position of superstars with respect to other sellers; (*iii*) an income/rewards distribution that is stretched out in its right-hand tail compared to the distribution of talent.

With regard to AIAs and AI-powered services and tools, all the above elements of superstar theory hold. First, poorly intelligent systems are imperfect substitutes for highly talented AIAs, exactly as outstanding singers are hardly substitutable with mediocre ones. Second, a larger quantity of low-quality AI-based services has less value than a smaller amount of high-quality AI-based solutions and tools, like it happens in surgery. Third, the cost of production of AI-powered services does not rise in proportion to the size of the seller's market. As for public goods, there are scale economies of joint consumption that allow few sellers to serve the entire market. And fewer sellers are needed the larger they are for covering the whole market demand (as in the case of theaters). Fourth, AI-based systems and services are protected by legally assigned property rights; thus, they are excludable. This generates monopoly power and economic rents for superstars, as for best-selling books. Finally, with reference to market outcomes, the early experience of the AI services market has already shown that few AIAs benefit from superstar effects in terms of notoriety, capitalization and profits [11]. According to superstar theory, the big five companies of AI (e.g., Apple, Microsoft, Alphabet, Meta and Tesla) already dominate the global market of AI-powered tools and technologies.

As Rosen [4] pointed out:

> The effect of scale economy on seller concentration is strikingly seen in the extreme case when internal and external diseconomies vanish […]. Then there literally is public goods technology and a single seller services the total market in equilibrium. That *person* is the most talented of all potential sellers. Even though there is one seller, essentially competitive market conditions are maintained by threats of potential entry (p.852, italics added).

As we show, the same claim holds for AI services and markets with a relevant caveat. Digital information is not rival, but it is excludable. Therefore, as Korinek and Ng [8] argue, an entrepreneur who develops a relevant innovation in the field of AI can reduce internal diseconomies at negligible marginal cost, and can benefit from the exclusive right to use patented innovation. Hence, with pure joint consumption and scale economies, the threat of entry vanishes, and global natural oligopolies are likely to emerge.

The relation between AI systems and superstar effects has been recently analyzed by Suh [12]. In his paper, the author focuses on the effect of AI-based automation on income inequality among workers and managers of a hierarchical organization. He highlights how the complexity of tasks automated by AIAs and supervision costs are crucial for income distribution. In the case of highly intelligent machines able to supervise workers at small costs, wage inequality among workers decreases, while income inequality between managers rises because of superstar effects. In the paper, technology and income inequality are related to superstar effects, but the latter are referred to users of AI-based services and solutions. Differently, in what follows, we discuss the magnification dynamics of superstars with direct reference to competing AIAs.

## 3. The model

In this section, we propose a simple market model for AI services inspired by superstar theory.

On the demand side, assume the representative consumer has a separable, and logarithmic utility function $u = u(x, y) = lnx + lny$, where $x$ is a composite commodity and $y$ indicates the consumption of AI-based services. Let us suppose that

$y = g(q, z) = qz$ with $q$ indicating the quantity purchased and $z$ the quality of each unit of the service. Measuring prices in units of $x$, the budget constraint is

$$I = x + p(z)q \tag{1}$$

where $I$ is income and $p(z)$ is the cost of one unit of service of quality $z$. As in Rosen [4], first order conditions for utility maximization yields to the differential equation

$$\frac{dp(z)}{dz} = p'(z) = \frac{p(z)}{z} \tag{2}$$

from which derives the price schedule $p(z) = vz$ with $v = \frac{p}{z}$.

Furthermore, marginal conditions for consumer choice are:

$$\frac{u_y}{u_x} = \frac{zx}{y} \text{ for } q \tag{3}$$

$$\frac{u_y}{u_x} = \frac{qx}{y} \text{ for } z \tag{4}$$

By combining Equations (3) and (4), the optimal choice of $z$ is such that $z = q$. Intuitively, the last equality stipulates that consumers prefer to balance the quantity and the quality of AI services they buy[2]. In short, too much low-quality AI services as well as too few AI-based solutions of very high quality yields utility losses with respect to a balanced consumption bundle.

Thus, individual demand is $n = \frac{p(z)}{v} = f(v)$, and the whole market demand for AI-based services $Y^D = \sum f(v) = F(v)$ with $\frac{dF}{dv} < 0$.

On the supply side, suppose many AI developers each of them owning one AI system. AIAs have different algorithmic intelligence levels (talent) $t$ with $t > \underline{t} > 1$ where $\underline{t}$ denotes a lower bound of intelligence under which the system cannot offer reliable services[3].

Let us assume that there is a regular distribution of talent/intelligence in the population of AIAs $\Phi(t)dt$. The quality of AI-based services $z$ is produced by both the talent and the size (e.g., $s > 1$) of the AI system in terms of sold units, that is:

$$z = (s(t)t)^{\frac{1}{\phi}} \tag{5}$$

In Equation (5), an increase of $\phi > 0$ measures SRTC, as in Koening [10], and $s$ indicates the size of AI systems in terms of units of service sold. Furthermore, as it is easy to check, the above expression yields a convex revenue function ($\frac{\partial^2 R}{\partial s \partial t} > 0$). Hence, by substituting (5) in (2), net revenues are given by:

$$vs(t)^{\frac{1+\phi}{\phi}} t^{\frac{1}{\phi}} - C(s(t)) \tag{6}$$

where $C(s)$ denotes the costs of producing $s$ units, with $C_s > 0$ and $C_{ss} \geq 0$. An AI developer with an agent of type $t$ chooses $s(t)$ in order to maximize (6); therefore, $s$ is chosen to satisfy

$$\frac{v(1+\phi)}{\phi}s(t)^{\frac{1}{\phi}}t^{\frac{1}{\phi}}-C_s=0 \tag{7}$$

so long as

$$\frac{v(1+\phi)}{\phi^2}s^{\frac{1+\phi}{\phi}}t^{\frac{1}{\phi}}-C_{ss}<0 \tag{8}$$

Then, differentiating (7) with respect to *t*, and rearranging terms, we get the "*superstar effect*":

$$\frac{\partial s}{\partial t}=\frac{-\dfrac{v(1+\phi)}{\phi^2}s^{\frac{1}{\phi}}t^{\frac{1}{\phi}}}{\left(\dfrac{v(1+\phi)}{\phi^2}s^{\frac{1-\phi}{\phi}}t^{\frac{1}{\phi}}-C_{ss}\right)}>0 \tag{9}$$

According to (9), the size of AIAs in terms of sold services increases with their level of intelligence/talent.

Finally, let $\tilde{s}$ be the solution to (7); then, the total amount of AI services supplied ($Y^S$) is:

$$Y^S=\int_{\underline{t}}^{\infty}z\tilde{s}(t)\Phi(t)dt=G(v),$$

with $\frac{dG}{dv}>0$. The conventional market equilibrium is obtained by equating $Y^S$ and $Y^D$.

## 4. SRTC and superstar effects

As is well known, digital innovation gives rise to increasing returns to scale. In digital markets, SRTC, by making large-scale production feasible, relaxes internal diseconomies and allows firms to serve a large market at low costs. For example, in Kovinek and Ng [8] a patented innovation generates increasing returns and reduces production costs of innovating AI superstars with respect to other firms. Differently, in the literature on SRTC in the labor market, the effect of *universal* (i.e., the result of unpatented, public-domain innovations) technical change on the skill premium plays a crucial role in explaining wage inequality changes[4].

By using our model, we claim that SRTC due to public-domain digital innovations supercharges superstar effects, and yields higher rewards for a few superstars with a large market size. More precisely, any public-domain innovation that augments: (*i*) increases the revenues of the most talented AIAs more than those of less talented ones; (*ii*) increases the AI services market's skewness in terms of AIAs' size and profits.

To see this, derive the revenue in (5) by $\phi$, and then what obtained (that is, $R'=\ln(s(t)t)$) by *t* and *s*. By using the Schwarz's theorem, we get that:

$$\frac{\partial^2 R}{\partial s\partial\phi}=\frac{1}{s(t)t}\left(\frac{\partial s}{\partial t}t+s(t)\right)>0 \tag{10}$$

$$\frac{\partial^2 R}{\partial t\partial\phi}=\frac{1}{s(t)}>0 \tag{11}$$

By combining equations from (9) to (11), the proof of the above claim is straightforward. Revenues increase with talent, and SRTC is better exploited by highly talented AIAs. Few highly talented agents benefit from superstar effects, and their market size increases with respect to the quality of services and the degree of SRTC. Thence our claim: SRTC increases marginal returns of both talent and size, and its effects are mainly exploited by a few superstar AIAs.

Let us conclude this section with some policy implications of the above discussion. Firstly, if SRTC supercharges superstar effects in the case of public-domain innovations, the legal protection of AI-related innovations through property rights systems can only amplify the charging. Secondly, superstar countries will experience most of the gains from the AI revolution, with developing countries increasingly left behind; this poses an important developmental issue. Finally, public investment to finance digital innovation, and to support AI-related basic research, can only partially mitigate monopolistic distortions due to the superstar phenomenon. Public institutions can apply taxes and subsidies, and punish fiscal evasion, but they cannot block the magnification dynamics, and its effects on profits, income and superstar rents.

## 5. Fixed costs and limit talent

The consequences of superstar effects on AI-services market competition is strikingly seen in the extreme scenario of a public goods technology. To address the case, let $K > 0$ be a fixed cost of production of AI-based services with $C(s) \equiv 0$ and $z = t$ (see Rosen [3]). Accordingly, net revenues are

$$R = vts(t) - K \tag{12}$$

The market participation constraint (i.e., $R > 0$) identifies a threshold value for AIAs' talent ($\tilde{t}$) such that:

$$t > \frac{K}{vs(t)} = \tilde{t} \tag{13}$$

Since $\frac{\partial \tilde{t}}{\partial s} < 0$, the *limit talent* for participating to the market decreases with AIAs' size. Furthermore, deriving $\tilde{t}$ for both *s* and *t*, we get that:

$$\frac{\partial^2 \tilde{t}}{\partial s \partial t} = \left[\frac{2}{s(t)}\left(\frac{K}{v}\right)\right]\frac{\partial s}{\partial t} \tag{14}$$

Equation (14) always has a positive sign if there are superstar effects (i.e., $\frac{\partial s}{\partial t} > 0$). Thus, low-talent AIAs not only will have small market size, but the limited talent they have to reach for to be competitive increases the stronger superstar effects are.

Nonetheless, machine learning is based not only on the level of algorithmic intelligence, but also on the amount of data available for learning processes (*big data*). Hence, low-talent AIAs of small size are likely to offer low-quality services[5].

To this well-established conclusion, this section adds a remark: if internal diseconomies vanish and fixed costs increase, superstar effects will raise theit on the talent/intelligence level AIAs need to have for selling AI-based services and solutions. If the average talent level among AIAs augments, the less talented ones will be gradually forced to exit the market. Such an exclusionary mechanism ends up reinforcing the market position of superstars.

## 6. Superstar effects and the "winner-takes-all" dynamics

Main papers on the superstar effect use static models. Thus, until now, we have followed the tradition by working on a static framework of analysis. Indeed, in its short history, superstar theory has devoted little attention to the "winner-takes-all" dynamics. Maybe because human superstars last shortly. In many cases, their rise is sudden and their fall imminent. On the contrary, AIAs have the chance to replicate themselves indefinitely. Furthermore, AIAs are evolving agents that learn and develop in time, and the pace of improvement in their cognitive capabilities will determine their market success. Hence, noteworthy is how to extend the analysis in dynamic terms. In particular, in this section, in order to address how superstar effects can trigger the "winner-takes-all" dynamics, we mention three possible extensions in a dynamic realm.

According to the "winner-takes-all" kind of competition, superstars are winners, and all other sellers are prey of the most talented and sized suppliers. A prey-predator evolutionary process yields a market outcome such that superstars predate the others, becoming the sole market winners. During that process, important positive feedback loops, where initial advantages in AI talent or scale self-reinforce, exist. In fact, the "winner-takes-all" dynamic has many similarities with complex systems behavior, and concepts like path dependence, bifurcations, co-evolution, and the like, can be very useful for explaining systemic risks of a runaway superstar dynamic in AI markets[6]. In this regard, for illustrative purposes, by using simple difference equations, we address three issues: (*i*) positive feedback loops from data accumulation; (*ii*) the co-evolution of AIAs' capabilities and market size; and, (*iii*) the prey-predator kind of competition that underlies the "winner-takes-all" dynamics. Let us discuss them in order.

(*i*) As is well-known, machine learning needs big data, and a continuously increasing amount of information for the training of AIAs. In the next decades, according to some AI theorists, an artificial intelligence explosion is likely to occur also thanks to the ever-increasing data availability[7]. For such an explosion, positive feedback loops in knowledge accumulation, i.e., self-reinforcing circles of learning and skills acquisition, play a crucial role. The knowledge amplification dynamics, which sustain the explosion of AIA's intelligence and capabilities, can be characterized as a difference equation of the kind:

$$k_{n+1} = ak_n + b \tag{15}$$

In Equation (15), $n$ indicates time, $k$ denotes AIAs' knowledge capabilities, $b$ is a positive parameter, and $a > 1$ expresses the amplification effect. As is well-known, the last inequality is enough for having unstable fixed points of (15) with a value of $k$ that increases exponentially over time.

(*ii*) The abovementioned intelligence explosion will increase AIAs capabilities and talent, and the race to accumulate data and knowledge will determine the winners and losers of the AI markets. The co-evolution of talent ($t$) and scale/size ($s$) of an AIA can be described in terms of coupled difference equations of the type:

$$t_{n+1} = at_n + bt_n s_n \tag{16}$$

$$s_{n+1} = cs_n + ds_n t_n \tag{17}$$

where *n* indicates time, and $a$, *b*, *c*, and *d* are positive parameters. The second term of the right-hand side of the above expressions relates the feedback loop to both AIA's talent and market size. According to (16) and (17), if AIAs' talent increases exponentially, thanks to an explosive growth of *k*, their market size will do the same. Therefore, those AIAs that slowly accumulate capabilities and data will be left behind along the way to stardom, and they will be, sooner or later, predated by superstars. A runaway superstar dynamics in AI markets will yield "winner-takes-all" market outcomes.

(*iii*) Finally, the "winner-takes-all" dynamics, in which predators and prey exist, is well-rendered, in formal terms, by competitive difference equations that describe the competitive interaction between two AIAs[8]. Let us consider the following example:

$$s_{n+1}^{\alpha} = \frac{s_n^{\alpha}}{a + cs_n^{\beta}} \tag{18}$$

$$s_{n+1}^{\beta} = \frac{s_n^{\beta}}{b + ds_n^{\alpha}} \tag{19}$$

In Equations (18) and (19), $a$, *b*, *c*, and *d* are arbitrary positive numbers, *n* indicates time, and *s* denotes the market size of two competing AIAs (e.g., $\alpha$ and $\beta$). As it is clear, the predatory nature of competition is reflected by the fact that both transition functions are decreasing with respect to other agent's size. Some asymptotic behaviors of solutions to equations (18) and (19) illustrate well a "winner-takes-all" dynamics. As Clark and Kulenovíc [17] show, the equilibria of Equations (18) and (19) are (0,0) and $(1 - b, 1 - a)$. For several constellations of above parameters, these equilibria are unstable and the evolution dynamics of the two AIAs ends at any point on each coordinate axis. Intuitively, the competitive interaction between the two AIAs decrees a sole winner, the superstar.

## 7. Conclusion

In this paper, we have proposed an updated version of Rosen's model [4] on the superstar effect to address the case of market competition between AIAs. Our findings show that SRTC, scale economies of joint consumption, "winner-takes-all" market dynamics, positive feedback loops in knowledge accumulation, and the like, can yield systemic risks of runaway superstar dynamics in AI-related markets.

In discussing the general effect of technological change on superstars' earnings and rewards, Shervin Rosen wrote:

> Even adjusted for 1981 prices, Mrs Billington must be a pale shadow beside Pavarotti. Imagine her income had radio and phonograph records existed in 1801! What changes in the future will be wrought by cable, video cassettes, and home computers? (p.857)

Elisabeth Billington, British opera superstar of the XIX century, earned in 1801 between 10,000 and 15,000 pounds, a very high income for the time. In 1990, Luciano Pavarotti, the Italian opera superstar, earned around eight billion Italian lire, an enormous income at 90s prices.

Thus, what changes in the future will be wrought by AI-based tools and technologies? According to our discussion, they will generate trillions of dollars for a few superstar AIAs, and a few superstar (global) service providers displaced in a few countries. Countries, or firms, without AI superstars will be likely left behind. Therefore, as our discussion highlights, it is no surprise that companies and governments around the world have entered a heated race for AI leadership. Consistently with superstar theory's predictions, even at an early stage, the AI rush seems already a "two-superstar game" between the US and China[9].

**Institutional review board statement:** Not applicable.

**Informed consent statement:** Not applicable.

**Conflict of interest:** The author declares no conflict of interest.

## Notes

1 For a review on superstar effects in multiple sectors (CEOs, financial professionals, actors and the like) see Kaplan and Rauh [7].

2 Note that even if $z$ and $q$ are substitutes in producing $y$ (i.e., $\frac{\partial^2 g}{\partial q \partial z} > 0$), a logarithmic utility such that $\frac{\partial^2 u}{\partial x \partial y} = 0$ yields perfect complementarity of $z$ and $n$ in terms of consumption.

3 In Rosen [4]'s model, this threshold indicates sellers with talent such that their net revenue is lower than opportunity costs.

4 See, among others, Acemoglu and Autor [13] and Autor et al. [14].

5 In our framework, AIAs' size is conceived in terms of units of sold services. However, in the case that the amount of available data for machine learning is proportional to market share, it is immediate to see how larger sizes imply more intelligent agents and higher-quality AI-based services.

6 I thank an anonymous reviewer for this fascinating suggestion.

7 The original argument for the AI explosion can be found in Good [15].

8 On competitive and cooperative difference equations see Smith [16].

9 US and China dominate the scene in terms of: number of AI startups, top firms developing AI systems, share of the global AI investment, share in global search engine market, major social platforms, AI patent applications and the like. See Köner [18].

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