DATA AND COMPUTING POWER: THE NEW FRONTIERS OF COMPETITION IN GENERATIVE AI

Documents de travail GREDEG
GREDEG Working Papers Series

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GREDEG WP No. 2025-38

https://ideas.repec.org/s/gre/wpaper.html

Data and Computing Power: The New Frontiers of Competition in Generative AI

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GREDEG Working Paper No. 2025-38

Abstract

Digital markets are increasingly dominated by entities that leverage technical specificities such as network effects, economies of scale, and scope, as well as significant advantages in data access and critical infrastructure, including computing power and cloud capacities. The advent of generative artificial intelligence (AI) marks a potential inflection point in this landscape. In this context, the primary barriers to entry are no longer merely data and open source foundation models but the availability of large, high-quality datasets and substantial computing power. This paper examines whether these barriers will entrench the dominant positions of Big Tech companies or if they will catalyze a reshuffling of competitive dynamics. By focusing on the dual challenges of data and computing power, this study identifies the key factors that will shape the future competitive landscape of the generative AI industry. This article contributes to the ongoing debate in industrial economics and strategic management regarding the potentially disruptive effects of generative AI on the market power of Big Tech firms. Can this technological shift recalibrate competitive dynamics, or will it ultimately serve to entrench existing power structures? At its core, the article seeks to interrogate a prevailing narrative—namely, the notion that innovation inherently sustains competitive processes, even in the face of short-term lock-in effects.

Keywords

Generative AI, data-based advantage, digital ecosystems, Big Techs

JEL codes

K21, L12, L13, L41

1. Introduction

The digital sector is characterized by significant and entrenched dominant positions, often taking the form of "moligopolies" – multi-product firms acting as gatekeepers within their respective ecosystems. These firms face competitive pressure from pivotal firms in other digital ecosystems and new entrants, particularly in emerging markets (Petit, 2020). Generative AI has the potential to reshape this landscape, but numerous competition authorities are stressing the importance of risks for competition in this field (OECD, 2023). For instance, for AI broadly considered the July 2024 Joint Statement of the EU Commission, British CMA, and US DoJ and FTC (2024) insisted on three majors competition risks: 1) the concentration of the control of key inputs, 2) the risks of entrenched or extended power market, and 3) the capacity to lock or to control competition through inter-firms' arrangements or contractual relationships.

It is essential to distinguish it from current AI models based on predictive or classification capabilities. Generative AI refers to deep learning models capable of generating text, images, and videos based on the data on which they have been trained. This development has been facilitated by transformers, which enable machine learning to train large models without the need to label all data beforehand (Uszkoreit et al., 2017). These models trace connections across vast amounts of data (text, images, code, etc.), leading to the creation of foundation models, or large language models (LLMs). Such models can generate new text from a query (prompt) by analyzing patterns previously learned during training, with the precision of the response improving with the specificity of the prompt.

In the generative AI field, two different levels should be distinguished. The first level involves the development of foundation models or LLMs by large companies like OpenAI. A foundation model can be described as a large scale and pretrained AI model on very diverse kind of data that purpose is not task specific. In other words, these fundamental language models are generic and do not need to be trained on data specific to a particular sector or player. These developments can be carried out at a later stage.

The second level involves fine-tuned models, which are trained on a foundation model for specific purposes by enterprises. These enterprises use more modest infrastructure for additional training but require very specific data sets. Additionally, we should consider the roles of users (entities generating outputs through prompts) and recipients (end-users consuming the service). The first three entities are simultaneously trading partners and actual or potential competitors, with products that are complementary, necessitating cooperation for investment and innovation. However, they should also be analyzed as "coopetitors" (Marty & Warin, 2023). Even though fine-tuned models are built upon foundation models and depend on specific capabilities and assets provided by upstream partners, the latter may still have the ability to foreclose their coopetitors and implement anticompetitive strategies. (Azoulay. et al., 2024). However, the history of competition in digital market may be not repeat in the one of generative AI possibly because of its specific characteristics and the current regulatory landscape.

Several characteristics of AI markets and the regulatory environment may give rise to hopes for more competitive functioning compared to current digital markets. Firstly, AI, particularly generative AI, is a disruptive technology (Carugati, 2024). Such technologies can lead to the emergence of new markets, challenging current dominant players in the digital economy. Economic history provides several examples of such dynamics, such as IBM vs. Microsoft and Intel, or Nokia vs. Apple and Google (Manne & Auer, 2020). More importantly, AI is a transformative technology (Acemoglu & Lensman, 2024), impacting not just specific markets but the entire digital economy. AI is a general-purpose technology (Bresnahan, 2024), enhancing its disruptive potential significantly (Agrawal et al., 2024). In examining the disruptive potential of generative AI technologies, it is evident that these advancements pose significant regulatory, ethical, and social challenges. As Wang and Wu (2024) articulate, the emergence of AI models like ChatGPT necessitates a harmonized legal framework that balances innovation with regulation to manage associated risks effectively.

This need for balance is underscored by the joint statement issued in July 2024 by the U.S., UK, and European authorities, emphasizing the importance of international cooperation in AI regulation (European Commission et al., 2024). Additionally, the French Competition Authority's June report (Autorité de la concurrence, 2024) highlights the specific risks and regulatory challenges posed by generative AI, further reinforcing the urgency for a cohesive and globally aligned legal approach. The regulatory issues that arise are of several kinds. We will focus our analysis solely on the area of competition, considering one particular issue, that of the economic and technological dependence in which complementors could find themselves[1]. In other words, how can we prevent them from being confined, as in the case of mobile operating systems, to the downstream level of applications, and how can we make possible an open competitive game based on merit (Azoulay et al., 2024)?

However, regulation of generative AI should not be reduced to this competition issue. This framework must address the ethical dilemmas posed by AI, such as algorithmic bias and privacy concerns, ensuring that technological benefits do not exacerbate existing social inequalities (Goldfarb, 2024). Moreover, the legal ambiguities surrounding intellectual property rights in AI-generated content highlight the urgent need for updated IP laws that define ownership and accountability in the digital age.

These considerations are particularly relevant in the context of international trade, where geopolitical factors and technological advancements intersect. The ability of generative AI to drive innovation across sectors can enhance economic efficiency and competitiveness. However, as Wang and Wu (2024) note, the socioeconomic implications, including job displacement and workforce disruption, must be carefully managed through policies that support workforce transition and equitable distribution of AI benefits (Goldfarb, 2024). Thus, a comprehensive approach to AI governance, informed by international collaboration and proactive legislation, is essential for fostering a balanced and inclusive global economy.

Secondly, new players distinct from the dominant Web 2.0 companies have emerged as leaders in the field, such as OpenAI, Midjourney, and Anthropic. Thirdly, a more "precautionary" regulatory framework is in place, which can provide a secure development space for these players. For instance, the European Union's Digital Markets Act (DMA), enacted in 2022, the Data Act, adopted in 2023, and the July 2024 AI Act are still in their infancy but may have disciplinary effects. With Big Techs under the scrutiny of antitrust authorities and previous antitrust decisions acting as "price signals," the development of new players may be facilitated. The risks of anti-competitive practices, such as foreclosure or leveraging, may be reduced, and some of the remedies already implemented or announced may create a more "new entrant friendly" environment. These new players may benefit from better access to data, ecosystems, cloud facilities, etc., a crucial factor underscored by the June 2023 report from the French Competition Authority (Autorité de la concurrence, 2023) on the significance of access to cloud infrastructures.

Against this backdrop, several competition concerns can be highlighted. AI markets are affected by competitive bottlenecks such as data, cloud, and computing infrastructures, market access facilities, and talents. Dominant players in digital markets may impair competition on the merits and extend their power in emerging markets, detracting from innovators, nascent competitors, and potential disruptors. The possible strategies to hinder potential and emerging competition are well known in the antitrust field: bundling and tying strategies (see EU Commission decision on Android, July 2018, case AT.40099), self-preferencing strategies (see EU Commission decision on Google Shopping, June 2017, case AT.39740), and foreclosure strategies based on the abuse of private regulatory power in

[1] In a subsequent contribution, we undertake a more detailed examination of the challenges posed by the development of generative AI, considered through the prism of international trade (Marty and Warin, 2025.

ecosystems or, in other words, the abuse of economic and technological dependence (see EU Commission decision related to Amazon in December 2022, case AT.40703).

While these potential risks are common across different AI markets, they are particularly relevant for generative AI. The Portuguese Competition Authority's November 2023 report on generative AI illustrates the key competitive parameters in this field and the associated risks (Portuguese Competition Authority, 2023).

A first set of parameters relates to the accumulated advantages of Big Techs (or digital incumbents). These advantages consist of their privileged access to consumers, financial resources, capacity to detect and absorb knowledge from their environment, and ability to ensure scalability. Incumbents should be analyzed as market actors capable of managing an innovation system and acting as intellectual monopolies (Rikap & Lundvall, 2020).

A second set of parameters involves resources controlled by incumbents, including access to cloud services, hardware, and middleware resources. Access to data, cloud computing capacity, and programming tools is essential for the development of foundational and fine-tuned models. Generative AI entails significant operational costs and reliance on cloud capacity (except for edge-based solutions[2]). Dependency on infrastructures cannot be avoided in the upstream stages of generative AI development, potentially favoring anti-competitive strategies. Access to critical infrastructures may be compromised, leading to market distortions favoring some market players, such as those with close links to digital incumbents (Marty & Warin, 2023). Similarly, Big Techs may control market dynamics to protect their core business and extend their economic power to emerging markets.

A third set of competition parameters is related to data. Could the data-based advantage of incumbents act as a barrier to entry for generative AI entrants? The role of data has generally been described as crucial in the digital economy, and AI is particularly dependent on data for training algorithms and enhancing predictive capabilities. Generative AI, specifically large language models, requires training on vast amounts of data. The quality of data is as important as the quantity. Big Techs are particularly favored by these characteristics, as their core function is based on the collection, curation, and use of large datasets for algorithmic predictions (Iansiti & Lakhrani, 2020). Knowing that performance depends on both training data and input data used in algorithm implementation, Big Techs seem particularly suited to control this transformative technology.

However, some factors described by the Portuguese Competition Authority may counteract this pessimistic scenario. If digital incumbents have the advantage of access to a diversified set of data, new entrants may develop specific (fine-tuned) models based on private data and offer valuable services to end-users. Additionally, even foundational models can be developed using open-source data. These open resources are not limited to data. Some foundational AI models may be accessible to downstream developers to build more sophisticated models. However, as Big Techs can hinder the development of large language models or distort them to favor affiliated companies, they can also act strategically in the downstream layer. As the Portuguese Competition Authority points out, the upstream segment of large language models tends to be concentrated, and first movers may leverage their dominant position downstream or exercise regulatory power to the detriment of their downstream complementors or competitors.

Returning to our main concern, essential inputs (data and infrastructures), the situation of generative AI is paradoxical. Data appears to be an essential input and the core of a potential advantage for Big Tech. However, data can be available as open resources, products sold by data brokers, or specific resources beyond Big Tech's control. Is data an essential input whose control can lead to foreclosure and leverage strategies? Increasingly, the phenomena of market foreclosure are tied not just to data but to the control of critical infrastructures. These infrastructures can be understood in both tangible

[2] The challenges of developing edge mode are essential to reduce dependency on cloud resources controlled by Big Tech, but the technical characteristics cannot be considered equivalent.

and intangible forms. On the one hand, tangible infrastructures include data centers and computing capacities, which are essential for the development and deployment of generative AI models. On the other hand, intangible infrastructures encompass standards, coding norms, and interoperability protocols that define the architecture of digital ecosystems.

The control over these infrastructures by dominant players can result in significant entry barriers for new entrants, as they may find themselves locked out of essential resources needed to compete effectively. For instance, the literature highlights the strategic importance of controlling both types of infrastructures. These intangible assets, particularly coding standards and interoperability protocols, play a critical role in shaping market dynamics and can be leveraged by incumbents to sustain competitive advantages and prevent market entry by rivals.

Therefore, the potential for foreclosure extends beyond data control to include these broader infrastructural elements, which are increasingly pivotal in the generative AI landscape.

The research question guiding this paper is: How do the dual barriers of data and computing power shape the competitive dynamics in the generative AI market, and what regulatory and strategic measures can mitigate these barriers to foster innovation and competition?

This paper is structured as follows. The second section offers a literature review structured around the tension between two competing narratives: one posits the potential destabilization of incumbent keystone players through the entry of new market participants driven by the emergence of disruptive innovation; the other, by contrast, emphasizes the likely perpetuation of incumbent dominance through control over critical assets and the strategic orchestration of inter-firm partnerships. The third section presents the role of data in digital markets, illustrating the narrative of data as an essential asset and a source of advantage. The fourth section discusses this conventional wisdom and questions the centrality of data in generative AI markets. The fifth section examines the role of infrastructural bottlenecks related to its industrialization. The sixth one investigates competitive risks associated with generative AI development.

2. A literature review on the disruptive effects of innovation in digital ecosystems: two competing narratives

This article aims to assess the risk that the development of generative AI—despite representing a major technological breakthrough—may ultimately fall short of reshaping the competitive landscape. In this respect, it engages with two converging strands of literature in applied industrial economics as it relates to competition. The first concerns the contestability of dominant positions, particularly in digital markets, in light of the potentially disruptive impact of certain innovations (Section 2.1). The second draws on recent analyses of the specific configurations of value chains within the generative AI economy, and their distinctive implications for competitive dynamics (Section 2.2).

2.1 Innovation and competition: Are Big Techs immune to disruptive innovation?

The literature on competition is largely structured around grand narratives. In the post-war period, the narrative of concentration—or "Bigness"—was central, under the dominance of the structure–conduct–performance (SCP) paradigm. By contrast, the closing decades of the 20th century and at least the first of the 21st have been marked by the ascendancy of consumer welfare as the sole legitimate and effective objective of competition law. These narratives have had a profound impact on the actual enforcement of competition rules. In the first case, the goal is to counteract market concentration, even at the expense of economic efficiency. In the second, high market dominance is not considered problematic in itself, provided it results from merit and yields a net positive outcome for consumers. In other words, these competing narratives function as "conventions" (in the sense of the economics of conventions, see Bessy (2015)) for interpreting antitrust legislation—by courts in particular—and thereby shape the range of legitimate expectations regarding judicial decision-making in competition disputes. As these narratives compete in the marketplace of ideas, their ascendancy can drive significant shifts in the enforcement of competition law.

The consumer welfare narrative rests on a strong underlying assumption that paves the way for an alternative paradigm centered on innovation. This assumption is that dominant positions are inherently fragile due to market contestability. The mere threat of new market entry disciplines the current dominant firm by incentivizing continued investment and by deterring excessive extraction of consumer surplus. If markets remain contestable—that is, open and governed by merit-based competition—new entrants or existing competitors may challenge and potentially displace the dominant position. In such a context, the dominant firm does not enjoy a "quiet life," but remains under constant pressure from rivals who may innovate and surpass it (Petit, 2020). This assumption is, in fact, embedded in the logic of the European Digital Markets Act (DMA), which seeks to preserve contestability as a means to safeguard the competitive process, even in digital markets where dominant positions may become entrenched due to tipping effects.

The innovation narrative finds its roots in Schumpeterian creative destruction. Entrenched market positions can be challenged by radical innovations introduced by new entrants, which serve to overcome bottlenecks and undermine the advantages conferred by incumbency (Vezzoso, 2024). The nature of the innovation is essential in this regard: it must be radical—what Christensen (2016) defines as disruptive innovation. This narrative therefore unfolds within a specific conceptual framework: regardless of the strength of current dominant positions, the emergence of disruptive innovation—possibly driven by new entrants—may reshuffle the competitive deck.

Consequently, in the face of apparently entrenched dominance, antitrust intervention aimed at deconcentrating markets might be not only unnecessary, but also potentially counterproductive—imposing clear costs in terms of welfare and innovation incentives. The logic here is that competition itself creates the incentives for firms to invest in new technologies capable of generating disruption. In this perspective, competition takes the form of leap-frog dynamics (Perez and Soete, 1988): the focus shifts from concern over current market structures to the preservation of sufficient technological and competitive turbulence (Petit and Teece, 2021; Spulber, 2023)

This innovation narrative represents a distinct "convention" from the consumer welfare approach (or effects-based analysis) that preceded it. The latter has been criticized for embedding a conservative—i.e., non-interventionist—bias, insofar as it assumes the self-regulating nature of markets. The innovation narrative, in turn, may lead to the acceptance of suboptimal competitive outcomes in the short term—even under an effects-based analysis—on the assumption that such situations are merely transitory. Unlike traditional models drawn from industrial organization (IO) economics, this perspective is grounded more in the management sciences, where attention is directed toward dynamic competition and firms' capacities for innovation and absorptive learning (Freeman, 1974; Petit and Teece, 2024).

Nevertheless, while the development of generative AI by actors outside the Big Tech ecosystem could be seen as a textbook application of this narrative, it remains the subject of strong criticism (Vezzoso, 2024; Stucke and Ezrachi, 2024). The criticisms are manifold. First, it is primarily new entrants and competitors who are incentivized to pursue disruptive innovation. Incumbent operators, by contrast, may be able to steer innovation in ways that reinforce their own market power. As a classic result in industrial economics suggests, a dominant firm will only be incentivized to innovate either to defend its position, to extend it, or to extract additional surplus from consumers or trading partners. Some innovations it develops may be designed to reduce market contestability—such as by strategically limiting interoperability with competitors', partners', or potential entrants' services. Other innovations may have a negative effect on welfare, for example by facilitating excessive data extraction from consumers or by increasing market access costs for third parties. In short, innovation can be predatory (Schrepel, 2018)

A second type of bias in innovation arises from the fact that a keystone player has strong incentives to develop internally—and to encourage among its complementors—not radical innovations that could devalue its prior investments and current market position, but rather complementary innovations that reinforce both. The keystone possesses both the incentives and the capacity to steer innovation trajectories (and associated investment decisions) within its ecosystem in directions aligned with its strategic interests—that is, toward innovations that complement its own assets and enhance value extraction. This tendency is not inherently problematic; it is in fact consistent with the very logic underpinning the formation and evolution of digital ecosystems (Marty and Warin, 2023). The keystone can outperform price signals as a coordination mechanism, facilitating complementary investment among otherwise independent firms by aligning interoperability and investment timing (Amendola et al., 2010).

Accordingly, the keystone may implement a selective filtering strategy, one that enables access to the market for complementary innovations (through provision of APIs, data, computational resources, etc.), while impeding the emergence of innovations likely to erode its position (Marty and Warin, 2020). In such conditions, innovation contributes not so much to *creative destruction* as to *creative accumulation* (Vezzoso, 2024). The keystone's own innovative capabilities—together with its ability to channel the innovation efforts of complementors—can bias innovation trajectories in its favour, thereby undermining the prospects for disruptive entries.

2.2 The Generative AI competitive landscape and the associated concerns

The risk of incumbents controlling the innovation dynamics is particularly pronounced in the field of generative AI. The development of generative AI markets relies upstream (for the development of LLMs) on specific resources held by Big Tech firms, and downstream on their capacities to distribute innovative solutions to a broad user base. Partnerships between Big Tech and generative AI firms could reinforce a dynamic of innovation capture and trajectory control by incumbents. However, assessing the situation is not straightforward, as the relative dependency relationships among actors along the value chain can be ambiguous. For instance, while Big Techs provide essential assets for generative AI players' development, this does not necessarily entail exclusivity agreements (Groza and Wierzbicka, 2024). In other words, keystones may not be able to impose single-homing practices characteristic of their ability to lock in their complementors.

Once again, two competing narratives can be contrasted, forming the key interpretative lens through which we propose to analyze the dynamics of the generative AI sector. In the first narrative, partnerships among different types of actors are understood as agreements between equals, less as legal strategies serving as alternatives to merger operations (which would be subject to competition authority scrutiny) and more as inter-firm cooperations based on resource pooling within a framework of hybrid organizational forms (Groza, 2025). In the second narrative, cooperation gives way to a control logic grounded in economic and technological dependency relationships (Vezzoso, 2024).

Within this locking-in strategy, the explanation in terms of hybridity would be supplanted by forms of control exercised through financing, reliance on specific complementary assets, and the use of proprietary standards. The generosity displayed by Big Tech firms towards generative AI companies would not only resemble strategies observed in biotech and pharmaceutical sectors, outsourcing risks while appropriating potential gains through complementary assets (Rikap, 2019), but would also form part of a broader strategy positioning Big Tech as intellectual monopolies underpinned by Corporate Innovation Systems (CIS). These systems are firm-specific yet produce similar consolidating effects (Rikap, 2024).

The Corporate Innovation Systems (CIS) approach portrays the keystone not only as an actor capable of appropriating the value generated within its ecosystem but also the knowledge produced therein. The strength of the keystone's position and its resilience relative to other pivotal firms in competing ecosystems are linked to its ability to foster innovation and generate collective learning. Within this framework, the development of generative AI is less a threat and more a promise of consolidation of the current competitive position.

The following sections examine, through this lens, the relationships between the resources offered by keystones to generative AI actors and the two alternative scenarios of disruption and consolidation, set against a backdrop of uncertainty regarding the competitive treatment of partnerships and the industrial dynamics of the sector (Vipra and Korinek, 2023).

3. The Role of Data in Generative AI

We successively consider the role of data in the Generative AI ecosystem, their influence on tipping phenomena, and how such a risk is managed by competition authorities

3.1 Generative AI ecosystems and data

Although often presented as a General-Purpose Technology (GPT), AI can also be conceived as a Large Technical System (LTS) (Vannuccini & Prytkova, 2023). The concept of GPT refers to technological innovations that meet three key criteria: first, a broad range of applications; second, dynamic development and innovation; and third, the ability to generate complementary innovations in related fields, creating a positive feedback loop (Bresnahan and Tratjenberg, 1995). It is important not to confuse this acronym with ChatGPT, developed by OpenAI, which stands for Chat Generative Pre-trained Transformer. The concept of LTS covers socio-technological networks that are functionally integrated into one or more industries. They cover both physical assets and intangible assets; here we are talking about hardware and software.

One of the advantages of applying the notion of LTS to AI, particularly to generative AI, is that it allows for an emphasis on the complementarities between technologies and the strategies developed by various firms. Additionally, it highlights the concept of "reverse salients," which can hinder the development of the technical system. As Vannuccini & Prytkova (2023) explain, reverse salients refer to components or actors within a system that lag behind the rest, creating bottlenecks that impede effective development. Generative AI is indeed a strong candidate for the LTS framework, as it involves a wide range of complementary firms with diverse profiles, including Big Tech companies, startups, foundations, and universities. Its development will depend on the synchronization, complementarity, and standardization of the technologies involved. Generative AI's progress relies on very specific human assets, data, programming languages, standards, and physical infrastructures, whether computational or related to storage. However, some of these crucial assets can act as reverse salients, potentially slowing down the development of the technical system or leading to its capture by certain players, particularly concerning data and computational infrastructures. This section will focus on the former.

Generative AI relies heavily on LLMs, which require vast amounts of high-quality data for training. These datasets must encompass a wide variety of content types and contexts to enable the models to generate accurate and relevant outputs. The quality of the data directly impacts the model's ability to understand and produce human-like text, images, and videos. High-quality data ensures that the model can learn nuanced patterns and relationships within the data, leading to better performance in real-world applications.

Acquiring the necessary data for training LLMs poses significant challenges. Data acquisition can be complex and costly, particularly when it involves proprietary or hard-to-access datasets. Once acquired, data must be curated to ensure it is clean, relevant, and free from biases. This curation process includes removing duplicates, correcting errors, and ensuring a balanced representation of different content types. Additionally, compliance with data protection regulations, such as the General Data Protection Regulation (GDPR) in the EU, adds another layer of complexity. Ensuring that data is used ethically and legally requires rigorous auditing and documentation processes.

Data brokers play a crucial role in the generative AI ecosystem by providing access to vast datasets that would otherwise be difficult to collect. These brokers aggregate data from various sources, including web scraping, public records, and commercial transactions. However, the cost of acquiring specific, high-quality data from brokers can be prohibitively expensive, especially for smaller firms or new entrants in the market. As the demand for high-quality datasets increases, so do the costs, further entrenching the position of established players who can afford these resources.

The quality of the data used to train LLMs has a profound impact on their performance. High-quality data enables models to learn more accurate and nuanced patterns, resulting in better generalization and fewer errors when generating outputs. Conversely, poor-quality data can lead to biased or incorrect outputs, diminishing the model's utility and reliability. The adage "garbage in, garbage out" is particularly pertinent in the context of AI, underscoring the importance of data quality in achieving optimal model performance.

Another promising avenue for fostering effective competition in the downstream markets of foundation models lies in the development of open-source practices (Schrepel and Pentland, 2023). This perspective is bolstered by the multi-layered nature of generative artificial intelligence. While developers focus on designing, training, and making foundational language models available, refiners can leverage fine-tuning or transfer learning to develop specific models tailored to the needs of user companies. These refined models can then be seamlessly integrated into the companies' digital services, enhancing their competitive edge.

The open-source community has made significant contributions to the field of generative AI by providing access to datasets and models that are freely available for use and further development. This has been well-documented in recent research; Goldfarb et al. (2024) explore the broader economic implications of open-source AI contributions in their working paper. Companies like Meta have released large datasets and pre-trained models that can be fine-tuned for specific tasks, lowering the barrier to entry for smaller firms and independent researchers. These open-source resources democratize access to advanced AI technologies, fostering innovation and competition in the field.

While the increased accessibility of data through open-source initiatives has lowered some barriers to entry, data still provides a significant competitive edge. The sheer volume and quality of data required to train state-of-the-art LLMs remain challenging for smaller entities to obtain and manage. Established firms with extensive datasets and sophisticated data infrastructure maintain an advantage, as they can continually improve their models' performance and stay ahead of the competition. Thus, while open-source data mitigates some competitive disadvantages, it does not entirely level the playing field.

Data can act as a barrier to entry in several ways. For instance, dominant firms may leverage their vast data repositories to develop superior AI models that new entrants cannot match. Anti-competitive practices such as exclusive data agreements, data hoarding, and restrictive data licensing can further entrench the market power of established players. Regulatory bodies have noted these concerns, emphasizing the need for policies that ensure fair access to data and prevent monopolistic behaviors (Autorité de la concurrence, 2024).

3.2 Discussing the Data-Based Advantage as a Source of Tipping of Digital Markets

We consider the extent to which data-based advantages can explain the phenomena of significant and entrenched market dominance in digital activities (A) and how competition law addresses issues related to data-based anti-competitive practices or the lack of contestability of market positions resulting from such an advantage (B).

The EU's Digital Markets Act (DMA) illustrates two primary competition concerns associated with the development of digital ecosystems. The first concern is the tipping phenomenon, which can lead to insufficient contestability of dominant positions. The second concern is the regulatory power of the dominant firm within each ecosystem, allowing it to impede access for its complementors (and potential competitors) and distort competition to its advantage. This raises fairness related concerns.

Data can be considered an asset that can generate tipping phenomena, as a data-based advantage can initiate a winner-takes-all process. It can also lead to exclusionary or exploitative abuses within the ecosystem by exploiting asymmetric access to the detriment of other participants.

However, data is not the only asset that can be controlled to explain such market dynamics. The tipping phenomenon in the case of digital platforms can result from several factors, such as network effects (both direct and indirect), economies of scale and scope, and the capacity of Big Tech companies to identify potential innovations and absorb the knowledge produced by their partners and complementors (Marty & Warin, 2020). These capacities are related not only to technical and financial resources but also to organizational characteristics. According to Rikap (2023), it is important to define Big Tech companies as intellectual monopolies capable of initiating partnerships with complementors, foundations, and universities to develop a continuous learning process that allows them to integrate new functionalities into their services at an exceptional pace.

Even if data is not the only factor that can cause a tipping point, the narrative of a data-based advantage is particularly strong in both academic literature and competition law enforcement. For instance, in the complaint against Google, the U.S. Department of Justice stated: 'Google has intentionally exploited its massive trove of user data to further entrench its monopoly in the digital advertising market' (see the August 2024 judgement of the US District Court for the District of Columbia, cases US v. Google (20-cv-3010 APM) and State of Colorado v. Google (case 20-cv-3715 APM)). In many competition cases, data is seen as the source of an irreducible competitive advantage, whether horizontal or vertical. A data-based advantage can entrench an existing dominant position by creating a positive feedback loop (the more data, the better the algorithmic performance). Vertically, a data-based advantage may facilitate leverage strategies. A platform player active in several markets may strategically use the available data to extend its dominant position to adjacent markets. Such a leveraging strategy may harm competition on the merits in the targeted market. The use of a wider range of data on consumer behavior and characteristics can lead to a better understanding of consumer preferences and willingness to pay. Practices like microtargeting, price personalization, and versioning strategies can rapidly capture a dominant position. Such strategies may be even more efficient if the dominant platform has developed cutting-edge algorithms with highly reliable predictive capabilities.

These risks were highlighted in the UK by the Furman report (*Unlocking Digital Competition*), which states that "[Data] may give the incumbent some form of unrivaled advantage, making successful rivalry less likely" (Furman et al., 2019, p. 34). Yesterday's innovators may not only be today's dominant players but also tomorrow's ones.

The data-based advantage could be at its maximum in the field of AI. Since generative AI requires huge amounts of data to train its large language models, we could conclude that the data-based advantage could play an even greater role here than in other fields. This competitive risk may be illustrated by the FTC's comments to the US Copyright Office: "The rapid development and deployment of AI also pose potential competitive risks. The growing importance of AI to the economy may further entrench the market dominance of large incumbent technology firms. These powerful and vertically integrated incumbents do control many of the inputs necessary to effectively develop and deploy AI tools, including cloud-based or local computing power and access to large stores of training data." (FTC, 2023).

In the academic literature, the collection, processing, use, and analysis of data are often analyzed as one of the main sources of competitive advantage for Big Tech companies. For example, according to Rikap and Lundvall (2020), "Data take the form of a new strategic resource and together with machine learning they introduce a new kind of endogenous permanent or dynamic innovation. New algorithms can be seen both as product and process innovations." In the field of AI, capabilities related to data valorization are described as the core of the "collision model" elaborated by Iansiti and Lakhrani (2020). Digital companies learn continuously by processing data, continuously training, and improving the algorithms embedded in them. Their advantage is not limited to their ability to learn. They also benefit from their scalability and scale amplification advantages. Both the data-based advantage, increasing returns to scale, and the ability to combine multiple activities converge in the ability to disrupt incumbents in bricks-and-mortar markets or less agile or diversified digital competitors. This advantage is dramatically enhanced by AI.

In this perspective, companies need to be structured as an AI factory, with processes oriented towards data collection, curation, analysis, integration into algorithms, training, and experimentation prior to and throughout the deployment of these algorithms. According to Iansiti and Lakhrani (2020), four layers should be articulated to perform such tasks and disrupt competitors. The first is the data pipeline, which aims to collect, clean, normalize, and secure data sustainably and in a scalable manner. The second layer is algorithm development. The quality of the data used in the training process, together with the quality of the code itself, is the main driver of predictive capabilities. The third layer is the experimentation platform. These predictive capabilities should be tested, corrected, and optimized using input data. The fourth and final layer is the hardware, middleware, and software infrastructure: their qualities, scalability, and efficiency are crucial for organizing the entire design, implementation, and correction process.

Data is not the only factor that can explain tipping in digital markets. Their peculiarities lead to winner-take-all phenomena even when we neutralize a theoretical data-based advantage. As mentioned above, economies of scale and scope and network externalities play a crucial role in the high degree of concentration characterizing these markets. Other factors, such as the financial capacity of Big Tech companies, also contribute to significant concentration. These result from the large portfolio of activities and the patience of external investors. They allow Big Tech companies to pursue both internal and external growth simultaneously.

External growth reflects the consolidation of acquisitions. By identifying potential threats and opportunities early on, mainly through their ability to channel information from their ecosystems, Big Tech companies can take control of potential disruptors or high-potential complements. Mergers and acquisitions are undoubtedly one of the main drivers of concentration, especially in digital markets (Kwoka and Valletti, 2021).

Internal growth includes developing new services, diversification projects, and investments in infrastructures, such as cloud capacity. Such investments are beyond the reach of competitors and provide Big Tech companies with a cutting-edge competitive advantage. These capacities are essential not only for offering efficient services but also for becoming unavoidable trading partners for software developers looking for reliable, efficient, and scalable computing resources (Narayan, 2022). However, this position also gives Big Tech companies infrastructural power (Jacobides et al., 2021). For example, they can hamper the development of competing services through self-preferencing strategies (Bougette et al., 2022), counteract multi-homing strategies to increase user dependency (see the French competition authority's sector inquiry in the cloud sector (Autorité de la concurrence, 2023)), and, through this pivotal position, gain an information advantage to the detriment of their trading partners (see, for example, the EU Commission's decision of December 2022 on Amazon practices). Such access to data may result in the pivotal player benefiting from a "god view," ensuring complete information on the markets in which it is involved and its partners. This may result from unbalanced contractual clauses due to asymmetric bargaining power in terms of access to digital ecosystems, marketplaces, app stores, or cloud capacities (Bougette et al., 2019). It can also result from partnerships with both complementors and non-profit organizations (Rikap and Lundvall, 2021). Again, the criticality of the assets controlled by Big Tech companies may enhance their ability to gather information and accentuate a potential data-based advantage.

3.3 The Apprehension of a Potential Data-Based Advantage by U.S. and E.U. Competition Laws Enforcements

This dynamic should be addressed by competition law enforcement. Case law has highlighted several instances where data-related concerns may be at the heart of the theory of harm. One example is the case of abuse of dominance proceedings based on abusive data extraction. The Bundeskartellamt/Facebook case in 2020 (Kerber, 2022) and the EU Commission's notice of February 2024 on the definition of the relevant market for the purposes of Union competition law (EU Commission, 2024) are notable. A key point relevant to our discussion is the possible use of the SSNQ test (small but significant non-transitory decrease in quality) as a substitute for the traditional SSNIP test, as demonstrated in the EU Commission's July 2018 Google Android decision. Once price is no longer a good basis for assessing competitive harm, other metrics, such as excessive data extraction or progressive degradation of service in terms of privacy protection, should be used.

Self-preferencing-based theories of harm also illustrate data-related competition concerns (Bougette et al., 2022). The EU Commission's Amazon decision of December 2022, which involves contractual provisions that lead to asymmetric access to data to the detriment of the platform's complementors, exemplifies this. Self-preferencing can also be based on non-transparent algorithmic decisions, as seen in the June 2017 Google Shopping decision (Case AT.39740, European Commission, 2017). More recently, the European Commission's draft communication on the enforcement priorities under Article 102, released in 2024, explicitly addresses self-preferencing for the first time, dedicating an entire paragraph to this practice—an update from the previous communication in February 2009.

Data and information-based competition concerns are not limited to unilateral anti-competitive practices. They may also be considered ex ante in the context of merger control. Several cases illustrate the consideration of risks related to increased information asymmetries between market participants or the increased risk of algorithmic manipulation. The EU's Google/Fitbit decision of December 2020 (case M.9660) is a relevant example (Chen et al., 2022). The merger was cleared with remedies to ensure a level playing field regarding access to Fitbit devices and the creation of data silos to avoid risks associated with data matching. In the US, the FTC's case against the Meta/Within merger in 2023 also highlights data-related concerns (see FTC, In the Matter of Meta/ Zuckerberg/ Within, file 2210040 – 9411).

The specific importance of data for competitive dynamics is further illustrated by the new merger guidelines issued by the FTC and the DoJ Antitrust Division in December 2023. A special guideline is dedicated to digital ecosystems, Guideline 9: "When a merger involves a multisided platform, the agencies will examine competition among platforms, on a platform, or to displace a platform." Among the specific features of platforms that may lead to market distortions (such as self-preferencing), the issue of access to data is specifically addressed in point 2.9: "Mergers involving firms that provide other important inputs to platform services may enable the platform operator to deny rivals the benefits of these inputs. For example, the acquisition of data that helps to facilitate matching, sorting or prediction services may enable the platform to weaken rival platforms by denying them such data."

These data-related competition concerns have led to various remedies: injunctions or commitments in antitrust cases and remedies in merger control. These remedies address some of the risks mentioned above and aim to control or correct the effects of incumbents' data-based advantages. Examples include data portability, interoperability of services, data silos (to avoid distortions of competition), or data lakes (to ensure a level playing field). These remedies help limit competitive risks and are complemented, especially in the EU, by several regulations that impose specific rules on market players, sometimes symmetrically, sometimes specifically for powerful players (e.g., gatekeepers). These regulations guarantee non-dominant players access to data, portability, and interoperability. They also aim to prevent arbitrary and artificial exit fees in the cloud sector.

However, the issue of data as a barrier to entry necessitates considering the essential facilities doctrine (EFD) (Marty, 2023). Can we mandate access to data controlled by an incumbent to create or restore a level playing field? From a competition law perspective, this is not straightforward. The EFD was struck down outside the scope of US antitrust law by the Supreme Court's Trinko decision in 2004. Even if the EFD is still used in the EU context, the conditions for its activation are narrowly defined by case law, as illustrated by the Bronner criteria (EU Court of Justice, Case C-7/97). Access can only be mandated if there is no alternative to the asset in question, if such access is strictly necessary to access the market, and if there is no objective justification for a refusal by the asset owner. Implementing the Essential Facilities Doctrine (EFD) involves a complex economic trade-off: it can increase competition in the short run and be welfare-enhancing, but it can also negatively affect incumbents' incentives to invest and maintain their assets, thereby being costly in terms of dynamic competition (Petit & Teece, 2021). Such a debate is relevant as incumbents have invested in collecting and curating this data.

It remains unclear whether data is a suitable candidate for EFD implementation, as debated by Graef (2019), who rethinks the application of the Essential Facilities Doctrine in the context of the EU digital economy. Firstly, data is not the best candidate to qualify as an essential facility. Some data have characteristics of non-rival and non-excludable goods. As soon as users become multi-homed, their data may be available to several market players. Some of this data can be qualified as personal data, and mandatory sharing may give rise to conflicts between the respective objectives of competition law and data protection law. Secondly, data may be available on the market through data brokers, although their activities raise significant concerns (FTC, 2014). Thirdly, if the EFD is activated, what is the appropriate scope of such access? Should it be limited to collected data or extended to observed and derived data? Should access be mandated for non-curated or curated data? Should a particular format be required? The costs to incumbents and the impact on their incentives would vary greatly. Fourthly, is data truly essential for market entry and disrupting incumbents? The economic history of digital markets provides several examples of disruption by new entrants despite a significant data disadvantage, as seen in the cases of Google in search engines, Zoom in videoconferencing tools, and TikTok in social networking applications. Algorithmic or user experience superiority may be more important in explaining a service's uptake and the incumbent's disruption, regardless of its initial market strengths. Lastly, it is not certain that data is characterized by increasing returns to scale. A sufficient 'amount' of 'properly curated' data may be enough to overcome the initial disadvantage of new entrants.

The criteria defined by the EU jurisprudence for activating the EFD do not inspire strong confidence that data could be a candidate for remedies imposed on this basis. One could consider the approach taken by the US Supreme Court in Trinko (Verizon v. Trinko, 540 U.S. 398): the imposition of such remedies makes more sense under a regulatory approach than under a competition law approach. Finally, the characterization of data as a barrier to entry is not obvious, even if algorithms need training and input data to be competitive in terms of predictive quality.

The role of data in digital platforms' competitive strategies is well-documented. As Bergemann and Bonatti (2024) illustrate, platforms like Amazon and Google leverage extensive datasets to optimize matching between consumers and products, thereby enhancing their bargaining power and driving revenue through targeted advertising. However, this data-centric approach inherently relies on significant computational power to process and analyze data in real-time. The effectiveness of managed advertising campaigns and personalized recommendations, as highlighted by Bergemann and Bonatti, underscores the need for robust computational infrastructure to support these data-driven strategies.

Therefore, while data serves as a cornerstone of competitive advantage, the computational capabilities that enable the processing and application of this data are equally critical, forming a symbiotic relationship that drives the efficiency and success of digital platforms. This interdependence is particularly evident in the reliance on cloud infrastructures, which provide the necessary computing power and storage capabilities. The French Competition Authority's 2023 report underscores the significant dependency on cloud services, highlighting the strategic role these infrastructures play in the broader digital economy.

Moreover, this dependency extends beyond cloud storage and computing power to encompass the complex interdependencies created through Application Programming Interfaces (APIs) and Software Development Kits (SDKs). These tools allow digital platforms to integrate various services seamlessly, creating a tightly woven ecosystem where platforms and their partners are mutually dependent. This interconnectedness, while fostering innovation and efficiency, also reinforces competitive bottlenecks, particularly in the generative AI market.

In Section 4, we delve deeper into these infrastructural bottlenecks. First, we explore the tangible aspects, such as cloud services and data centers, that act as critical inputs for generative AI. Then, we examine the more intangible infrastructures, including APIs, SDKs, and coding standards, which not only facilitate integration but also create significant barriers to entry. These elements collectively shape the competitive landscape of generative AI, where control over infrastructure can lead to market foreclosure and strategic leverage by dominant players.

4. The Critical Role of Computing Power in the B2B Context

In the B2B context, computing power is of paramount importance due to the critical need for speed and efficiency. Generative AI applications in business environments demand robust computational resources to handle complex tasks and large datasets efficiently. These tasks range from real-time data analysis and decision-making to the generation of intricate models and simulations. The efficiency of these processes directly impacts the competitiveness and operational effectiveness of businesses.

4.1 Infrastructure Needs for Large Language Models Versus Fine-Tuned Models

The infrastructure requirements for LLMs and fine-tuned models differ significantly. Training LLMs requires extensive computational resources, including high-performance GPUs or TPUs, and scalable cloud infrastructure capable of handling massive data throughput. Fine-tuned models, while also demanding, typically require less computational power for additional training but still benefit from robust infrastructure for optimal performance. Both scenarios necessitate significant investments in computing power to ensure timely and accurate results.

Access to affordable and scalable cloud computing resources remains a significant challenge for many businesses. While cloud service providers offer scalable solutions, the costs associated with high-performance computing can be prohibitive, particularly for small and medium-sized enterprises (SMEs). Ensuring cost-effective access to these resources is critical for enabling broader adoption of generative AI technologies. This challenge underscores the importance of strategic partnerships and innovative pricing models to democratize access to computing power.

The provided network graph (see Figure 1) visualizes the citation bi-partite networks of cloud platform products and services mentioned across industry solutions pages, unified for Microsoft Azure, Amazon Web Services (AWS), and Google Cloud Platform (GCP). The dashed lines reveal overlapping industry-focused areas, and the color scale reflects the frequency of 'AI' and machine-learning mentions. The layout is Force Atlas 2, with node scaling based on the indegree (mention) count.

- Node clusters: The green cluster represents Microsoft Azure, featuring services such as Azure Machine Learning, Azure Kubernetes Service, Azure Cognitive Services, and Azure DevOps. The density and size of nodes indicate high mention frequency and interconnectedness among these services. The orange cluster represents AWS, with significant nodes for Amazon EC2, AWS Lambda, Amazon SageMaker, and AWS Command Line Interface (CLI), the latter of which is particularly large, signifying its central role and frequent mentions. The blue cluster represents GCP, with prominent nodes for Google Kubernetes Engine, BigQuery, Cloud Storage, and Vertex AI, indicating their critical roles and high mention frequency.
- Service categories: All three clusters feature significant nodes for compute services (e.g., Azure Virtual Machines, Amazon EC2, Google Compute Engine), highlighting the importance of scalable compute resources in cloud platforms. Nodes like Azure Data Lake, Amazon Redshift, and Google BigQuery emphasize the role of data storage and analytics in cloud ecosystems. Services such as Azure OpenAI Service, AWS Bedrock, and GCP's Vertex AI reflect the growing emphasis on generative AI capabilities across platforms.
- Overlapping industry-focused areas: The dashed lines and interconnected nodes across clusters indicate shared focus areas and interoperability among the cloud platforms. For instance, AI and machine learning services are commonly mentioned across Azure, AWS, and GCP, signifying their critical role in industry solutions.
- Frequency of mentions: The color scale reflects the frequency of 'AI' and machine-learning mentions, with darker colors indicating higher frequency. This helps identify the most discussed and utilized services in the industry.

Strategic partnerships with cloud service providers play a crucial role in overcoming these challenges. Collaborations such as those between Microsoft and OpenAI, or Google and Anthropic, illustrate how access to advanced cloud infrastructure can enhance the development and deployment of generative

AI models. These partnerships provide businesses with the computational power necessary to run sophisticated AI models and integrate them seamlessly into their operations. For instance, Microsoft's Azure OpenAI Service offers businesses access to OpenAI's advanced models, optimized for Azure's cloud infrastructure, enabling efficient and scalable AI deployment. Similarly, Google's cloud partnerships with AI firms allow for the leveraging of Google's powerful cloud infrastructure and specialized hardware, such as TPUs, to accelerate AI model training and deployment.

Azure's market share reached 24% of the global cloud market in Q1 2024, reflecting significant growth driven by extensive data center regions and strong enterprise adoption. AWS retained the largest market share at 31%, while GCP held 11%, illustrating the competitive dynamics among the leading cloud providers.[3] This competitive landscape highlights the importance of both data and computing power in shaping the generative AI market, where the ability to leverage high-quality datasets and robust computational resources is crucial for maintaining a competitive edge.

The interplay between data and computing power is further emphasized in the capabilities offered by these platforms. Azure's OpenAI Service, AWS's Bedrock and CodeWhisperer, and GCP's Vertex AI and Bard showcase their strengths in generative AI, enabling businesses to leverage advanced text generation, code generation, and image synthesis capabilities. These services illustrate how major cloud platforms are positioned within the AI and generative AI industry, highlighting the critical role of computing power in supporting sophisticated AI applications.

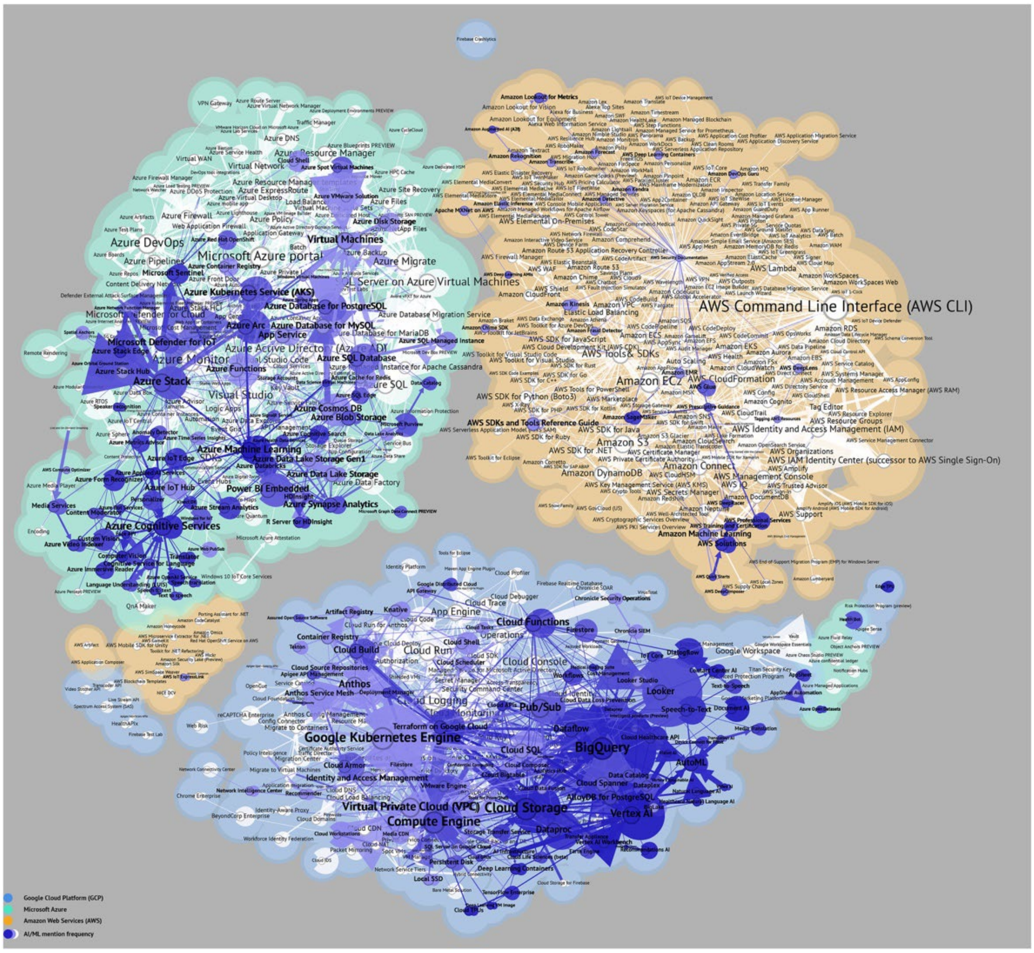

Figure 1. Cloud AI stacks, Source : van der Vlist et al. (2024)

[3] "Microsoft Azure Market Share & Buyer Landscape Report." HG Insights, 2024. HG Insights
"Global Cloud Market Share Q1 2024." Canalys, 2024. Canalys
"Cloud Infrastructure Market Share Q1 2024." Synergy Research Group, 2024. Synergy Research

By integrating robust computational resources and strategic partnerships, businesses can harness the full potential of generative AI, driving innovation and operational efficiency across various sectors. The competitive landscape of cloud AI stacks, underscored by market share dynamics and the emphasis on computing power, provides a comprehensive understanding of the strategic positioning of Microsoft Azure, AWS, and GCP in the generative AI market.

4.2 Integrating Generative AI Through Scripts and APIs

The trend towards integrating generative AI through scripts and APIs is reshaping how businesses deploy and utilize AI technologies. This approach allows businesses to embed AI functionalities directly into their existing software and workflows, enhancing automation and efficiency. By leveraging APIs, companies can access advanced AI capabilities without developing these technologies in-house, reducing both time and cost.

Scripts and APIs facilitate the seamless integration of generative AI into multi-agent systems, which are increasingly prevalent in various industries. Multi-agent systems consist of multiple autonomous entities, or agents, that interact and collaborate to achieve specific goals. These agents can perform different tasks, communicate with each other, and make decisions independently, enhancing the overall system's efficiency and effectiveness.

The integration of generative AI through scripts and APIs has significant implications for the development and deployment of multi-agent systems. These systems benefit from the enhanced computational capabilities provided by generative AI, which enables them to handle more complex tasks and make more informed decisions. The speed and efficiency afforded by powerful computing resources are essential for the real-time functioning of multi-agent systems, ensuring they can adapt to changing conditions and optimize performance continuously.

Moreover, the ability to integrate generative AI through APIs allows for greater flexibility and scalability in multi-agent systems. Businesses can easily update or expand their AI capabilities by incorporating new APIs or modifying existing scripts, ensuring their systems remain at the cutting edge of technological advancements. This modularity is crucial for maintaining competitiveness in fast-paced industries where technology evolves rapidly.

However, the reliance on substantial computing power also poses challenges. Ensuring that multi-agent systems have access to the necessary computational resources can be costly and requires careful planning and investment. Additionally, businesses must consider issues related to data security, privacy, and compliance, particularly when integrating third-party AI services through APIs.

Computing power is a critical factor in the successful implementation of generative AI in the B2B context, where speed and efficiency are paramount. The trend towards integrating generative AI through scripts and APIs is transforming business operations, particularly in the development and deployment of multi-agent systems. While this approach offers significant advantages in terms of flexibility and scalability, it also necessitates substantial investment in computational resources and careful management of associated risks.

As businesses continue to adopt generative AI, the importance of robust and efficient computing infrastructure will only increase, driving further innovation and optimization in various industries. However, as highlighted in Section 3, physical infrastructures, such as cloud services and data centers, along with intangible factors like standards, APIs, and downstream market access, can be even more decisive in shaping competitive dynamics than data access alone. These elements collectively serve as critical bottlenecks that can reinforce market power and create significant barriers to entry.

Moving into Section 5, we will explore the competitive risks associated with generative AI development. This section is structured into three key areas: the uncertainty surrounding competitive dynamics, the need for a cautious and flexible competition policy, and the importance of balancing regulatory interventions with innovation incentives. Given their interconnected nature, the latter two areas will be discussed together, offering a comprehensive approach to the challenges posed by generative AI.

5. Competitive Scenarios and Policy Implications

This section examines two potential scenarios for the competitive dynamics in the generative AI sector: consolidation in favor of Big Tech or competitive disruption. It also considers the regulatory measures that may be necessary to address these outcomes.

5.1 Competitive Scenarios in Generative AI: Consolidation vs. Disruption

Analyzing the competition concerns related to generative AI involves exploring specific value chains and potential competitive scenarios. Two primary scenarios emerge: the consolidation by Big Tech or their disruption by new entrants.

Scenario 1: Consolidation by Big Tech

In this scenario, Big Tech companies consolidate their dominance by leveraging their control over both upstream and downstream resources. This includes cloud activities, relationships with GPU providers, the capacity to develop proprietary processors (e.g., TPUs), extensive data repositories, programming languages, and tools (SDKs, APIs). Their financial strength and strategic bottleneck positions in multiple markets enable them to negotiate exclusivity on data, particularly those used for fine-tuned models. Financial and technical resources are also crucial for meeting regulatory compliance and curation requirements, placing smaller players at a disadvantage (Geradin et al., 2021).

Big Tech's gatekeeper role allows them to foreclose competitors' market access and implement self-preferencing strategies, ensuring their products and services maintain a competitive edge. For instance, they can prioritize their services in search results or favor their platforms in app stores, making it difficult for new entrants to gain visibility and market share. Control over emerging markets for generative AI may also be achieved through vertical integration, not just through acquisitions but also through strategic partnerships. These partnerships can result in lock-in effects, making downstream players dependent on upstream technologies and assets. By integrating vertically, Big Tech firms can create comprehensive ecosystems where every layer, from infrastructure to application, is under their control, further solidifying their market position.

This scenario is the one presented by Azoulay et al (2024). Lock-in can be achieved upstream via a technology stack, i.e. a set of assets that are critical to developers. As seen above, this stack is made up of a set of layers combining physical assets (graphics processors, cloud capabilities) and software resources (programming languages, etc.).

This lock-in can also be reinforced downstream through the distribution of generative AI solutions in applications controlled by these same Big Techs. As in the coopetition models described above, it is not irrational for a firm developing a fine-tuned model to enter such an environment (Marty and Pillot, 2021). The logic at work could then be similar to that of digital ecosystems in general. Becoming part of an ecosystem and benefiting from the resources it makes available to its complementors can enable a company to scale up rapidly, to have access to rare computational resources as well as talents and technical capabilities, and finally to leverage network and learning effects by gaining access to a large portfolio of users.

Scenario 2: Disruption of Big Tech

Despite their current dominance, Big Tech companies are not unchallenged in the market for large language models. Microsoft's advantage stems from its partnership with OpenAI, which does not imply exclusive distribution. Google and Amazon, despite their efforts, do not offer similar products, and Apple and Meta have not significantly challenged other GAFAM companies in this emerging market. Some developers of foundational models are adopting vertical integration strategies, creating ecosystems of complementors using their products. Restricting Big Tech behavior might be counterproductive, as they may act as challengers to emerging dominant players (Manne & Auer, 2024).

In this scenario, new entrants or smaller companies leverage innovative approaches to disrupt the dominance of Big Tech. They might adopt vertical integration strategies, controlling both the development and deployment of AI models. For example, some companies might develop proprietary models that are specifically tailored to unique datasets, offering superior performance in niche markets. These companies can challenge Big Tech by providing specialized solutions that address specific needs more effectively than generic models.

Moreover, new entrants can benefit from open-source initiatives and collaborative efforts within the AI community. Contributions from organizations like Meta and the open-source community provide alternatives to proprietary models, potentially mitigating data-based competitive advantages. However, the quality of open-source data and models can vary, affecting their substitutability with those developed by major players. Thus, while open-source initiatives can democratize access to AI technologies, the competitive edge often lies in the ability to access and utilize high-quality, specific data.

This scenario, advocated in particular by Schrepel and Pentland (2023), may evoke the moligopoly hypothesis constructed by Petit (2020). One of the Big Techs could use the development of generative AI to shake up the acquired positions of its competitors. The strategy of making fundamental language models available in open source can then be likened to that followed almost two decades ago for mobile operating systems. Openness makes it possible to attract complementors. The resources and talents they bring to the table make the platform more attractive than competing platforms. It should also be noted that this "platformisation" strategy is also being implemented by other players in the ecosystem. For example, OpenAI offers developers plug-in modules for developing their own specific applications.

Openness can therefore be strategically opportune in that it can make it possible to lock in its complementors through the specific resources made available (Marty & Warin, 2023), all the more so if the openness is only partial (Azoulay et al., 2024). An open system should have the characteristics of transparency, re-usability, extensibility and controllability (Widder et al., 2023). However, even an open model can retain black-box characteristics. In this light, greater openness could be part of a strategy to control competitive dynamics, which could be described, according to Teece (1986), by a dual control over knowledge (notion of appropriability) and over complementary assets. Azoulay et al (2024) use this theoretical framework to show how, through partial and controlled openness, firms controlling essential assets can combine openness, increased competitiveness, locking out complementors and capturing value.

These scenarios create conflicting competition policy prescriptions. If Big Tech dominance is viewed as potentially obsolete, restricting their behavior could reduce competition in the generative AI market, depriving consumers of welfare gains and innovative products (risk of false positives). Conversely, marginalizing Big Tech could pose symmetrical risks. In the broader context of digital markets, despite entrenched dominant positions, gatekeepers might not dominate new markets and could be overtaken by more agile and innovative new entrants. Thus, regulation of digital markets might seem unnecessary and counterproductive, reducing competition in new markets. Furthermore, generative AI solutions could disrupt core products of Big Tech, such as search engines.

5.2 Balancing Competition Policy

Balancing competition policy in the context of generative AI requires addressing both structural and behavioral factors. Big Tech companies can remain essential due to their vast information, technical, and financial resources, which provide fundamental advantages in infrastructure and organizational structuring as intellectual monopolies. They can absorb knowledge and innovations from other players and protect their dominant positions through anti-competitive practices, such as refusing access to essential resources, discrimination, self-preferencing, and envelopment strategies (Condorelli &

Padilla, 2020). They can also bypass merger rules through partnerships, integrating their services contractually rather than through formal acquisitions.

Promoting or protecting competition in generative AI markets necessitates a cautious approach, based on resolute competition law enforcement and informed implementation of ex ante regulation, such as the Digital Markets Act, the Data Act, and the AI Act. These regulations should focus on ensuring access to "quasi-essential" resources, such as cloud infrastructures and data, while considering their potential side-effects. Recognizing that generative AI cannot be assimilated to conventional AI models is crucial.

For instance, the AI Act imposes compliance costs that can disproportionately affect smaller players due to their limited resources. This can potentially hinder the development of open-source models and innovations from smaller companies. Therefore, regulatory frameworks need to balance ensuring compliance without stifling innovation and competitiveness among smaller firms.

Hacker et al. (2023) emphasizes the importance of tailored regulations that consider the unique challenges faced by smaller entities in the AI ecosystem. This approach aligns with the concept of regulatory sandboxes, which have been proposed in the context of the EU AI Regulation to allow for controlled experimentation and innovation within a flexible regulatory framework. Regulatory sandboxes offer a way to test new technologies in a real-world environment with regulatory oversight, reducing the compliance burden on smaller entities while ensuring that innovations are developed safely and ethically.

Additionally, the notion of responsive regulation advocates for a dynamic regulatory approach that can adapt to the fast-paced changes in the AI landscape. This involves regulators being responsive to the behavior of firms, adjusting their interventions based on the level of compliance and risk, rather than applying a one-size-fits-all approach. This method is particularly beneficial in the AI ecosystem, where the rapid evolution of technology demands a regulatory framework that is both flexible and robust.

However, there is a potential risk associated with competition policy adopting an 'asymmetric regulation' approach, where different standards or obligations are imposed on firms based on their size or market power. While this could help level the playing field, it also carries the risk of stifling competition by overly penalizing larger firms or creating barriers for their innovation efforts. This concern is echoed in reports from the International Center for Law & Economics (ICLE), which caution against the unintended consequences of asymmetric regulation, suggesting that it could lead to regulatory overreach and ultimately harm consumers by reducing market dynamism (Radic et al., 2024)[4].

A flexible approach to competition policy is essential, employing tools such as market investigations, interim measures, and less formalistic approaches to concentration control, including ex-post assessments and monitoring of 'integration by contract' schemes. The Bundeskartellamt's supervision of the cooperation between OpenAI and Microsoft exemplifies this approach.

Regulatory efforts are particularly necessary because AI, particularly generative AI, is a general-purpose technology capable of exerting significant influence across various markets (Brynjolfsson & McAfee, 2016). Public policy should not be limited to antitrust or regulation but should encompass broader dimensions, such as industrial policies (Marty and Warin, 2025) and technical standards definitions (Luchs et al., 2023). The issue of technical standards being set by independent bodies is therefore essential to guarantee interoperability, prevent lock-in and use standards to achieve broader

[4] Significantly, the position taken by Radic et al (2024, p.57) according to which the role assigned to regulations in the digital sector is 'to intercede aggressively to redraw markets, redesign products, pick winners, and redistribute rents' could be set against a classic opposition between the option of a competition policy aimed at sanctioning anti-competitive practices and that of an industrial policy aimed at balancing the operation of an LTS.

objectives, particularly in ethical terms. Industrial policies can support the growth of smaller players by providing funding, resources, and support for research and development. Establishing technical standards can ensure interoperability and fair competition, allowing smaller firms to compete on a level playing field with established giants. This is also the case for the recommendations of Azoulay et al (2024) regarding the 'fractionalisation of infrastructure'. In this case, the rationale may be to apply the theory of essential facilities to physical assets that an entrant would not be able to put in place under reasonable conditions of cost, implementation time or recovery of capital invested, or simply at scale from the outset. As is often the case, the application of the theory of essential facilities can come up against strong legal constraints, but also limits in economic terms. These relate to the direct costs of regulation (setting the access tariff and monitoring its application) but also to the indirect effects on firms' investment incentives. Another option, which is more voluntarist but even riskier in terms of imperfect information, is the deployment of public infrastructures. While data remains a crucial factor in the competitive dynamics of generative AI, its role as a barrier to entry is complex and multifaceted. Open-source models and data provide alternatives, but quality and specificity remain critical competitive parameters. The availability of infrastructure and technical expertise also shapes the competitive landscape. Regulatory measures and antitrust enforcement are vital in ensuring a level playing field, fostering innovation, and protecting consumer welfare in the generative AI market. A balanced approach that considers the unique challenges and opportunities of generative AI will be crucial in navigating the competitive landscape and promoting a dynamic, innovative market environment.

6. Conclusion

The development and deployment of generative AI are fundamentally influenced by dual barriers: data and computing power. While the democratization of algorithms through open-source initiatives and accessible research has reduced their role as a barrier, the critical challenges now lie in securing access to large, high-quality datasets and the substantial computational resources needed to process them. Data remains a key competitive asset, where its quality and specificity significantly impact the performance of AI models. In the B2B context, computing power is essential for ensuring the speed and efficiency of AI applications, directly affecting business competitiveness and operational effectiveness.

To overcome data-related barriers, enhancing open data initiatives can play a significant role. Encouraging the development and sharing of open-source datasets can provide smaller players with access to the resources needed to train competitive AI models, facilitated through public-private partnerships and regulatory support. Ensuring data portability and interoperability through appropriate policies can help level the playing field by allowing businesses to switch between service providers without losing critical data. Additionally, establishing platforms for data sharing and collaboration among businesses and researchers can enhance access to diverse and high-quality datasets, fostering innovation and reducing reliance on proprietary data.

Addressing the challenges associated with computing power requires promoting affordable and scalable access to cloud computing resources. Governments and large enterprises can provide subsidies or credits to startups and small businesses to alleviate the financial burden of accessing high-performance computing infrastructure. The development and deployment of edge computing solutions can also help reduce reliance on centralized cloud infrastructure, as edge computing processes data closer to the source, reducing latency and improving efficiency. Strategic partnerships between smaller firms and tech giants can be structured to leverage computational resources on fair terms, preventing anti-competitive practices.

Looking ahead, several future directions can help address these barriers. Developing comprehensive regulatory frameworks that balance innovation with competition is crucial to prevent data monopolies and ensure equitable access to computational resources. Increased investment in research on efficient algorithms and hardware can reduce the computational burden, with innovations in AI hardware, such as specialized processors, enhancing performance and lowering costs.

Considering generative AI as an LTS may also lead to a rethink of the modes of public intervention. As Vannuccini and Prytkova (2023) point out, it is not the same externality that is targeted in the development of a GPT and in that of an LTS. In the first case, it is a question of resolving the under-investment of players in relation to a collectively optimal level, while in the second, it is a question of resolving investment coordination problems (Robinson and Mazzucato, 2019) and counteracting reverse salient effects. These are crucial assets whose scarcity or control by a single type of player can lead to sub-optimal dynamics both in terms of technology development and, as we saw above, foreclosure.

The first question, as we have seen, is that of data. Should it be considered as common property, or should we prefer to develop a market, for the sake of quality and integrity, for example? The second option could lead to power struggles and a strengthening of the position of certain Big Techs. A second question relates to standards and programming languages. For the same reasons, should we favour open standards for libraries and programming frameworks? We saw above that the logic of openness advocated by certain operators can also lead to consolidation or lock-in effects, which are even more 'effective' when programming languages are not standardised. A third question relates to the critical infrastructure assets we have just described. Should they be the subject, if not of a pooling, at least of the constitution of a 'public' pool allowing free and undistorted access to firms wishing to develop their fine-tuned models? This, for example, is the thrust of some of the proposals made by the French Competition Authority in its opinion on competition in the generative AI sector (Autorité de la concurrence, 2024).

It appears that Big Tech and/or certain major players in the AI sector can control the competitive dynamic through various channels. The first may involve controlling and retaining strategic assets. The second may consist of a platform strategy based on imperfect open source. The assets made available to third parties are sufficiently attractive to create a community of complementors but place them in a situation of dependency. This can be the result of foundation models that retain the characteristics of black-boxes (due to partial disclosure) or the induced spread of specific programming languages and standards that act as barriers to exit. A third essential channel needs to be considered, particularly in that it echoes well-known concerns in competition economics applied to the digital sector: the bundling effects of the services offered by Big Techs. These last ones can offer access to data, interfaces and programming languages, processors and storage capacities, and finally to an ecosystem of users that is all the easier to reach because applications specific to generative AI can be integrated into applications that are familiar to users. Although it makes the deployment of generative AI more effective and facilitates its development, this bundling mechanism can produce the same lock-in phenomena as strategies used in other areas of the digital economy.

Faced with these risks, public policy responses can be, as we have seen, particularly broad but always difficult to implement. These range from the application of competition rules (to punish practices of eviction or exploitation of dominant positions, to use the categories of European law) to the implementation of a proactive industrial policy, via action on technical standards or the imposition of regulatory frameworks (enabling ex ante action to prevent situations considered to be sub-optimal). The risks to the process of competition (and innovation) increase along this continuum.

Two avenues must be considered. The first pertains to competition authorities, the second to the generative AI firms themselves.

From a competition standpoint, an overly restrictive approach to partnerships could hinder the development of dynamic ecosystems. Provided they do not entail exclusivity clauses, such partnerships should not be construed as contractual integrations whose competitive effects might resemble those of mergers yet escape prior merger control scrutiny. As Groza and Wierzbicka (2024) note, the preferred analytical angle may rather be that of inter-firm cooperation, where any potential restrictive effects must be weighed against resulting efficiency gains. Inter-firm coordination is essential to undertake risky investment trajectories and economic transitions, particularly when supporting the development and deployment of general-purpose technologies (Gaffard and Quéré, 2006). However, the evidentiary burden of demonstrating such efficiency gains should rest with the firms, not the competition authority, which operates in a context of asymmetric and incomplete information. Likewise, a light-touch regulatory framework should be implemented to mitigate risks of lock-in and appropriation of gains, by fostering multi-homing strategies, interoperability among different ecosystems (notably in cloud services), and data portability (Tirole, 2023). The aim is to create a regulatory environment that limits distortions of competitive dynamics caused by the control of (quasi) essential assets.

Regarding firms' strategies themselves, the goal is to prevent—despite any short-term advantages—situations leading to contractual or de facto exclusivities, i.e., economic and technological dependency. This entails developing contractual and technical architectural solutions capable of preventing lock-in and framing effects within a given technological trajectory (such as open protocols; see Moure et al., 2025).

By focusing on these solutions and future directions, the AI industry can overcome the dual barriers of data and computing power, fostering a more competitive and innovative landscape. Ensuring equitable access to these critical resources will enable a wider range of players to contribute to and benefit from advancements in generative AI, ultimately driving progress across various sectors.

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