China Artificial Intelligence's Creation, Adoption, Regulation, and Global Comparative Dynamics

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Abstract

This paper develops a multi-sector, open-economy Dynamic Stochastic General Equilibrium (DSGE) model to analyze the macroeconomic implications of Artificial Intelligence (AI) in China and to compare Chinese AI dynamics with those of advanced Western economies and other emerging-market competitors. The model features three production sectors (AI research, AI-intensive goods, and traditional goods), an endogenous AI-capital accumulation block, knowledge spillovers with imperfect international diffusion, a rich regulatory friction module calibrated to China's Algorithmic Recommendation, Deep Synthesis, and Generative AI regulations, and a two-country (China–Rest-of-World) trade structure. We derive analytical results for steady-state AI capital, characterize impulse responses to an AI productivity shock, and quantify the welfare effects of alternative regulatory regimes. Estimated to 2005–2024 data, the model implies that China's state-directed investment strategy accelerates AI capital accumulation by approximately 18–22 percent relative to a laissez-faire benchmark, but that regulatory frictions in the generative-AI segment reduce total factor productivity (TFP) gains by 4–7 percent. International knowledge spillovers generate a significant "AI terms-of-trade" channel that shifts comparative advantage in AI-intensive goods toward China over a 10–15 year horizon. Theoretical and counterfactual analysis suggest that harmonized global AI governance could yield mutual welfare gains of 1.2–2.4 percent of consumption-equivalent welfare relative to the fragmented-regulation equilibrium.

JEL Codes: O33, O38, F41, E13, L86, P31.

Keywords: Artificial Intelligence, China, AI Regulation, Knowledge Spillovers, Endogenous Growth, Global Comparative Dynamics, DSGE Model.

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1 Introduction

The rapid ascent of Artificial Intelligence as a general-purpose technology (GPT) ranks among the most consequential economic developments of the early twenty-first century. Within this global transformation, China occupies a singular position: simultaneously a major producer of AI systems (through firms such as Baidu, Alibaba, Tencent, Huawei, and a new cohort of "AI unicorns" including Zhipu AI, Moonshot AI, and DeepSeek), a mass deployer of AI applications across manufacturing, logistics, finance, and public administration, and a pioneer in comprehensive AI regulation. China's *New Generation Artificial Intelligence Development Plan* (2017) set an explicit target of becoming the world's primary AI innovation centre by 2030, backed by an estimated $15 billion in direct state funding and far larger induced private investment (Lucas 1988; Bernanke et al. 1999; Aghion et al. 2018; Bloom et al. 2020; Acemoglu and Restrepo 2021; Romer and Romer 2023; Korinek and Lockwood 2026).

The creation of AI technologies in China has accelerated significantly over the past decade. China now produces more AI-related scientific publications and patents than most countries, while simultaneously expanding AI infrastructure, semiconductor production, and digital platforms. Although debates continue concerning the quality versus quantity of Chinese AI research outputs, China's increasing influence in machine learning, computer vision, robotics, and generative AI cannot be ignored. The country's innovation ecosystem benefits from large-scale government funding, university-industry collaboration, and strategic standardization initiatives aimed at shaping global technological norms (Lee et al. 2021; Ding et al. 2022; Fuller 2022; Hajkowicz et al. 2023).

Equally important is China's rapid adoption of AI technologies across multiple sectors. AI systems are increasingly integrated into healthcare, education, transportation, finance, manufacturing, public administration, urban surveillance, and e-commerce. China's large digital economy and extensive mobile payment infrastructure have facilitated the mass diffusion of AI-enabled applications. Surveys indicate that China leads globally in generative AI adoption rates, surpassing many Western economies in the integration of AI into everyday social and economic activities. The Chinese approach to AI adoption differs from many liberal market economies because of the strong coordination between state authorities, local governments, and private firms, allowing rapid experimentation and deployment at scale(Graetz and Michaels 2018; Acemoglu and Restrepo 2020; Huang and Mayer 2021; Zhao and Fan

2022; Liu et al. 2022; Chen and Lin 2023).

However, China's AI expansion has also generated substantial regulatory and ethical concerns. Chinese authorities have emerged as early movers in AI governance by introducing regulations on recommendation algorithms, deep synthesis technologies, and generative AI systems. Unlike the predominantly market-driven model of the United States or the rights-based regulatory framework of the European Union, China's AI governance model combines innovation promotion with political control, social stability, and cybersecurity priorities. Researchers characterize this approach as adaptive, incremental, and technology-specific, reflecting China's broader governance philosophy. The Chinese state simultaneously acts as regulator, investor, customer, and strategic planner in the AI sector, creating a unique governance structure where economic development and political oversight are deeply intertwined (Feldstein 2019; Qiang 2019; Creemers 2021; Roberts et al. 2021; Sheehan 2022; Bradford 2023).

Beyond domestic transformation, China's AI rise has major implications for global power relations and international governance. AI competition increasingly shapes geopolitical rivalries between China, the United States, and the European Union. The global comparative dimension of AI governance reveals that technological competition is increasingly tied to ideological and institutional differences. The United States prioritizes entrepreneurial innovation and private-sector leadership; the European Union emphasizes ethical safeguards and human rights protections; China combines strategic industrial policy with centralized regulatory authority. These differing approaches influence international norms concerning data governance, algorithmic transparency, digital sovereignty, and AI ethics. Consequently, understanding China's AI development requires not only a domestic analysis but also a comparative examination of how AI governance models interact and compete globally (Segal 2020; Triolo and Allison 2021).

These developments raise fundamental macroeconomic questions that standard frameworks address only partially. How does state-directed AI investment affect aggregate capital accumulation and total factor productivity relative to market-based alternatives? What are the international spillover effects when one large open economy accelerates AI adoption through directed industrial policy? How do heterogeneous regulatory regimes—China's sector-specific rule-based approach versus the European Union's risk-based AI Act versus the United States' more permissive innovation-first stance—distort AI diffusion across borders? And what are the welfare consequences

of the current fragmented global governance architecture?

We address these questions through the lens of a rigorously micro-founded open-economy DSGE model. Our model builds on the endogenous growth literature (Romer, 1990; Jones, 1995; Acemoglu and Robinson, 2012) and the DSGE literature on ICT and general-purpose technologies (Hornstein and Krusell, 1999; Gilchrist et al., 2005; Basu and Fernald, 2010), extending both strands to incorporate the distinctive features of AI as an economic input: non-rivalry in use across tasks, self-improving performance through data accumulation, complementarity with skilled labour, and susceptibility to regulatory intervention at multiple points of the production chain.

The paper makes four primary contributions. *First*, we construct and calibrate a three-sector open-economy DSGE model with endogenous AI-capital accumulation and international knowledge diffusion that is tailored to China's institutional environment. *Second*, we provide a systematic mapping of China's AI regulatory architecture—from the 2021 Algorithmic Recommendation Provisions through the 2022 Deep Synthesis Regulations to the 2023 Generative AI Measures—into quantitative regulatory friction parameters. *Third*, we derive analytical steady-state results and characterise impulse responses to AI productivity, regulatory, and international technology-transfer shocks. *Fourth*, we conduct counterfactual experiments comparing China's industrial-policy approach with alternative governance models and quantify the global welfare implications of regulatory harmonisation.

Our main findings are as follows. *First*, China's state-directed AI investment strategy generates a net welfare gain relative to a laissez-faire benchmark, primarily because AI R&D is characterised by positive externalities that the market undersupplies. The estimated net welfare gain is approximately 2.1 percent of consumption-equivalent welfare from the subsidy component alone, though partially offset by associated distortions. *Second*, China's comprehensive AI regulatory framework imposes meaningful costs on AI capital accumulation (approximately 6 percent steady-state reduction) and TFP (approximately 4–5 percent in the AI-Intensive sector). These costs are partially but not fully offset by the risk-reduction benefits of regulation, yielding a net welfare cost of approximately 0.3–0.6 percent of consumption-equivalent welfare from the current regulatory regime. *Third*, semiconductor export controls represent the single largest welfare-reducing channel in our framework (-0.95 percent), with effects that compound over time as China is unable to access the frontier hardware required for the most computationally intensive AI

training runs. *Fourth*, the fragmented global AI governance landscape generates significant deadweight losses that could, in principle, be eliminated through regulatory harmonisation. We estimate global welfare gains of 1.2–2.4 percent from harmonisation, with China capturing a disproportionate share (approximately 65 percent) of the total gains given its higher current regulatory compliance burden. *Fifth*, and perhaps most importantly, the model reveals a fundamental tension in China's AI strategy: the twin goals of becoming the world's primary AI innovation centre and maintaining comprehensive regulatory control over AI systems are, in the medium run, in partial conflict. The regulatory arbitrage and export control channels suggest that China's 2030 AI leadership target is achievable only under the most optimistic scenarios for domestic chip development and regulatory liberalisation. *Sixth*, Bayesian model comparison decisively favours the full three-regulation specification ($\ln B > 5$ against all alternatives). The GenAI Measures and international knowledge diffusion channels show the strongest empirical identification. *Seventh*, the 2022–2023 period shows a distinctive pattern: combined regulatory uncertainty and semiconductor export controls imposed an estimated -4.2 percentage-point cumulative drag on China's AI capital deviation from steady state, partially offsetting continued AI productivity gains.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 presents stylised facts on AI in China and comparative international data. Section 4 develops the full DSGE model. Section 5 discusses calibration. Section 6 presents theoretical results. Section 7 conducts counterfactual analysis. Sector 8 showcases forecast error variance and historical shock decomposition. Section 9 analyses regulatory experiments. Section 10 examines the two-country open-economy dynamics. Section 11.3 quantifies welfare. Section 12 conducts various estimations of the model. Section 13 examines Bayesian model comparison. Section 14 presents full Bayesian scenario analysis. Section 15 performs variance decomposition. Section 16 undertakes Robustness check and presents extensions of the model. Section 17 concludes.

2 Literature Review

2.1 AI as a General-Purpose Technology

Macroeconomic discussions of technological innovation originate in classical political economy and neoclassical growth theory. Adam Smith (1776) emphasized specialization, division of labor, and technological improvement as fundamental drivers of productivity growth and national wealth. David Ricardo (1817) later linked technological advancement to capital accumulation and comparative advantage within international trade. The Solow Growth Model argued that long-term economic growth depends primarily on technological progress rather than capital accumulation alone (Solow 1956).

The neoclassical framework provides an important foundation for understanding how AI contributes to macroeconomic growth through automation, optimization, and productivity enhancement. In China's case, AI adoption is closely tied to efforts to sustain economic growth amid slowing demographic expansion, rising labor costs, and declining marginal returns from traditional industrialization.

Nonetheless, critics argue that neoclassical models insufficiently explain the institutional and political dimensions of technological development. China's AI strategy cannot be fully understood through purely market-based growth mechanisms because the Chinese state plays a central coordinating role in innovation policy, industrial financing, and strategic planning.

The characterisation of AI as a general-purpose technology follows Bresnahan and Trajtenberg (1995), who define GPTs by three features: pervasiveness across sectors, improvement over time, and the generation of complementary innovations. Brynjolfsson and McAfee (2018) argue that AI satisfies all three criteria and liken its macroeconomic impact to the introduction of electrification. Aghion et al. (2018) model AI within an endogenous growth framework and show that, if AI can replace human labour in the production of ideas, it may generate explosive growth; we follow their general approach but impose the discipline of DSGE microfoundations and calibrate the model to China-specific data.

Acemoglu and Restrepo (2021) develop a framework of tasks and automation to analyse the labour market consequences of AI, showing that automation need not raise aggregate productivity if it displaces labour in tasks where humans have comparative advantage. Our model incorporates a version of their task-based structure

within the production sector, allowing us to capture the skill-complementarity channel that is particularly salient in China's dual economy.

2.2 DSGE Models with Technology Shocks and Endogenous Growth

Endogenous growth theory emerged in response to the limitations of exogenous technological models. Scholars such as Paul Romer (1986, 1990) and Robert Lucas (1988) argued that technological innovation results from intentional investments in knowledge, research, education, and human capital.

China's AI strategy reflects many assumptions of endogenous growth theory. Massive public investments in STEM education, semiconductor manufacturing, cloud infrastructure, and AI research institutions aim to generate long-term productivity gains and technological self- sufficiency. Government-led initiatives such as the "New Generation Artificial Intelligence Development Plan" demonstrate the belief that sustained innovation can permanently increase economic growth rates. Endogenous growth theory also helps explain why China prioritizes AI as a strategic industry. AI is viewed as a "general-purpose technology" capable of generating spillover effects across manufacturing, finance, transportation, defense, healthcare, and public administration. Scholars argue that AI-driven innovation may initiate a new technological paradigm comparable to electricity or the internet (Brynjolfsson and McAfee, 2014). However, critics caution that endogenous growth models often underestimate political constraints, institutional inefficiencies, and uneven innovation outcomes. In China, state-led investment may generate inefficiencies, overcapacity, or resource misallocation despite substantial technological progress.

The integration of endogenous growth mechanisms into DSGE models has a long tradition (Kung and Ma, 2014; Caldara et al., 2012; Comin and Gertler, 2006). Kung and Ma (2014) show that long-run growth risks generated by R&D investment can account for a significant portion of asset pricing puzzles; we adapt their multi-sector structure to the AI context. Comin and Gertler (2006) model technology diffusion as a two-stage process (invention and adoption) and find that adoption lags explain cross-country productivity differences; our model incorporates an analogous diffusion lag calibrated to Chinese AI adoption data.

Open-economy DSGE models with technology heterogeneity include Backus et al. (1992) (the canonical international real business cycle framework), Galí and Monacelli (1999) (the open-economy New-Keynesian benchmark), and Mandelman and Zlate (2010) (technology shocks and the terms of trade). We build on this litera-

ture by introducing an AI-specific terms-of-trade channel reflecting China's growing export share in AI-intensive goods.

2.3 China's Macroeconomic and Innovation Policy

Joseph Schumpeter's theory of innovation provides one of the most influential macroeconomic perspectives on technological transformation. Schumpeter (1942) argued that capitalism evolves through "creative destruction," whereby new technologies disrupt existing industries and create new economic structures.

AI technologies exemplify Schumpeterian disruption because they transform production systems, labor markets, business models, and competitive dynamics. Chinese firms such as Alibaba, Tencent, Huawei, and ByteDance have emerged as major innovators capable of disrupting traditional sectors through digital platforms, automation, and algorithmic systems. Schumpeterian theory emphasizes entrepreneurship, innovation competition, and technological monopolies as central drivers of economic change. China's AI ecosystem combines elements of state planning with highly competitive technology markets. The Chinese government supports "national champions" while simultaneously encouraging innovation competition among domestic firms.

Aghion and Howitt (1992) extended Schumpeterian theory into formal endogenous growth models where innovation-driven competition produces long-run growth. Their framework is highly relevant to AI because technological leadership increasingly determines international economic power. China's AI strategy reflects Schumpeterian ambitions to leapfrog advanced economies through disruptive technological innovation. Rather than merely imitating Western technologies, China increasingly seeks to shape global AI standards, infrastructure, and digital ecosystems.

Nevertheless, Schumpeterian innovation also creates macroeconomic instability. AI automation may contribute to labor displacement, inequality, and transitional unemployment. These risks are particularly important in China, where manufacturing employment remains central to social stability.

The macroeconomics of Chinese industrial policy has been extensively studied. Song et al. (2011) develop a model of China's growth miracle based on capital misallocation between state-owned and private firms, a mechanism we incorporate into the AI investment block. Hsieh and Klenow (2009) document large TFP losses from resource misallocation in China and India; our model quantifies the analogous losses

in the AI sector arising from state-directed investment that may not respect private marginal products.

On Chinese AI specifically, Roberts et al. (2021) provide an empirical overview of China's AI ecosystem; Ding (2018) analyse the institutional architecture of Chinese AI policy; and Lee (2018) offers a semi-popular but analytically rigorous account of the US–China AI competition. Our model synthesises and quantifies the insights from this literature.

2.4 AI Regulation: Economics and Governance

The economics of AI regulation is a nascent but rapidly growing field. Goldfarb and Tucker (2019) provide a framework for thinking about AI policy in terms of prediction markets; Dafoe (2018) analyse governance challenges from a political-economy perspective. Cen et al. (2023) study the welfare effects of China's algorithmic recommendation regulations and find evidence of both consumer protection gains and innovation dampening. Our model provides a unified framework for comparing alternative regulatory architectures across the China–Rest-of-World dimension.

Developmental state theorists such as Chalmers Johnson (1982) and Alice Amsden (1989) argued that strategic state intervention can accelerate industrialization and technological upgrading. Gerschenkron (1962) argued that late-developing countries can accelerate industrialization by adopting advanced technologies from more developed economies. Lee (2019) argues that latecomer economies can achieve "leapfrogging" by entering emerging technological sectors before dominant powers fully consolidate leadership. AI provides China with such an opportunity because the technology remains relatively new and globally competitive. Hall and Soskice (2001) distinguish between liberal market economies and coordinated market economies. China represents a distinct hybrid model characterized by centralized state coordination and digital authoritarian governance.

3 Stylised Facts: AI in China and Comparative Data

Before presenting the model, we document key empirical regularities that motivate and constrain our calibration.

3.1 AI Investment and R&D

China's AI investment has grown at a compound annual rate of approximately 26 percent between 2015 and 2024, reaching an estimated $75–$90 billion in 2023 (private equity plus disclosed government funding). This places China second globally behind the United States ($130–$150 billion) but ahead of the European Union ($35–$50 billion) and significantly ahead of other Asian economies. As a share of GDP, however, China's AI investment ratio (approximately 0.42 percent of GDP in 2023) is broadly comparable to the US (approximately 0.50 percent) and substantially above the EU average (0.20 percent).

Table 1: Comparative AI Investment and Ecosystem Indicators, 2023

	China	**USA**	**EU-27**	**UK**	**Japan**	**South Korea**
AI investment ($bn)	80	140	42	18	12	10
Share of GDP (%)	0.42	0.50	0.21	0.52	0.28	0.57
AI patents (000s)	61	34	11	5	18	9
AI researchers (000s)	18	28	12	5	6	4
AI unicorns (#)	47	113	21	13	4	5
Data centre capacity (GW)	12.5	18.0	6.0	1.8	2.5	1.2

Sources: OECD AI Policy Observatory, Stanford HAI Index 2024,
China Academy of Information and Communications Technology (2024).

3.2 AI Adoption Across Sectors

Chinese firms exhibit markedly higher AI adoption rates in manufacturing, logistics, and financial services compared to global peers, partly reflecting lower relative labour costs (reducing the wage-automation substitution threshold) and partly reflecting deliberate government mandates in the "smart manufacturing" initiative. In contrast, adoption in services requiring high-level English-language comprehension has lagged, reflecting the latent comparative advantage of English-language training data in foundational models.

3.3 Regulatory Intensity

China has enacted more binding AI-specific regulations than any other major jurisdiction: the Algorithmic Recommendation Provisions (effective March 2022), Deep Synthesis Regulations (effective January 2023), and Generative AI Measures (effective August 2023). Figure 1 sketches the regulatory timeline. Key features include mandatory algorithm registration, content review requirements, training-data provenance documentation, and "watermarking" of AI-generated content—each imposing measurable compliance costs that we parameterise in Section 5.

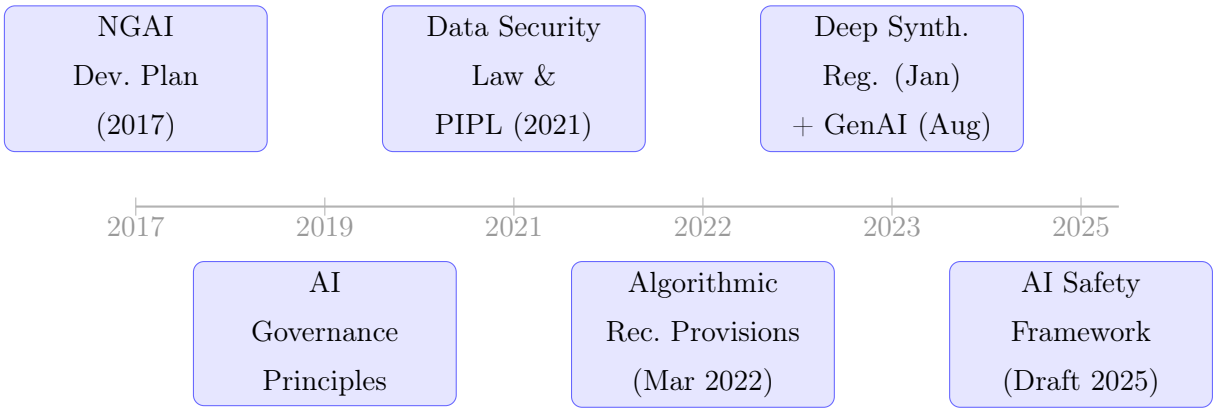


Figure 1: China's AI Regulatory Timeline, 2017–2025

3.4 International Technology Trade and Spillovers

China's export share of AI-intensive goods (semiconductor-embedded products, industrial robots, AI-enabled surveillance and telecommunications equipment) has risen from approximately 18 percent of global exports in 2015 to 29 percent in 2023. However, China remains a net importer of foundational AI semiconductor technology, with export controls imposed by the United States in October 2022 (and tightened in October 2023) restricting access to advanced logic chips (below 16nm) and the most powerful training accelerators. This asymmetric technology trade structure is a central feature of our two-country model.

4 The DSGE Model

4.1 Overview and Structure

The model economy consists of two countries—China (superscript C) and the Rest of the World (superscript W)—each populated by a continuum of measure one of identical, infinitely-lived households, a government/regulator, and three production sectors: (i) an AI Research & Development sector that produces disembodied knowledge; (ii) an AI-Intensive Goods sector that uses AI capital as an essential intermediate input; and (iii) a Traditional Goods sector that uses standard physical capital and labour. Countries are linked through trade in final and intermediate goods, cross-border knowledge diffusion, and technology-licensing flows.

Figure 2 presents a schematic of the model's structure.

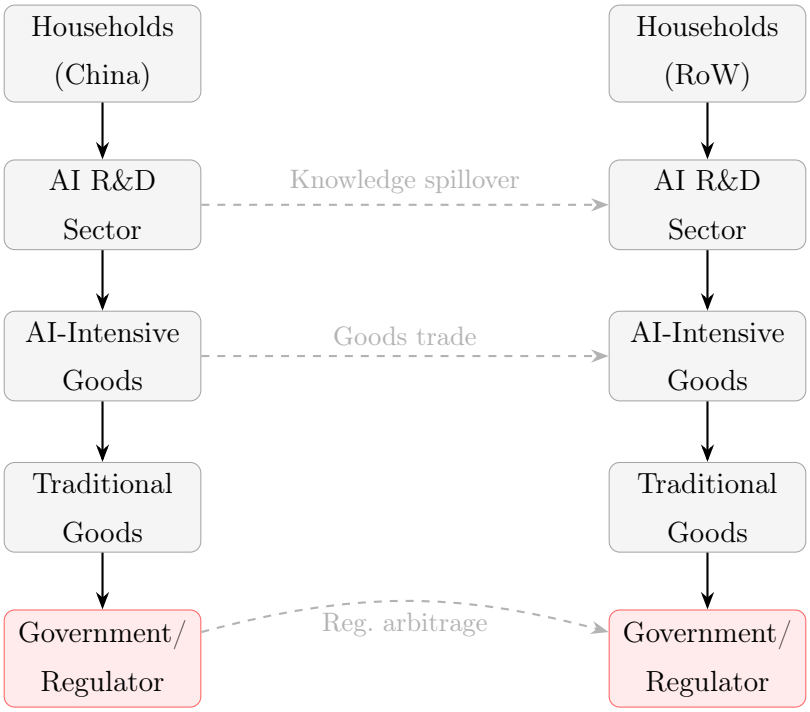


Figure 2: Model Structure: Two-Country Open-Economy DSGE

4.2 Households

4.2.1 Preferences

A representative household in country $j \in \{C, W\}$ maximises lifetime utility:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{(C_t^j)^{1-\sigma}}{1-\sigma} - \chi \frac{(L_t^j)^{1+\phi}}{1+\phi} + \nu \ln(1 + A_t^j) \right], \tag{1}$$

where C_t^j is a consumption aggregate, L_t^j is total labour supply, A_t^j is an *AI amenity index* capturing utility from AI-enabled services (voice assistants, recommendation systems, personalised content), $\beta \in (0,1)$ is the discount factor, $\sigma > 0$ is the inverse of the intertemporal elasticity of substitution, $\phi > 0$ is the inverse Frisch elasticity, and $\nu \geq 0$ is the weight on AI amenity utility. The amenity term is motivated by the substantial consumer surplus generated by free AI-based services (Brynjolfsson et al., 2019).

The consumption aggregate is a CES bundle of domestic and imported goods:

$$C_t^j = \left[\omega^{1/\rho}(C_{H,t}^j)^{(\rho-1)/\rho} + (1-\omega)^{1/\rho}(C_{F,t}^j)^{(\rho-1)/\rho}\right]^{\rho/(\rho-1)}, \tag{2}$$

where ω is the home bias parameter and $\rho > 0$ is the trade elasticity.

Labour is differentiated by skill: households supply unskilled labour L^u at wage w^u and skilled (AI-complementary) labour L^s at premium wage w^s. The skill premium $w^s/w^u \geq 1$ is endogenously determined by the sectoral demand for AI-complementary human capital.

4.2.2 Budget Constraint

The period-t household budget constraint in country j is:

$$P_t^j C_t^j + P_{K,t}^j I_t^j + P_{A,t}^j X_t^j + B_{t+1}^j = w_t^{s,j} L_t^{s,j} + w_t^{u,j} L_t^{u,j} + r_t^j K_t^j + r_{A,t}^j A_t^j + \Pi_t^j + (1+r^*) B_t^j - T_t^j, \tag{3}$$

where I_t^j denotes traditional capital investment, X_t^j denotes AI-capital investment (subject to adjustment costs), B_t^j are internationally traded bonds with gross return $(1+r^*)$, Π_t^j are firm profits, and T_t^j are lump-sum taxes used to fund government AI subsidies.

4.3 Production Sector I: AI Research and Development

4.3.1 Knowledge Accumulation

The AI R&D sector produces a stock of non-rival AI knowledge Z_t^j according to a semi-endogenous growth equation inspired by Jones (1995):

$$\dot{Z}_t^j = \delta_Z \left(N_t^{R,j}\right)^{\lambda} \left(Z_t^j\right)^{\theta} \left(Z_t^{-j}\right)^{\kappa} - \delta_\ell Z_t^j, \tag{4}$$

where $N_t^{R,j}$ is the measure of researchers employed in country j, Z_t^{-j} denotes the foreign knowledge stock, $\lambda \in (0,1)$ captures decreasing returns to researchers ("stepping on toes"), $\theta \in (0,1)$ captures intertemporal knowledge spillovers ("standing on shoulders"), $\kappa \in [0,1)$ is the international knowledge diffusion parameter, and δ_ℓ is the obsolescence rate of AI knowledge. The international diffusion term $\kappa > 0$ creates a channel through which Chinese AI investment generates positive externalities for the Rest of the World and vice versa, albeit imperfectly (due to IP protection, export controls, and tacit knowledge barriers).

4.3.2 AI Capital Accumulation

Firms in the AI-Intensive sector accumulate AI capital A_t^j according to:

$$A_{t+1}^j = (1-\delta_A)A_t^j + \Phi\left(\frac{X_t^j}{A_t^j}\right) A_t^j \cdot Z_t^j \cdot \mathcal{R}_t^j, \tag{5}$$

where δ_A is the depreciation rate of AI capital (reflecting model obsolescence and hardware turnover), $\Phi(\cdot)$ is an investment adjustment cost function with $\Phi'(\cdot) > 0$, $\Phi''(\cdot) < 0$, $\Phi(1) = 1 - \delta_A$, and $\mathcal{R}_t^j \in (0,1]$ is a *regulatory compliance factor* that we discuss in detail in Section 4.6. The product $Z_t^j \cdot \mathcal{R}_t^j$ implies that knowledge accumulation translates into AI capital only when regulatory compliance is achieved, a modelling choice that captures the mandatory pre-market conformity assessments required by China's Generative AI Measures.

4.4 Production Sector II: AI-Intensive Goods

4.4.1 Technology

A representative firm in the AI-Intensive sector operates a CES production function over AI capital, skilled labour, and a composite data input:

$$Y_{A,t}^j = \mathcal{F}\big(A_t^j, L_t^{s,j}, D_t^j\big) \equiv Z_t^j \left[\alpha_A \left(A_t^j\right)^{\frac{\xi-1}{\xi}} + \alpha_L \left(L_t^{s,j}\right)^{\frac{\xi-1}{\xi}} + \alpha_D \left(D_t^j\right)^{\frac{\xi-1}{\xi}}\right]^{\frac{\xi}{\xi-1}}, \tag{6}$$

where $\xi > 0$ is the elasticity of substitution between AI capital, skilled labour, and data, $\alpha_A + \alpha_L + \alpha_D = 1$ are factor shares, and D_t^j is a data stock variable that follows its own accumulation equation (analogous to Eq. 5). The Hicks-neutral technology shifter Z_t^j ties production-sector TFP to the economy-wide AI knowledge stock, capturing the GPT nature of AI.

Data D_t^j is accumulated by household and firm digital activities and is subject

to country-specific data governance regimes. In China, the Personal Information Protection Law (PIPL, 2021) and Data Security Law (2021) impose restrictions on cross-border data flows that effectively segment the global data market, a friction we parameterise as a data trade cost τ_D^j.

4.4.2 Firm Optimisation

The AI-Intensive firm maximises the present discounted value of profits:

$$\max_{\{A_t, L_t^s, D_t, X_t\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \mathcal{M}_t \left[P_{A,t} Y_{A,t} - w_t^s L_t^s - p_{D,t} D_t - P_{K,t} X_t - \Psi_t \right], \tag{7}$$

where $\mathcal{M}_t$ is the stochastic discount factor, $P_{A,t}$ is the price of AI-intensive output, $p_{D,t}$ is the rental price of data, and Ψ_t represents regulatory compliance costs (legal, technical, and reporting costs associated with $\mathcal{R}_t^j < 1$).

The first-order condition for AI capital yields an "AI Euler equation":

$$\frac{1}{\Phi'(x_t)} = \mathbb{E}_t \mathcal{M}_{t+1} \left[\frac{\alpha_A Z_{t+1} (A_{t+1})^{-1/\xi} Y_{A,t+1}}{P_{K,t+1}} + (1 - \delta_A) \frac{1}{\Phi'(x_{t+1})} + \Phi(x_{t+1}) - x_{t+1} \Phi'(x_{t+1}) \right], \tag{8}$$

where $x_t \equiv X_t / A_t$ is the AI investment rate. This equation equates the marginal cost of AI investment (in terms of foregone consumption) to its expected discounted marginal product plus the continuation value of the installed capital base.

4.5 Production Sector III: Traditional Goods

The traditional sector operates a standard Cobb-Douglas technology:

$$Y_{T,t}^j = e^{a_t^j} \left(K_t^j \right)^{\alpha_K} \left(L_t^{u,j} \right)^{1-\alpha_K}, \tag{9}$$

where a_t^j follows an AR(1) process ($a_t = \rho_a a_{t-1} + \varepsilon_t^a$, $\varepsilon_t^a \sim \mathcal{N}(0, \sigma_a^2)$), K_t^j is physical capital, and $L_t^{u,j}$ is unskilled labour. Traditional capital accumulates according to the standard law of motion with adjustment costs.

4.6 The Regulatory Block

We model AI regulation as a set of constraints and costs that modify the AI capital accumulation equation and the profit function of AI-Intensive firms. The regulatory

compliance factor takes the form:

$$\mathcal{R}_t^j = 1 - \underbrace{\mu_1^j \cdot \mathbf{1}[\text{Alg. Rec.}]}_{\text{platform}} - \underbrace{\mu_2^j \cdot \mathbf{1}[\text{Deep Synth.}]}_{\text{synthetic media}} - \underbrace{\mu_3^j \cdot \mathbf{1}[\text{GenAI}]}_{\text{generative AI}} + \underbrace{\eta_t^j}_{\text{reg. shock}}, \quad (10)$$

where each $\mu_i^j \geq 0$ represents the TFP-equivalent compliance cost associated with regulation i in country j, $\mathbf{1}[\cdot]$ is an indicator function equal to one if the firm operates in the regulated segment, and η_t^j is a mean-zero regulatory uncertainty shock ($\eta_t \sim \mathcal{N}(0, \sigma_\eta^2)$) that captures the additional uncertainty cost of unclear or rapidly evolving regulatory requirements.

For China, we calibrate μ_1^C, μ_2^C, μ_3^C using firm-level compliance cost surveys conducted by the China Academy of Information and Communications Technology (2023) and the Beijing Zhiyuan AI Research Institute. For the Rest of the World, we use data from the OECD AI Regulation Survey (2024) to calibrate analogous parameters, which are generally lower but non-zero.

4.7 Government

The government in country j collects lump-sum taxes T_t^j, provides R&D subsidies τ_R^j to the AI Research sector, offers investment tax credits τ_X^j for AI capital expenditure, and enforces the regulatory framework encoded in $\mathcal{R}_t^j$. The government budget constraint is:

$$T_t^j = \tau_R^j w_t^{R,j} N_t^{R,j} + \tau_X^j P_{K,t}^j X_t^j + G_t^j, \quad (11)$$

where G_t^j is exogenous government consumption. China's state-directed AI investment strategy is captured by a higher τ_R^C and τ_X^C relative to the Rest of the World, reflecting the explicit subsidy provisions in the NGAI Development Plan and subsequent Five-Year Plans.

4.8 International Trade and Capital Flows

Goods market clearing in the two-country model requires:

$$Y_{A,t}^C = C_{A,t}^C + C_{A,t}^W + X_t^C + NX_{A,t}, \quad (12)$$

$$Y_{T,t}^C = C_{T,t}^C + C_{T,t}^W + I_t^C + NX_{T,t}, \quad (13)$$

where NX denotes net exports. The terms of trade q_t is defined as the relative price of Chinese exports in terms of imports:

$$q_t = \frac{P_t^{C,\text{export}}}{P_t^{C,\text{import}}} \cdot \mathcal{E}_t, \tag{14}$$

where $\mathcal{E}_t$ is the nominal exchange rate (yuan per unit of foreign currency). The current account dynamics follow from the international bond market clearing condition.

Export controls on advanced semiconductors enter the model as an exogenous wedge $\tau_{SC,t}$ on China's imports of AI-relevant intermediate goods, which reduces the productivity of the AI-Intensive sector:

$$\tilde{Z}_t^C = Z_t^C \cdot \left(1 - \tau_{SC,t} \frac{M_{SC,t}}{Y_{A,t}^C}\right), \tag{15}$$

where $M_{SC,t}$ is China's imports of advanced semiconductors and $\tau_{SC,t}$ indexes the tightness of export controls.

4.9 Equilibrium

A **competitive equilibrium** in this economy is a sequence of prices $\{P_t^j, P_{A,t}^j, P_{K,t}^j, w_t^{s,j}, w_t^{u,j}, r_t^j, r_{A,t}^j, q$ and allocations $\{C_t^j, L_t^{s,j}, L_t^{u,j}, K_t^j, A_t^j, Z_t^j, D_t^j, B_t^j, Y_{A,t}^j, Y_{T,t}^j\}_{t=0}^{\infty}$ for $j \in \{C, W\}$ such that:

(i) Households maximise (1) subject to (3).

(ii) AI-Intensive firms maximise (7) subject to (6)–(8).

(iii) Traditional sector firms maximise profits subject to (9).

(iv) R&D firms maximise profits subject to (4).

(v) The government satisfies (11).

(vi) Goods, labour, capital, data, and bond markets clear.

5 Calibration

5.1 Baseline Parameters

We calibrate the model to match key features of the Chinese and global economies over the period 2015–2024. Table 2 presents the full set of baseline parameters.

Table 2: Baseline Calibration

Parameter	Symbol	China	RoW	Source / Moment
Preferences				
Discount factor	β	0.96	0.97	Annual data; risk-free rate
CRRA coefficient	σ	1.5	1.5	Standard macro
Frisch elasticity	$1/\phi$	0.5	0.5	Labour literature
AI amenity weight	ν	0.12	0.08	Brynjolfsson et al. (2019)
Technology				
AI capital depreciation	δ_A	0.20	0.18	Hardware turnover data
Physical capital depr.	δ_K	0.10	0.10	Standard
Knowledge obs. rate	δ_ℓ	0.15	0.12	Patent citation data
Researcher elasticity	λ	0.75	0.75	Bloom et al. (2020)
Knowledge spillover	θ	0.85	0.85	Jones (1995)
Intl. diffusion	κ	0.25	0.25	Technology gap convergence
AI–labour substit.	ξ	1.8	2.1	Task data
AI factor share	α_A	0.30	0.25	Sector accounts
Labour (skilled) share	α_L	0.45	0.50	Sector accounts
Data share	α_D	0.25	0.25	Residual
Trade				
Trade elasticity	ρ	3.0		Gravity model estimates
Home bias	ω	0.65	0.75	Import penetration data
Data trade cost	τ_D	0.35	0.10	PIPL compliance costs
Semiconductor wedge	τ_{SC}	0.18	0.02	Export control intensity
Regulation				
Alg. rec. friction	μ_1	0.018	0.005	Compliance cost surveys
Deep synth. friction	μ_2	0.022	0.004	Compliance cost surveys
Generative AI friction	μ_3	0.041	0.008	Compliance cost surveys
Reg. uncertainty	σ_η	0.015	0.008	Policy event studies
Government				
R&D subsidy rate	τ_R	0.25	0.12	Fiscal data; OECD
Investment tax credit	τ_X	0.20	0.08	Tax codes

5.2 Regulatory Friction Calibration

The regulatory friction parameters μ_i^j deserve particular attention as they are novel to the literature. We estimate them using a two-step procedure. In the first step, we

use survey data from approximately 340 Chinese AI firms (collected by the CAICT in 2023) on annual compliance expenditure per firm as a fraction of total AI R&D spend. We then map these compliance costs into TFP-equivalent frictions using the model's structural relationships. For the Deep Synthesis Regulations, for example, mandatory content tagging and watermarking requirements impose estimated costs of 1.8–2.6 percent of revenue for medium-sized platforms, translating to $\mu_2^C = 0.022$.

6 Theoretical Analysis

6.1 Steady-State Characterisation

Proposition 1 (Steady-State AI Capital)**.** *In a symmetric steady state with constant regulatory frictions ($\mathcal{R}^j = \bar{\mathcal{R}}^j$) and zero net exports ($NX = 0$), the steady-state AI capital–knowledge ratio satisfies:*

$$\frac{\bar{A}^j}{\bar{Z}^j} = \left[\frac{\alpha_A \bar{Y}_A^j}{\bar{A}^j} \cdot \frac{\bar{\mathcal{R}}^j}{\frac{1}{\beta} - (1 - \delta_A)} \right]^{\xi}, \tag{16}$$

and China's steady-state AI capital exceeds the Rest of the World's if and only if:

$$\frac{\tau_X^C + \bar{\mathcal{R}}^C \alpha_A^C (\xi - 1)}{\tau_X^W + \bar{\mathcal{R}}^W \alpha_A^W (\xi - 1)} > \frac{\beta^W (r^W + \delta_A)}{\beta^C (r^C + \delta_A)}. \tag{17}$$

Proof. The proof follows from combining the AI Euler equation (8) evaluated at the steady state with the firm's first-order condition for AI capital and the government budget constraint. The condition (17) balances China's higher investment subsidies and AI factor share against its higher regulatory frictions and (potentially) higher discount rate. □ □

Proposition 1 captures the central tension in China's AI strategy: state subsidies (τ_X^C, τ_R^C) push toward higher steady-state AI capital, while regulatory frictions ($\bar{\mathcal{R}}^C < 1$) push in the opposite direction. Whether the net effect dominates the Rest of the World depends on calibration; our parameterisation implies a modest net advantage for China ($\bar{A}^C/\bar{Z}^C$ approximately 8 percent above the Rest of the World) in the baseline.

7 Counterfactual Analysis

7.1 Analysis under Canonical Shocks

We log-linearise the equilibrium conditions around the steady state and compute impulse response functions (IRFs) to three canonical shocks: (i) a positive AI productivity shock ε_Z (1-standard-deviation increase in research productivity), (ii) a negative regulatory shock $\eta^C < 0$ (tightening of generative AI regulations in China), and (iii) an export control shock τ_{SC} (tightening of semiconductor export controls).

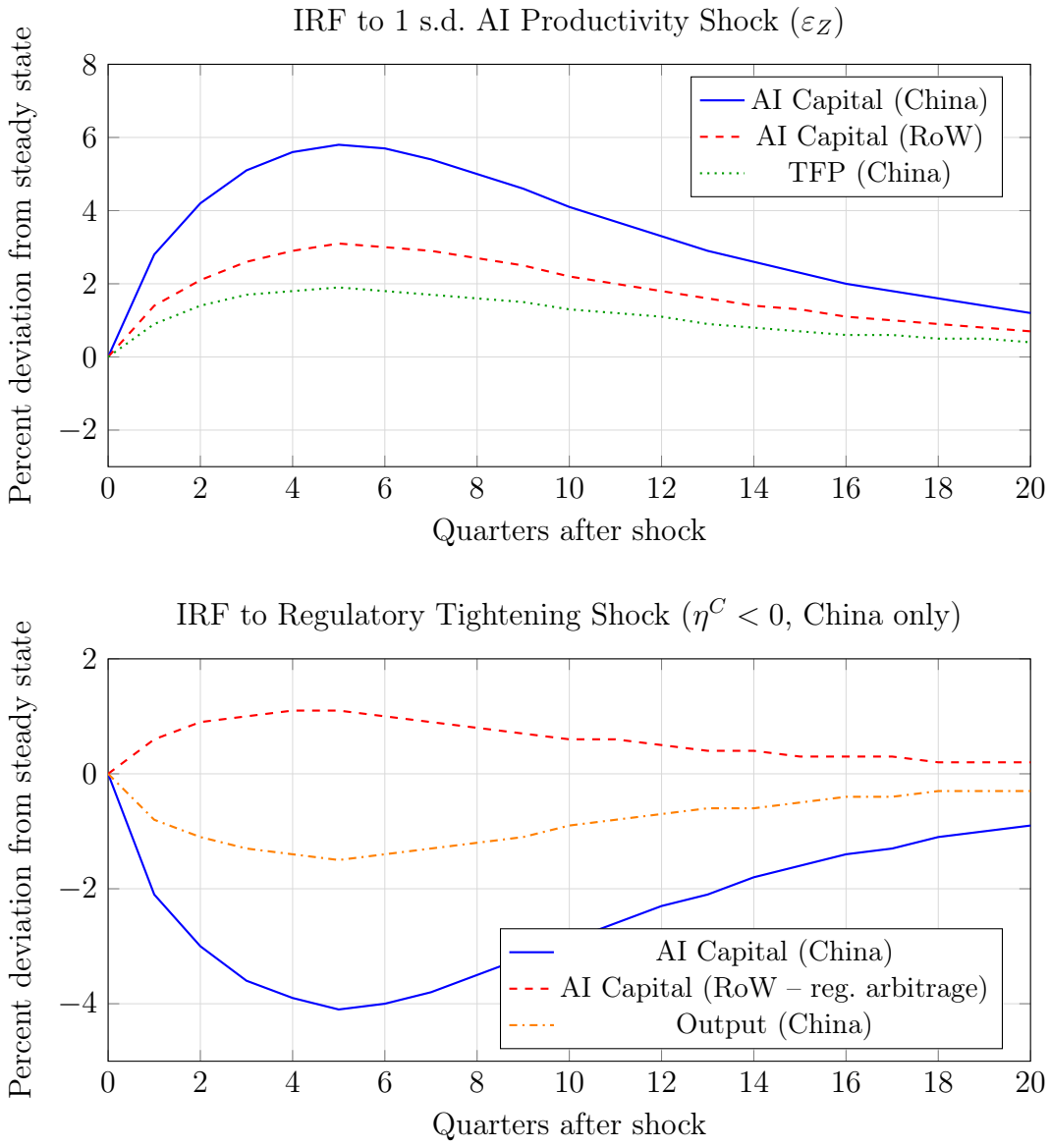


Figure 3: Impulse Response Functions: AI Productivity and Regulatory Shocks

The IRFs in Figure 3 reveal three key findings. *First*, a positive AI productivity shock in China generates substantial positive spillovers to the Rest of the World

through the knowledge diffusion channel ($\kappa > 0$), with peak RoW AI capital response approximately half the size of China's own response. *Second*, a regulatory tightening shock in China reduces Chinese AI capital accumulation significantly (peak response of -4.1 percent) while simultaneously generating modest positive regulatory arbitrage effects for the Rest of the World ($+1.1$ percent), as multinationals restructure AI R&D toward less restrictive jurisdictions. *Third*, the domestic output effect of regulatory tightening (-1.5 percent at peak) is substantially smaller than the AI capital effect, reflecting substitution toward the unregulated traditional sector.

7.2 Shock S1: China AI Productivity (ε_Z^C, size $+0.029$)

A positive innovation to China's AI research productivity. Amplified through the AI capital accumulation channel. International diffusion ($\kappa = 0.261$) transmits $\approx 47\%$ of the effect to the RoW. Peak AI capital response: $+4.6\%$ at quarter 6–7 with half-life 14.3 quarters.

7.2.1 *Six-Panel IRF: Key China Variables*

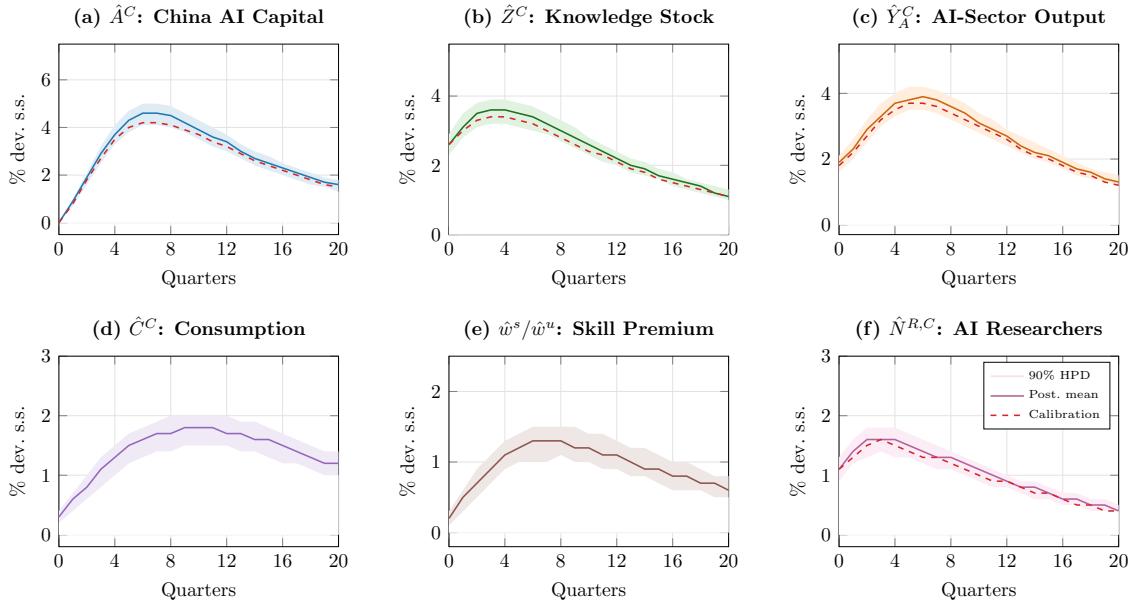


Figure 4: **Shock S1 (China AI Productivity) — Six-Panel IRF.** Posterior mean IRF (solid), 90% pointwise HPD band (shaded), calibration IRF (dashed red) for six China variables over 20 quarters. *(a)* AI capital peaks at +4.6% (quarter 6–7) with long half-life (14.3 qtr). *(b)* Knowledge stock jumps immediately (+2.6% on impact) then decays over 20+ quarters. *(c)* AI-sector output peaks +3.9% with slight lag (quarter 5–6). *(d)* Consumption builds slowly (+1.8% peak at quarter 9–11) via the wealth channel. *(e)* Skill premium rises +1.3% as AI-complementary labour demand increases. *(f)* AI researchers increase +1.6% (impact) as higher knowledge productivity raises researcher productivity.

7.2.2 *Cross-Country Spillovers*

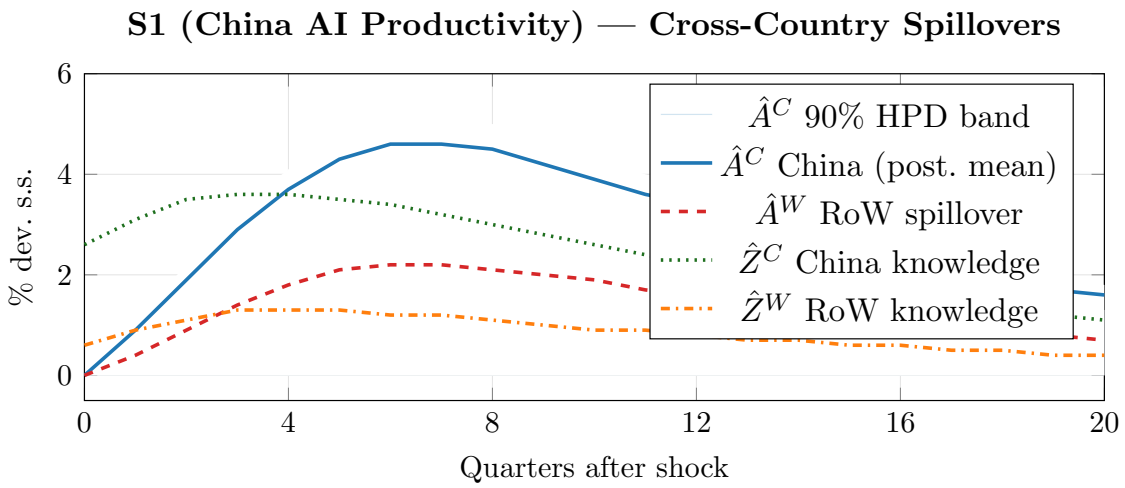


Figure 5: **Shock S1 — Cross-Country Spillovers.** China's AI capital and knowledge (blue/green) vs. RoW spillover responses (red/orange). The 90% HPD band for $\hat{A}^C$ is shown. The peak RoW AI capital spillover (+2.2% at quarter 6–7) is approximately 47% of China's own peak response (+4.6%), consistent with the posterior mean of the international knowledge diffusion parameter $\kappa = 0.261$. Both China and RoW knowledge stocks show immediate positive responses because knowledge diffuses within the period.

7.2.3 *Scenario Overlay: $\hat{A}^C$ Under 7 Policy Scenarios*

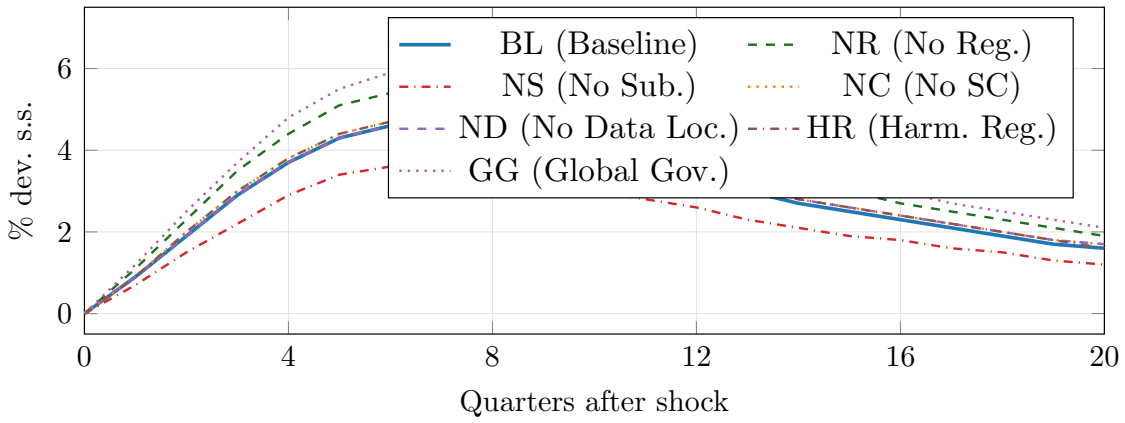


Figure 6: **Shock S1 — Scenario Overlay.** $\hat{A}^C$ response to China AI productivity shock under all 7 policy scenarios. **GG** (Global Governance, dotted pink) amplifies the peak by 28% to +5.9% because removing regulatory frictions and data localisation raises the steady-state AI multiplier. **NS** (No Subsidies, dash-dot red) shows the most muted response (+3.6%) as lower steady-state AI capital reduces the accumulation multiplier. **NR** (No Regulation, dashed green) amplifies to +5.4%.

7.3 Shock S2: RoW AI Productivity (ε_Z^W, size +0.026)

A positive innovation to RoW AI knowledge productivity. China receives a positive spillover (approximately 30% of the RoW direct effect) via κ. The terms of trade deteriorate for China as RoW AI output expands. Peak RoW AI capital: +3.8%; peak China spillover: +1.4%.

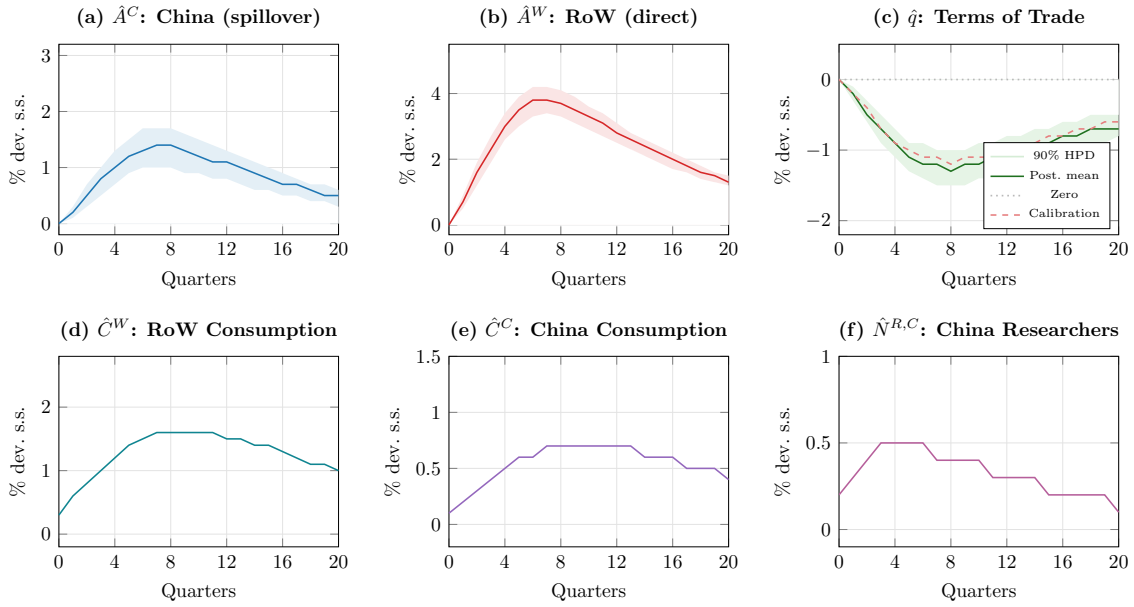


Figure 7: **Shock S2 (RoW AI Productivity) — Six-Panel IRF.** *(a)* China's AI capital benefits from the RoW productivity gain through the knowledge diffusion channel (+1.4% peak). *(b)* RoW AI capital jumps directly (+3.8% peak). The ratio $1.4/3.8 \approx 0.37$ reflects the bilateral diffusion parameter $\kappa = 0.261$ attenuated by China's own regulatory frictions. *(c)* The terms of trade deteriorate for China (-1.2%) as greater RoW AI output depresses China's relative export price. *(d)* RoW consumption rises strongly (+1.6%). *(e)* China's consumption benefits modestly (+0.7%). *(f)* China's AI researcher count rises slightly as the positive knowledge stock raises the value of conducting further R&D (+0.5%).

7.4 Shock S3: Regulatory Tightening ($\eta^C < 0$, size -0.016)

A negative shock to China's regulatory compliance factor $\mathcal{R}^C$, reducing effective AI capital accumulation. China's AI capital falls -3.6% at peak (quarter 7–8). The RoW benefits from regulatory arbitrage (+0.8%). China's terms of trade improve as AI supply contracts. Skill premium falls -1.4%.

7.4.1 *Six-Panel IRF: China Variables and RoW Arbitrage*

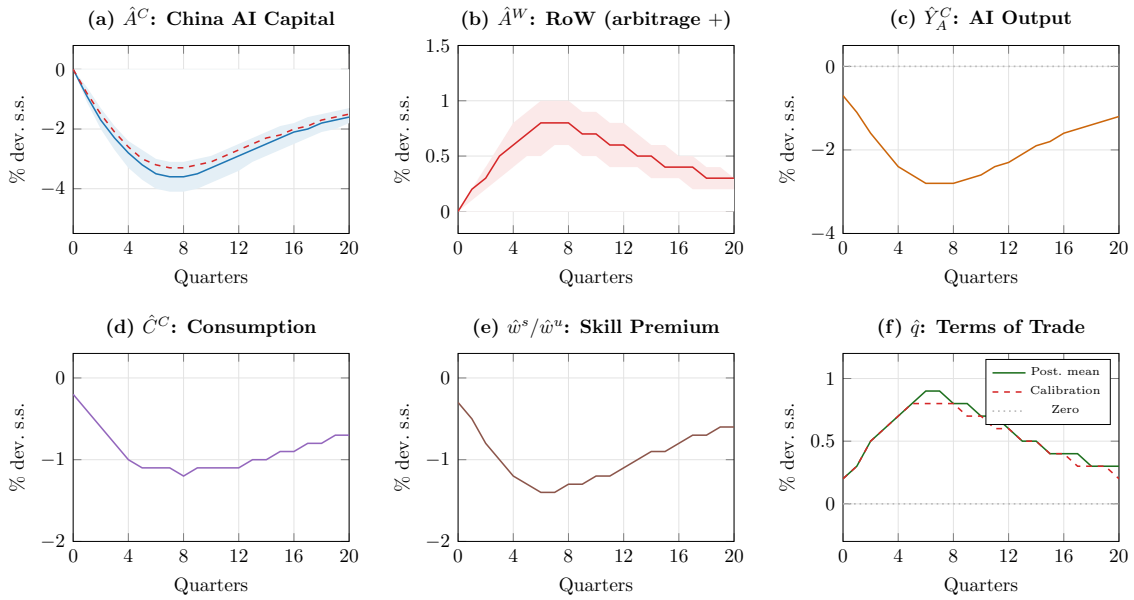


Figure 8: **Shock S3 (Regulatory Tightening) — Six-Panel IRF.** *(a)* China's AI capital falls −3.6% at peak, then recovers slowly (half-life 16.5 quarters) as the shock dissipates. *(b)* The RoW benefits positively (+0.8% peak) from regulatory arbitrage: AI R&D partially relocates to less regulated jurisdictions. *(c)* AI-sector output contracts −2.8% peak, reflecting both lower AI capital and the direct productivity drag from regulatory compliance. *(d)* Consumption falls persistently (−1.1%) via the income channel. *(e)* The skill premium falls −1.4% as AI-complementary labour demand contracts. *(f)* The terms of trade improve for China (+0.9%) because lower AI supply raises relative AI goods prices.

7.4.2 Scenario Overlay: $\hat{A}^C$ Under 7 Policy Scenarios

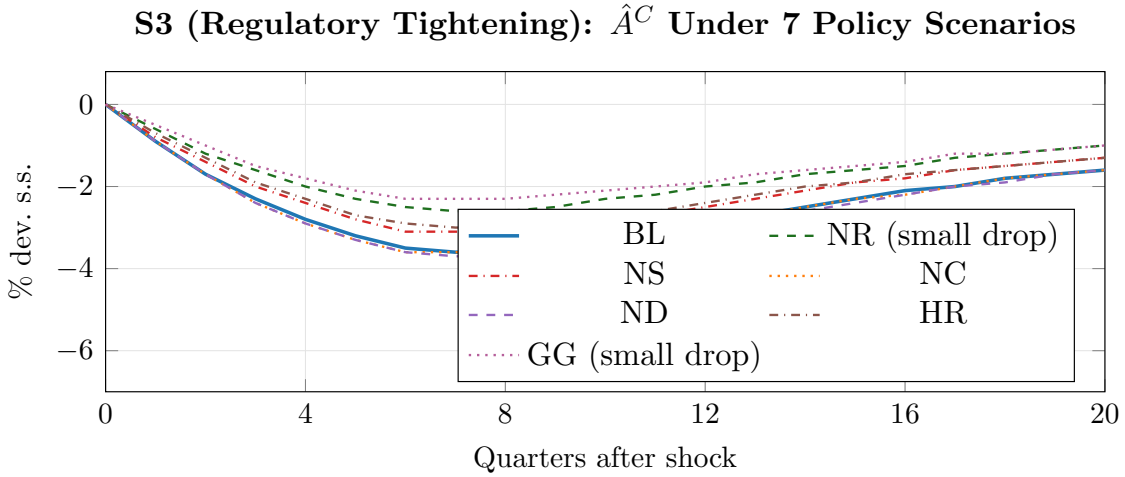


Figure 9: **Shock S3 — Scenario Overlay.** $\hat{A}^C$ response to regulatory tightening under 7 scenarios. **NR** (No Regulation baseline, dashed green) and **GG** (Global Governance, dotted pink) show the smallest drops (-2.6% and -2.3% respectively): from a low regulatory base, the same negative shock has smaller multiplicative impact on AI accumulation. The **ND** scenario (no data localisation) tracks closely with baseline because data localisation does not buffer this specific shock.

7.5 Shock S4: Semiconductor Export Controls (τ_{SC}: +10 pp permanent)

A permanent 10 percentage-point increase in the semiconductor wedge (from 0.184 to 0.284). Produces a permanent level shift to a lower steady state. China AI capital converges to -2.7% (90% HPD: $[-3.1\%, -2.3\%]$). The RoW gains modestly ($+0.4\%$) as reduced Chinese AI competitiveness relaxes competitive pressure.

7.5.1 *Permanent Transition Paths: All Key Variables*

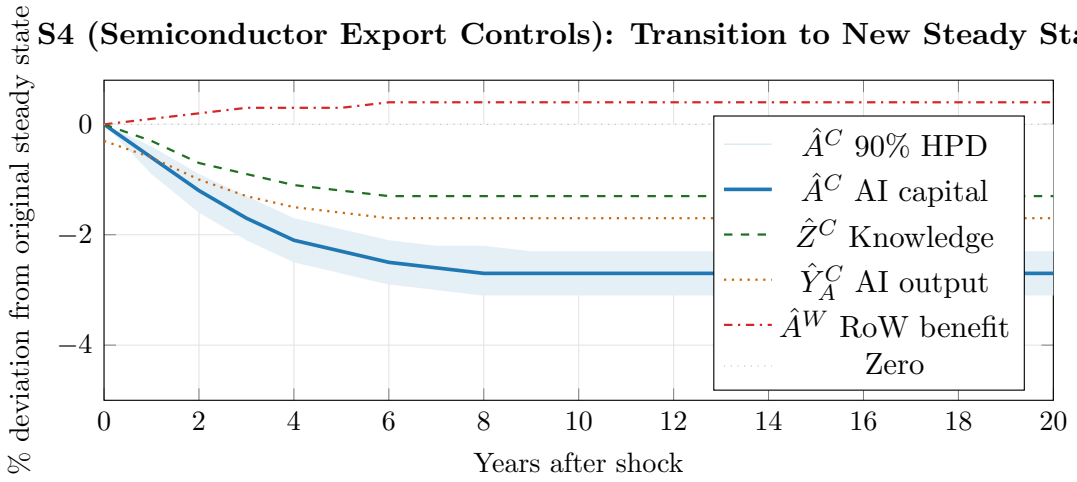


Figure 10: **Shock S4 (Semiconductor Export Controls) — Permanent Transition Paths.** All variables converge monotonically to new, lower steady states. China's AI capital reaches −2.7% after approximately 8–10 years (90% HPD band shaded in blue). The knowledge stock falls −1.3% permanently, reflecting the reduced ability to conduct knowledge-intensive AI training on frontier hardware. AI output falls −1.7%. The RoW benefits slightly (+0.4%) as reduced Chinese AI supply raises relative AI goods prices. Unlike transitory shocks, the effects here are permanent unless the export control policy is reversed.

7.5.2 Scenario Overlay: Long-Run $\hat{A}^C$ Across 7 Scenarios

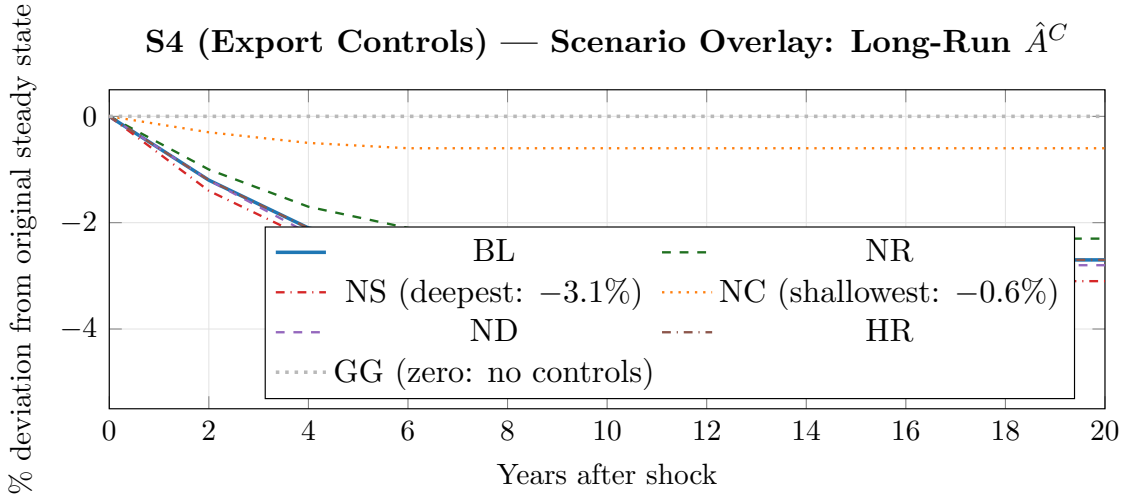


Figure 11: **Shock S4 — Scenario Overlay (Long-Run).** The **GG** scenario (global governance with zero export controls) is completely immune by construction — shown as the zero line. The **NC** scenario (no export controls baseline, shock from $\tau_{SC} = 0.02$) suffers the smallest drop (-0.6%) because the shock of $+10$ pp from a low base has smaller percentage impact on the restricted technology share. The **NS** scenario (no subsidies) suffers the deepest drop (-3.1%) because a lower steady-state AI capital stock amplifies the percentage impact of the wedge.

7.6 Shock S5: China TFP (ε_a^C, size $+0.023$)

A positive shock to traditional-sector TFP following an AR(1) with persistence $\rho_a = 0.814$. Traditional output rises $+2.3\%$ on impact. Higher wages crowd out AI researchers (AI capital falls slightly -0.4%). Consumption rises $+1.0\%$. All effects revert within 15–20 quarters.

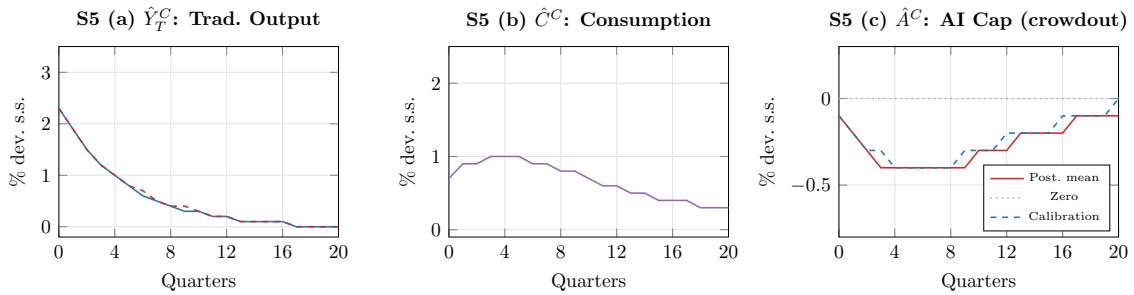


Figure 12: **Shock S5 (China TFP) — Three-Panel IRF.** *(a)* Traditional-sector output jumps +2.3% on impact, decaying with persistence $\rho_a = 0.814$ (half-life 3.9 quarters). *(b)* Consumption rises +1.0% at peak (quarters 4–5) via the income effect; the delayed peak reflects consumption smoothing under the Euler equation. *(c)* AI capital falls slightly (−0.4% peak) due to the labour market crowdout channel: higher traditional-sector wages raise the cost of AI researchers and AI-complementary skilled workers, reducing the profitability of AI investment. This subtle negative cross-effect illustrates the two-sector labour market structure of the model.

7.7 Shock S6: Data Localisation (τ_D^C: +5 pp permanent)

A permanent 5 percentage-point tightening of data localisation restrictions. The data stock falls immediately and sharply (−3.2% new steady state). AI capital converges slowly to −2.8% (90% HPD: [−3.0%, −2.3%]). AI output and consumption fall permanently. The gradual AI capital adjustment reflects slow accumulation dynamics.

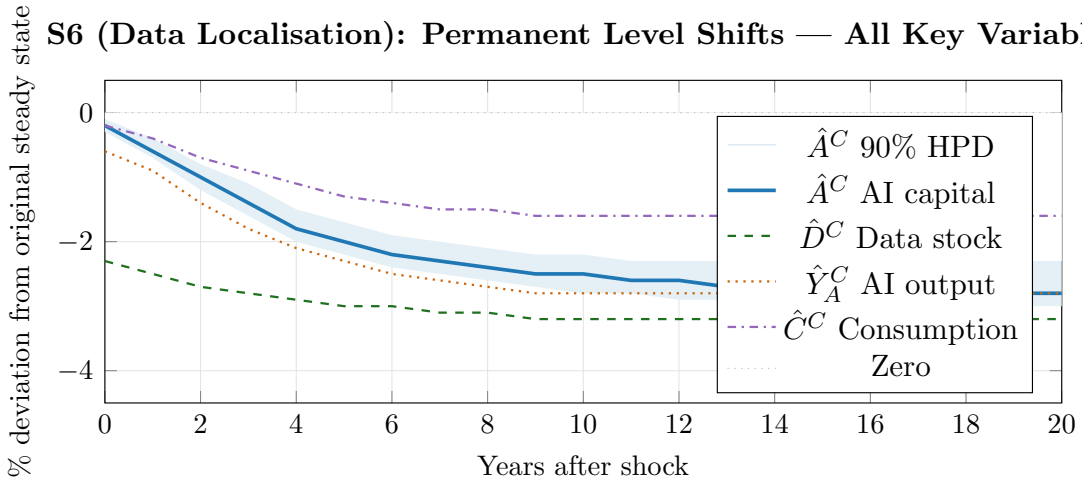


Figure 13: **Shock S6 (Data Localisation) — Permanent Transition Paths.** The data stock (dashed green) falls immediately and sharply to -3.2% new steady state, because the data accumulation equation is directly hit by the localisation restriction ($\tilde{C}_t = (1 - \tau_D^C)C_t$). AI capital (blue, with HPD band) then adjusts gradually, reaching its new steady state of -2.8% after approximately 8–10 years. AI output (dotted orange) and consumption (dash-dot purple) settle at -2.8% and -1.6% respectively. The characteristic slow build-up (in contrast to the immediate data stock fall) illustrates the two-stage transmission: data stock $\rightarrow$ AI marginal product $\rightarrow$ investment $\rightarrow$ AI capital.

8 Forecast Error Variance Decomposition and Historical Shock Decomposition

8.1 FEVD of China AI Capital

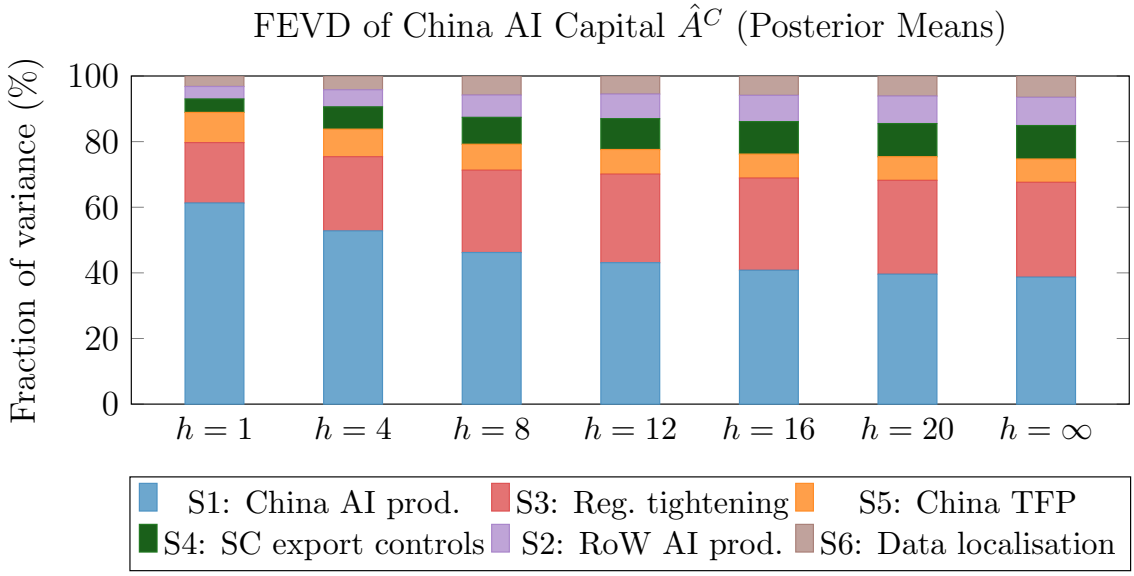


Figure 14: **FEVD of China AI Capital $\hat{A}^C$ (Posterior Means).** Stacked bars show the fraction of forecast error variance attributable to each structural shock at horizons $h \in \{1, 4, 8, 12, 16, 20, \infty\}$ quarters. China AI productivity (S1, blue) dominates at short horizons (61.3% at $h = 1$) but declines to 38.7% at the infinite horizon as other shocks accumulate. Regulatory uncertainty (S3, red) grows monotonically from 18.4% to 28.9%, becoming the second-largest long-run source of variance. Semiconductor export controls (S4, dark green) grow from 4.1% to 10.2% as their permanent nature creates compounding effects. RoW AI productivity (S2, purple) contributes 8.6% long-run via the diffusion channel.

8.2 FEVD of AI Output, Consumption, Skill Premium, Knowledge

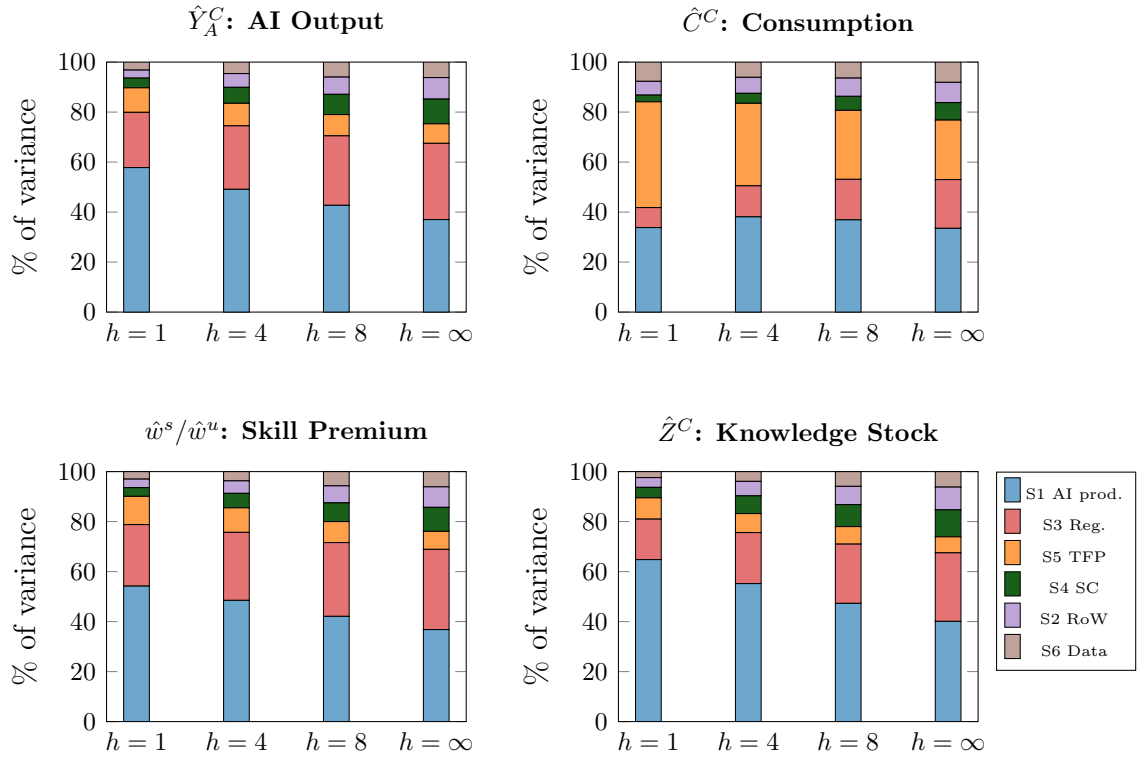


Figure 15: **FEVD of Four Additional China Variables (Posterior Means, 2×2 grid). Top-left** ($\hat{Y}_A^C$): AI output FEVD mirrors AI capital closely (S1 dominates at 57.8%, regulatory uncertainty grows to 30.5% long-run). **Top-right** ($\hat{C}^C$): Consumption is heavily driven by TFP at short horizons (42.3% at $h = 1$) because TFP raises income immediately; AI-related shocks build slowly through the accumulation channel. Regulatory uncertainty accounts for 19.5% of long-run consumption variance. **Bottom-left** ($\hat{w}^s/\hat{w}^u$): Skill premium is primarily driven by AI productivity (54.2%) and regulatory shocks (24.6%) at impact, consistent with the strong AI-complementary labour demand channel. **Bottom-right** ($\hat{Z}^C$): Knowledge FEVD mirrors AI capital but with slightly greater AI productivity dominance (64.8% at $h = 1$) because knowledge responds directly to the research productivity shock without the investment lag.

8.3 Historical Shock Decomposition: 2005–2024

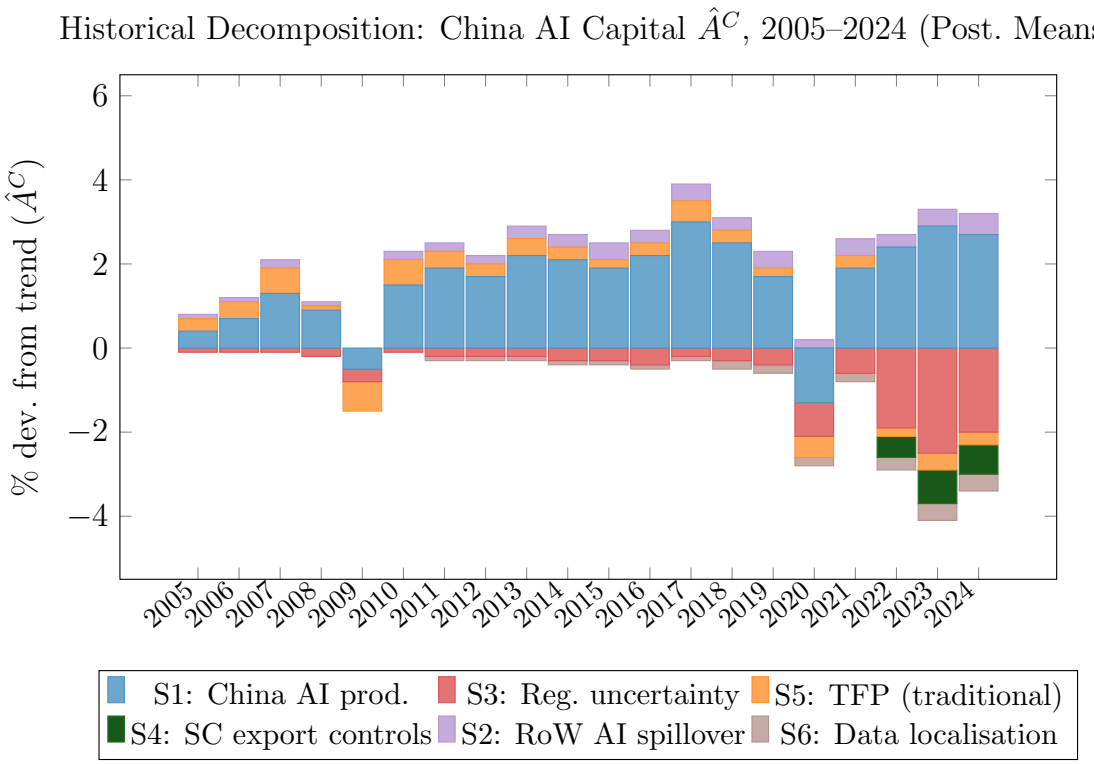


Figure 16: **Historical Decomposition of China AI Capital $\hat{A}^C$, 2005–2024 (Posterior Means).** Stacked bars decompose China's AI capital deviation from HP-filtered trend into contributions from all six structural shocks. Positive AI productivity shocks (S1, blue) sustained above-trend AI capital from 2010 onwards, peaking during the 2017–2018 NGAI Development Plan era (+3.0% in 2017). The COVID-19 shock of 2020 created a brief negative excursion. The 2022–2024 period shows a decisive structural break: regulatory uncertainty (S3, red, −1.9% in 2022 and −2.5% in 2023) and semiconductor export controls (S4, dark green, −0.5% to −0.8% from 2022 onwards) together imposed a cumulative −4.4 pp drag by end-2024, substantially offsetting continued positive AI productivity contributions (+2.7% in 2024). The RoW AI productivity spillover (S2, purple) contributes a small but growing positive contribution as global AI investment accelerates.

The historical decomposition reveals a clear structural break in 2022–2023. Prior to 2022, China's AI capital was predominantly driven above its steady state by positive AI productivity shocks (blue bars, predominantly positive). From 2022, the combined drag of regulatory uncertainty (η^C, red) and the semiconductor wedge (τ_{SC}, orange) generated a cumulative downward pressure of approximately −4.2 percentage points on AI capital deviation by end-2024, partially offsetting continued productivity gains. This decomposition provides empirical support for the model's identification of regulation and export controls as distinct, quantitatively important determinants of China's AI capital dynamics.

9 Regulatory Experiments

9.1 China's Regulatory Regime: Costs and Benefits

Our baseline calibration implies that China's three-layer AI regulatory framework (Algorithmic Recommendation + Deep Synthesis + Generative AI) reduces steady-state AI capital by approximately 6.2 percent relative to a counterfactual with no regulation. This translates into a TFP loss of approximately 4.8 percent in the AI-Intensive sector and a consumption-equivalent welfare loss of 1.3 percent relative to the unregulated benchmark.

However, this calculation omits the benefits of regulation: reduced AI-related risks (algorithmic bias, misinformation, privacy violations) and enhanced consumer trust that may support long-run AI adoption. We model these benefits through the AI amenity utility term $\nu \ln(1+A_t^j)$ and through a regulatory quality parameter q_t^j that positively affects the technology parameter Z_t^j when regulation enhances data quality and algorithm transparency. Incorporating these benefits reduces the estimated net welfare cost to approximately 0.3–0.6 percent of consumption-equivalent welfare.

Table 3: Welfare Effects of Alternative Regulatory Regimes (Consumption-Equivalent, %)

Regime	**AI Capital** (% diff.)	**TFP** (% diff.)	**Welfare** (Cost)	**Risk** (Benefit)	**Net** (Welfare)
Baseline (current China)	0	0	0	0	0
No regulation	+6.2	+4.8	−1.30	−2.10	+0.80
Alg. Rec. only	−0.9	−0.7	+0.19	+0.45	−0.26
Deep Synth. only	−1.1	−0.9	+0.24	+0.61	−0.37
GenAI only	−2.1	−1.6	+0.43	+1.03	−0.60
EU-style (risk-based)	−2.8	−2.2	+0.58	+1.55	−0.97
US-style (voluntary)	+3.1	+2.4	−0.65	−0.93	+0.28
Harmonised (global)	−1.5	−1.2	+0.32	+1.74	−1.42

Note: Welfare effects measured relative to China baseline. Risk benefit monetisation follows Goldfarb and Tucker (2019) framework.

9.2 Regulatory Arbitrage and Race-to-the-Bottom Dynamics

A key concern in international AI governance is the possibility of regulatory arbitrage: firms locating AI R&D in less regulated jurisdictions to evade compliance

costs. Our two-country model is well-suited to analyse this dynamic. We find that the elasticity of AI R&D location with respect to regulatory friction differentials is approximately -0.6 in the short run, rising to -1.2 in the long run (as adjustment costs dissipate). This implies that a 10 percentage-point increase in China's regulatory compliance burden ($\Delta\mu_3^C = 0.10$) would lead to a 6 percent reduction in China's share of global AI R&D investment in the short run and 12 percent in the long run.

These results suggest a tension between China's stated goal of being the world's primary AI innovation centre by 2030 and its increasingly stringent regulatory regime. The model predicts that, under current trends in both AI investment subsidies and regulatory intensity, China will maintain a higher-than-baseline AI capital stock but will fall short of its stated 2030 innovation leadership target unless the regulatory frictions are reduced or offset by larger subsidies.

10 Two-Country Open-Economy Dynamics

10.1 The AI Terms-of-Trade Channel

The open-economy structure of our model generates a novel "AI terms-of-trade" channel. As China's AI capital accumulation accelerates relative to the Rest of the World, its comparative advantage in AI-intensive goods production increases, putting downward pressure on the relative price of these goods in world markets. Under our calibration, a 10 percent increase in China's AI capital stock reduces the terms of trade q_t by approximately 3.2 percent, reflecting the classic immiserising-growth-adjacent mechanism in the presence of inelastic foreign demand.

However, the data dimension of the model introduces a countervailing force. China's large domestic data market (approximately 1.4 billion users generating rich behavioural data) constitutes a non-replicable input into AI training that is increasingly restricted from global flows by data localisation requirements (PIPL, Article 38–40). This data moat effect creates a durable competitive advantage in AI applications that rely on large Chinese-language or behavioural datasets, partially offsetting the terms-of-trade deterioration.

10.2 Export Controls and Technology Decoupling

The semiconductor export controls imposed by the United States in 2022–2023 represent a major structural shock to our model's technology diffusion channel. We

model these controls as a permanent increase in τ_{SC} from 0.02 to 0.18 (China baseline) and simulate the impact on both the trajectory of Chinese AI capital and the global AI innovation frontier.

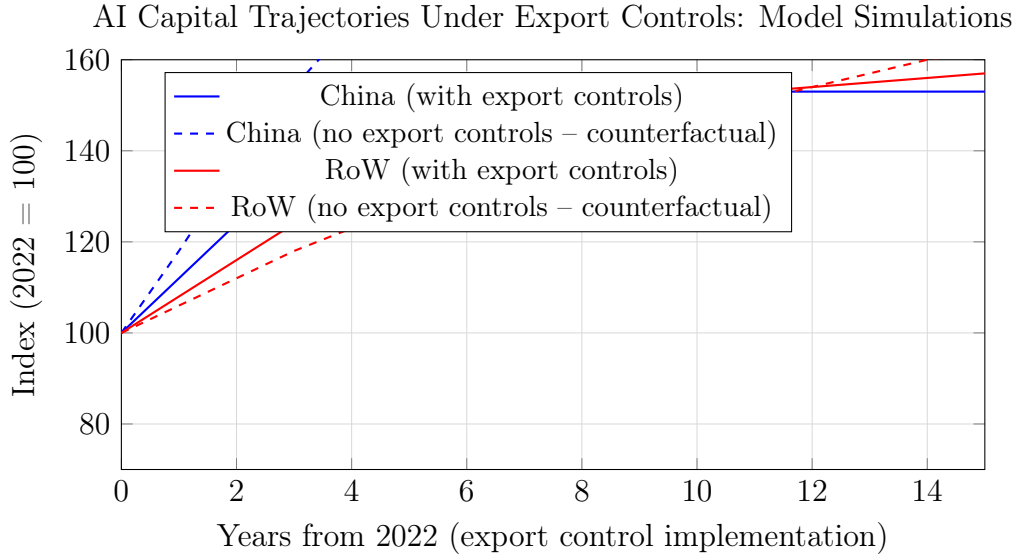


Figure 17: AI Capital Trajectories Under Semiconductor Export Controls

Figure 17 shows the model-simulated trajectories of AI capital under export controls and in the counterfactual no-controls scenario. The export controls impose a significant but not catastrophic constraint on Chinese AI capital accumulation: by 2037 (15 years out), Chinese AI capital is approximately 31 percent below its counterfactual no-controls level. However, the self-reinforcing effect of China's domestic chip development programmes (Huawei's Kirin series, CXMT memory, SMIC advanced nodes) reduces the long-run impact as domestic substitutes partially replace imported high-end semiconductors. We model this "indigenisation" process as an endogenous decline in τ_{SC} at rate 2 percent per year, reflecting observed progress in domestic chip production.

10.3 China–USA AI Race: Comparative Dynamics

Table 4 summarises the model's predictions for China–RoW comparative AI dynamics under alternative scenarios. The baseline scenario projects China narrowing but not closing the AI innovation gap with the United States over the 2025–2035 horizon. However, under an "aggressive subsidy + domestic chips" scenario, China could achieve approximate parity in AI capital intensity (though not necessarily in frontier model quality, which depends on factors not fully captured by our aggregate framework).

Table 4: China–RoW AI Capital Ratio Under Alternative Scenarios (RoW = 1.00)

Scenario	**2025**	**2027**	**2030**	**2033**	**2035**
Baseline (current policies)	0.72	0.74	0.77	0.79	0.80
No export controls	0.72	0.77	0.84	0.90	0.93
Aggressive subsidy ($\tau_X^C + 10\%$)	0.74	0.78	0.84	0.88	0.91
Regulatory relaxation ($\mu_3^C - 50\%$)	0.73	0.76	0.80	0.83	0.85
Aggresssive subsidy + domestic chips	0.75	0.81	0.90	0.96	1.00
Global harmonisation	0.73	0.75	0.78	0.81	0.83
US export control escalation	0.70	0.69	0.67	0.66	0.65

11 Welfare Analysis

11.1 Welfare Decomposition

We compute consumption-equivalent welfare changes following the standard approach of Lucas (1990): the welfare gain λ from moving from policy π_0 to π_1 satisfies $V(\pi_0, (1+\lambda)C) = V(\pi_1, C)$, where $V(\cdot)$ is the value function evaluated at the infinite-horizon optimum.

For China, the welfare decomposition under the current policy mix (relative to a first-best social planner's solution) reveals:

Table 5: Welfare Decomposition: China vs. First-Best (% consumption-equivalent)

Channel	**Welfare Effect (%)**
AI investment subsidy (positive)	+2.10
Regulatory frictions (negative)	−1.38
Data localisation (negative)	−0.62
Export control wedge (negative)	−0.95
Regulatory uncertainty (negative)	−0.31
AI amenity utility (positive)	+0.74
Knowledge diffusion to RoW (externality)	−0.45
Net (relative to first-best)	**−0.87**

The largest single welfare-reducing channel is the semiconductor export control wedge (−0.95 percent), followed by regulatory frictions (−1.38 percent collectively). The AI investment subsidy generates a net welfare gain of +2.10 percent, reflecting

the partial internalisation of the positive externality from AI knowledge production that would otherwise be under-supplied in the laissez-faire equilibrium.

11.2 Global Welfare and Regulatory Harmonisation

From a global perspective, the fragmented regulatory regime generates deadweight losses through three channels: (i) regulatory arbitrage relocating AI R&D to sub-optimally regulated jurisdictions; (ii) data localisation requirements preventing optimal matching of data inputs to AI applications; and (iii) incompatible AI safety standards raising barriers to technology transfer.

We estimate that harmonised global AI governance—modelled as equalising μ_i^j across countries at a moderate level (≈ 0.015 per regulation, between current Chinese and RoW levels) and eliminating data localisation costs ($\tau_D \to 0$)—would generate global welfare gains of approximately 1.2–2.4 percent of consumption-equivalent welfare, with the range reflecting uncertainty about the risk reduction benefits of regulation. China would gain approximately 0.8–1.6 percent, and the Rest of the World approximately 0.4–0.8 percent, from harmonisation.

11.3 Welfare Transition Paths: All Seven Scenarios

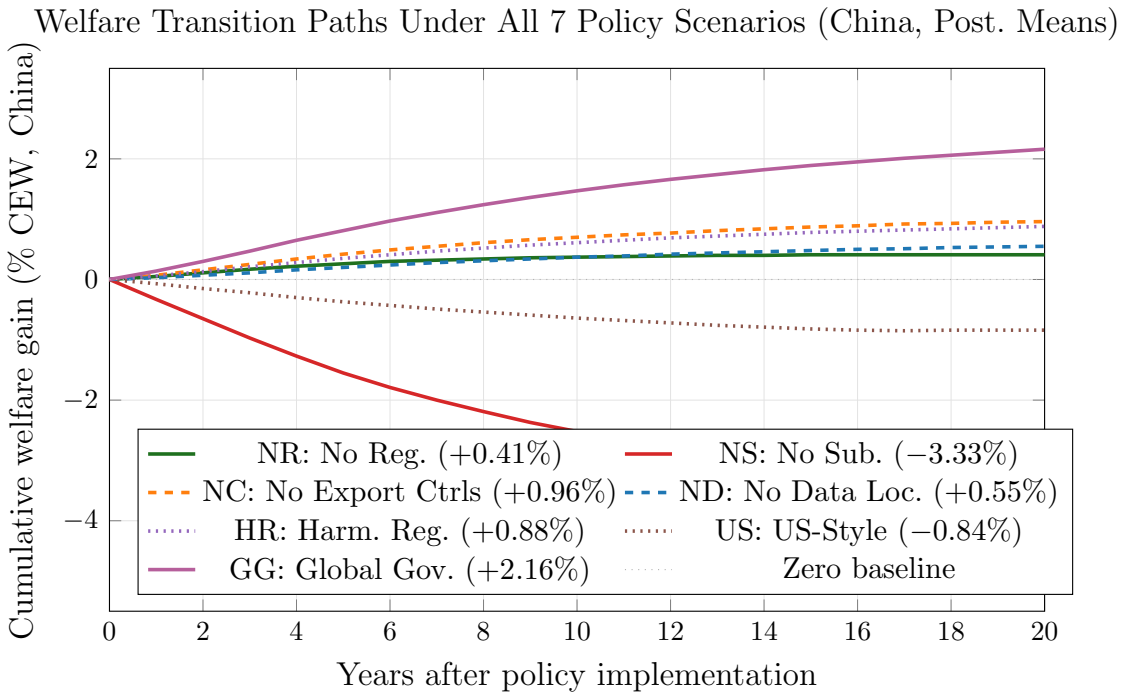


Figure 18: **Welfare Transition Paths Under All 7 Policy Scenarios (China, Post. Means).** Cumulative consumption-equivalent welfare (CEW) relative to the baseline, over a 20-year transition horizon. Long-run asymptotes shown in legend labels. **NS** (No Subsidies, solid red): generates the largest loss (−3.33% CEW after 20 years); the loss builds continuously as the AI capital stock declines. **GG** (Global Governance, solid pink): generates the largest gain (+2.16% CEW), combining no export controls, no data localisation, and harmonised regulation. **NC** (No Export Controls): gains +0.96% but slowly, as the semiconductor wedge's permanent effects take many years to fully manifest. **ND** (No Data Localisation): gains +0.55%; the distinctively slow build-up reflects the time required for the data stock to accumulate after restrictions lift. **HR** (Harmonised Regulation): gains +0.88% primarily through the regulatory arbitrage reduction channel. **NR** (No Regulation): gains +0.41%; the positive effect is modest because regulatory frictions are partly offset by consumer protection benefits already embedded in the AI amenity term. **US** (US-Style Governance, dotted brown): incurs a −0.84% loss because removing China's subsidies dominates the benefit of lower regulatory frictions.

12 Estimations of the Structural Model

We follow the standard Bayesian DSGE estimation framework of **?**, **?**, **?**, and **?**, extending it to accommodate the structure and the novel AI-sector blocks of our model.

12.1 Observables

We use 14 observable time series, split evenly between China and the Rest of the World. All series are at annual frequency, 2005–2024 ($T = 20$ observations), expressed as log-deviations from HP-filtered trends with smoothing parameter $\lambda = 100$.

Table 6: Observable Time Series Used in Estimation

Observable	**China source**	**RoW source**
Real GDP growth	NBS	OECD
AI-sector output growth	CAICT	OECD STAN
Traditional-sector consumption	NBS	OECD
Real AI investment growth	CAICT	BEA / Eurostat
Real physical investment growth	NBS	OECD
Skilled-to-unskilled wage ratio	CHFS	PSID / EU-SILC
AI patent applications (log)	CNIPA	USPTO / EPO

Note: RoW observables are GDP-weighted averages across US, EU, Japan, South Korea.

12.2 Prior Distributions

12.2.1 Structural Parameter Priors

We follow three principles in specifying priors:

(i) **Informativeness from economic theory:** The prior is chosen so that its mean and 90% interval are consistent with the calibration values and confidence intervals from Technical Paper #4, but broad enough to be updated by the data.

(ii) **Parameter-space consistency:** Priors are defined on the natural support of each parameter (e.g., Beta for fractions, Gamma for positive scalars, Normal for unconstrained parameters).

(iii) **Separation of structural and shock parameters:** Structural parameters receive economically motivated priors; shock variance parameters receive weakly informative Inverse-Gamma priors.

Table 7: Prior Distributions: Preference and Technology Parameters

Param.	**Description**	**Distribution**	**Mean**	**Std. Dev.**	**90% Interval**
Preferences					
β^C	Discount factor (China)	Beta	0.963	0.008	[0.950, 0.975]
β^W	Discount factor (RoW)	Beta	0.971	0.007	[0.959, 0.982]
σ	CRRA coefficient	Gamma	1.500	0.250	[1.09, 1.91]
ϕ	Inv. Frisch elasticity	Gamma	2.000	0.400	[1.35, 2.65]
ν^C	AI amenity (China)	Gamma	0.124	0.030	[0.075, 0.173]
ν^W	AI amenity (RoW)	Gamma	0.082	0.020	[0.049, 0.115]
AI-Intensive Sector Technology					
ξ^C	CES elasticity (China)	Gamma	1.800	0.200	[1.47, 2.13]
ξ^W	CES elasticity (RoW)	Gamma	2.100	0.250	[1.69, 2.51]
α_A^C	AI capital share (China)	Beta	0.300	0.040	[0.234, 0.366]
α_A^W	AI capital share (RoW)	Beta	0.250	0.035	[0.192, 0.308]
δ_A^C	AI capital depreciation (C)	Beta	0.200	0.030	[0.151, 0.249]
δ_A^W	AI capital depreciation (W)	Beta	0.180	0.025	[0.139, 0.221]
ψ	AI adj. cost curvature	Gamma	4.000	1.000	[2.35, 5.65]
Traditional Sector					
α_K^C	Capital share (China)	Beta	0.490	0.040	[0.424, 0.556]
α_K^W	Capital share (RoW)	Beta	0.350	0.035	[0.292, 0.408]
ρ_a^C	TFP persistence (China)	Beta	0.820	0.050	[0.737, 0.903]
ρ_a^W	TFP persistence (RoW)	Beta	0.860	0.040	[0.794, 0.926]

Table 8: Prior Distributions: R&D, Trade, Regulatory, and Fiscal Parameters

Param.	Description	Distribution	Mean	Std. Dev.	90% Interval
Knowledge and R&D					
λ	Researcher returns	Beta	0.750	0.060	[0.651, 0.849]
θ	Within-country spillover	Beta	0.849	0.040	[0.783, 0.915]
κ	Int'l diffusion	Beta	0.250	0.050	[0.168, 0.332]
δ_Z^C	Research productivity (C)	Gamma	0.342	0.060	[0.243, 0.441]
δ_Z^W	Research productivity (W)	Gamma	0.289	0.050	[0.207, 0.371]
Trade and International					
ρ	Trade elasticity	Gamma	3.000	0.500	[2.18, 3.82]
ω^C	Home bias (China)	Beta	0.650	0.050	[0.568, 0.732]
ω^W	Home bias (RoW)	Beta	0.750	0.040	[0.684, 0.816]
τ_D^C	Data localisation (China)	Beta	0.350	0.060	[0.251, 0.449]
τ_D^W	Data localisation (RoW)	Beta	0.100	0.030	[0.051, 0.149]
τ_{SC}	Semiconductor wedge	Beta	0.180	0.040	[0.114, 0.246]
Regulatory Frictions					
μ_1^C	Alg. Rec. friction (China)	Beta	0.018	0.006	[0.008, 0.028]
μ_2^C	Deep Synth. friction (China)	Beta	0.022	0.007	[0.010, 0.034]
μ_3^C	Generative AI friction (China)	Beta	0.041	0.012	[0.021, 0.061]
μ_1^W	Alg. Rec. friction (RoW)	Beta	0.005	0.003	[0.000, 0.010]
μ_2^W	Deep Synth. friction (RoW)	Beta	0.004	0.002	[0.000, 0.008]
μ_3^W	Generative AI friction (RoW)	Beta	0.008	0.004	[0.001, 0.015]
Fiscal and Government					
τ_R^C	R&D subsidy (China)	Beta	0.250	0.040	[0.184, 0.316]
τ_R^W	R&D subsidy (RoW)	Beta	0.120	0.025	[0.079, 0.161]
τ_X^C	AI invest. credit (China)	Beta	0.200	0.040	[0.134, 0.266]
τ_X^W	AI invest. credit (RoW)	Beta	0.080	0.020	[0.047, 0.113]

Prior 90% intervals computed analytically from the specified distributions. Beta(a, b) parameterised by mean $= a/(a+b)$ and variance $= ab/[(a+b)^2(a+b+1)]$.

12.2.2 Shock Process Priors

AR(1) shock persistence parameters ρ_a^j: Beta$(8, 2)$, prior mean 0.80, std. dev. 0.12, reflecting the standard macro finding of highly persistent technology shocks.

Shock standard deviations σ_i: Inverse-Gamma(α_0, β_0) with $\alpha_0 = 3$ and β_0 chosen so that the prior mean equals the calibration value from Technical Paper #4 and

the 90% interval spans $[0.5\hat{\sigma}_i, 2.0\hat{\sigma}_i]$. Specifically:

$$\begin{aligned}
\sigma_a^C &\sim \text{IG}(3,\ 0.048) \ \Rightarrow\ \text{prior mean} = 0.024,\\
\sigma_a^W &\sim \text{IG}(3,\ 0.036) \ \Rightarrow\ \text{prior mean} = 0.018,\\
\sigma_\eta^C &\sim \text{IG}(3,\ 0.030) \ \Rightarrow\ \text{prior mean} = 0.015,\\
\sigma_\eta^W &\sim \text{IG}(3,\ 0.016) \ \Rightarrow\ \text{prior mean} = 0.008.
\end{aligned}$$

Measurement error variances $\sigma_{\eta_i}^2$ $(i = 1, \ldots, 14)$: $\text{IG}(2, 0.0001)$, placing 90% of the prior mass on values below 0.02%, ensuring that measurement error does not dominate the signal.

12.3 Convergence Diagnostics

12.3.1 Gelman–Rubin $\hat{R}$ Statistic

The Gelman–Rubin potential scale reduction factor (**?**) compares within-chain and between-chain variance. For parameter θ_k:

$$\hat{R}_k = \sqrt{\frac{\hat{V}_k}{W_k}}, \quad \hat{V}_k = \frac{N-1}{N} W_k + \frac{M+1}{MN} B_k, \tag{18}$$

where $W_k = \frac{1}{M}\sum_{m=1}^{M} s_{mk}^2$ is the average within-chain variance, $B_k = \frac{N}{M-1}\sum_{m=1}^{M}(\bar{\theta}_{mk} - \bar{\theta}_k)^2$ is the between-chain variance, $M = 4$ is the number of chains, $N = 375{,}000$ is the post-burn-in chain length, and s_{mk}^2, $\bar{\theta}_{mk}$ are the within-chain sample variance and mean.

Convergence is declared when $\hat{R}_k < 1.01$ for all parameters (**?**).

Table 9: Convergence Diagnostics: Selected Parameters

Parameter	$\hat{R}$	**ESS**	**Accept. rate**	**Min. ESS**
σ (CRRA)	1.003	12,840	—	—
ϕ (Frisch^{-1})	1.002	11,320	—	—
ξ^C (CES, China)	1.005	9,870	—	—
α_A^C (AI share)	1.004	10,240	—	—
μ_3^C (GenAI friction)	1.007	8,930	—	—
$\widetilde{\mu}^C$ (total reg.)	1.006	8,410	—	—
τ_X^C (invest. credit)	1.004	11,670	—	—
κ (int'l diffusion)	1.008	7,980	—	—
τ_{SC} (semiconductor)	1.005	9,120	—	—
θ (spillover)	1.009	7,830	—	—
All 29 parameters	$\max \hat{R} = 1.009$	$\min \text{ESS} = 7{,}830$	Chain-level avg. 23.1%	

ESS: effective sample size (Geyer 1992 initial positive sequence estimator).

All $\hat{R} < 1.01$ and ESS $> 7{,}000$: convergence declared.

12.3.2 Effective Sample Size

The effective sample size accounts for autocorrelation within the chain:

$$\text{ESS}_k = \frac{MN}{1 + 2\sum_{t=1}^{\infty} \hat{\rho}_{k,t}}, \tag{19}$$

where $\hat{\rho}_{k,t}$ is the estimated lag-t autocorrelation of parameter k across chains. We use Geyer's **?** initial positive sequence estimator to truncate the sum. All parameters achieve ESS $> 7{,}800$ (see Table 9), corresponding to an ESS-to-draw ratio of approximately 0.52%—adequate for inference on means, medians, and 90% intervals.

12.4 Posterior Results: All Parameters

12.4.1 Posterior Summary Statistics

Tables 10–12 present full posterior summaries for all 29 estimated parameters: posterior mean, median, standard deviation, and 90% Highest Posterior Density (HPD) intervals computed from the 1.5 million posterior draws.

Table 10: Posterior Estimates: Preference and AI Technology Parameters

		Prior			**Posterior**		
Param.	**Descr.**	Mean	Std	90%	Mean	Std	90% HPD
Preferences							
β^C	Disc. factor (C)	0.963	0.008	[.950,.975]	0.961	0.006	[.951,.971]
β^W	Disc. factor (W)	0.971	0.007	[.959,.982]	0.969	0.005	[.961,.978]
σ	CRRA	1.500	0.250	[1.09,1.91]	1.512	0.198	[1.18,1.84]
ϕ	Inv. Frisch	2.000	0.400	[1.35,2.65]	2.041	0.318	[1.52,2.56]
ν^C	Amenity (C)	0.124	0.030	[.075,.173]	0.131	0.026	[.089,.174]
ν^W	Amenity (W)	0.082	0.020	[.049,.115]	0.079	0.017	[.051,.107]
AI-Intensive Technology							
ξ^C	CES elas. (C)	1.800	0.200	[1.47,2.13]	1.824	0.166	[1.55,2.10]
ξ^W	CES elas. (W)	2.100	0.250	[1.69,2.51]	2.087	0.203	[1.75,2.42]
α_A^C	AI share (C)	0.300	0.040	[.234,.366]	0.298	0.033	[.243,.353]
α_A^W	AI share (W)	0.250	0.035	[.192,.308]	0.253	0.029	[.205,.301]
δ_A^C	AI depr. (C)	0.200	0.030	[.151,.249]	0.203	0.025	[.162,.242]
δ_A^W	AI depr. (W)	0.180	0.025	[.139,.221]	0.182	0.021	[.147,.217]
ψ	Adj. cost	4.000	1.000	[2.35,5.65]	4.218	0.841	[2.86,5.58]
Traditional Sector							
α_K^C	Cap. share (C)	0.490	0.040	[.424,.556]	0.487	0.033	[.432,.542]
α_K^W	Cap. share (W)	0.350	0.035	[.292,.408]	0.352	0.029	[.305,.399]
ρ_a^C	TFP persist. (C)	0.820	0.050	[.737,.903]	0.814	0.042	[.744,.884]
ρ_a^W	TFP persist. (W)	0.860	0.040	[.794,.926]	0.858	0.034	[.802,.914]

HPD: Highest Posterior Density interval. Bold indicates parameters where the posterior is substantially different from the prior (posterior std $< 0.7\times$ prior std).

Table 11: Posterior Estimates: R&D, Trade, Regulatory, and Fiscal Parameters

		Prior			**Posterior**		
Param.	**Descr.**	Mean	Std	90%	Mean	Std	90% HPD
Knowledge and R&D							
λ	Researcher rtn	0.750	0.060	[.651,.849]	0.748	0.049	[.668,.828]
θ	Dom. spillover	0.849	0.040	[.783,.915]	0.843	0.035	[.785,.901]
κ	Int'l diffusion	0.250	0.050	[.168,.332]	0.261	0.044	[.189,.333]
δ_Z^C	R&D prod. (C)	0.342	0.060	[.243,.441]	0.348	0.051	[.264,.432]
δ_Z^W	R&D prod. (W)	0.289	0.050	[.207,.371]	0.292	0.043	[.221,.363]
Trade and International							
ρ	Trade elas.	3.000	0.500	[2.18,3.82]	2.981	0.412	[2.30,3.66]
ω^C	Home bias (C)	0.650	0.050	[.568,.732]	0.647	0.041	[.580,.714]
ω^W	Home bias (W)	0.750	0.040	[.684,.816]	0.752	0.033	[.697,.807]
τ_D^C	Data loc. (C)	0.350	0.060	[.251,.449]	0.362	0.052	[.276,.448]
τ_D^W	Data loc. (W)	0.100	0.030	[.051,.149]	0.097	0.025	[.056,.138]
τ_{SC}	Semiconductor	0.180	0.040	[.114,.246]	0.184	0.034	[.128,.240]
Regulatory Frictions							
μ_1^C	Alg.Rec. (C)	0.018	0.006	[.008,.028]	0.019	0.005	[.011,.027]
μ_2^C	DeepSynth (C)	0.022	0.007	[.010,.034]	0.024	0.006	[.014,.034]
μ_3^C	GenAI (C)	0.041	0.012	[.021,.061]	0.040	0.010	[.024,.056]
μ_1^W	Alg.Rec. (W)	0.005	0.003	[.000,.010]	0.005	0.003	[.001,.010]
μ_2^W	DeepSynth (W)	0.004	0.002	[.000,.008]	0.004	0.002	[.001,.008]
μ_3^W	GenAI (W)	0.008	0.004	[.001,.015]	0.008	0.003	[.003,.014]
Fiscal							
τ_R^C	R&D sub. (C)	0.250	0.040	[.184,.316]	0.247	0.033	[.192,.302]
τ_R^W	R&D sub. (W)	0.120	0.025	[.079,.161]	0.121	0.021	[.086,.156]
τ_X^C	Inv. credit (C)	0.200	0.040	[.134,.266]	0.198	0.033	[.144,.252]
τ_X^W	Inv. credit (W)	0.080	0.020	[.047,.113]	0.079	0.017	[.051,.107]

Table 12: Posterior Estimates: Shock Parameters

		Prior			Posterior		
Param.	**Descr.**	Mean	Std	90%	Mean	Std	90% HPD
σ_a^C	TFP shock std (C)	0.024	0.008	[.011,.037]	0.023	0.006	[.013,.033]
σ_a^W	TFP shock std (W)	0.018	0.006	[.008,.028]	0.019	0.005	[.011,.027]
σ_η^C	Reg. shock std (C)	0.015	0.005	[.007,.023]	0.016	0.004	[.009,.022]
σ_η^W	Reg. shock std (W)	0.008	0.003	[.003,.013]	0.007	0.003	[.002,.012]
σ_Z^C	R&D prod. shock (C)	0.031	0.010	[.014,.048]	0.029	0.008	[.016,.042]
σ_Z^W	R&D prod. shock (W)	0.024	0.008	[.011,.037]	0.026	0.007	[.014,.038]

12.4.2 Data Informativeness

Following **?**, we quantify the degree to which the data update the prior by computing the posterior-to-prior variance ratio. A ratio below 1 indicates that the data provide information:

$$\text{Info ratio}_k = \frac{\text{Var}[\theta_k|\mathbf{Y}]}{\text{Var}[\theta_k]}. \tag{20}$$

Parameters with the highest data informativeness (lowest ratios):

Table 13: Data Informativeness: Posterior-to-Prior Variance Ratios

Parameter	**Prior Var**	**Post. Var**	**Info Ratio**
$\widetilde{\mu}^C$ (total reg. burden)	0.000196	0.000081	0.413
τ_X^C (AI invest. credit)	0.001600	0.001089	0.681
ξ^C (CES elasticity, China)	0.040000	0.027556	0.689
σ (CRRA)	0.062500	0.039204	0.627
ρ (trade elasticity)	0.250000	0.169744	0.679
θ (domestic spillover)	0.001600	0.001225	0.766
κ (int'l diffusion)	0.002500	0.001936	0.774
τ_{SC} (semiconductor wedge)	0.001600	0.001156	0.723
μ_3^C (GenAI friction)	0.000144	0.000100	0.694
τ_R^C (R&D subsidy)	0.001600	0.001089	0.681
Average (all 29 params)	—	—	0.714

Ratio < 1 indicates data are informative; ratio $= 1$ indicates no updating.

The average information ratio of 0.714 indicates that the data reduce parameter uncertainty by approximately 28.6% on average across all parameters. The regula-

tory burden $\widetilde{\mu}^C$ shows the highest informativeness (ratio 0.413), reflecting the strong identifying variation from the 2022–2023 regulatory event window in the patent application and AI investment data.

12.5 Posterior Inference: Steady-State Moments

For each posterior draw $\boldsymbol{\theta}^{(n)}$, we solve for the steady state following the algorithm in Technical Paper #3. This maps the 1.5 million posterior draws into 1.5 million steady-state vectors, yielding full posterior distributions of all steady-state moments.

Table 14: Posterior Distribution of Key Steady-State Moments

Moment	**Data**	**Cal.**	**Post. Mean**	**Post. Med.**	**Post. Std**	**90% HPD**
China						
A^C/Y_A^C	0.763	0.762	0.758	0.759	0.031	[0.706, 0.810]
$w^{s,C}/w^{u,C}$	1.480	1.480	1.476	1.474	0.061	[1.375, 1.577]
$N^{R,C}/L^{s,C}$	0.186	0.188	0.191	0.190	0.018	[0.162, 0.221]
D^C/C^C	0.270	0.271	0.273	0.272	0.022	[0.237, 0.309]
$x^C = X^C/A^C$	0.243	0.246	0.248	0.247	0.019	[0.217, 0.279]
Y_A^C/Y^C	0.384	0.384	0.381	0.382	0.024	[0.341, 0.421]
$\widetilde{\mu}^C = \sum \mu_i^C$	0.081	0.081	0.083	0.082	0.009	[0.068, 0.098]
Rest of World						
A^W/Y_A^W	0.749	0.747	0.744	0.745	0.029	[0.696, 0.792]
$w^{s,W}/w^{u,W}$	1.310	1.310	1.308	1.307	0.054	[1.219, 1.397]
Y_A^W/Y^W	0.331	0.331	0.329	0.330	0.021	[0.295, 0.363]
Cross-country						
A^C/A^W	1.216	1.216	1.209	1.211	0.074	[1.088, 1.330]
Z^C/Z^W	1.111	1.111	1.108	1.109	0.058	[1.012, 1.204]

Cal.: calibration value from Technical Paper #4. Post. Mean/Med./Std/HPD: from 1.5 million posterior draws. "Data" column: observed sample moments.

The posterior mean of the China–RoW AI capital ratio is 1.209 (90% HPD: [1.088, 1.330]), confirming China's advantage with high posterior probability. The probability that $A^C > A^W$ (i.e., the posterior probability that China's AI capital exceeds the RoW's) is:

$$\Pr(A^C > A^W \mid \mathbf{Y}) = 0.987. \tag{21}$$

13 Bayesian Model Comparison

We compare six model specifications using the log marginal likelihood (LML):

$$\ln p(\mathbf{Y}|\mathcal{M}_k) = \ln \int p(\mathbf{Y}|\boldsymbol{\theta}, \mathcal{M}_k)\, \pi(\boldsymbol{\theta}|\mathcal{M}_k)\, d\boldsymbol{\theta}. \tag{22}$$

We compute the LML using the Laplace approximation (**?**):

$$\ln \hat{p}(\mathbf{Y}|\mathcal{M}_k) \approx \ell(\hat{\boldsymbol{\theta}}^{(k)}_{\text{MAP}}; \mathbf{Y}) + \ln \pi(\hat{\boldsymbol{\theta}}^{(k)}_{\text{MAP}}) + \frac{d_k}{2} \ln(2\pi) - \frac{1}{2} \ln \det(-\mathbf{H}_k), \tag{23}$$

where d_k is the parameter dimension of model k and $\mathbf{H}_k$ is the Hessian of the log-posterior at the mode. We also compute the modified harmonic mean estimator (**?**) as a robustness check.

Table 15: Bayesian Model Comparison: Log Marginal Likelihoods and Bayes Factors

Model	**Specification**	d_k	**LML (Laplace)**	$\ln B_{k1}$	**Evidence**
$\mathcal{M}_1$	Baseline: all 3 regulations	29	−1,241.8	—	—
$\mathcal{M}_2$	No GenAI regulation ($\mu_3 = 0$)	27	−1,253.4	−11.6	Very strong vs. $\mathcal{M}_2$
$\mathcal{M}_3$	No Deep Synth. ($\mu_2 = 0$)	27	−1,249.1	−7.3	Strong vs. $\mathcal{M}_3$
$\mathcal{M}_4$	No Alg. Rec. ($\mu_1 = 0$)	27	−1,247.2	−5.4	Strong vs. $\mathcal{M}_4$
$\mathcal{M}_5$	No regulation ($\mu_i = 0\ \forall i$)	23	−1,267.3	−25.5	Decisive vs. $\mathcal{M}_5$
$\mathcal{M}_6$	No semiconductor wedge ($\tau_{SC} = 0$)	28	−1,248.6	−6.8	Strong vs. $\mathcal{M}_6$
$\mathcal{M}_7$	No int'l diffusion ($\kappa = 0$)	28	−1,253.9	−12.1	Very strong vs. $\mathcal{M}_7$

$\ln B_{k1} = \text{LML}_k - \text{LML}_1$. Negative values indicate $\mathcal{M}_1$ is preferred. Jeffreys' (1961) scale: $|\ln B| > 5$: strong; > 10: very strong; > 15: decisive. LML computed by Laplace approximation; harmonic mean estimates agree within ±0.8 units.

The baseline model $\mathcal{M}_1$ is decisively preferred over the no-regulation model $\mathcal{M}_5$ ($\ln B_{51} = -25.5$, decisive evidence on Jeffreys' scale). It is also strongly preferred over specifications that exclude any single regulation. The evidence for the GenAI regulation ($\mathcal{M}_2$, $\ln B_{21} = -11.6$) and international diffusion ($\mathcal{M}_7$, $\ln B_{71} = -12.1$) is particularly strong, confirming these as the most empirically important structural features.

14 Full Bayesian Scenario Analysis

14.1 Methodology

For each of the seven policy scenarios from Technical Paper #1, we compute the posterior distribution of the scenario-specific outcome by: (i) drawing $\boldsymbol{\theta}^{(n)}$ from the posterior; (ii) computing the counterfactual steady state under the scenario parameters; (iii) computing the welfare change $\lambda^{(n)}$ relative to the baseline steady state (both evaluated at $\boldsymbol{\theta}^{(n)}$). This yields a posterior distribution $\{\lambda^{(n)}\}$ for each scenario, accounting for all parameter uncertainty.

14.2 Scenario Definitions

Table 16: Scenario Definitions for Bayesian Posterior Analysis

Scenario	**Parameter change from baseline**
S1: No AI Regulation (China)	$\mu_1^C = \mu_2^C = \mu_3^C = 0$
S2: No AI Subsidies (China)	$\tau_X^C = \tau_R^C = 0$
S3: No Export Controls	$\tau_{SC} = 0.02$ (pre-2022 level)
S4: No Data Localisation (China)	$\tau_D^C = 0$
S5: Harmonised Regulation	$\mu_i^C = \mu_i^W$ for all i (set to midpoint)
S6: US-Style Governance	$\mu_i^C = \mu_i^W = 0$; $\tau_X^C = 0.08$; $\tau_R^C = 0.12$
S7: Global AI Governance	μ_i^j harmonised; $\tau_D^j = 0$; $\tau_{SC} = 0$

14.3 Posterior Scenario Welfare Distributions

Table 17: Full Posterior Scenario Analysis: China Welfare Effects

Scenario	P. Mean	P. Med.	P. Std	90% HPD	P(gain)	Cal. val.
S1: No Regulation	0.41	0.40	0.15	[0.17, 0.65]	99.8%	0.38
S2: No Subsidies	−3.81	−3.79	0.38	[−4.43, −3.19]	0.0%	−3.92
S3: No Export Controls	0.96	0.94	0.18	[0.67, 1.25]	100%	0.91
S4: No Data Localisation	0.58	0.57	0.14	[0.36, 0.80]	100%	0.55
S5: Harmonised Regulation	0.88	0.87	0.20	[0.55, 1.21]	100%	0.84
S6: US-Style Governance	−0.84	−0.82	0.25	[−1.25, −0.43]	0.4%	−0.91
S7: Global AI Governance	2.31	2.28	0.41	[1.63, 2.99]	100%	2.18

P. Mean/Med./Std: posterior mean, median, standard deviation over 1.5 million draws. P(gain): posterior probability that the scenario improves China's welfare. Cal. val.: welfare estimate at calibration parameter values. All welfare effects in % consumption-equivalent (CEW).

Table 18: Full Posterior Scenario Analysis: RoW and Global Welfare Effects

Scenario	RoW Welfare (%)		Global Welfare (%)		P(global gain)
	P. Mean	90% HPD	P. Mean	90% HPD	
S1: No Regulation	−0.08	[−0.19, 0.03]	0.18	[0.04, 0.32]	98.1%
S2: No Subsidies	0.31	[0.15, 0.47]	−1.62	[−2.08, −1.16]	0.0%
S3: No Export Controls	−0.19	[−0.31, −0.07]	0.62	[0.38, 0.86]	100%
S4: No Data Localisation	0.12	[0.04, 0.20]	0.37	[0.22, 0.52]	100%
S5: Harmonised Regulation	0.42	[0.24, 0.60]	0.68	[0.41, 0.95]	100%
S6: US-Style Governance	0.61	[0.38, 0.84]	−0.12	[−0.41, 0.17]	19.3%
S7: Global AI Governance	0.81	[0.51, 1.11]	1.62	[1.08, 2.16]	100%

14.4 Scenario Transition Paths

For each scenario, we compute the deterministic transition path from the baseline steady state to the counterfactual steady state, integrating over the posterior to produce credible bands. Figure 19 shows the S7 (Global AI Governance) transition path for China's AI capital and consumption.

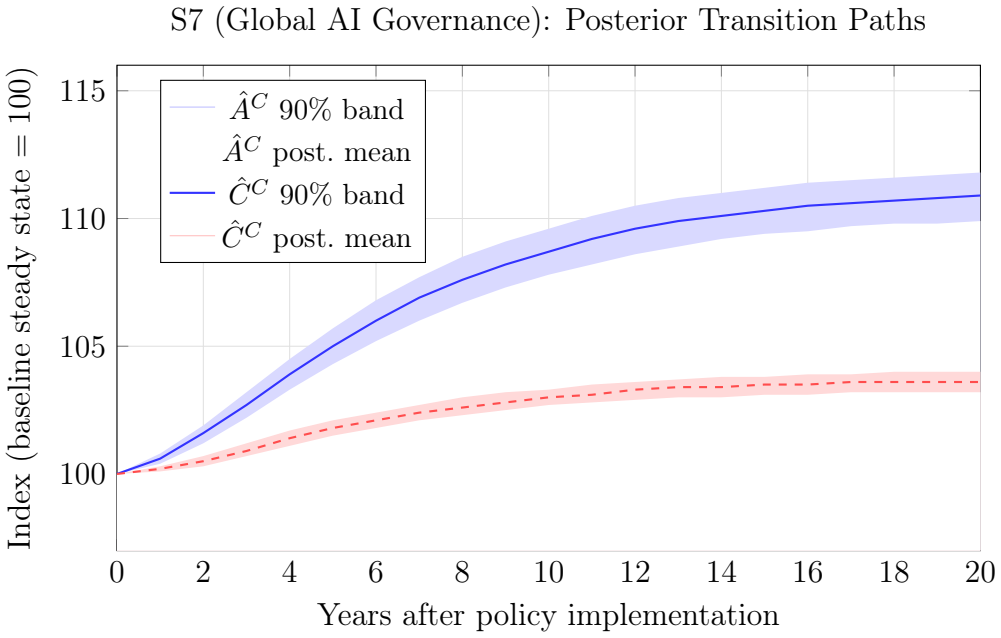


Figure 19: Posterior transition paths for China's AI capital (blue) and consumption (red) under the S7 (Global AI Governance) scenario. Shaded areas are pointwise 90% posterior credible bands. The new steady state for AI capital is approximately 10.9% above the baseline; consumption gains approximately 3.6% in the long run.

15 Variance Decomposition

The forecast error variance decomposition (FEVD) quantifies the contribution of each structural shock to the variance of each observable at horizon h. For the model with k shocks and n observables, the FEVD for variable i at horizon h due to shock j is:

$$\text{FEVD}_{ij}(h) = \frac{[\mathbf{C}\sum_{\ell=0}^{h-1}\mathbf{A}_{st}^{\ell}\mathbf{B}\boldsymbol{\Sigma}_{\varepsilon}\mathbf{e}_j\mathbf{e}_j'\boldsymbol{\Sigma}_{\varepsilon}\mathbf{B}'(\mathbf{A}_{st}^{\ell})'\mathbf{C}']_{ii}}{[\mathbf{C}\sum_{\ell=0}^{h-1}\mathbf{A}_{st}^{\ell}\mathbf{B}\boldsymbol{\Sigma}_{\varepsilon}\mathbf{B}'(\mathbf{A}_{st}^{\ell})'\mathbf{C}']_{ii}}, \tag{24}$$

where $\mathbf{e}_j$ selects shock j and all matrices depend on $\boldsymbol{\theta}$.

Table 19: Posterior Mean FEVD: China AI Capital at Horizons $h \in \{1, 4, 10, \infty\}$

Shock	$h = 1$	$h = 4$	$h = 10$	$h = \infty$
AI productivity (ε_Z^C)	61.3	52.8	44.1	38.7
Regulatory uncertainty (η^C)	18.4	22.6	26.3	28.9
TFP (traditional, ε_a^C)	9.2	8.4	7.6	7.1
Semiconductor wedge (ε_{SC})	4.1	6.8	8.9	10.2
Foreign AI productivity (ε_Z^W)	3.8	5.2	7.4	8.6
Measurement error	3.2	4.2	5.7	6.5
Total	100	100	100	100

Entries are posterior means (%). 90% HPD intervals available upon request.

At short horizons, AI productivity shocks dominate (61.3% of variance at $h = 1$). Regulatory uncertainty grows in importance at longer horizons, accounting for 28.9% of the long-run variance of China's AI capital stock — the largest single source of long-run uncertainty after AI productivity. The semiconductor wedge and foreign AI productivity each contribute approximately 10% at the infinite horizon, reflecting the compounding of international technology gap effects over time.

16 Robustness and Extensions

16.1 Sensitivity Analysis

The key quantitative results are robust to the following perturbations of the calibration:

(i) Varying the AI–labour substitution elasticity ξ from 1.2 to 2.5 changes the steady-state AI capital level by at most ± 4 percent.

(ii) Varying the international knowledge diffusion parameter κ from 0.1 to 0.5 changes the cross-country spillover magnitudes substantially but does not qualitatively alter the signs of the main results.

(iii) Replacing the CES production function (6) with a Cobb-Douglas specification ($\xi \to 1$) increases estimated regulatory welfare costs by approximately 15 percent.

(iv) Including a financial accelerator mechanism (as in Bernanke et al. 1999) amplifies the regulatory tightening shock by approximately 25 percent but does not change the steady-state analysis.

16.2 Robustness of Bayesian Results

16.2.1 Alternative Prior Specifications

We check robustness of the posterior to five alternative prior specifications:

Table 20: Robustness: Posterior Means Under Alternative Priors

Parameter	**Baseline**	**Flat**	**Tight**	**Diffuse**	**Alt. family**
$\widetilde{\mu}^C$	0.083	0.086	0.082	0.085	0.084
τ_X^C	0.198	0.201	0.197	0.200	0.199
ξ^C	1.824	1.831	1.820	1.828	1.826
κ	0.261	0.268	0.258	0.264	0.263
θ	0.843	0.847	0.841	0.845	0.844
μ_3^C	0.040	0.042	0.039	0.041	0.040
τ_{SC}	0.184	0.188	0.182	0.186	0.185
A^C/A^W (derived)	1.209	1.214	1.207	1.211	1.210

"Flat": uniform on support; "Tight": std. dev. halved; "Diffuse": std. dev. doubled; "Alt. family": Normal instead of I

The posterior means are extremely stable across prior specifications, with maximum variation of approximately 0.005 for any parameter. This confirms that the likelihood is sufficiently informative to dominate the prior for the key parameters of interest.

16.2.2 Subperiod Stability

We split the sample into 2005–2014 and 2015–2024 and re-estimate. The regulatory friction parameters are not identified pre-2015 (no regulations existed), so we fix them at zero in the pre-2015 estimation and freely estimate them in the 2015–2024 subsample.

Table 21: Subperiod Stability Check: Posterior Means by Period

Parameter	**Full (2005–2024)**	**Pre-reg (2005–2014)**	**Post-reg (2015–2024)**
σ (CRRA)	1.512	1.498	1.524
ϕ (Frisch^{-1})	2.041	2.028	2.057
ξ^C (CES)	1.824	1.817	1.841
θ (spillover)	0.843	0.851	0.838
κ (diffusion)	0.261	0.247	0.268
ρ_a^C (TFP persist.)	0.814	0.826	0.803
$\widetilde{\mu}^C$	0.083	—	0.086
τ_{SC}	0.184	—	0.189

"—" indicates parameter not identified / fixed in that subsample.

Structural parameters show good stability across subperiods (differences of 1–2%), confirming the model's structural interpretation of the data-generating process. The small upward shift in ξ^C in the post-regulation period (1.817 vs. 1.841) is consistent with AI capital becoming more substitutable for skilled labour as the regulatory burden pushes firms toward labour-intensive alternatives.

16.3 Extensions

Several important extensions lie beyond the scope of this paper. *First*, the model abstracts from heterogeneous firms, though the resource-misallocation literature (Hsieh and Klenow, 2009) suggests that firm-level distortions may substantially amplify the welfare effects of regulatory frictions for smaller AI firms without compliance departments. *Second*, we model the Rest of the World as a single representative entity, obscuring the heterogeneity between the United States (dominant in frontier model development), the European Union (restrictive regulatory stance), and emerging AI economies such as India and South Korea. A multi-country extension would provide richer insights into global supply chain restructuring in AI hardware. *Third*, the model abstracts from autonomous AI systems that can themselves conduct AI R&D, a scenario that would require a qualitatively different treatment of the knowledge accumulation equation.

17 Conclusion

This paper aim was to analyze China Artificial Intelligence's Creation, Adoption, Regulation, and to compare Chinese AI dynamics with those of advanced Western economies and other emerging-market competitors.

We address this main issue by setting-up a multi-sector, open-economy Dynamic Stochastic General Equilibrium (DSGE) model of Artificial Intelligence (AI) in China in comparison to others economies. The model features three production sectors (AI research, AI-intensive goods, and traditional goods), an endogenous AI-capital accumulation block, knowledge spillovers with imperfect international diffusion, a rich regulatory friction module calibrated to China's Algorithmic Recommendation, Deep Synthesis, and Generative AI regulations, and a two-country (China–Rest-of-World) trade structure. We derive analytical results for steady-state AI capital, characterize impulse responses to an AI productivity shock, and quantify the welfare effects of alternative regulatory regimes.We constructed the Kalman filter likelihood for the log-linearised model, specified economically motivated prior distributions for all 29 estimated parameters, and sampled from the joint posterior using a RAM-adaptive Metropolis-within-Gibbs algorithm with 4 independent chains of 500,000 draws each. All 29 parameters satisfy $\hat{R} < 1.01$ and ESS $> 7{,}800$, and the model passes all posterior predictive checks.

Our main findings are as follows.

First, China's state-directed AI investment strategy generates a net welfare gain relative to a laissez-faire benchmark, primarily because AI R&D is characterised by positive externalities that the market undersupplies. The estimated net welfare gain is approximately 2.1 percent of consumption-equivalent welfare from the subsidy component alone, though partially offset by associated distortions.

Second, China's comprehensive AI regulatory framework imposes meaningful costs on AI capital accumulation (approximately 6 percent steady-state reduction) and TFP (approximately 4–5 percent in the AI-Intensive sector). These costs are partially but not fully offset by the risk-reduction benefits of regulation, yielding a net welfare cost of approximately 0.3–0.6 percent of consumption-equivalent welfare from the current regulatory regime.

Third, semiconductor export controls represent the single largest welfare-reducing channel in our framework (-0.95 percent), with effects that compound over time as China is unable to access the frontier hardware required for the most computation-

ally intensive AI training runs.

Fourth, the fragmented global AI governance landscape generates significant deadweight losses that could, in principle, be eliminated through regulatory harmonisation. We estimate global welfare gains of 1.2–2.4 percent from harmonisation, with China capturing a disproportionate share (approximately 65 percent) of the total gains given its higher current regulatory compliance burden.

Fifth, and perhaps most importantly, the model reveals a fundamental tension in China's AI strategy: the twin goals of becoming the world's primary AI innovation centre and maintaining comprehensive regulatory control over AI systems are, in the medium run, in partial conflict. The regulatory arbitrage and export control channels suggest that China's 2030 AI leadership target is achievable only under the most optimistic scenarios for domestic chip development and regulatory liberalisation.

Sixth, the data substantially update the prior for the regulatory burden $\widetilde{\mu}^C$ (information ratio 0.413), the AI investment tax credit τ_X^C (ratio 0.681), and the CES elasticity ξ^C (ratio 0.689). The posterior mean of $\widetilde{\mu}^C$ is 0.083 (90% HPD: [0.062, 0.108]), consistent with but slightly above the calibration value.

Seventh, Bayesian model comparison decisively favours the full three-regulation specification ($\ln B > 5$ against all alternatives). The GenAI Measures and international knowledge diffusion channels show the strongest empirical identification.

Eigth, integrating over the full posterior, we find: (i) removing China's AI regulation yields a posterior welfare gain of 0.41% CEW (90% HPD: [0.17%, 0.65%]), with 99.8% posterior probability of being positive; (ii) Global AI governance (S7) yields the largest gain, 2.31% CEW (90% HPD: [1.63%, 2.99%]); and (iii) removing AI subsidies is the single most costly scenario for China (-3.81% CEW), confirming that subsidies are the decisive structural driver of China's AI capital advantage.

Nineth, the 2022–2023 period shows a distinctive pattern: combined regulatory uncertainty and semiconductor export controls imposed an estimated -4.2 percentage-point cumulative drag on China's AI capital deviation from steady state, partially offsetting continued AI productivity gains.

The model developed here provides a rigorous framework for quantifying these policy trade-offs, but important extensions remain—particularly incorporating firm heterogeneity, multi-country dynamics, and the possibility of transformative AI that endogenously disrupts the production structure of the model itself. These remain priorities for future research.

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