Competition in AI Markets*

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World Bank

Background Paper for the World Development Report 2026: Artificial Intelligence for Development

July 2026

Abstract

Artificial intelligence markets concentrate around a small set of essential inputs: advanced chips, hyperscale computing, foundation models, and data. Control over these inputs shapes competitive outcomes across the wider economy. This paper examines the implications for competition policy, with a focus on developing economies. It identifies six pillars of competition risk: infrastructure concentration, input monopolization, state-owned enterprise distortions, conglomerate entrenchment, algorithmic coordination, and exclusionary collaborations. It then presents a diagnostic framework (AI-MCPAT) that integrates value chain layer analysis, risk factor assessment, and cascade mapping to trace how upstream distortions propagate through production networks. Because most concentration originates beyond any single country's jurisdiction, the policy priority for most economies lies in demand-side and access instruments, including procurement design, interoperability and portability requirements, competitive neutrality, and open data regimes, supported by cross-jurisdictional cooperation, rather than in restructuring global supply.

Keywords: artificial intelligence; competition policy; market concentration; digital markets; state-owned enterprises; developing economies

* The authors thank Elwyn Davies and the World Development Report 2026 team for helpful comments. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

† Paul Phumpiu Chang passed away during the preparation of this paper, which is published in his memory. Its core arguments reflect his thinking.

1. Structural Characteristics of AI Markets

The rapid scaling of artificial intelligence (AI) markets has emphasized the role of market regulators. AI has emerged not only at a fast pace but as a foundational technology deployed across sectors, potentially akin to electricity or digitalization. A question now at the forefront of policymaking is whether AI will follow a trajectory similar to digitalization, or whether its distinct characteristics require meaningful adjustments to existing policy tools. Additionally, in many jurisdictions AI is framed as a strategic or developmental priority. While this may justify public investment and regulatory facilitation, it can also create reluctance to scrutinize market distortions. Safeguarding competition in the interest of sustaining jobs, innovation, and productivity will require separating innovation promotion from competition assessment.

Competition policy is grounded in the principle that markets deliver better outcomes when firms compete on merit. Competition is not a static market condition captured by a single indicator such as market share or excess profits. It is a dynamic process that unfolds through entry and exit, investment decisions, innovation, pricing, and strategic coordination. Competitive markets enable more productive firms to expand, allow prices to reflect scarcity and guide investment, and ensure that commercial success reflects efficiency rather than privileged access to finance, data, infrastructure, or regulatory protection.

Assessing competition requires a multidimensional approach. Market structure is relevant, but so is the persistence of dominant positions, firm behavior, and financial performance. High concentration does not in itself indicate weak competition if markets remain contestable or highly productive. Conversely, markets with many firms may exhibit limited rivalry where entry barriers are significant or incentives to compete are limited. A market may appear competitive on the surface while structural dependencies (e.g., upstream concentration of critical inputs) or cross-market linkages harm contestability. In AI markets, these structural dimensions are amplified and increasingly central to policy assessment.

Competition pressures in AI are less driven by end-user application rivalry and more by control over inputs. A diverse range of AI products for end users on the surface does not imply a contestable market, concealing competition risks underneath. Advanced chips, data centers, cloud computing infrastructure, high-quality training data, intermediary services, and specialized technical talent all compose a set of essential inputs or “essential facility” (Tucker, 2024). In turn all these inputs exhibit strong scale economies (e.g. “hyper scalers”)[1] and are becoming more concentrated, not less (Korinek and Vipra 2025). Both the European Commission and the UK Competition and Markets Authority, based on reviews of AI markets, find that outcomes of end users are largely predetermined by control of critical upstream infrastructure.[2] A further structural feature distinguishes AI from earlier waves of digitalization: the inputs where concentration is

[1] Coeure (2025). France's Competition Authority's cloud market study focused on "the upstream segment of the AI value chain, in particular on hyperscalers": the major cloud providers controlling the foundational compute infrastructure on which AI development depends.

[2] European Commission (2024); CMA (2024a). The CMA’s examination of AI accelerator chips found that competitive dynamics downstream are largely predetermined by upstream input control.

greatest are supplied globally by a handful of firms, so for most economies the relevant competition risks originate outside domestic jurisdiction.

AI input/output interdependencies require a shift from single-market analysis to ecosystem-level competition assessments. The multitude of inputs utilized by AI have their own distinct markets, all serving as AI input dependencies. As a result these markets are linked by the AI supply chain, resulting in competitive vulnerabilities that no individual sectoral analysis will detect. These vertical interdependencies in turn shape competitive outcomes (Hagiu and Wright, 2025). Single-market analysis, which examines concentration or churn within individual sectors, misses this by design. Enforcement practice is increasingly reflecting this recognition that competitive effects in AI do not fit neatly into conventional market definition frameworks.[3] Secondly, ecosystem level assessments may expand beyond direct AI inputs and into other sectors through spillovers. For example, a firm controlling cloud infrastructure may impact banking, healthcare, and manufacturing all at once through networks of spillover effects.

The scope of AI competition risks depends on the underlying economic structure. Ecosystem-level competition risks are not homogenous across economies. In economies with a small number of dominant sectors, AI competition risks tend to concentrate in a few critical chokepoints. In these cases control of upstream inputs translates directly into economy-wide leverage. In more structurally diverse economies, risks are distributed across a wider range of value chain relationships. This as a result makes sector coordination and conglomerate entrenchment the more relevant concerns rather than any individual infrastructure bottleneck.

Early advantages can compound into structural dominance faster than conventional enforcement can detect. AI systems improve through user inputs: a firm with large proprietary datasets trains better models, better models attract more users, and more users generate more data. The cycle reinforces itself, and by the time market share or pricing behavior signals dominance, the competitive structure may already be locked in. Rising training costs as models increase in complexity further limit entry (Martens 2024). The concern is not only the speed of entrenchment but its potential irreversibility. Infrastructure dominance can lock in a few years; ecosystem lock-in becomes permanent within five to ten. Waiting for harm to be proven through conventional enforcement may mean acting after the moment of effective remedy has passed.

These dynamics challenge the adequacy of traditional enforcement models. Where competitive harm materializes rapidly and becomes difficult to reverse, waiting for observable market outcomes may delay intervention beyond the point of effective remedy. This concern has increasingly been recognized by competition authorities. As Margrethe Vestager (previous EU Competition Commissioner and Executive Vice President) noted, the potential risks to an open and contestable marketplace in AI are significant, and enforcement tools may need to adapt accordingly (Vestager 2024). The policy implication is not the abandonment of ex post enforcement, but the complementing of it with earlier diagnostic tools and ex ante safeguards.

[3] Tarantino (European Commission 2025) argued competition experts must look beyond individual assets to how conglomerates entrench reach across the wider ecosystem, stopping short of explicitly endorsing an ecosystem theory of harm. The ecosystem framing in enforcement practice draws more directly from the EC and CMA market studies (European Commission 2024; CMA 2024a).

Competition authorities will be challenged not only analytically but epistemically. Formal indicators such as market share or price effects may lag structural entrenchment. Judgment about ecosystem dependency, cumulative advantage, and irreversibility therefore becomes as important as measurable outcomes.

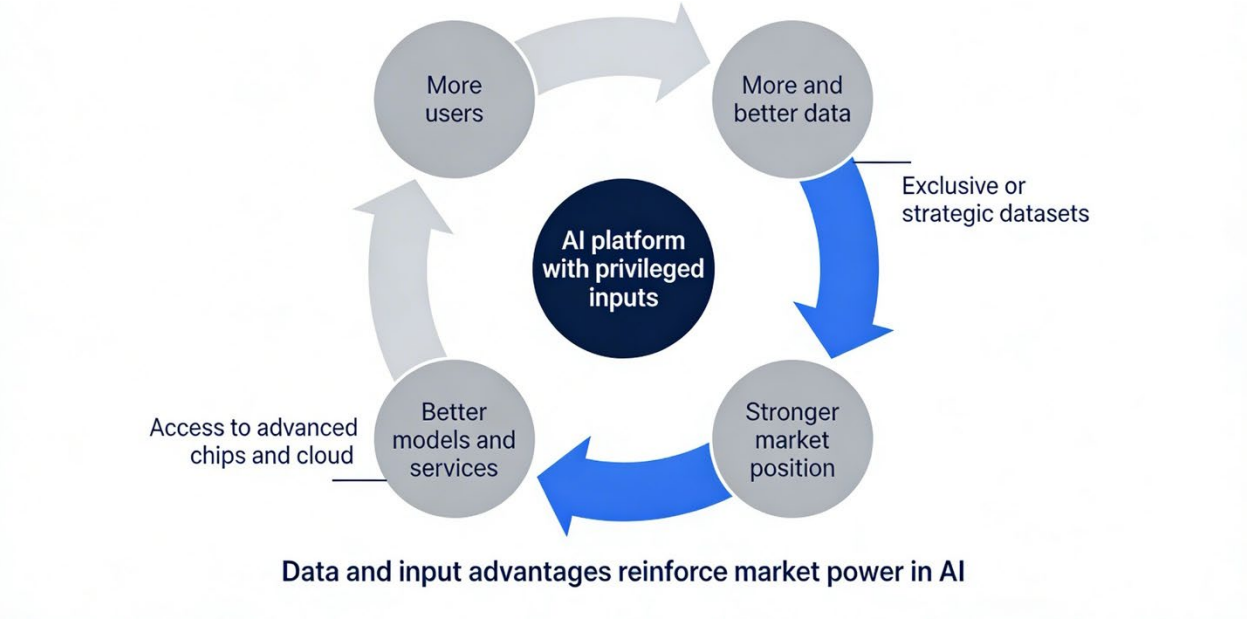
2. AI Market Competition Risk Pillars

Risks to competition in AI markets can be structured around six pillars. Each operates through a different mechanism; together they constitute the structural landscape against which enforcement responses should be designed.

Infrastructure concentration refers to control over the foundational computing and data infrastructure that all AI applications depend upon. When available capacity is concentrated in a handful of providers, they can impose conditions on all downstream users, such as exclusive deals and discriminatory pricing. The effect not only impacts AI deployment but also cascades economy-wide because the chokepoint is not sector-specific. A related concern arises at the level of foundation models. These models serve as the basis for a wide range of downstream applications and are typically accessed through APIs embedded in application architecture. Control over API access terms can shape interoperability, entry conditions, and competitive positioning across the downstream layer (Schrepel and Pentland 2025).

Input monopolization refers to exclusive control over the non-infrastructure inputs AI development requires. This includes specialized talent, proprietary training datasets, and in some cases hardware manufacturing. This concentration persists even if cloud infrastructure is to become more competitive. Control over these complementary inputs may raise rivals' costs or limit entry. Data asymmetry or exclusivity reinforces the advantage further through the feedback loops between data, models, and users. This can lead to compounding advantages (Figure 1).

FIGURE 1: DATA AND INPUT ADVANTAGES REINFORCE MARKET POWER IN AI



Source: Authors' elaboration

The competitive significance of data concentration depends on whether alternative sources exist. There are competing views on the role of data in AI markets. In some cases, access to unique datasets may generate increasing returns to scale. In others, data may exhibit diminishing marginal returns as models converge in performance. Much depends on the type of data involved. Most generative AI models are trained on broadly similar publicly available datasets, reducing the likelihood that such data function as an essential facility (Tucker 2024). Important exceptions arise where access is restricted by privacy or copyright regulation, limiting availability to a small number of licensed holders. In other cases, data completeness rather than volume is decisive. Health records, financial transaction data, and government administrative datasets may be genuinely non-substitutable because they capture comprehensive system-level information (Tucker 2024; AdC 2024b).[4]

A further distinction can be drawn between training data used to develop foundation models and input data used in downstream applications (Gans 2024). Competitive implications may differ across these stages.

State-owned enterprise distortions arise when government-controlled firms receive advantages that private competitors do not. In AI markets, this often happens through control over key inputs such as government data, telecom networks, cloud infrastructure, energy supply, or preferential financing. The risks are greater in countries where the state has a strong presence in infrastructure sectors that underpin AI deployment. When ownership is combined with regulatory discretion or

[4] Tucker (2024); AdC (2024b). The Portuguese competition authority's data paper identifies data licensing agreements, increasingly common between AI developers and news publishers, social networks, and stock image repositories, as a growing concentration mechanism. Where dominant developers secure exclusive or preferential licensing terms, this replicates the essential facility dynamic even in data markets that would otherwise appear competitive.

soft budget constraints, entry can be limited and private investment discouraged.[5] Even strong financial performance may reflect protection rather than efficiency. The result is not only weaker competition in AI services, but distortions across the broader ecosystem that depends on fair access to data and infrastructure.

Private conglomerate entrenchment mirrors state presence but through market position rather than public ownership. Conglomerates, defined as two or more firms linked together through ownership links, may amplify competition concerns by operating as one single cross sectoral entity. Conglomerates have power to entrench their reach from one value chain link to another across the wider ecosystem.[6] A firm spanning cloud, data collection, and consumer applications can self-preference and raise rivals' costs at each layer. Importantly, it can do so without holding a dominant position in any individual market. Cross-market effects of this kind are invisible in sector-by-sector analysis.

On the other hand, conglomerate presence in AI markets may have positive impacts such as facilitating knowledge transfer, lower transaction costs, and greater resilience in less developed markets. Conglomerate structure is therefore not necessarily anticompetitive. What matters is whether a firm uses its presence across multiple markets to block competitors from accessing the inputs, customers, or distribution channels they need to compete. Monitoring of such structures is therefore essential.

Algorithmic coordination challenges traditional competition law by enabling coordinated market outcomes without communication, agreement, or clear intent. This coordination arises when pricing and other firm decisions are based on algorithms rather than direct human decisions. In aggregate, across multiple firms, these can lead to anti-competitive outcomes through algorithmic feedback loops, without any communication or agreement between firms.

The competitive harm is equivalent to intentional human decision making, however the legal basis for intervention is not clear. The challenge, as Cordeiro Macedo (2025) puts it, is distinguishing an algorithm used for collusion from one used for legitimate price monitoring. In many cases this may prove difficult to distinguish.[7] Recent US litigation over shared pricing software suggests enforcement may be more tractable than assumed, though within limits. In the rental housing cases, competing landlords each supplied nonpublic pricing data to a common software provider, which used it to generate pricing recommendations for all of them; no firm communicated directly with its rivals (the hub [software] and spoke [individual user] model). Courts allowed these claims to proceed on the theory that pooling competitively sensitive data through a shared algorithm can support a finding of unlawful coordination (Fisher 2025), and a settlement with the US Department of Justice restricts the leading provider from using competitors'

[5] See World Bank (2023), Businesses of the State (BOS) and Private Sector Development: A Policy Toolkit for Practitioners, which provides a framework for assessing state footprint, competitive distortions, and reform options.

[6] European Commission (2025). Tarantino argued competition experts should focus on how conglomerates "entrench their reach from one sector to another" rather than on individual assets, noting that key elements of the AI supply chain rely on markets already "oligopolistic" in structure.

[7] Cordeiro Macedo (2025); CNMC (2025). Spain's Brava algorithm achieves above 90 percent accuracy in bid-rigging detection and has been shared with other antitrust authorities through the European Competition Network, with extension to pure algorithmic collusion as the agency's stated next priority. Tucker (2024) identifies a further enforcement problem: when pricing and acquisition decisions are driven by algorithmic prediction rather than human judgment, the documentary evidence competition authorities rely on to establish anticompetitive intent (executive emails, board minutes) will not exist.

nonpublic data in its pricing recommendations. Parallel claims against hotel operators were dismissed where the recommendations were nonbinding and no agreement among the users themselves was shown.

Exclusionary collaborations and sub-threshold acquisitions can lock out rivals from the market. Large technology platforms typically acquire multiple potential competitors annually, mostly below merger review thresholds, absorbing emerging alternatives before they can scale. The most consequential exclusionary practice may be the least visible. Dominant AI market players rely on a multitude of intermediary service providers such as cloud hosting, data pipelines, and other specialized services linking data-compute-end user applications. Firms may embed exclusive or preferential terms into these partnerships without the need to acquire firms. "Killer" acquisitions may also be used to prevent competitors from utilizing certain inputs, not only infrastructure but also data (Gans 2024). The mix of these collaboration strategies can avoid triggering mandatory merger notifications.[8]

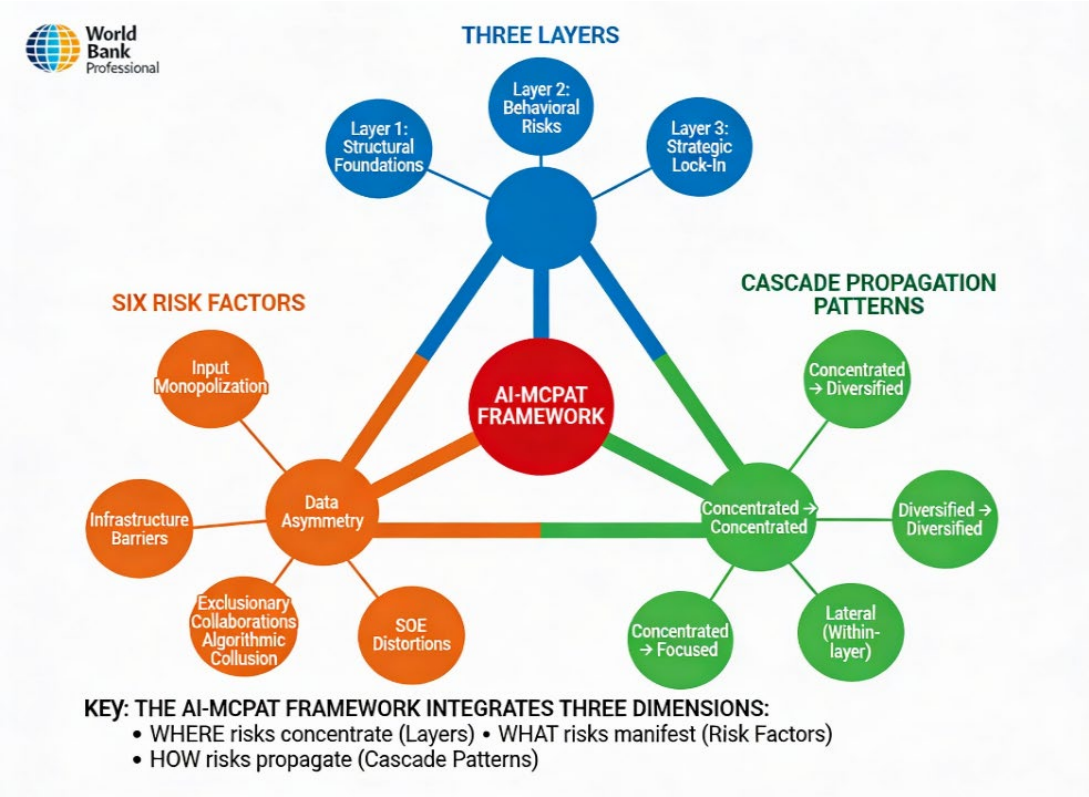
3. A Framework for Competition Policy in AI

Traditional competition analysis is inadequate for AI-intensive economies. Traditional approaches examine individual markets in isolation, assessing market structure, firm conduct, and competitive outcomes within clearly defined sectoral boundaries. This methodology fails in AI markets, where competitive dynamics operate across value chain layers, propagate through production dependencies, and generate effects that transcend conventional market definitions. Assessing competition in these markets requires authorities to simultaneously integrate three interconnected analytical dimensions.

The AI-MCPAT (AI Markets and Competition Policy Assessment Toolkit) framework addresses these challenges by organizing competition analysis around three complementary dimensions. This framework integrates structural analysis, behavioral assessment, and propagation mapping. It focuses on where competitive problems concentrate (layers), what mechanisms firms use to exploit market power (risk factors), and how competitive distortions spread across dependent sectors (cascade patterns) (Figure 2).

[8]CMA (2024b); CADE (2024); DOJ and FTC (2024). Amazon's $4 billion investment in Anthropic included a commitment to use AWS as primary cloud provider for mission-critical workloads including safety research. CADE opened probes into four such arrangements in 2024; the DOJ and FTC used Section 6(b) orders to investigate others outside HSR reach.

FIGURE 2: AI - MCPAT FRAMEWORK



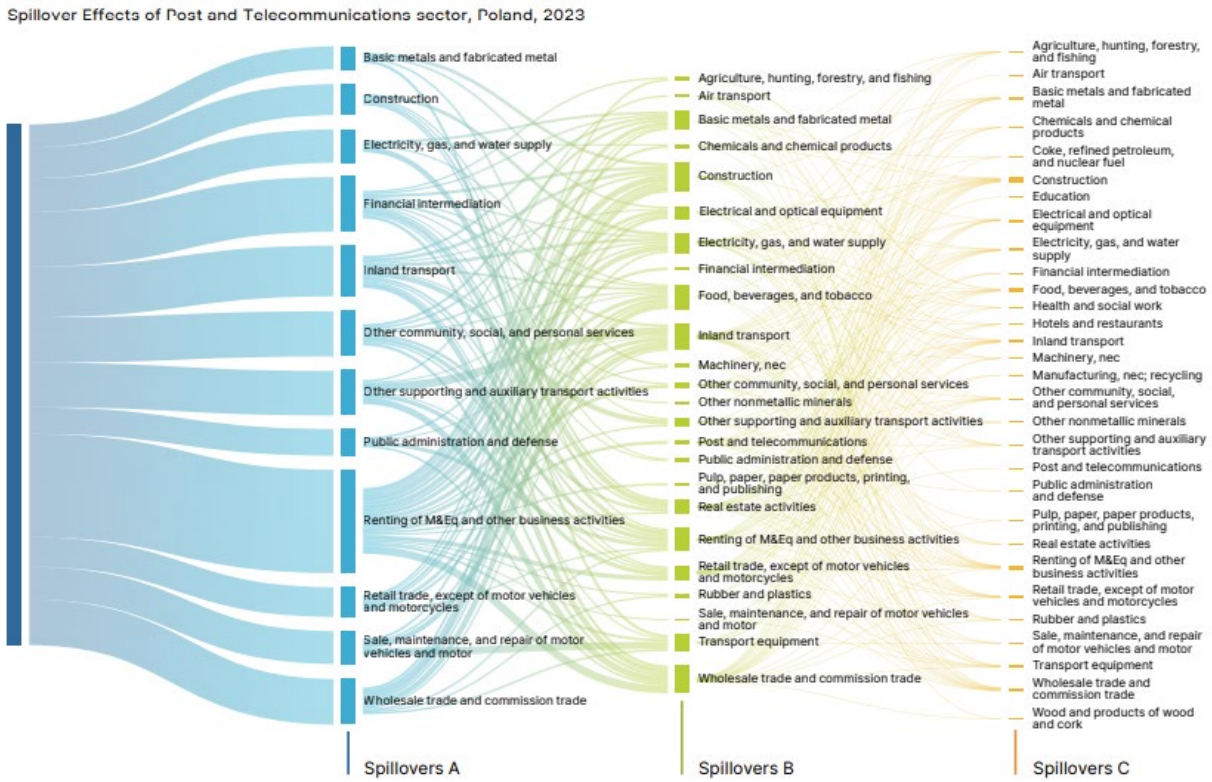
Source: Adapted from World Bank (2026), EU Regular Economic Report 11.

Layer analysis helps authorities identify the value chain position where market dominance emerges and becomes entrenched. The framework categorizes these into three levels: Layer 1 Structural Foundations (infrastructure control), Layer 2 Behavioral Risks (strategic conduct), and Layer 3 Strategic Lock-In (ecosystem foreclosure). Because not all economies face the same threats, layer analysis helps authorities pinpoint where competitive problems actually occur. For example, some markets face obvious Layer 1 infrastructure dominance that can be addressed via direct access mandates, while others face invisible Layer 2 coordinated behaviors requiring cross-sector analysis spanning the entire economy. Furthermore, mature markets may already suffer from Layer 3 lock-in due to accumulated acquisitions and exclusive partnerships, which requires ecosystem restructuring to restore competition. Authorities must determine which layer dominates their market to allocate resources effectively, rather than assuming enforcement always begins at Layer 1.

Risk factor analysis characterizes the specific mechanisms firms use to exploit market power. This dimension pinpoints how dominance operates, whether through infrastructure barriers or input monopolization, such as control over hardware, cloud computing, or specialized talent. It also identifies dominance achieved through exclusive data asymmetry, exclusionary collaborations like sub-threshold acquisitions, algorithmic collusion through automated pricing, and state-owned enterprise (SOE) distortions. Identifying the exact mechanism is critical because each requires distinct investigative approaches and remedial tools.

Cascade analysis traces how upstream competitive distortions propagate to dependent downstream sectors. This dimension determines the breadth of competitive harm, distinguishing between concentrated problems that affect specific dependent sectors and dispersed problems that spread invisibly across entire economies. Understanding whether harm is concentrated or dispersed dictates the enforcement strategy: targeted, direct interventions work for visible chokepoints, while distributed coordination requires sustained, cross-sector monitoring (Figure 3).

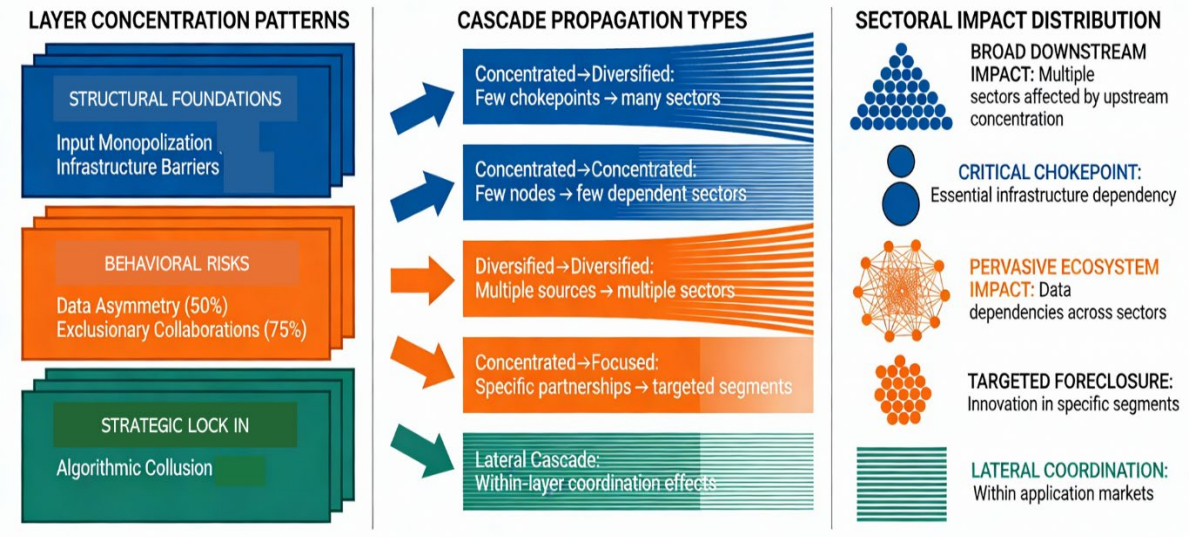
FIGURE 3: POLAND'S DISPERSED TELECOMMUNICATION SPILLOVERS INDICATE CROSS-SECTORAL COORDINATION RISKS



Source: Authors' elaboration based on EORA and ADB IO data.

By answering three key diagnostic questions, authorities can move systematically from detection to calibrated response. These guiding questions are: Which layer dominates your market, through what mechanism does dominance operate, and how broadly do competitive distortions propagate? Answering these systematically positions authorities to allocate investigative capacity and remedial tools proportionate to actual competitive harm, rather than applying uniform responses across diverse market structures (Figure 4).

FIGURE 4: AI COMPETITION RISK TRANSMISSION



Source: Authors' elaboration

The Layer-Cascade-Impact diagram visually traces how problems originate, spread, and generate distinct patterns of sectoral harm. Organized across three panels moving from left to right, it illustrates where concentration occurs, how it propagates, and what sectoral impact results. This structure enables competition authorities to work backward from observed market problems to their structural causes.

Ultimately, this integrated framework transforms enforcement from reactive, case-by-case adjudication into strategic capacity allocation. Rather than investigating every concern independently, authorities can identify common causes, target upstream problems, and calibrate their interventions. For example, an analysis of Croatia revealed a concentrated cascade indicating Layer 1 dominance, which requires direct infrastructure remedies, while Poland exhibited a diversified cascade pointing to Layer 2 and Layer 3 issues, necessitating cross-sector monitoring and acquisition screening. This provides a systematic assessment based on observable market characteristics, which is critical for competition authorities operating with limited investigative resources.

A fourth, cross-cutting question concerns jurisdictional reach: whether the authority conducting the diagnostic can act on what it finds. For most economies, the answer differs by layer. Layer 1 concentration in chips, cloud capacity, and foundation models sits largely outside domestic jurisdiction; no single authority in a developing economy can remedy global upstream concentration unilaterally. Layer 2 conduct and Layer 3 lock-in, by contrast, materialize partly within domestic markets, in distribution agreements, procurement contracts, data access terms, and local partnerships, where national instruments retain traction. The framework therefore sorts findings into three response categories: risks the authority can address unilaterally (domestic conduct, competitive neutrality, procurement design), risks requiring coordination with peer authorities (scrutiny of global partnerships and acquisitions), and risks where the economy is a policy-taker and the realistic objective is securing open terms of access rather than restructuring supply. This prevents scarce diagnostic capacity being spent on problems no domestic instrument can reach.

4. Implications for developing economies

Developing economies face all six risk pillars. But they do not hold equal leverage over each. Some pillars are within domestic reach. For example, governments can reform how state assets are governed. They can separate regulatory from commercial functions. They can establish neutral public data access rules. The infrastructure, foundation models, and input monopolization pillars on the other hand are more challenging. Chips, cloud capacity, and foundation models are controlled by a handful of global providers. The likely scenario is where developing economies deploy adapted models. Promisingly, these adapted models can benefit from local inputs such as data. The competition priority therefore shifts from preventing upstream concentration to ensuring the terms of access remain open and facilitate the development of indigenous AI markets (applications, local training data) downstream.[9] Most developing economies will be importers of upstream AI technology, which makes the terms of importation the central policy variable: access to models and infrastructure, pricing, and conditions of portability and exit. Self-sufficiency is unrealistic; specialization is not. Domain-specific models built on locally specific data in sectors where an economy already has depth, such as agriculture, logistics, or health, are the realistic entry points, and competition policy protects them by keeping model access, data access, and procurement open to entrants.

State owned enterprises are both a risk and a policy lever. Where SOEs participate across multiple stages of the data value chain (generation and collection, processing, usage, storage, and sharing) they accumulate structural advantages private competitors cannot replicate. Privileged data access may favor other SOEs operating outside the data value chain, and often takes the form of routine procurement rather than explicit policy. Private entities without state links may find that entry becomes structurally difficult, crowding out private investment. At the same time, certain data typically held by the state is the most impactful for AI models. Administrative data relating to health, finance, and transport is locally specific data that can feed indigenous AI solutions. Nor is this confined to language models: as AI extends into robotics and physical applications, sectoral and operational data generated locally may become one of the few upstream inputs developing economies actually control.

SOE influence in AI markets extends beyond data. SOEs may also hold privileged positions in telecom networks, cloud infrastructure, energy supply, and financing. They can work together to exaggerate their structural advantages across multiple AI-relevant inputs simultaneously. An underlying principle stands on separating regulatory from commercial functions and limiting favorable terms for SOEs versus private enterprises.[10] Open data regimes, interoperability requirements, and competitive neutrality obligations are instruments that countries can prioritize to separate regulatory from commercial functions.

[9] Momtaz (2024); Cordeiro Macedo (2025). Authorities in Egypt and Brazil have both identified that standard competition enforcement tools, designed for domestic market concentration, do not map onto the bargaining asymmetry these economies actually face with global AI providers.
[10] World Bank (2023)

SOE reform is one lever among several, and for most economies not the largest. Because the supply side of the AI supply chain (chips, hyperscale cloud, frontier models) lies beyond domestic reach, the instruments with the most traction operate on the demand side and on the terms of access. Public procurement is the most direct: governments are typically among the largest domestic buyers of cloud and AI services, and procurement design, including multi-vendor requirements, data portability and exit clauses, limits on exclusivity, and open standards in tendering, shapes market structure without requiring enforcement action against global providers. Procurement can also seed local markets: opening government AI application contracts to genuine competition creates entry points for domestic developers that infrastructure policy cannot.

A second set of instruments targets dependencies directly. Interoperability and data portability requirements lower switching costs between cloud and model providers; limits on egress fees and self-preferencing address lock-in at the infrastructure layer; and open access regimes for models and APIs broaden the terms on which downstream developers build (AdC 2024a). These instruments appear above in the SOE context (competitive neutrality, open data, interoperability), but they apply equally to private incumbents, and they are enforceable domestically regardless of where the upstream provider sits.

Operationalizing competition policy for AI requires reorienting institutional purpose, not just adding resources. Mazzucato and Kattel (2026) draw a distinction between structural capacities (mandates, budgets, frameworks) and dynamic capabilities that allow institutions to experiment and adapt. Few developing economies have developed strengths in the latter. Authorities will increasingly need diagnostic capacity before they implement traditional enforcement tools. This will be particularly the case for economies where infrastructure dependencies are more spread out across sectors. These economies face greater accumulating risks, behavioral coordination, sub-threshold acquisitions, and gradual data consolidation. In these cases preventive monitoring is most needed. Japan's JFTC has demonstrated this model through a non-binding promotion act combined with a regularly updated market study, flagging data access, vertical integration, and lock-in concerns while avoiding premature conclusions (McConnell 2025).

Cross-jurisdictional cooperation and regulatory alignment are practical necessities, not aspirational goals. Global AI platforms operate across jurisdictions simultaneously while competition authorities remain national. The same partnership arrangements are being examined by multiple authorities with different thresholds and different outcomes, creating arbitrage opportunities and duplicating investigative costs.[11] For developing-country authorities with limited resources and no direct leverage over global platforms, partnering with and learning from larger jurisdictions is often the only realistic path to influencing platform behavior (Momtaz 2024). Knowledge sharing, joint market studies, and analytical alignment with larger authorities reduce

[11] CADE (2024) explicitly referenced CMA investigations when opening its own AI partnership probes. Germany has called for DMA amendments explicitly covering AI services and a transaction-value threshold for merger control; France argues existing Articles 101 and 102 provide sufficient basis if applied earlier. Portugal has signaled it will probe partnerships the CMA already closed (German Federal Government 2025; Coeure 2025; Portugal Competition Authority 2025).

this exposure without requiring developing economies to build enforcement capacity from scratch (Coeure 2025).[12]

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[12] CADE (2024) explicitly referenced CMA investigations when opening its own AI partnership probes, illustrating how developing-country authorities can leverage larger jurisdiction analysis rather than duplicating it.

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