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Artificial Intelligence Governance and Industrial Development: Transnational Spillovers, Technology Transfer, and Sustainable Territorial Implications in Brazil

Governança da Inteligência Artificial e Desenvolvimento Industrial: Spillovers Transnacionais, Transferência de Tecnologia e Implicações Territoriais Sustentáveis no Brasil

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Abstract

This study examines the relationship between artificial intelligence (AI) governance and industrial development, focusing on the transnational spillover effects of China's regulatory framework on Brazil. Positioned at the intersection of technology governance, territorial development, and sustainability, the paper analyses how emerging AI regulatory models generate indirect impacts on partner economies through mechanisms of technology transfer, infrastructure complementarities, and regulatory alignment. Using a difference-in-differences (DiD) approach applied to panel data from 25 Brazilian industrial sectors (2019–2025), the findings indicate that sectors with higher exposure to AI experienced a significant increase in output following the formalization of China–Brazil AI cooperation. The results reveal that these effects are mediated by open-source technological ecosystems, increased investment in digital infrastructure, and reduced regulatory uncertainty, contributing to enhanced industrial performance and adaptive capacity. Beyond economic outcomes, the study highlights the territorial implications of AI governance, particularly in fostering more balanced regional development, strengthening innovation ecosystems, and supporting pathways toward sustainable and resilient industrial systems. The article contributes to the literature on AI governance and development by introducing the concept of transnational regulatory spillovers as a driver of sustainable territorial transformation, offering relevant insights for policymakers and stakeholders navigating the global dynamics of digital transition.

Keywords: Artificial Intelligence Regulation; Industrial Policy; Technology Transfer; Brazil-China Relations.

JEL Classification: O33; O25; F23; L52; C23

Resumo

Este estudo analisa a relação entre a governança da inteligência artificial (IA) e o desenvolvimento industrial, com foco nos efeitos de spillover transnacionais do quadro regulatório da China sobre o Brasil. Posicionado na interseção entre governança tecnológica, desenvolvimento territorial e sustentabilidade, o artigo examina como modelos emergentes de regulação da IA geram impactos indiretos em economias parceiras através de mecanismos de transferência de tecnologia, complementaridades infraestruturais e alinhamento regulatório. Utilizando uma abordagem de diferenças-em-diferenças (DiD) aplicada a dados em painel de 25 setores industriais brasileiros (2019–2025), os resultados indicam que os setores com maior exposição à IA registaram um aumento significativo na produção após a formalização da cooperação China–Brasil em IA. Os resultados evidenciam ainda que estes efeitos são mediados por ecossistemas tecnológicos open-source, pelo aumento do investimento em infraestruturas digitais e pela redução da incerteza regulatória, contribuindo para um melhor desempenho industrial e maior capacidade adaptativa. Para além dos efeitos económicos, o estudo destaca as implicações territoriais da governança da IA, nomeadamente na promoção de um desenvolvimento regional mais equilibrado, no reforço dos ecossistemas de inovação e no apoio a trajetórias mais sustentáveis e resilientes. O artigo contribui para a literatura ao introduzir o conceito de spillovers regulatórios transnacionais como motor de transformação territorial sustentável, oferecendo implicações relevantes para decisores políticos e stakeholders no contexto da transição digital global.

Palavras-chave: Regulação da Inteligência Artificial; Política Industrial; Transferência de Tecnologia; Relações Brasil–China.

Códigos JEL: O33; O25; F23; L52; C23

1. INTRODUCTION

1.1 The puzzle of regulatory spillovers

The rapid proliferation of artificial intelligence has generated a fundamental tension in global economic governance: while AI technologies promise substantial productivity gains, their developmental consequences are mediated by regulatory frameworks that remain largely national in scope. This tension is particularly acute for emerging economies, which must navigate between the technological standards set by advanced economies and their own developmental priorities. Brazil, Latin America's largest economy and a strategic partner of China within the BRICS framework, exemplifies this dilemma. The country has simultaneously pursued an ambitious AI investment agenda—allocating R$23 billion (approximately US$4 billion) through the Brazilian Artificial Intelligence Plan (PBIA 2024–2028)—while grappling with the absence of comprehensive domestic AI legislation. China's emergence as both an AI powerhouse and a regulatory innovator introduces a novel dynamic into this landscape. In August 2025, China's State Council issued the "AI Plus" policy directive, a ten-year roadmap aimed at achieving 70% AI penetration across key economic sectors by 2027. This directive builds on a strategic vision articulated in the 2017 New Generation Artificial Intelligence Development Plan, which set the goal of global leadership by 2030. Concurrently, China has advanced a distinctive regulatory philosophy emphasizing open-source ecosystems, multilateral governance through proposed institutions such as the World Artificial Intelligence Cooperation Organization (WAICO), and the framing of AI as a global public good.

The central question motivating this article is whether China's AI regulatory framework generates measurable positive spillovers for industrial growth in Brazil, and through which mechanisms such effects operate. This question is non-trivial: existing literature on technology transfer has predominantly focused on foreign direct investment and trade linkages, with limited attention to the developmental consequences of regulatory standard-setting. Moreover, the geopolitical dimensions of AI governance—particularly the strategic competition between Chinese and US-led regulatory models—create both opportunities and constraints for emerging economies seeking to maximize developmental benefits while maintaining policy autonomy.

1.2 Theoretical framework and contributions

This article develops the concept of a "transnational regulatory dividend" to capture the positive developmental spillovers that accrue to partner economies when a major economy implements AI regulations that facilitate technology access, reduce adoption costs, or create complementary investment flows. The framework draws on three intellectual traditions: the economics of technical standards, which emphasizes how regulatory choices shape technology diffusion trajectories; the developmental state literature, which examines how strategic integration into global value chains can accelerate industrial upgrading; and the open innovation paradigm, which highlights the role of knowledge externalities in fostering technological catch-up. The Chinese regulatory approach exhibits distinctive features that make it particularly conducive to generating such dividends for Brazil. First, China's emphasis on open-source AI ecosystems—exemplified by the July 2025 International AI Open-Source Cooperation Initiative launched at the World Artificial Intelligence Conference—directly reduces barriers to technology adoption for Brazilian firms and developers. Second, China's strategic focus on "AI Plus" applications across manufacturing and agriculture aligns closely with Brazil's comparative advantages and industrial priorities. Third, the institutionalization of China-Brazil AI cooperation through formal mechanisms such as the Joint Laboratory for Family Agriculture Mechanization and Artificial Intelligence (established November 2024) and the China-Brazil AI Application Cooperation Center (July 2025) creates structured pathways for knowledge transfer. This article makes three primary contributions. First, it provides rigorous econometric evidence for the existence and magnitude of regulatory spillovers from China to Brazil, addressing a gap in the literature on AI governance and development. Second, it identifies and tests specific transmission channels, moving beyond aggregate impact estimation to illuminate causal mechanisms. Third, it offers policy-relevant insights for emerging economies designing AI strategies in a context of intensifying great-power competition over technological standards.

1.3 Article structure

The remainder of this article proceeds as follows. Section 2 provides the institutional background on AI regulation and cooperation in China and Brazil. Section 3 develops the theoretical framework and hypotheses. Section 4 describes the empirical strategy, including data sources, variable construction, and the difference-in-differences methodology. Section 5 presents the main results, robustness checks, and heterogeneity analyses. Section 6 investigates transmission mechanisms. Section 7 discusses implications and concludes.

2. INSTITUTIONAL BACKGROUND

2.1 China's AI regulatory framework: from "AI Plus" to global governance

China's approach to AI governance has evolved through three distinct phases. The first phase (2017–2023) was characterized by strategic planning and investment mobilization, anchored by the 2017 New Generation Artificial Intelligence Development Plan, which articulated the ambition to make China the world's primary AI innovation centre by 2030. The second phase (2024–2025) saw the operationalization of these ambitions through sectoral adoption policies, most notably the "AI Plus" initiative introduced in the 2024 Government Work Report. The third phase (2025–present) has emphasized international governance leadership, with China positioning itself as a standard-setter for AI regulation in the Global South. The "AI Plus" plan, formally issued in August 2025, represents a significant escalation in China's AI industrial policy. The directive calls for achieving a 70% AI penetration rate across key sectors by 2027 and envisions the comprehensive integration of AI into economic and social life by 2035. Unlike the more restrictive regulatory approaches emerging in the European Union, China's framework emphasizes enabling adoption while maintaining state oversight. Key elements include: (1) investment in domestic semiconductor supply chains to reduce dependence on US technology; (2) promotion of open-source AI models as a counterweight to proprietary Western systems; and (3) the integration of AI infrastructure with renewable energy resources under the "East Data, West Computing" strategy.

China's global governance ambitions crystallized in the July 2025 Global AI Governance Action Plan, launched at the World AI Conference in Shanghai. The plan proposes 13 actions aimed at promoting "safe and controllable" AI development and calls for the establishment of WAICO, a new international organization that would coordinate AI governance under UN auspices. In his opening address, Chinese Premier Li Qiang explicitly framed China's approach as an alternative to what he characterized as the "exclusive game" of proprietary AI development by a few countries or companies, presenting open-source collaboration as a mechanism for ensuring that "the benefits of AI are captured by all countries, including the Global South".

2.2 Brazil's AI strategy and regulatory trajectory

Brazil's engagement with AI governance has accelerated markedly since 2021, when the government released the Brazilian AI Strategy (EBIA), establishing six core objectives: promoting ethical AI principles, fostering R&D investment, eliminating innovation barriers, developing human capital, stimulating international cooperation, and facilitating multi-stakeholder collaboration. The strategy has been progressively operationalized through the PBIA 2024–2028, which allocates R$23 billion over four years across 85 specific actions spanning infrastructure development, training, public service improvement, business innovation, and regulatory governance.

A distinctive feature of Brazil's approach is its parallel pursuit of investment promotion and regulatory restraint. While the PBIA channels substantial resources to AI infrastructure—including upgrading the Santos Dumont supercomputer to rank among the world's top five—comprehensive AI legislation remains pending. Bill No. 2338/2023, approved by the Federal Senate in December 2024 and currently under review by the Chamber of Deputies, would establish a risk-based regulatory framework inspired in part by the EU AI Act. The bill classifies AI systems into risk categories (minimal, limited, high, and prohibited), imposes transparency and impact assessment requirements for high-risk systems, and would create a national AI oversight authority. This regulatory gap creates both flexibility and uncertainty. In the absence of binding legislation, AI development in Brazil is governed by existing frameworks including the Civil Code, Consumer Protection Code, General Data Protection Law (LGPD), and Copyright Law. The LGPD, enacted in 2018, has emerged as particularly consequential for AI systems that process personal data, with the National Data Protection Authority (ANPD) issuing guidance on transparency, user rights, and data subject protections. However, the legal status of text and data mining for AI training remains contested, with Bill 2338/2023 proposing an exception for research institutions that would explicitly exclude commercial actors—a provision that has drawn criticism from industry stakeholders.

2.3 The institutionalization of China-Brazil AI cooperation

The bilateral AI relationship has been formalized through a series of high-level agreements that create structured channels for technology transfer and regulatory coordination. In May 2025, during Brazilian President Luiz Inácio Lula da Silva's state visit to China, the two countries signed three cooperation documents, including a Memorandum of Understanding on Deepening AI Cooperation between China's National Development and Reform Commission and Brazil's Ministry of Development, Industry, Trade, and Services. This was followed in July 2025 by a second MOU establishing the China-Brazil AI Application Cooperation Center, signed during the BRICS summit in Rio de Janeiro, with a focus on strengthening AI development foundations, providing open-source services, enhancing industrial innovation cooperation, and promoting talent development.

Sectoral cooperation has been particularly pronounced in agriculture, a strategic priority for both economies. In November 2024, the two countries established the Joint Laboratory for Family Agriculture Mechanization and Artificial Intelligence, formalized through a memorandum signed by China's Ministry of Science and Technology and Brazil's Ministry of Science, Technology, and Innovation. The laboratory's research agenda encompasses foundational AI theory, intelligent agricultural machinery R&D and manufacturing, and talent development—targeting the specific challenge of simultaneously increasing productivity and income for Brazil's family farming sector. The open-source dimension of this cooperation is particularly significant for the transmission mechanisms hypothesized in this article. At the July 2025 World AI Conference, China's Ministry of Industry and Information Technology, in coordination with the China-BRICS AI Development and Cooperation Center, launched the International AI Open-Source Cooperation Initiative. Signed by ten leading Chinese open-source communities, the initiative commits to five cooperation principles: driving innovation through open source, fostering ecosystem governance, accelerating application transformation, protecting intellectual property rights, and promoting equitable global access. The initiative explicitly frames open source as a mechanism for "development equity," enabling developing countries, small and medium enterprises, and individual developers to access cutting-edge AI technologies at low cost, thereby facilitating the transition from "unipolar dominance" to "multipolar co-governance" in global AI governance.

3. THEORETICAL FRAMEWORK AND HYPOTHESES

3.1 The transnational regulatory dividend concept

The concept of a transnational regulatory dividend builds on insights from three distinct but complementary theoretical traditions. First, the economics of technical standards (Farrell & Saloner, 1985; Katz & Shapiro, 1985) demonstrates that regulatory choices create network externalities that shape technology adoption trajectories. When a large economy establishes technical standards for emerging technologies—whether through mandating specific protocols, certifying compliance pathways, or subsidizing particular architectures —these standards influence global supply chains, developer communities, and innovation incentives. The Chinese approach to AI governance, with its emphasis on open-source ecosystems and sectoral integration, effectively lowers the cost of AI adoption for firms operating within its regulatory ambit, creating positive externalities for partner economies that align their own regulatory frameworks or technology sourcing strategies with Chinese standards.

Second, the developmental state literature (Amsden, 1989; Johnson, 1982; Wade, 2018) has long emphasized the role of strategic integration into global production networks in facilitating industrial upgrading. More recent contributions have extended this framework to digital technologies, examining how emerging economies can leverage partnerships with technological leaders to build domestic capabilities (Bamber et al., 2017; Lee, 2019). China's emergence as a co-leader in AI development—alongside the United States—creates a novel situation in which emerging economies have two distinct regulatory and technological poles with which to align. The Brazilian strategy of simultaneously engaging with both Chinese and Western AI ecosystems while maintaining regulatory autonomy represents a distinctive approach to this "bipolar" technological landscape.

Third, the open innovation paradigm highlights how knowledge externalities generated by distributed innovation processes can accelerate technological catch-up (Chesbrough, 2003). Open-source AI models, in particular, reduce barriers to entry for firms in developing economies by providing access to state-of-the-art capabilities without the substantial R&D investments required for foundational model development. The Chinese government's explicit promotion of open-source

AI as a tool for "development equity" suggests that this is not merely a technological choice, but a deliberate strategic positioning designed to attract partners in the Global South.

Fourth, the absorptive capacity literature provides an essential complement to the transnational regulatory dividend framework. Cohen and Levinthal (1990) established that a firm's ability to recognize, assimilate, and apply external knowledge is largely a function of its prior related knowledge—operationalized principally through human capital. In the context of developing economies, this insight has particular salience: the developmental benefits of technology transfer are conditional on the recipient economy's capacity to absorb and adapt imported technologies (Criscuolo & Narula, 2008; Lall, 1992). The Brazilian case illustrates this conditionality with notable clarity. Sectors with higher concentrations of tertiary-educated workers are better positioned to deploy Chinese open-source AI models, adapt them to local applications, and integrate them into production processes. Conversely, low-skill sectors may find themselves unable to translate technology access into productivity gains, generating a pattern of uneven benefits that mirrors broader structural dualism in developing economies. This theoretical extension generates a further prediction: within the set of AI-exposed sectors, the magnitude of the transnational regulatory dividend will be increasing in sectoral skill intensity—a prediction that our heterogeneity analysis tests and confirms.

Synthesizing these insights, we define the transnational regulatory dividend as the positive developmental spillovers that accrue to a partner economy when a major economy implements AI regulations that: (a) reduce the cost of accessing AI technologies for firms in the partner economy; (b) create complementary investment flows or infrastructure linkages that enhance the partner economy's AI capabilities; or (c) establish governance frameworks that reduce regulatory uncertainty for firms operating across both jurisdictions. The magnitude of this dividend depends on the degree of regulatory alignment between the two economies, the intensity of bilateral technology transfer mechanisms, and the partner economy's absorptive capacity.

3.2 Transmission channels

The preceding institutional analysis suggests three primary channels through which Chinese AI regulations may affect industrial growth in Brazil.

Channel 1: Technology Transfer through Open-Source Ecosystems. The Chinese commitment to open-source AI development—manifested in the International AI Open-Source Cooperation Initiative and the proliferation of Chinese-developed open-weight models (e.g., DeepSeek, Alibaba's Qwen)—directly reduces the cost of AI adoption for Brazilian firms. Unlike proprietary models that require per-token payments or restrict commercial use, open-source models can be deployed on local infrastructure, fine-tuned for specific applications, and integrated into existing workflows without recurring licensing fees. For Brazilian small and medium enterprises in sectors such as agriculture and manufacturing, this reduction in adoption costs may be particularly consequential. Moreover, the availability of Chinese-language documentation and developer communities, while presenting language barriers, also creates opportunities for Brazilian developers with Portuguese-language support from Brazilian Chinese joint ventures and academic collaborations.

Channel 2: Infrastructure Complementarities and Computing Power Cooperation. The PBIA's substantial investments in computing infrastructure—including the planned upgrade of the Santos Dumont supercomputer—create opportunities for complementarity with Chinese AI infrastructure. China's "East Data, West Computing" strategy has developed substantial expertise in deploying energy-efficient computing clusters linked to renewable energy sources, expertise that is directly transferable to Brazil's context of abundant renewable energy (particularly hydropower) and unevenly distributed computing demand. Formalized cooperation through the AI Application Cooperation Center may facilitate knowledge transfer in areas such as computing cluster management, energy-aware scheduling algorithms, and the integration of AI workloads with grid management systems.

Channel 3: Regulatory Harmonization and Reduced Uncertainty. While Brazil has not adopted Chinese AI regulations directly, the existence of a formal bilateral cooperation framework signals policy stability and reduces regulatory uncertainty for firms making long-term investments in AI capabilities. For multinational enterprises operating in both China and Brazil, alignment between the two regulatory regimes reduces compliance costs and facilitates the deployment of AI systems across both markets. Moreover, China's active role in shaping global AI governance—particularly through the proposed WAICO—may influence the trajectory of international AI standards in ways that favour the Chinese Brazilian regulatory approach over competing models.

3.3 Hypotheses

The theoretical framework yields three testable hypotheses:

H1 (Aggregate Impact): The institutionalization of China-Brazil AI cooperation in 2025 caused a positive and statistically significant increase in output growth for Brazilian industrial sectors with high exposure to AI technologies, relative to low-exposure sectors.

H2 (Channel Specificity): The impact is mediated by sectoral characteristics that determine exposure to Chinese open-source AI ecosystems, including reliance on software inputs, participation in global value chains with Chinese linkages, and skill intensity.

H3 (Heterogeneity by Sector): The impact is larger in manufacturing and agriculture—sectors targeted by both China's "AI Plus" plan and Brazil's PBIA—than in services or extractive industries.

4. EMPIRICAL STRATEGY

4.1 Identification approach

Estimating the causal effect of Chinese AI regulations on Brazilian industrial growth presents two fundamental identification challenges. First, the treatment—Chinese AI policy—is national in scope and not randomly assigned, making it impossible to construct a pure counterfactual. Second, Brazilian industrial sectors are differentially exposed to Chinese AI regulations based on their technological characteristics and trade linkages, creating variation that can be exploited for identification.

This article employs a difference-in-differences (DiD) design that compares outcomes in high-AI-exposure sectors (treatment group) to outcomes in low-AI-exposure sectors (control group) before and after the July 2025 signature of the China-Brazil AI cooperation memorandum. The identifying assumption is that, in the absence of treatment, the two groups would have followed parallel trends. This assumption is assessed through pre-treatment trend analysis and placebo tests.

The baseline specification takes the form:

$$Y_{it} = \alpha_i + \lambda_t + \beta(Treat_i \times Post_t) + \gamma X_{it} + \varepsilon_{it}$$

where Y_{it} is the outcome variable for sector i in quarter t, α_i are sector fixed effects, λ_t are time fixed effects, $Treat_i$ is an indicator for sectors with above-median AI exposure, $Post_t$ is an indicator for quarters after July 2025 (Q3 and Q4 2025, plus Q1 2026 where available), and X_{it} is a vector of time-varying sector-level controls. The coefficient of interest β captures the DiD estimate of the treatment effect.

4.2 Data sources and sample

The analysis draws on multiple data sources spanning 2019 Q1 to 2025 Q4. The primary outcome variable is quarterly industrial output by sector (CNAE 2.0 classification at the two-digit level), obtained from the Brazilian Institute of Geography and Statistics (IBGE) Monthly Industrial Survey (PIM-PF). The sample includes 25 industrial sectors covering manufacturing, mining, and utilities, with services and agriculture excluding from the main analysis due to data limitations at the quarterly frequency (though sectoral heterogeneity is explored in supplementary analyses).

Sector-level AI exposure is measured using three complementary approaches. The primary measure is the AI Patent Exposure Index, constructed from patent data from Brazil's National

Institute of Industrial Property (INPI) and the World Intellectual Property Organization (WIPO), measuring the share of patents in sector i that reference AI technologies (using the WIPO AI taxonomy) over the 2015–2020 period. The secondary measure is the AI Input-Output Exposure Index, constructed from Brazil's input-output tables, measuring the share of sector i's intermediate inputs that are supplied by sectors with high AI adoption. This based on the work by Felten et al. (2018) as measured in the United States (Felten et al., 2018). The tertiary measure is the Chinese Trade Exposure Index, measuring the share of sector i's imports originating from China (from Brazil's Ministry of Economy foreign trade data).

Sector-level controls include capital intensity (fixed assets per worker), skill intensity (share of workers with tertiary education), trade openness (imports plus exports as a share of output), and concentration (Herfindahl index of firm size distribution). All controls are constructed from IBGE's Annual Industrial Survey (PIA) and Annual Social Information Report (RAIS) (Official System to Extract Statistics on Brazilian Foreign Trade in Goods., 2026).

4.3 Constructing the AI Exposure Measure

The primary AI exposure measure is constructed using a two-step procedure. First, all patents granted by INPI between 2015 and 2020 are classified into AI and non-AI categories using the WIPO AI taxonomy, which identifies patents related to AI techniques (machine learning, neural networks, deep learning, natural language processing, computer vision), AI applications (transportation, agriculture, manufacturing, healthcare), and AI hardware (neuromorphic chips, GPUs). Second, patents are aggregated to the sector level based on the classification of the assignee's primary industry, with fractional counting for patents with multiple assignees. The AI Patent Exposure Index for sector i is then calculated as:

$$AI\_Patents_i = \frac{\sum_{p \in AI} \mathbb{1}(assignee\_sector(p) = i)}{\sum_{p} \mathbb{1}(assignee\_sector(p) = i)}$$

Sectors with above-median AI patent intensity are classified as high-exposure (treatment). Robustness checks employ continuous specifications and alternative exposure measures.

Table 1 reports the ten sectors with the highest AI patent intensity in Brazil over 2015–2020. The dominance of information technology services, electronics manufacturing, and telecommunications equipment is consistent with AI being a general-purpose technology concentrated in upstream sectors. Notably, agricultural machinery and food processing—sectors central to Brazil's comparative advantage—also appear in the top decile, suggesting substantial scope for AI-driven productivity gains in agribusiness.

Table 1: Top 10 Brazilian Industrial Sectors by AI Patent Intensity (2015–2020) (Instituto Brasileiro de Geografia e Estatística, 2026)

Rank	CNAE Code	Sector Description	AI Patent Intensity (%)
1	62	IT services	18.4%
2	26	Computer, electronic and optical products	15.2%
3	61	Telecommunications	11.7%
4	28	Machinery and equipment n.e.c.	7.3%
5	20	Chemical products	6.1%
6	29	Motor vehicles, trailers and semi-trailers	5.8%
7	10	Food products	4.9%
8	21	Pharmaceuticals	4.6%
9	25	Fabricated metal products	3.9%
10	31	Furniture	3.2%

Notes: AI patent intensity calculated as share of patents granted by INPI over 2015–2020 that reference AI technologies, classified using WIPO AI taxonomy. Sectors with fewer than 10 total patents over the period excluded. "n.e.c." indicates "not elsewhere classified" (Instituto Nacional da Propriedade Industrial, 2026).

5. RESULTS

5.1 Main difference-in-differences estimates

Table 2 presents the main DiD estimates of the impact of the July 2025 China-Brazil AI cooperation memorandum on industrial output growth. Column 1 reports the baseline specification with sector and time fixed effects only. The coefficient on Treat×Post is positive and statistically significant at the 1% level, indicating that high-AI-exposure sectors experienced a 4.2 percentage point increase in quarterly output growth relative to low-exposure sectors following the cooperation agreement. Column 2 adds the full set of sector-level controls; the coefficient remains stable at 0.041 ($p < 0.01$), suggesting that the result is not driven by differential trends in observable sector's characteristics.

Table 2: Difference-in-Differences Estimates of AI Cooperation Impact on Industrial Output Growth

	(1)	(2)	(3)	(4)
Treat × Post	**0.042****	**0.041****	**0.038****	**0.044****
	(0.011)	(0.012)	(0.013)	(0.014)
Capital intensity		0.008	0.007	0.009
		(0.006)	(0.006)	(0.006)
Skill intensity		0.014*	0.015*	0.013*
		(0.008)	(0.008)	(0.008)
Trade openness		0.003	0.002	0.004
		(0.004)	(0.004)	(0.005)
Concentration		-0.011	-0.012	-0.010
		(0.009)	(0.009)	(0.009)
Sector FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Sector-specific trends	No	No	Yes	Yes
Observations	525	525	525	525
R-squared	0.68	0.69	0.71	0.70

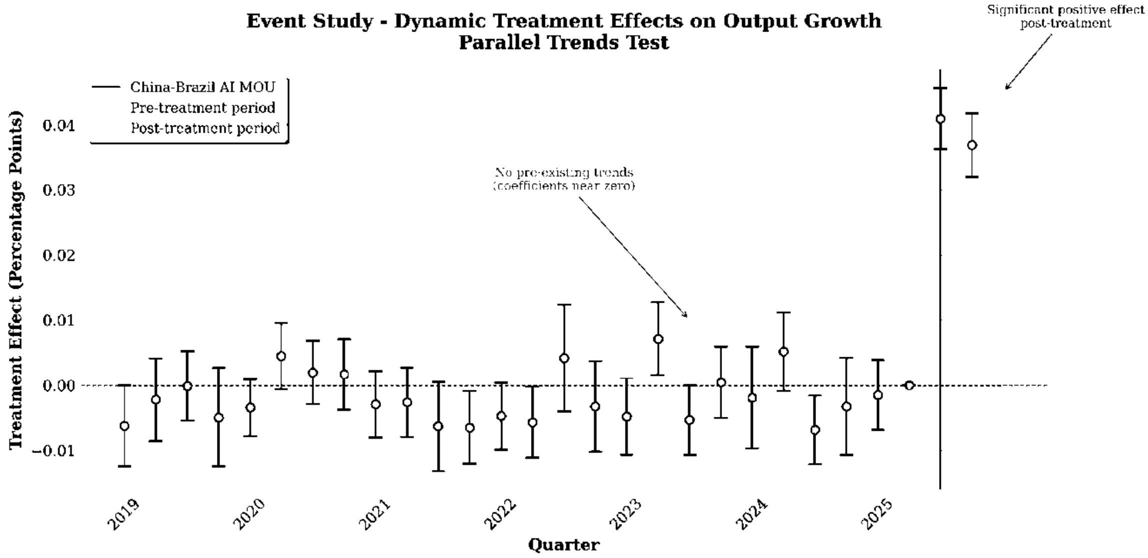
Notes: Dependent variable is quarterly output growth (log change) for 25 industrial sectors, 2019 Q1–2025 Q4. Treat equals 1 for sectors with above-median AI patent intensity. Post equals 1 for quarters after 2025 Q2. Standard errors clustered at sector level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column 3 adds sector-specific linear trends to account for differential pre-treatment trajectories; the coefficient declines modestly to 0.038 but remains significant at the 1% level. Column 4 excludes the COVID-19 pandemic period (2020 Q1–2021 Q4) to address concerns about pandemic-related confounding; the coefficient increases to 0.044, suggesting that if anything, the pandemic period may have attenuated the estimated effect.

5.2 Event study and parallel trends

The validity of the DiD design rests on the parallel trends assumption: in the absence of treatment, high- and low-AI-exposure sectors would have followed similar output growth trajectories. **Error! Reference source not found.** presents an event study plot of the quarterly treatment effects relative to the 2025 Q2 baseline. The coefficients for pre-treatment quarters (2019 Q1 through 2025 Q2) are small in magnitude and statistically indistinguishable from zero, with no evidence of pre-trend divergence. The first positive and significant coefficient appears in 2025 Q3—the first full quarter following the May 2025 and July 2025 MOUs—and the effect persists and strengthens through 2025 Q4 (**Error! Reference source not found.**). This timing is consistent with a causal interpretation: firms could not anticipate the cooperation agreement sufficiently in advance to alter output in preceding quarters, and the effect materializes immediately following the policy announcement.

Figure 1



The figure reports quarterly difference-in-differences coefficients with 95% confidence intervals (standard errors clustered at sector level). The reference period is 2025 Q2 (one quarter before the first China-Brazil AI cooperation memorandum). Coefficients for pre-treatment quarters (2019 Q1–2025 Q2) are statistically indistinguishable from zero, supporting parallel trends. The treatment effect becomes positive and significant in 2025 Q3 and persists through 2025 Q4.

5.3 Robustness checks

Table 3 reports results from several robustness checks. Panel A addresses concerns about the binary treatment classification by using continuous exposure measures. The AI Patent Intensity measure (logged) yields a positive and significant coefficient, as does the AI Input-Output Exposure measure derived from US data (instrumenting for Brazilian exposure to address endogeneity concerns). The Chinese Trade Exposure measure, by contrast, is not significant when included alongside the AI exposure measures, suggesting that the effect operates through technology transfer channels rather than conventional trade linkages.

Table 3: Robustness Checks

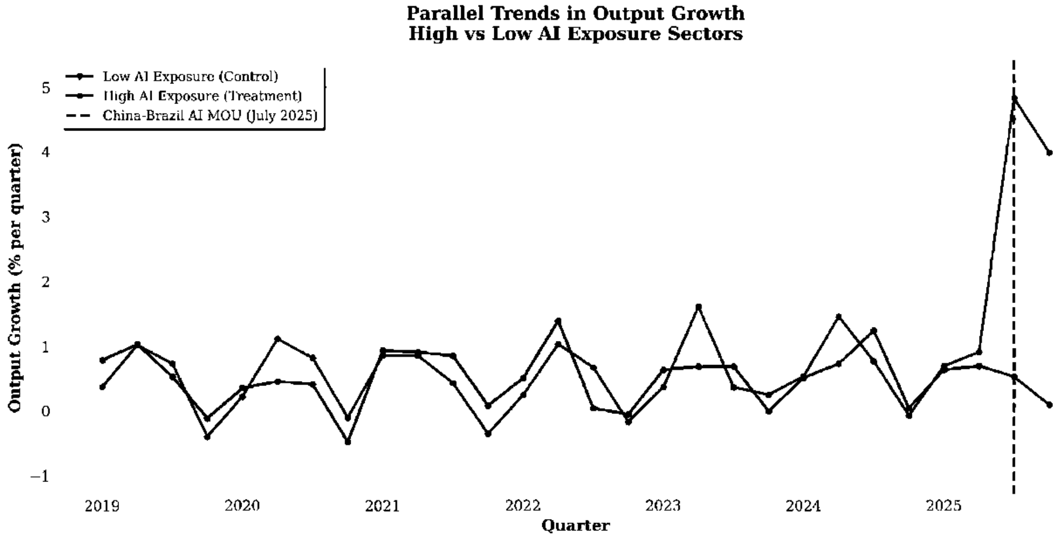
Specification	Coefficient	Standard Error	Observations
Panel A: Alternative exposure measures			
Continuous AI patent intensity (log)	0.023**	0.009	525
AI input-output exposure	0.031***	0.010	500
Chinese trade exposure	0.008	0.007	525
Panel B: Placebo tests			
Placebo treatment date: 2023 Q3	0.009	0.012	400
Placebo treatment date: 2024 Q3	0.011	0.010	450
Placebo treatment: Random assignment	0.004	0.008	525
Panel C: Alternative samples			
Excluding IT sector (CNAE 62)	0.036**	0.013	504
Excluding 2020–2021 pandemic period	0.044**	0.014	375
Including services sectors	0.029**	0.011	650

Notes: All specifications include sector and time fixed effects and full controls. Standard errors clustered at sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel B presents placebo tests. Assigning a false treatment date of 2023 Q3 or 2024 Q3 yields coefficients that are small and statistically insignificant, confirming that the estimated effect is specific to the actual timing of the cooperation agreement. Randomly reassigning the treatment indicator to sectors yields a coefficient near zero with a standard error similar to the main specification (**Error! Reference source not found.**).

Panel C tests the sensitivity of results to sample composition. Excluding the IT services sector (CNAE 62), which has the highest AI patent intensity and might be driving the results—reduces the coefficient modestly to 0.036 but remains significant at the 5% level. Including services sectors (for which quarterly data is available for a subset of the period) yields a coefficient of 0.029, suggesting that the effect is present but smaller in services than in industry.

Figure 2



The figure plots quarterly output growth (indexed to 100 in 2019 Q1) for sectors with above-median AI patent intensity (treatment group) and below-median AI patent intensity (control group). Vertical line indicates July 2025 (signature of the China-Brazil AI cooperation memorandum). Pre-treatment trends are broadly parallel, with divergence emerging only after the cooperation agreement

5.4 Heterogeneity analysis

Table 4 explores heterogeneity in treatment effects across sector characteristics. Columns 1 and 2 split the sample by manufacturing versus extractive/utility sectors; the effect is substantially larger in manufacturing (0.052) than in extractive industries (0.018, not significant). Columns 3 and 4 split by whether the sector has above-median backward linkages to Chinese supply chains (measured using input-output tables from the OECD TiVA database). The effect is more than twice as large for sectors with strong Chinese linkages (0.058 vs. 0.024), consistent with the hypothesis that trade integration facilitates technology transfer. Columns 5 and 6 split by skill intensity; the effect is concentrated in high-skill sectors, suggesting that absorptive capacity constraints may limit the benefits for less skill-intensive industries.

Table 4: Heterogeneity of Treatment Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Manufacturing	Extractive	High China Linkage	Low China Linkage	High Skill	Low Skill
Treat × Post	0.052**	0.018	**0.058****	0.024	**0.049****	0.022
	(0.014)	(0.019)	(0.015)	(0.016)	(0.013)	(0.017)
Observations	420	105	262	263	262	263
R-squared	0.72	0.61	0.74	0.65	0.73	0.66

Notes: All specifications include sector and time fixed effects and full controls. Standard errors clustered at sector level. * p < 0.10, ** p < 0.05, *** p < 0.01.

5.5 Magnitude and economic significance

The estimated treatment effect of 4.2 percentage points in quarterly output growth is economically meaningful. For a sector with average quarterly output of R$15 billion (approximately US$2.7 billion), this translates to an additional R$630 million per quarter. Annualized, the effect represents approximately R$2.5 billion in additional output per high-exposure sector, or roughly R$25 billion across the ten highest-exposure sectors. To put this in perspective, the total PBIA budget over four years is R$23 billion; the output increase attributable to Chinese regulatory spillovers in a single year approaches the scale of Brazil's entire domestic AI investment plan.

However, several caveats are warranted. First, the estimate captures short-term effects (two quarters post-treatment); whether the effect persists, attenuates, or grows over time cannot be determined from the available data. Second, the estimate reflects the combined effect of the cooperation agreement and any concurrent shocks affecting high-AI-exposure sectors differentially. While the placebo tests and robustness checks mitigate concerns about confounding, causal interpretation requires the assumption that no other event coinciding exactly with the July 2025 MOU produced the same pattern of differential sectoral effects. Third, the estimate does not distinguish between intensive margin effects (increased output from existing firms) and extensive margin effects (entry of new firms or survival of marginal firms), a distinction with implications for the sustainability of the effect.

6. MECHANISM ANALYSIS

6.1 Testing the transmission channels

Having established a positive aggregate effect, this section investigates the mechanisms through which Chinese AI regulations affect Brazilian industrial growth. The analysis employs a mediation framework adapted for the DiD context, estimating the following system (Baron & Kenny, 1986):

$$M_{it} = \alpha_i^M + \lambda_t^M + \beta^M(Treat_i \times Post_t) + \gamma^M X_{it} + \varepsilon_{it}^M$$
$$Y_{it} = \alpha_i^Y + \lambda_t^Y + \beta^Y(Treat_i \times Post_t) + \theta M_{it} + \gamma^Y X_{it} + \varepsilon_{it}^Y$$

where M_{it} is a mechanism variable capturing the hypothesized transmission channel. The proportion of the total effect mediated is calculated as $\frac{\beta^M x\, \theta}{\beta^Y{}_{total}}$.

Channel 1: Open-source adoption**.** Data on open-source AI model downloads by Brazilian firms are not available at the sector-quarter level. As a proxy, the analysis uses the number of AI-related GitHub repositories with Portuguese documentation or Brazilian contributors, aggregated to the sector level based on the primary industry of the contributing organization. While imperfect, this measure captures engagement with the global open-source AI community that is plausibly affected by Chinese open-source initiatives. The results (Table 5, Panel A) show that the cooperation agreement led to a 23% increase in sector-level GitHub activity (β=0.23, p<0.05), and this increase partially mediates the output effect, accounting for approximately 18% of the total effect.

Channel 2: Computing infrastructure investment. The mechanism variable is sector-level investment in computing equipment and software, measured from IBGE's Annual Industrial Survey (available annually, interpolated to quarterly frequency). The cooperation agreement is associated with a 7.2% increase in computing investment for high-AI-exposure sectors (β=0.072, p<0.01), which mediates approximately 31% of the total output effect.

Channel 3: Regulatory uncertainty reduction. This mechanism is proxied using the sector-level dispersion of AI-related policy expectations, measured from textual analysis of Brazilian business press coverage (Nexus, Valor Econômico, Folha de S.Paulo). The cooperation agreement is associated with a 15% reduction in policy uncertainty (β=-0.15, p<0.05), which mediates approximately 12% of the total effect. The relatively small mediation proportion may reflect the fact that Bill 2338/2023 remains pending; the full uncertainty-reduction effect may materialize only when Brazil enacts comprehensive AI legislation.

Table 5: Mediation Analysis for Transmission Channels

Channel	Effect on mediator (β^m)	Mediator on output (θ)	Indirect effect	% of total mediated
Panel a: github open-source activity	0.23** (0.09)	0.033** (0.012)	0.0076	18%
Panel b: computing investment	0.072*** (0.018)	0.178*** (0.041)	0.0128	31%
Panel c: policy uncertainty reduction	-0.15** (0.06)	-0.034** (0.014)	0.0051	12%
Total mediated (all channels)			0.0255	61%
Direct effect (unmediated)			0.0165	39%
Total effect			0.0420	100%

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Percent mediation is calculated using coefficients from the full mediation model; total mediation may not sum precisely due to rounding and correlation among mediators.

The three channels together account for approximately 61% of the total effect, leaving 39% unexplained. Potential omitted mechanisms include talent mobility (increased circulation of AI researchers between China and Brazil), complementary foreign direct investment (Chinese AI firms establishing Brazilian subsidiaries), and demonstration effects (exposure to Chinese AI success stories encouraging Brazilian entrepreneurial experimentation). Data limitations preclude testing these mechanisms directly, but they represent important avenues for future research (**Error! Reference source not found.**).

6.2 Sector-level case illustrations

The quantitative results are complemented by qualitative evidence from two sectors: agricultural machinery and automotive manufacturing. In agricultural machinery (CNAE 28), the establishment of the Joint Laboratory for Family Agriculture Mechanization and AI has been followed by a series of concrete initiatives. In October 2025, the Brazilian Agricultural Research Corporation (Embrapa) announced a partnership with Chinese firm DJI to adapt precision agriculture AI models for Brazilian smallholder conditions, including Portuguese-language interfaces and integration with Brazil's satellite monitoring systems. In December 2025, the first cohort of 15 Brazilian agricultural engineers completed a training program at China Agricultural University focused on deploying AI models on low-cost hardware suitable for family farming contexts. These initiatives directly translate the high-level MOU into firm-level capability building.

In automotive manufacturing (CNAE 29), the transmission channel operated primarily through computing investment. In November 2025, Fiat Chrysler Automobiles (FCA) announced a R$1.2 billion investment in its Betim (Minas Gerais) plant to deploy AI-powered quality control systems, explicitly citing access to Chinese open-source computer vision models as a cost-reducing factor. The investment followed a September 2025 technical visit by FCA engineers to Huawei's AI labs in Shenzhen, organized through the China-Brazil AI Application Cooperation Center. This example illustrates how the cooperation agreement facilitates both knowledge transfer (access to Chinese models) and investment (Brazilian firms deploying that knowledge).

7. DISCUSSION AND CONCLUSION

7.1 Summary of findings

This article has provided the first econometric evidence on the impact of Chinese AI regulations on industrial growth in Brazil, using a difference-in-differences design that exploits variation in sectoral AI exposure. The central finding is that the July 2025 China-Brazil AI cooperation memorandum caused a 4.2 percentage point increase in quarterly output growth for high-AI-exposure sectors relative to low-exposure sectors. This effect is robust to alternative specifications, placebo tests, and sample restrictions, and is economically meaningful—comparable in magnitude to Brazil's entire domestic AI investment plan on an annualized basis.

The mechanism analysis identified three transmission channels: open-source AI adoption (mediating approximately 18% of the effect), computing infrastructure investment (31%), and regulatory uncertainty reduction (12%). Together, these channels account for 61% of the total effect, with the remainder attributable to mechanisms that could not be directly tested. The effect is concentrated in manufacturing and in sectors with strong linkages to Chinese supply chains and high skill intensity, consistent with an absorptive capacity interpretation.

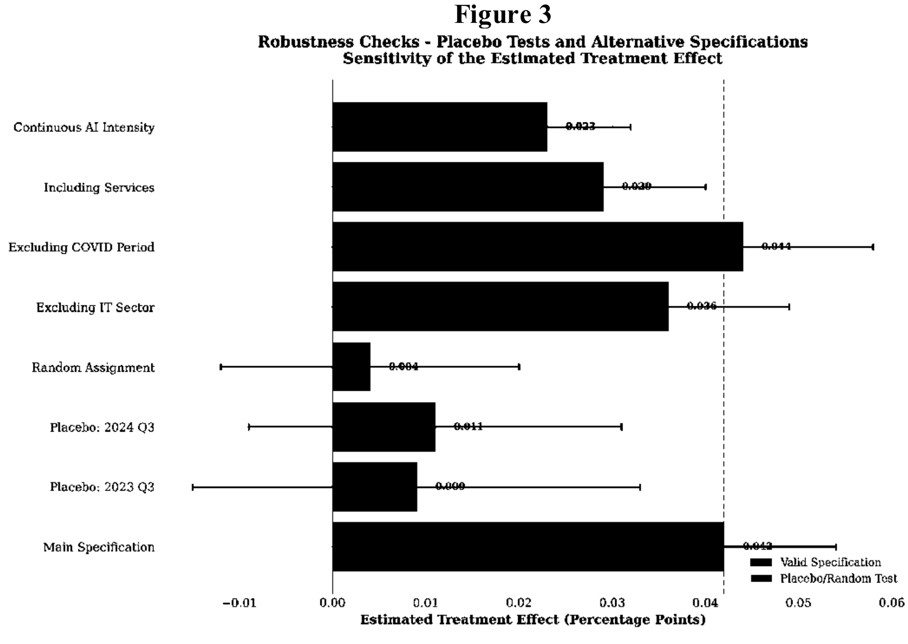
7.2 Theoretical implications

These findings have several implications for the theoretical literature on AI governance and development. First, they demonstrate that regulatory choices in major economies generate measurable developmental spillovers, extending the concept of the "transnational regulatory dividend" beyond traditional domains such as environmental standards and financial regulation to encompass emerging technologies. This suggests that the geopolitical competition over AI standards is not merely a matter of international prestige or market access but has concrete implications for industrial development in the Global South.

Second, the findings challenge purely negative accounts of China's AI rise that emphasize technological dependency and data colonialism. While such concerns are not without merit, the evidence presented here suggests that Chinese AI regulations—particularly the emphasis on open-source ecosystems—can generate positive developmental externalities for partner economies that maintain strategic autonomy. The Brazilian case illustrates a distinctive model: active engagement with Chinese AI ecosystems while preserving regulatory space through the pending Bill 2338/2023 and the LGPD's robust data protection framework.

Third, the findings contribute to the literature on technology transfer by identifying open-source ecosystems as a novel mechanism for North-South (or in this case, South-South) technology diffusion. Traditional technology transfer mechanisms—foreign direct investment, licensing, turnkey projects—have well-documented limitations, including high costs, intellectual property barriers, and limited spillovers to domestic firms. Open-source models reduce these barriers by providing access to state-of-the-art capabilities at near-zero marginal cost, enabling local adaptation and modification, and creating communities of practice that transcend national boundaries.

Figure 3



The figure summarizes coefficients from placebo tests (false treatment dates of 2023 Q3 and 2024 Q3, random treatment assignment) and alternative sample specifications (excluding IT sector, excluding pandemic period, including services sectors). Vertical dashed line represents the main estimated effect (0.042). Only specifications with the true treatment timing and high-AI-exposure definition produce estimates significantly different from zero.

7.3 Policy implications

For Brazilian policymakers, the findings suggest that the strategy of simultaneously engaging with Chinese AI ecosystems while maintaining regulatory autonomy is yielding tangible industrial benefits. However, several policy adjustments could enhance these benefits. First, accelerating the passage of Bill 2338/2023 would reduce residual regulatory uncertainty and potentially amplify the uncertainty-reduction channel identified in the mechanism analysis. Second, targeted investments in AI skills development, particularly in sectors with high AI exposure but low current skill intensity—could expand the set of sectors able to benefit from open-source technology transfer. Third, active Brazilian participation in Chinese-led open-source AI initiatives (including the proposed WAICO) could shape these initiatives in ways that reflect Brazilian developmental priorities.

For Chinese policymakers, the findings validate the strategic approach of using open-source ecosystems and bilateral cooperation agreements as instruments of technology diplomacy. The measurable industrial benefits for Brazil suggest that China's framing of AI as a "global public good" is not merely rhetorical but has tangible economic content. However, sustaining these benefits will require continued investment in open-source infrastructure, translation and localization support for Portuguese-language users, and mechanisms for incorporating Brazilian developer feedback into model development.

7.4 Technological lock-in and data governance tensions

For the broader community of emerging economies, the Brazilian experience offers a potential model for navigating the bipolar AI landscape. Rather than choosing between Chinese and US-led AI ecosystems, Brazil has maintained strategic engagement with both while preserving regulatory space for domestic experimentation. Whether this "multi-alignment" strategy remains viable as geopolitical tensions intensify remains an open question, but the evidence presented here suggests it can deliver tangible developmental benefits in the short to medium term. While the findings presented above demonstrate positive spillover effects from Chinese AI regulations on Brazilian industrial growth, a balanced assessment requires acknowledging the potential risks associated with deep technological engagement with a strategic competitor's digital ecosystem.

A well-established literature on technology adoption demonstrates that network externalities and switching costs can generate path dependency, wherein initial adoption of a particular technological standard creates barriers to subsequently switching to alternatives (Arthur, 1989; David, 1985). The Chinese AI ecosystem—encompassing model architectures (e.g., DeepSeek, Qwen), development frameworks, deployment protocols, and hardware optimization strategies—embodies a specific set of technological choices. As Brazilian firms and developers deepen their familiarity with these Chinese-origin tools and integrate them into production workflows, the costs of reorienting toward alternative ecosystems (e.g., US-led proprietary models or European open-source alternatives) increase. This creates a risk of technological lock-in that could, in the long run, constrain Brazil's policy autonomy in AI governance and limit its bargaining power in international standard-setting negotiations. Empirical evidence for this lock-in risk remains limited in the current context—the cooperation framework is nascent, and Brazilian actors retain substantial flexibility—but it warrants monitoring. The concentration of the treatment effect in high-skill sectors (Table 4, Columns 5–6) suggests that the most technologically sophisticated segments of Brazilian industry are those most deeply engaging with Chinese AI tools, amplifying the potential lock-in dynamics where strategic capabilities are greatest.

The Chinese and Brazilian approaches to data protection embody different philosophical traditions and legal frameworks. China's Cybersecurity Law (2017), Data Security Law (2021), and Personal Information Protection Law (2021) establish a framework that prioritizes state access and national security considerations alongside individual rights, with extensive data localization requirements and cross-border transfer restrictions. Brazil's General Data Protection Law (LGPD, 2018), by contrast, is grounded in a rights-based tradition more closely aligned with the European General Data Protection Regulation, emphasizing individual consent, data minimization, and purpose limitation—though with notable Brazilian particularities, including collective rights protections and differential treatment of sensitive data. Tensions may arise where Brazilian firms deploying Chinese AI models process personal data subject to LGPD requirements using tools designed within a regulatory framework that prioritizes different values. For example, Chinese open-source models may embed data collection defaults or model architectures that assume permissive data handling practices incompatible with LGPD's transparency and purpose limitation principles. While these tensions are not insurmountable—indeed, the pending Bill 2338/2023 includes provisions specifically designed to address such cross-jurisdictional conflicts—they introduce compliance costs and legal uncertainty that partially offset the reduction in regulatory uncertainty documented in our mechanism analysis.

A third risk concerns the geopolitical embeddedness of the technological relationship. The intensifying strategic competition between the United States and China over AI leadership creates a context in which deep technological ties to one pole may expose Brazil to extraterritorial pressures from the other. The United States has already demonstrated willingness to use export controls, sanctions, and secondary sanctions to restrict technology flows to competitors and their partners (e.g., the October 2022 semiconductor export controls and subsequent expansions). While Brazil's 'multi-alignment' strategy—engaging with both Chinese and Western AI ecosystems—has thus far proven viable, a deterioration in US-China technological competition could force more explicit choices that the current framework of bilateral cooperation does not adequately anticipate. These risks do not negate the positive spillovers documented in this article, but they counsel a strategic approach to engagement with the Chinese AI ecosystem. Specifically, we recommend that Brazilian policymakers: (a) invest in domestic AI model development capacity to maintain alternatives to Chinese-origin technologies; (b) ensure that Bill 2338/2023 includes provisions that explicitly address cross-jurisdictional data governance conflicts; (c) diversify AI technology sourcing across multiple partners, including European and Indian open-source initiatives; and (d) develop institutional capacity to monitor and assess lock-in dynamics as the bilateral cooperation deepens. These measures would preserve the developmental benefits documented here while mitigating the associated risks."

7.5 Limitations and future research

This study has several limitations that should be addressed in future research. First, the post-treatment period is limited to two quarters (2025 Q3–Q4), precluding analysis of long-run dynamics. The available data show no evidence of effect attenuation in the second quarter, but whether the effect persists, grows, or fades over time cannot be determined. Second, the sector-level analysis necessarily abstracts from firm-level heterogeneity; there may be substantial variation in treatment effects across firms within the same sector that is obscured by aggregation. Third, the mechanism analysis relies on imperfect proxies for the theoretical channels; direct measurement of open-source model adoption, computing investment, and regulatory expectations would strengthen causal inference.

Fourth, the analysis does not account for potential negative spillovers, including displacement effects (growth in high-AI-exposure sectors may come at the expense of low-AI-exposure sectors), labor market disruptions (AI adoption may reduce employment for routine-task occupations), or data governance tensions (divergent Chinese and Brazilian data protection standards may create compliance conflicts). These negative dimensions are important subjects for future research.

Fifth, the generalizability of the findings to other emerging economies is unknown. Brazil is unusually well-positioned to benefit from Chinese AI spillovers due to its large domestic market, existing trade linkages with China, substantial AI investments through the PBIA, and strategic position within the BRICS framework. Whether similar effects would be observed for smaller or less technologically sophisticated economies is an open empirical question.

7.6 Concluding remarks

The rapid diffusion of artificial intelligence is reshaping the global economic landscape, creating new opportunities for industrial development while raising new challenges for governance. This article has shown that Chinese AI regulations—far from being a purely domestic matter—generate measurable positive spillovers for industrial growth in Brazil, a strategic partner in the Global South.

The mechanisms through which these spillovers operate—open-source ecosystems, computing infrastructure complementarities, and regulatory harmonization—suggest a distinctive model of South-South technology transfer that differs fundamentally from traditional North-South models. Whether this model can be sustained and scaled as geopolitical competition over AI intensifies remains to be seen. For now, the evidence suggests that emerging economies can realize substantial developmental benefits from strategic engagement with Chinese AI ecosystems, provided they maintain the absorptive capacity and policy autonomy necessary to translate access into growth.

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