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Digitalization through fiscal competition☆,☆☆

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ABSTRACT

This paper studies how fiscal competition among local governments shapes digitalization. We develop a dynamic two-region spatial general equilibrium model with digital services and manufacturing sectors. Frontier digital technology spills over to manufacturing and raises its productivity, while manufacturing activity generates data that feeds back into digital innovation. These bidirectional cross-sector externalities create a self-reinforcing growth loop whose strength is increasing in the manufacturing sector's digital adaptability. However, since private agents fail to internalize these externalities, the laissez-faire equilibrium is Pareto-inefficient, with resources under-allocated to the digital services sector. A digital output subsidy and a manufacturing R&D data subsidy can jointly correct these externalities and implement the First-Best allocation. We further introduce tournament competition into the decentralized economy. Local governments compete for mobile digital talent by setting the two subsidy instruments to improve their regions' relative growth performance. Aggregate welfare responds non-monotonically to tournament competition intensity. Moderate competition partially corrects the externalities and raises allocative efficiency above the laissez-faire level, while excessive competition drives subsidies beyond the social optimum into over-subsidization. This implies that well-designed fiscal competition can alleviate the externalities inherent in digitalization and enhance aggregate welfare.

1. Introduction

The development of the digital economy has rapidly risen to the forefront of intergovernmental fiscal competition worldwide. Regional jurisdictions across diverse institutional settings increasingly deploy competitive fiscal instruments to attract digital industries. In China, provincial and municipal governments vie to establish state-led digital industry clusters, directing public resources toward computing infrastructure and talent subsidies (Aghion et al., 2015; Zheng et al., 2017). Across the European Union, member states compete through divergent corporate tax regimes, inducing digital multinationals to concentrate profits in low-tax jurisdictions (Devereux et al., 2008; Tørsløv et al., 2023). In the United States, states engage in escalating subsidy wars, committing

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billions in grants and tax credits to lure digital technology firms (Slattery and Zidar, 2020; Slattery, 2025). A fundamental welfare question arises as to whether intergovernmental competition and its fiscal incentives genuinely accelerate digital development and enhance aggregate welfare, or predominantly generate allocative distortions that impose a net social cost.

Addressing this question requires confronting several features that distinguish digital economy competition from competition over traditional industries. First, specialized digital talent constitutes the primary productive factor. The core inputs to digital production, such as the code developed by software engineers, the algorithmic models built by data scientists, and the product architectures designed by technology managers, are embodied in mobile workers rather than in fixed physical capital. Digital talent is therefore both geographically footloose and intensely contested across jurisdictions (Akcigit et al., 2016; Moretti and Wilson, 2017). Second, digital technologies generate cross-industry spillovers that operate through multiple channels. Digital knowledge diffuses across sectors, raising adopting firms' total factor productivity, while consumption activity generates data that feeds back into the digital innovation process, creating reciprocal linkages between the digital frontier and the broader economy (Bresnahan and Trajtenberg, 1995; Bloom et al., 2013). Third, digital markets exhibit pronounced winner-take-all dynamics, in which the leading search engine, social network, or e-commerce platform captures the dominant share of its market (Autor et al., 2020; Babina et al., 2024). These features jointly imply that the welfare consequences of competitive fiscal policies in the digital economy are qualitatively richer than those arising in conventional factor-competition contexts.

We develop a dynamic two-region spatial general equilibrium model in which each region comprises a digital services sector and a manufacturing sector. In the digital services sector, specialized digital talent applies technology-based knowledge and data-based knowledge generated by economic activity to drive technological progress. Manufacturing technology draws on the firm's own accumulated knowledge and on frontier digital technology that spills over from the digital services sector, with the relative weight governed by the manufacturing sector's digital adaptability. The two sectors interact through bidirectional cross-sector externalities. The digital sector's advances raise the technology frontier available to manufacturing, while manufacturing activity generates data that feeds back into digital innovation. These bidirectional cross-sector externalities create a self-reinforcing growth loop in which digital innovation raises manufacturing productivity, which in turn generates more data that accelerates digital innovation further. However, since private agents fail to internalize these externalities, laissez-faire under-allocates resources to the digital services sector and is Pareto-inefficient. This result motivates the introduction of government intervention to reallocate resources toward the digital services sector.

Building on this framework, we introduce fiscal instruments and fiscal competition. The optimal subsidy pair consists of a digital output subsidy and a manufacturing R&D data subsidy, both financed by a manufacturing tax under a balanced budget constraint. The two subsidy instruments can jointly correct the bidirectional cross-sector externalities and implement the First-Best allocation. Rather than relying on the optimal subsidy pair, we next consider whether decentralized tournament competition can deliver comparable efficiency gains. The government's objective combines own-region welfare with relative growth performance against the rival region. This formulation reflects the promotion tournament mechanism widely documented in China's intergovernmental governance. Because digital talent is mobile across regions, fiscal competition motivates each region to raise subsidies to attract scarce digital talent from rivals. The welfare consequences exhibit an inverted-U pattern in tournament competition intensity, driven by a trade-off between externality correction and over-subsidization. As tournament competition intensity rises, intergovernmental competitive pressure induces larger subsidies that partially correct the bidirectional cross-sector externalities. The subsidies move toward their First-Best levels and welfare rises above the laissez-faire level, up to a peak competition intensity. Beyond this threshold, the subsidies move away from their First-Best levels into over-subsidization. Resources are reallocated toward the digital services sector beyond the social optimum, and welfare declines. This non-monotonic relationship implies the existence of an optimal tournament design in which moderate competition serves as an effective instrument for externality correction.

Complementing the theory, we provide motivating empirical evidence using Chinese city-level and firm-level panel data spanning 2011 to 2019. At the city level, digitalization in other cities is significantly and robustly negatively associated with local digitalization. At the firm level, the local spillover effect and the inter-city competition effect work in opposite directions. Local digitalization is positively associated with manufacturing firms' digital technology adoption, consistent with beneficial within-city knowledge spillovers. In contrast, digitalization in other cities is negatively associated with manufacturing firms' digital technology adoption, consistent with competitive reallocation of mobile resources across cities. These patterns are consistent with the model's mechanism whereby fiscal competition reallocates mobile resources across regions and ultimately shapes local digitalization outcomes.

This paper contributes to four strands of the economics literature. The first strand is the theory of fiscal competition among decentralized governments. The canonical race-to-the-bottom result establishes that interjurisdictional competition for mobile capital depresses tax rates and public good provision below efficient levels (Wilson, 1986; Zodrow and Mieszkowski, 1986; Wildasin, 1988). The objects of fiscal competition have broadened beyond physical capital to encompass mobile skilled workers and high-tech firms. Tax differentials drive the location choices of superstar inventors (Akcigit et al., 2016) and star scientists (Moretti and Wilson, 2017). Governments have increasingly shifted from tax competition toward discretionary firm-specific subsidies, which attract business activity at other jurisdictions' expense and transfer much of the resulting surplus to firms (Slattery and Zidar, 2020; Ferrari and Ossa, 2023; Slattery, 2025). Cooperative tax policies can generate Pareto improvements by internalizing cross-border fiscal externalities (Edwards and Keen, 1996), and harmonized R&D subsidies correct both strategic distortions and under-investment in innovation (Borota Milicevic et al., 2026).

The second strand examines tournament competition over relative growth performance. The theory of rank-order tournaments shows that rank-based pay can match the efficiency of output-based pay in motivating productive effort, with the advantage of filtering out common shocks (Lazear and Rosen, 1981; Green and Stokey, 1983). Yardstick competition extends this logic to the

public sector, where voters or central authorities use peer performance as a benchmark for evaluating incumbents (Besley and Case, 1995). The clearest illustration is China's regionally decentralized governance, whose multi-divisional organizational structure promotes yardstick competition among provincial governments (Maskin et al., 2000). Empirical evidence confirms that the turnover and promotion of Chinese provincial leaders depend on GDP growth relative to predecessors and neighbors (Li and Zhou, 2005). Local officials maximize a composite objective that combines own-region welfare with relative growth performance against rival regions (Li et al., 2019; Fang et al., 2025). However, tournament incentives generate distortions, including local protectionism and biased resource allocation against competing regions (Xu, 2011; Fang et al., 2025).

The third strand concerns the growth effects of digital technology and cross-sector technology spillovers. Growth accounting establishes that information technology drives productivity acceleration across advanced economies (Oliner and Sichel, 2000; Stiroh, 2002; Jorgenson et al., 2008), though realizing these gains requires complementary organizational and human capital investments (Brynjolfsson and Hitt, 2000; Bloom et al., 2012). These growth effects extend well beyond IT-producing sectors, as broadband diffusion and automation technologies have been shown to raise productivity across a wide range of industries (Czernich et al., 2011; Akerman et al., 2015; Graetz and Michaels, 2018). More recently, artificial intelligence (AI) has emerged as a general-purpose technology with the potential to sustain exponential growth when applied to the production of ideas (Aghion et al., 2019). Task-based models show that the net effect of AI depends on the balance between automation displacement and new task creation (Acemoglu and Restrepo, 2018, 2019). Recent empirical studies further document substantial individual productivity gains from the adoption of generative AI (Noy and Zhang, 2023; Brynjolfsson et al., 2025).

The fourth strand addresses the economic role of data and its contribution to growth. Growth models that incorporate data as a nonrival input show that data sharing generates increasing returns and sustains long-run growth through enhanced product variety and knowledge spillovers (Jones and Tonetti, 2020; Cong et al., 2021, 2022). Data further mitigates information frictions by reducing uncertainty in future predictions and addressing information asymmetries in bilateral matching on data platforms (Farboodi and Veldkamp, 2020, 2026; Bergemann et al., 2022; Qiu and Wang, 2026). Data accumulation exhibits diminishing returns because prediction errors can at most be reduced to zero (Farboodi and Veldkamp, 2026). Data-intensive intangible assets underpin the rise of high-markup superstar firms (Autor et al., 2020; Crouzet et al., 2022), and data-enabled learning creates persistent competitive advantages (Goldfarb and Tucker, 2019; Bergemann and Bonatti, 2024). Data challenges standard growth frameworks through its nonrivalry, externalities, and increasing returns (Veldkamp and Chung, 2024).

This paper makes three contributions to the literature. First, we contribute to the literature on digital technology, data, and growth. The existing literature examines the spillover effects of digital technology or the growth effects of data nonrivalry. We instead analyze bidirectional cross-sector flows of technology and data, and thereby extend the microfoundations of the digital economy's growth effects. The technology spillover from the digital sector and the data feedback from the non-digital sector interact to create a self-reinforcing growth loop. Second, we contribute to the literature on the welfare analysis of fiscal policy. We show that the bidirectional cross-sector externalities of the digital economy yield growth gains but also render the laissez-faire equilibrium Pareto-inefficient, with resources under-allocated to the digital services sector. Fiscal policy therefore operates not as support for the digital sector but as correction of the cross-sector externalities, implemented with a digital output subsidy and a data subsidy to the non-digital sector. Third, we contribute to the fiscal competition and promotion tournament literature. We develop a novel analytical framework that integrates digital market failures with strategic interaction among local governments. Moderate competition induces local governments to raise subsidies, and the tournament objective of relative growth performance thereby corrects the digital market failures, moving the allocation toward the social optimum. These insights also extend to an economic union like the European Union, where fiscal policy coordinated across member states could correct such market failures and accelerate the digital transformation.

The remainder of the paper is organized as follows. Section 2 presents motivating evidence on city-level digitalization and manufacturing firms' digital technology adoption. Section 3 develops the two-region laissez-faire model with digital services and manufacturing sectors, and establishes the bidirectional cross-sector externalities. Section 4 derives the fiscal instruments that implement the First-Best allocation and analyzes the welfare consequences of decentralized tournament competition. Section 5 provides quantitative analyses. Finally, Section 6 concludes.

2. Motivating evidence

In this section, we present stylized facts on the economic effects of regional digitalization, focusing on two key dimensions: the impact of digitalization in other cities on local digitalization at the city level, and the influence of both local and other-city digitalization on digital technology adoption at the manufacturing firm level. In particular, our empirical tests exploit two-dimensional variation in digitalization, both across cities and over time.

2.1. Empirical specification

We construct econometric specifications at both the city and firm levels. To investigate the influence of digitalization in other cities on local digitalization, we establish a city-level specification of the form

$$Digit_local_{ct} = \beta Digit_other_{ct} + \boldsymbol{X}_{ct}^{\top}\boldsymbol{\gamma} + \vartheta_c + \delta_t + \zeta Trend_{p(c)t} + \xi_{ct},$$

where the subscripts c and t refer to city and year, respectively, and $p(c)$ denotes the province that c belongs to. The dependent variable, $Digit_local_{ct}$, captures the digitalization of city c in province p during year t. The explanatory variable of interest, $Digit_other_{ct}$, measures the average digitalization of other cities in province p during year t. Moreover, $\boldsymbol{X}_{ct}$ is a vector of city-specific

covariates covering economic development, population density, and industrial structure. We include city and time (year) fixed effects ϑ_c and δ_t. To account for time-varying province-level factors, we further include a province-specific time trend $Trend_{p(c)t}$. Lastly, ξ_{ct} is the error term, with standard errors clustered at the city level.

To examine how local and other-city digitalization shape manufacturing firms' digital technology adoption, we estimate a firm-level specification of the form

$$Digit_firm_{fct} = \beta_1 Digit_local_{ct} + \beta_2 Digit_other_{ct} + \boldsymbol{W}_{ft}^{\top}\boldsymbol{\eta} + \boldsymbol{X}_{ct}^{\top}\boldsymbol{\gamma} + \theta_f + \delta_t + \zeta Trend_{p(c)t} + \xi_{fct},$$

where the subscript f denotes the manufacturing firm, c denotes the city where firm f is registered, while the remaining subscripts are as defined in the city-level specification. The dependent variable, $Digit_firm_{fct}$, captures the digital technology adoption of firm f during year t. The two explanatory variables of interest, $Digit_local_{ct}$ and $Digit_other_{ct}$, measure the digitalization level of the city where the firm is registered and the average digitalization of other cities within the same province, respectively. In addition to city-level covariates, we control for a vector of firm characteristics, $\boldsymbol{W}_{ft}$, including firm size, leverage, profitability, asset tangibility, cash holdings, firm age, and ownership concentration. This specification additionally includes firm fixed effects, θ_f, capturing all time-invariant firm attributes, such as unobserved corporate culture. As in the city-level specification, standard errors are clustered at the city level.

The parameters of interest in these specifications are β, β_1, and β_2. At the city level, β measures the association between other-city digitalization and local digitalization. At the firm level, β_1 and β_2 capture the effects of local and other-city digitalization on manufacturing firms' digital technology adoption, respectively. To account for potential within-city correlation, we follow the approach in Matray (2021) and cluster standard errors at the city level in both specifications.

2.2. Data and variables

2.2.1. Data

We employ two distinct panel datasets, one at the city level and the other at the firm level. The city-level digitalization data is drawn from the Key Digital Technology Patent Database (KDTD) of the China National Research Data Service Platform (CNRDS). This database focuses on key technological innovations aligned with national strategic priorities and targets emerging digital industries and frontier technologies. It strictly follows the 2023 Key Digital Technology Patent Classification System and covers seven major fields[1]: AI, advanced semiconductors, quantum information, Internet of Things, blockchain, industrial internet, and metaverse technologies. As digital technologies constitute the foundation of digitalization, patent data in these frontier fields serves as an appropriate proxy for measuring the degree of digitalization.

To capture firm-level digital technology adoption, we use the digital application index from the China Stock Market and Accounting Research (CSMAR) Database. The digital application index comprises three standardized digital indicators covering technological innovation, process innovation, and business innovation. Each digital indicator is measured as the total frequency of specified digital-related keywords in firms' annual reports (excluding the management discussion and analysis section) and then standardized.[2] The digital application index is calculated as a weighted sum of the three standardized indicators, with weights of 0.6342 for the technological innovation indicator, 0.2378 for the process innovation indicator, and 0.1280 for the business innovation indicator. This digital application index summarizes the breadth and intensity of a firm's digital technology adoption, with higher values reflecting deeper and broader adoption.

These two data sources enable us to construct comprehensive city- and firm-level panels. Both datasets cover the period 2011–2019. We choose 2011 as the starting year because China's 12th Five-Year Plan (2011–2015) elevated informatization to a national strategic priority. This marked the beginning of a sustained policy effort to promote the digital economy through infrastructure investment, industrial upgrading programs, and targeted fiscal support at both central and local government levels. The sample ends in 2019 to avoid potential distortions associated with the COVID-19 pandemic.

First, we construct a panel of Chinese cities. Economic and demographic statistics originate from the China Statistical Yearbook and the China City Statistical Yearbook. We process the data as follows: (i) observations with missing values for key variables are removed; and (ii) to reduce the influence of outliers, all continuous variables are winsorized at the 1% level on both tails. The final sample comprises 280 unique cities, with a total of 2511 city-year observations.

Second, we construct a panel of Chinese A-share listed manufacturing firms. Firm-level operational and financial data is sourced from the CSMAR Database. The sample is constructed as follows: (i) observations prior to the firm's listing are excluded; (ii) firms designated as ST, *ST, or PT are dropped; (iii) firms whose registered city changes during the sample period are removed; (iv) firms with leverage below 0 or above 1 are removed; (v) observations with missing values for key variables are excluded; and (vi) all continuous variables are winsorized at the 1% level on both tails. The final sample consists of 1917 unique firms, corresponding to 12,742 firm-year observations.[3]

[1] An official document on the classification for key digital technology patents in China, source: https://www.cnipa.gov.cn/art/2023/9/25/art_75_187769.html.

[2] The technological innovation indicator includes keywords related to digital technologies (e.g., digital twins, metaverse, 5G, industrial internet). The process innovation indicator includes keywords related to digitalized operations (e.g., smart manufacturing, digital marketing, mobile payment). The business innovation indicator includes keywords related to new digital business models (e.g., internet finance, Fintech, smart healthcare, internet plus).

[3] These 1917 firms constitute the set of Chinese manufacturing firms for which systematic measures of digital technology adoption are available, since such disclosure is confined to listed companies. The sample is therefore determined by data availability rather than by selection on firm characteristics, and it is economically substantial: in 2019 the combined operating revenue of these firms accounted for 45.28% of that of all listed industrial firms and for 10.87% of the national operating revenue of industrial enterprises above designated size. Our findings accordingly hold for listed manufacturing firms and may not extend to small and medium-sized enterprises or to unlisted firms. Because listed firms are typically front-runners in digital adoption, the estimates are best read as providing leading-indicator insights into the digital transformation trajectory of the broader manufacturing sector.

Table 1
The impact of digitalization in other cities on local digitalization.

	(1) *Digit_local*1	(2) *Digit_local*2	(3) *Digit_local*1	(4) *Digit_local*2
*Digit_other*1	−0.7968***		−0.7604***	
	(0.1856)		(0.1782)	
*Digit_other*2		−0.5227***		−0.4741***
		(0.1847)		(0.1779)
City controls	No	No	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province FE × Time trends	Yes	Yes	Yes	Yes
Observations	2511	2511	2511	2511
R-squared	0.8892	0.8688	0.8903	0.8703

Notes: *Digit_local*1 and *Digit_local*2 are dependent variables. *Digit_local*1 is measured by the sum of invention patents and utility model patents in key digital technologies, while *Digit_local*2 is measured by invention patents in key digital technologies; both are for the city in that year and are scaled by the population (per 10,000 persons). Columns (1)–(2) do not include city controls, whereas columns (3)–(4) do. Standard errors in parentheses are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2.2.2. Variable definition

Measures of city-level digitalization. Following Wan et al. (2026), we use patent applications in key digital technologies for each city from the KDTD data to measure city-level digitalization. Patent applications reflect both a city's technological engagement and its commitment to digitalization. We use two types of patent data: one is the total of invention patent applications and utility model patent applications, reflecting overall digitalization levels; the other focuses on invention patent applications only, which are subject to stricter inventive-step requirements than utility model patents and better capture substantive progress in digital capabilities.

Specifically, we construct two sets of city-level digitalization measures. First, we capture local digitalization with *Digit_local*1 and *Digit_local*2. *Digit_local*1 is defined as the sum of invention patent applications and utility model patent applications in key digital technologies for city c in year t, scaled by the local population (per 10,000 persons). *Digit_local*2 measures only the number of invention patent applications in key digital technologies per 10,000 persons for city c in year t. Second, we compute the average digitalization levels of other cities within the same province during the same year, denoted as *Digit_other*1 and *Digit_other*2. *Digit_other*1 corresponds to the provincial average of *Digit_local*1, while *Digit_other*2 corresponds to the provincial average of *Digit_local*2.

Measures of firm-level digital technology adoption. We measure firm-level digital technology adoption with firms' digital application index. This index captures the extent to which firms adopt digital technologies across technological innovation, process innovation, and business innovation. We define two indicators of firm-level digital technology adoption, *Digit_firm*1 and *Digit_firm*2. *Digit_firm*1 is defined as the digital application score of firm f in year t, ranging between 0 and 100. *Digit_firm*2 is measured as the natural logarithm of firm f's digital application score in year t. Therefore, *Digit_firm*1 captures the absolute magnitude of a firm's digital technology adoption, whereas *Digit_firm*2 reflects its relative intensity and mitigates potential skewness.

Control variables. Inspired by earlier studies (Gaspar et al., 2024; Feng and Yuan, 2025), we include city- and firm-level control variables to isolate the effect of digitalization. At the city level, we control for economic development (*Econ_development*), measured as the natural logarithm of real per capita GDP deflated to 2003 prices; population density (*Pop_density*), measured as the natural logarithm of population per square kilometer; and industrial structure (*Ind_structure*), defined as the share of secondary industry in GDP.

At the firm level, we include firm size (*Size*), measured as the natural logarithm of total assets; leverage (*Lev*), defined as total liabilities divided by total assets; profitability (*Roa*), measured as net profit scaled by total assets; asset tangibility (*Tang*), defined as net fixed assets scaled by total assets; cash holdings (*Cash*), measured as net operating cash flow scaled by total assets; firm age (*Age*), measured as the natural logarithm of years since the firm's establishment; and ownership concentration (*Top*1), defined as the ownership share of the largest shareholder.

Descriptive statistics for all variables are reported in Online Appendix A.

2.3. Empirical results

2.3.1. City-level evidence

Table 1 reports the city-level results. We use *Digit_local*1 and *Digit_local*2 as alternative dependent variables and progressively add city-level covariates to assess robustness. In the baseline specification with city fixed effects, year fixed effects, and province-specific time trends but without additional controls, columns (1)–(2) yield significantly negative coefficients on *Digit_other*1 and *Digit_other*2. This indicates that local digitalization tends to be lower when other cities within the same province exhibit higher digitalization. Columns (3)–(4) augment the specification with controls for economic development, population density, and industrial structure. The negative coefficients remain stable in both magnitude and statistical significance, suggesting that the estimated

Table 2
The impact of city digitalization on manufacturing firms' digital technology adoption.

Panel A: Using Digit_local1 and Digit_other1				
	(1) *Digit_firm*1	(2) *Digit_firm*2	(3) *Digit_firm*1	(4) *Digit_firm*2
*Digit_local*1	0.0984**	0.0022**	0.0874**	0.0019**
	(0.0397)	(0.0009)	(0.0368)	(0.0008)
*Digit_other*1	−0.6648***	−0.0167***	−0.6793***	−0.0170***
	(0.2277)	(0.0051)	(0.2224)	(0.0050)
Firm controls	No	No	Yes	Yes
City controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province FE × Time trends	Yes	Yes	Yes	Yes
Observations	12,742	12,742	12,742	12,742
R-squared	0.6103	0.6049	0.6163	0.6112
Panel B: Using Digit_local2 and Digit_other2				
	(5) *Digit_firm*1	(6) *Digit_firm*2	(7) *Digit_firm*1	(8) *Digit_firm*2
*Digit_local*2	0.1779***	0.0039**	0.1624**	0.0035**
	(0.0674)	(0.0015)	(0.0634)	(0.0014)
*Digit_other*2	−0.8963***	−0.0218***	−0.9278***	−0.0224***
	(0.3236)	(0.0071)	(0.3195)	(0.0070)
Firm controls	No	No	Yes	Yes
City controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province FE × Time trends	Yes	Yes	Yes	Yes
Observations	12,742	12,742	12,742	12,742
R-squared	0.6104	0.6050	0.6165	0.6114

Notes: *Digit_firm*1 and *Digit_firm*2 are dependent variables. *Digit_firm*1 is measured by the firm's digital application score in each year, whereas *Digit_firm*2 is measured by the natural logarithm of its digital application score. Columns (1)–(2) and (5)–(6) do not include firm controls, whereas columns (3)–(4) and (7)–(8) do. Standard errors in parentheses are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

relationship is not driven by observable city characteristics. Across all specifications, city-level panel estimates reveal a significant negative relationship between other-city digitalization and local digitalization, with coefficients ranging from −0.7968 to −0.4741.[4]

2.3.2. Firm-level evidence

Table 2 reports the firm-level results, with *Digit_firm*1 and *Digit_firm*2 as alternative dependent variables. All regressions include the full set of fixed effects specified in the firm-level equation. Panel A uses *Digit_local*1 and *Digit_other*1 as the key explanatory variables, while Panel B uses the alternatives *Digit_local*2 and *Digit_other*2. In both panels, the coefficients on *Digit_local*1 and *Digit_local*2 are significantly positive across all columns, whereas those on *Digit_other*1 and *Digit_other*2 are significantly negative, with results robust to the flexible inclusion of firm-level controls. This indicates that local digitalization is positively associated with manufacturing firms' digital technology adoption, while other-city digitalization is negatively associated with manufacturing firms' digital technology adoption. Taken together, the firm-level panel estimates reveal that local and other-city digitalization exert opposing effects, with the former significantly promoting digital adoption and the latter suppressing it. The two opposing effects are comparable in magnitude when scaled by the standard deviation of the respective regressor in the estimation sample.[5]

2.3.3. Summary and discussion

The empirical analysis provides correlational evidence informative about the theoretical mechanisms, and it establishes two stylized facts. The first is the inter-city crowding out of digital innovation. Local digitalization is significantly and negatively related to digitalization in other cities, indicative of a mutual crowding-out rooted in inter-regional competition. The second is the dual firm-level response to local spillovers and inter-city competition. Manufacturing firms' digital technology adoption is significantly and positively related to local digitalization, and significantly and negatively related to other-city digitalization.

[4] To gauge the economic magnitude of these estimates, we take column (4) as an example. A one-standard-deviation increase in *Digit_other*2 (s.d. = 1.31 in the city-level estimation sample) is associated with a decrease of approximately 0.621 (= 0.4741 × 1.31) invention patent applications in key digital technologies per 10,000 persons, which is approximately half the *Digit_local*2 sample mean of 1.20.

[5] To illustrate the economic magnitude of these estimates, we take column (8) as an example. Since *Digit_firm*2 is the natural logarithm of the digital application score, each coefficient measures the proportional change in that score. A one-standard-deviation increase in *Digit_local*2 (s.d. = 10.33 in the firm-level estimation sample) is associated with an increase of approximately 3.62% (= 0.0035×10.33×100%) in the digital application score, whereas a one-standard-deviation increase in *Digit_other*2 (s.d. = 1.76 in the firm-level estimation sample) is associated with a decrease of approximately 3.94% (= 0.0224 × 1.76 × 100%).

These stylized facts motivate and discipline the theoretical model developed below, which formalizes the interplay between cross-sector digital spillovers and inter-regional competition. Three features of the model correspond to the evidence. First, the inter-city crowding out matches the inter-regional competition for mobile digital talent. Digital innovation relies on software engineers, data scientists, and technology managers. Such talent is rivalrous and mobile across regions, so talent drawn into one region leaves the other with less innovation capacity. Second, the positive local spillover at the firm level matches the spillover of frontier digital technology from the digital services sector to the manufacturing sector, one of the two bidirectional externalities between the sectors. Manufacturing firms absorb advances originating in the local digital sector, which yields positive co-movement between local digitalization and firm-level adoption. Third, rival cities reach a manufacturing firm through two countervailing channels. The expansion of rival digital sectors spills technology across city boundaries while drawing digital talent away from the firm's city. The negative association with other-city digitalization indicates that inter-regional competition dominates.

Building on this evidence, we explore two further features of the digital economy. The first is the data feedback that flows from manufacturing activity into digital innovation and forms the second direction of the bidirectional cross-sector externalities. The second is the Pareto inefficiency that these bidirectional externalities generate in the laissez-faire allocation. The analysis that follows turns to the fiscal instruments that correct these externalities, together with the alternative of a fiscal competition tournament. In sum, the model supplies a theoretical foundation for the empirical patterns observed in the digital economy.

3. Benchmark model: The laissez-faire economy

This section develops a two-region spatial general equilibrium model of the digital economy as the benchmark without government intervention. The framework features bidirectional externalities between the digital services and manufacturing sectors through technology spillovers and data feedback, which determine the economy's balanced growth path.

3.1. Environment

Consider an economy in infinite discrete time. The economy comprises two symmetric regions indexed by $i, j \in \{A, B\}$ with $j \neq i$, where i is the home region and j the other region. Each region contains a digital services sector, indexed by D, and a manufacturing sector, indexed by M. There is a fixed supply of homogeneous regular labor $\bar{L}$, employed in goods production in both sectors. Labor is perfectly mobile across regions and sectors, allocated as L_i^D and L_i^M in region i. There is also a fixed supply of specialized digital talent $\bar{H}$, employed exclusively in the digital sector's innovation process. Digital talent is perfectly mobile across regions, allocated as H_i^D in region i.

Consumers in each region purchase manufacturing goods and digital services from both local and remote producers. Manufacturing goods shipped between regions incur iceberg transport costs $\tau \geq 1$ (one unit shipped, $1/\tau$ units arrive), whereas digital services arrive without such transport loss. Digital services, such as AI, cloud computing, the Internet of Things, and big data analytics, can be transmitted across regions at negligible cost, unlike physical goods that require transportation. As both types of goods are produced and consumed, the associated economic activity generates data as a byproduct (Varian, 2018; Jones and Tonetti, 2020; Veldkamp and Chung, 2024; Farboodi and Veldkamp, 2026).

The digital services sector in each region consists of a representative firm. Advances in digital technology are driven by the combination of digital talent, technology-based knowledge, and data-based knowledge. This frontier digital technology diffuses to manufacturing firms through cross-sector technology spillovers. Specifically, digital technology reduces the costs of search, replication, transportation, tracking, and verification, thereby broadly benefiting economic activity across industries (Goldfarb and Tucker, 2019). Moreover, as a general-purpose technology, digital technology is pervasive across sectors, and its advances raise the R&D productivity of application sectors through innovational complementarities (Bresnahan and Trajtenberg, 1995; Brynjolfsson et al., 2021). The spillover mechanism reflects the widely recognized phenomenon whereby digital technologies permeate sectoral boundaries and enhance manufacturing productivity.[6]

The manufacturing sector in each region consists of a representative firm. The firm operates a continuum of production lines, ranked by the difficulty of digital transformation on a $[0, 1]$ uniform distribution. Production lines near zero are the easiest to digitalize (e.g., electronic components, precision instruments, information-intensive processes), while those near one are the hardest (e.g., traditional heavy manufacturing, basic materials processing, textile and garment production). The parameter m denotes the manufacturing sector's digital adaptability, where a high m indicates that more production lines can absorb digital spillovers. The first m fraction of production lines adopts frontier digital technology, while the remaining $(1 - m)$ fraction still relies on traditional manufacturing technology. Beyond technology spillovers from the digital to the manufacturing sector, the two sectors also interact through a data feedback channel. Manufacturing activity generates data that feeds back into the digital sector's data-based knowledge. Specifically, usable manufacturing data originates from the output of the digitally adopting production lines, and the strength of this data feedback rises with digital adaptability m, so that wider digital adoption enlarges the data input to digital innovation.[7]

[6] For example, cloud-based enterprise resource planning systems enable small and medium-sized manufacturing firms to access computational capabilities previously limited to large enterprises. AI algorithms enable automated quality inspection that significantly improves production accuracy. Internet-of-Things sensor networks combined with big data analytics permit real-time optimization of supply chain logistics across the manufacturing spectrum.

[7] Online Appendix F.1 extends the benchmark model by letting heterogeneous manufacturing firms choose whether to adopt frontier digital technology or remain on traditional manufacturing technology, rather than treating digital adoption as exogenous and governed by m. The main conclusions are preserved and strengthened: a wider digital technology lead now also expands the set of adopters, so the self-reinforcing growth effect is amplified.

3.2. Consumer preference

In period t, the representative consumer in region i has a period utility function that takes the logarithmic Cobb–Douglas form[8]:

$$u_i(t) = \beta \ln C_i^D(t) + (1-\beta)\ln C_i^M(t),$$

where the parameter $\beta \in (0,1)$ is the expenditure share allocated to digital services. The consumer maximizes discounted lifetime utility:

$$U_i = \sum_{t=1}^{\infty} \frac{1}{(1+\rho)^{t-1}} u_i(t) = \sum_{t=1}^{\infty} \frac{1}{(1+\rho)^{t-1}} \left[\beta \ln C_i^D(t) + (1-\beta)\ln C_i^M(t)\right],$$

where the parameter ρ is the rate of time preference.

Within each sector, consumption is a CES aggregate of local and imported regional varieties with elasticity of substitution $\sigma > 1$ and home-bias parameter $\alpha \in (1/2, 1)$:

$$C_i^D(t) = \left[\alpha^{1/\sigma}\left(c_{ii}^D(t)\right)^{(\sigma-1)/\sigma} + (1-\alpha)^{1/\sigma}\left(c_{ji}^D(t)\right)^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)},$$

$$C_i^M(t) = \left[\alpha^{1/\sigma}\left(c_{ii}^M(t)\right)^{(\sigma-1)/\sigma} + (1-\alpha)^{1/\sigma}\left(c_{ji}^M(t)\right)^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)},$$

where $c_{ii}^k(t)$ denotes consumption of region i's local variety in sector $k \in \{D, M\}$, and $c_{ji}^k(t)$ denotes consumption of the variety imported from region j. Let $p_i^k(t)$ denote the producer price of region i's variety in sector k. The corresponding price indices are

$$P_i^D(t) = \left[\alpha\left(p_i^D(t)\right)^{1-\sigma} + (1-\alpha)\left(p_j^D(t)\right)^{1-\sigma}\right]^{1/(1-\sigma)},$$

$$P_i^M(t) = \left[\alpha\left(p_i^M(t)\right)^{1-\sigma} + (1-\alpha)\left(\tau p_j^M(t)\right)^{1-\sigma}\right]^{1/(1-\sigma)}.$$

3.3. Digital services sector

For the representative digital services firm in region i, the production technology is concave in labor:

$$Y_i^D(t) = Z_i^D(t) \cdot \left(L_i^D(t)\right)^{\eta},$$

where $Z_i^D(t)$ denotes digital productivity and $\eta \in (0,1)$ is the labor output elasticity. Given CES demand with elasticity σ, the firm charges a constant markup $\sigma/(\sigma-1) > 1$ over marginal cost. The firm chooses labor $L_i^D(t)$ to maximize profit:

$$\max_{L_i^D(t)} \quad \pi_i^D(t) = p_i^D(t) Y_i^D(t) - w_i^L(t) L_i^D(t),$$

where $w_i^L(t)$ denotes the labor wage. The first-order condition yields $w_i^L(t) L_i^D(t) = [\eta(\sigma-1)/\sigma] \cdot p_i^D(t) Y_i^D(t)$, so that labor receives a fraction $\eta(\sigma-1)/\sigma$ of revenue. We assume that digital talent holds the patents and thereby owns the firms in the digital services sector. The residual profit goes to talent as compensation $w_i^H(t) H_i^D(t)$:

$$w_i^H(t) H_i^D(t) = p_i^D(t) Y_i^D(t) - w_i^L(t) L_i^D(t) = \left[1 - \frac{\eta(\sigma-1)}{\sigma}\right] p_i^D(t) Y_i^D(t).$$

As in Jones and Tonetti (2020), Cong et al. (2021), and Abis and Veldkamp (2024), digital technology evolves as digital talent combines technology-based and data-based knowledge to generate innovation:

$$Z_i^D(t) = \kappa^D \left(Z_i^D(t-1)\right)^{1-\xi} \left(D_i(t-1)\right)^{\xi} H_i^D(t), \tag{1}$$

where the parameter $\kappa^D > 0$ is the digital innovation efficiency. Technology-based knowledge $Z_i^D(t-1)$ and data-based knowledge $D_i(t-1)$ are accumulated in the last period $t-1$, while digital talent $H_i^D(t)$ applies these inputs in period t to generate new technology. The parameter $\xi \in (0,1)$ governs the relative contributions of the two knowledge sources. The data input $D_i(t-1)$ will be specified in Section 3.5 after both sectors have been introduced.

[8] In the structural transformation literature, Ngai and Pissarides (2007) and Desmet and Rossi-Hansberg (2014) assume CES preferences over manufacturing and services with an elasticity of substitution below one. Accordingly, labor reallocates from the fast-growing manufacturing sector to the slow-growing service sector. In our paper, however, the digital services sector holds a technological lead over manufacturing, anchoring the technology frontier that spills over to the rest of the economy. This distinguishes it from the traditional low-growth service sector. Since our core interest lies in the growth effects of bidirectional cross-sector externalities rather than the sectoral reallocation driven by complementarity, we assume the Cobb–Douglas form for analytical tractability without loss of qualitative generality. Online Appendix F.2 extends the analysis to CES preferences and shows that the main conclusions are qualitatively preserved.

3.4. Manufacturing sector

For the representative manufacturing firm in region i, the production technology is concave in labor:

$$Y_i^M(t) = Z_i^M(t) \cdot \left(L_i^M(t)\right)^{\eta},$$

where $Z_i^M(t)$ denotes manufacturing productivity.[9]

The manufacturing firm's technology combines frontier technology spillovers from the digital sector with the firm's own technology accumulated through past R&D. Geographically, the technology spillovers originate in both regions: a local spillover from the home region's digital frontier Z_i^D and a cross-region spillover from the other region's digital frontier Z_j^D, as digital technology diffuses across borders. The firm's pre-R&D baseline technology (i.e., the technology before the current-period R&D decision) is a linear combination of the last-period digital technology spillover and the firm's own last-period technology:

$$Z_i^{M-}(t) = m \cdot \left(Z_i^D(t-1)\right)^{1-\upsilon}\left(Z_j^D(t-1)\right)^{\upsilon} + (1-m) \cdot Z_i^M(t-1), \tag{2}$$

where the weight $m \in (0, \bar{m})$ is the digital adaptability introduced above, so that a higher m tilts the baseline technology toward the digital spillover component.[10] The upper bound $\bar{m} \in (0, 0.5)$ ensures the manufacturing sector retains a sufficiently autonomous technological base and an independent capacity for its own technological progress. The local and cross-region sources of the digital spillover enter the pre-R&D baseline technology with weights $1-\upsilon$ and υ, respectively. Since technology spillovers decay with geographic distance (Keller, 2002), the local digital spillover predominates, with $\upsilon \in (0, \bar{\upsilon})$ for an upper bound $\bar{\upsilon} \in (0, 0.5)$.[11]

Given the pre-R&D baseline technology $Z_i^{M-}(t)$, the firm invests in R&D to obtain effective productivity:

$$Z_i^M(t) = \kappa^M \cdot \left(\psi_i^M(t)\right)^{\phi} \cdot \left(Z_i^{M-}(t)\right)^{1-\phi},$$

where $\psi_i^M(t)$ is R&D investment measured in units of the manufacturing good and purchased at the given price $p_i^M(t)$, the parameter $\kappa^M > 0$ is the R&D efficiency, and the parameter $\phi \in (0,1)$ is the R&D technology elasticity.

The firm charges a constant markup $\sigma/(\sigma-1)$ over marginal cost given CES demand, and jointly chooses labor $L_i^M(t)$ and R&D investment $\psi_i^M(t)$ to maximize profit:

$$\max_{L_i^M(t), \psi_i^M(t)} \quad \pi_i^M(t) = p_i^M(t) Y_i^M(t) - w_i^L(t) L_i^M(t) - p_i^M(t) \psi_i^M(t).$$

The first-order conditions imply $w_i^L(t) L_i^M(t) = [\eta(\sigma-1)/\sigma] \cdot p_i^M(t) Y_i^M(t)$ and $p_i^M(t)\psi_i^M(t) = [\phi(\sigma-1)/\sigma] \cdot p_i^M(t) Y_i^M(t)$. The residual profit accrues to the representative consumer as the owner of the manufacturing firm.

3.5. Data generation

Data is generated as a byproduct of economic activity. Such byproduct data arises from both consumption and production activities. On the consumption side, online platforms record users' profiles, search queries, and transaction histories. Connected devices, from household appliances to networked vehicles, continuously capture usage patterns, location traces, and sensor readings. On the production side, sensor-equipped machinery streams real-time process and quality data from factory operations. The research and testing that accompany new technologies generate extensive experimental records.

We assume that the volume of data generated is proportional to the goods output of digitally connected activity (Jones and Tonetti, 2020; Cong et al., 2021). Specifically, the data generated by the digital sector equals the output (equivalently, the consumption) of digital services. The data generated by the manufacturing sector equals the output of its digitally adopting (the m fraction) production lines, comprising both manufacturing consumption and R&D investment.[12] Furthermore, usage patterns, transaction histories, and sensor readings are most readily collected and held by the producer. We therefore assume that all such

[9] Both sectors share the same labor output elasticity η, which simplifies the algebra. Allowing sector-specific elasticities would modify the sectoral labor ratio but would not alter the qualitative results.

[10] Frontier digital technology enters the manufacturing firm's pre-R&D baseline technology as a non-priced externality, meaning that manufacturing firms benefit without compensating the digital sector. This follows the standard treatment of knowledge spillovers in endogenous growth theory (Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992). Frontier knowledge is inherently nonrivalrous and only partially excludable, so it raises other agents' productivity without requiring market transactions. Innovators' discoveries and ideas diffuse freely through the economy via publication, professional networks, labor mobility, and informal communication. This allows subsequent producers to build on the existing technology frontier at no direct cost. In our setting, digital technology plays an analogous role: open-source software libraries, publicly available algorithms, and standardized digital protocols enable manufacturing firms to absorb digital advances without directly purchasing digital services. If instead manufacturing firms were required to purchase digital services to access the spillover, the cost of adoption would partially internalize the bidirectional cross-sector externalities and reduce the scope for welfare-improving subsidies. The welfare gap between laissez-faire and the First-Best allocation would narrow because the market price of digital services would already convey part of the return back to the digital sector. Nevertheless, the under-provision of digital activity and the welfare gains from government intervention would be preserved as long as the market price does not fully reflect the social value of the spillover.

[11] The parameter υ measures the strength of the cross-region digital technology spillover. A rival city's digital expansion reaches local manufacturing firms in two opposing ways. It spills digital technology across city boundaries while competing away local digital talent. The stylized facts of Section 2 show the net effect to be negative and inter-regional competition to be the stronger force, which requires restricting υ to the range consistent with that finding.

[12] Manufacturing R&D investment generates data on the same basis as consumption, since R&D spending is the purchase of manufactured goods: laboratory equipment, measurement instruments, and testing materials are all expenditures on manufacturing output. Accordingly, the experimental and testing records generated by such R&D activity enter the digital sector's data-based knowledge alongside consumption data.

data flows into the digital sector of the region where the good or service is produced, wherever it is ultimately consumed, and that no usable data flows between the two regions' digital sectors.[13] This restriction on cross-region data flows reflects the growing prevalence of data protection regulations, which impose substantial restrictions on the transfer and use of consumer data (Acquisti et al., 2016; Goldberg et al., 2024). As a conservative benchmark, we therefore rule out cross-region data flows, so that each region's digital innovation relies on the data generated by home-produced goods and services.

The data generation equation is given by

$$\mathcal{D}_i(t-1) = c_{ii}^D(t-1) + c_{ij}^D(t-1) + \left[c_{ii}^M(t-1) + c_{ij}^M(t-1) + \psi_i^M(t-1)\right] \cdot \frac{m\left(Z_i^D(t-1)\right)^{1-\upsilon}\left(Z_j^D(t-1)\right)^{\upsilon}}{m\left(Z_i^D(t-1)\right)^{1-\upsilon}\left(Z_j^D(t-1)\right)^{\upsilon} + (1-m)Z_i^M(t-1)}. \tag{3}$$

The first two terms on the right-hand side capture data from locally produced digital services, whether consumed locally (c_{ii}^D) or exported (c_{ij}^D). The remaining term captures data from locally produced manufacturing consumption (c_{ii}^M, c_{ij}^M) and R&D investment (ψ_i^M), weighted by the digital spillover share $m(Z_i^D)^{1-\upsilon}(Z_j^D)^{\upsilon}/[m(Z_i^D)^{1-\upsilon}(Z_j^D)^{\upsilon} + (1-m)Z_i^M]$. This weight equals the share of the digital spillover component in the pre-R&D baseline technology Eq. (2), which reflects that only the production lines that adopt digital technology yield data useful for digital innovation. For tractability, we assume data fully depreciates each period, so sustained innovation requires ongoing activity.

The data generation mechanism distinguishes digital innovation from traditional innovation. The model thus embeds two conceptually distinct cross-sector forces: the technology channel in Eq. (2) is a conventional knowledge spillover, whereas the data feedback channel in Eq. (3) rests on a different economic logic. First, data is a natural byproduct of economic activity, and its generation requires no additional resources. Consumption and R&D investment generate data while serving their own purposes. Technological progress instead requires innovative talent or R&D investment, and the latter comes at the cost of current consumption. Relatedly, the data-generating agent and the data-using agent need not coincide. Consumers generate data through their purchases of digital services and manufacturing goods in Eq. (3), whereas the agent that uses the data is the digital services firm in Eq. (1). Studies of consumption data also report that such data yields productive gains for firms yet imposes a privacy cost on consumers (Acquisti et al., 2016; Miller and Tucker, 2018; Abowd and Schmutte, 2019; Jones and Tonetti, 2020). Under learning-by-doing or knowledge accumulation, by contrast, experience or knowledge is generally both generated and used within the producing agent. Second, the direction of data flows does not follow the technology ranking. A knowledge spillover runs down the technology ladder, from the leader to the laggard, as the technology channel in Eq. (2) does when frontier digital technology spills over to manufacturing. The data channel instead flows to where data has productive value. Data flows from wherever economic activity occurs to the digital sector that puts it to use. The technologically lagging manufacturing sector therefore supplies the data for innovation in the technologically leading digital sector. These two properties keep the data feedback outside the standard knowledge-spillover framework, and the two channels combine into a bidirectional loop between the two sectors.

3.6. General equilibrium and balanced growth

Fig. 1 summarizes the two-sector framework. The digital technology spillover and the manufacturing data feedback together constitute the bidirectional cross-sector externalities.[14] The solid arrow between the two sectors represents the digital technology spillover that upgrades manufacturing pre-R&D baseline technology; it comprises a local spillover within the region and a cross-region spillover from the other region. The dashed arrow between the two sectors represents the manufacturing data feedback, through which manufacturing activity generates data that feeds back into digital innovation. Together, these two channels create a self-reinforcing growth loop: higher digital technology improves manufacturing technology, which expands the manufacturing activity that generates more data, which in turn accelerates digital innovation and further increases digital technology.

Definition 1 (*Laissez-Faire Equilibrium*)**.** The equilibrium in the laissez-faire (LF) economy consists of sequences of allocations $\{L_i^D(t), L_i^M(t), H_i^D(t), c_{ii}^D(t), c_{ij}^D(t), c_{ii}^M(t), c_{ij}^M(t), \psi_i^M(t)\}_{i\in\{A,B\},t=1}^{\infty}$ and prices $\{w_i^L(t), w_i^H(t), p_i^D(t), p_i^M(t)\}_{i\in\{A,B\},t=1}^{\infty}$ such that consumers maximize utility subject to their budget constraints, firms in both sectors maximize profits, and the following market clearing conditions hold:

[13] We abstract from data trading and the related issues of data property rights, data pricing, and data market design. In practice, data can be sold or licensed across jurisdictions and across sectors. A growing literature studies the economics of such data transactions (Arrieta-Ibarra et al., 2018; Ichihashi, 2020; Jones and Tonetti, 2020; Acemoglu et al., 2022; Bergemann et al., 2022; Bergemann and Bonatti, 2024; Liu et al., 2025). This literature highlights several features that distinguish data markets from conventional goods markets. First, data is nonrival. The same dataset can be sold to multiple buyers without being depleted. This undermines sellers' commitment power and depresses data prices through a "data dilution" effect. Second, individual data contains social information that is predictive of other individuals' behavior. This social dimension generates externalities that distort both pricing and trading volume. Third, data transactions involve substantial frictions. It is difficult to assign property rights over data, to verify data quality before purchase, and to prevent unauthorized resale. Fourth, platform market power shapes how data is collected, governed, and distributed, with implications for consumer welfare. Online Appendix F.3 relaxes this abstraction by introducing data ownership and trading frictions, including consumers' privacy costs and firms' creative-destruction costs. The additional trading frictions reduce data usage and weaken the growth effect of the data feedback channel, but the main conclusions of this paper are qualitatively preserved.

[14] Beyond the growth effects analyzed in this section, Section 4.1 compares the laissez-faire allocation with the First-Best allocation and shows that these externalities render laissez-faire Pareto-inefficient.

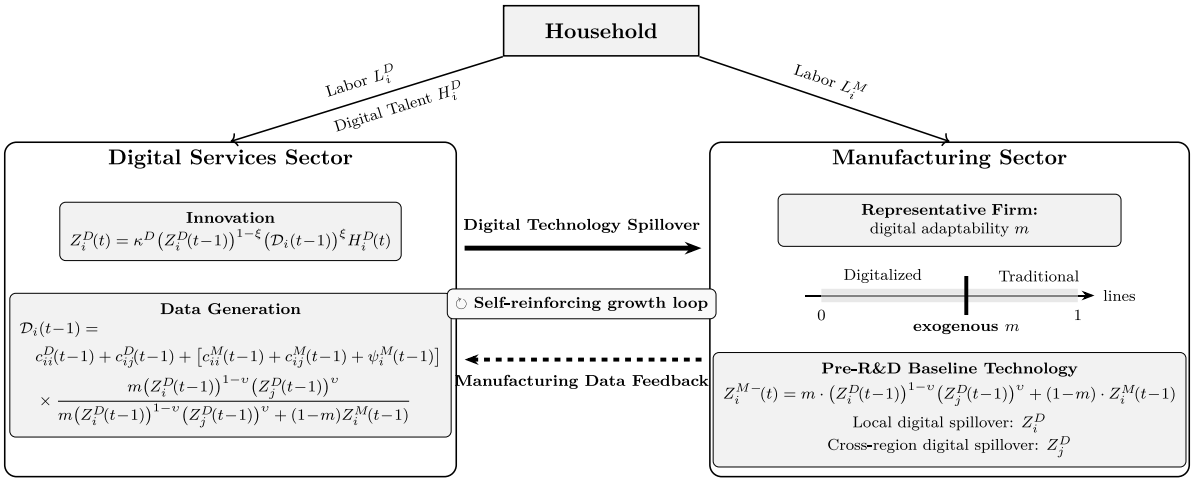


Fig. 1. Two-sector framework with bidirectional cross-sector externalities.
Notes: The figure shows the bidirectional cross-sector externalities between the two sectors. The solid arrow denotes the digital technology spillover that upgrades manufacturing technology, combining a local digital spillover within the region with a cross-region digital spillover from the other region. The dashed arrow denotes the manufacturing data feedback, whereby manufacturing activity generates data for digital innovation.

(i) **Factor market clearing:** Both regular labor and digital talent are perfectly mobile, so their wages are equalized across all regions and sectors:

$$w_A^L = w_B^L \equiv w^L, \quad w_A^H = w_B^H \equiv w^H.$$

Regular labor clears as $\sum_i (L_i^D + L_i^M) = \sum_i L_i = \bar{L}$. Digital talent clears as $\sum_i H_i^D = \bar{H}$, with talent flowing to the region offering higher returns until w^H is equalized.

(ii) **Goods market clearing:** Digital output satisfies $Y_i^D = c_{ii}^D + c_{ij}^D$, the sum of local consumption and exports. Manufacturing output satisfies $Y_i^M = c_{ii}^M + \tau c_{ij}^M + \psi_i^M$, the sum of local consumption, iceberg-adjusted exports, and R&D investment.

(iii) **Trade balance:** Each region's export revenue equals its import expenditure, so that $p_i^D c_{ij}^D + p_i^M \tau c_{ij}^M = p_j^D c_{ji}^D + p_j^M \tau c_{ji}^M$.

With symmetric fundamentals and perfect factor mobility, the equilibrium is identical across regions, and we henceforth suppress the regional index. On the balanced growth path (BGP), output, consumption, and technology levels in both sectors grow at the same rate. The laissez-faire steady-state growth rate satisfies

$$g^{LF} = \kappa^D (\boldsymbol{\Phi}^{LF})^{\xi} \left(\frac{\bar{L}}{2}\right)^{\eta\xi} \frac{\bar{H}}{2} - 1. \tag{4}$$

Eq. (4) embeds an endogenous growth engine following Romer (1990), with the steady-state growth rate increasing in the talent stock $\bar{H}/2$. In addition, the bidirectional cross-sector externalities between the two sectors generate a self-reinforcing growth effect, captured by the effective data intensity $\boldsymbol{\Phi}^{LF}$. This composite term aggregates both the digital sector's own data and the manufacturing sector's data feedback:

$$\boldsymbol{\Phi}^{LF} = \underbrace{(\Theta_L^{LF})^{\eta}}_{\text{digital data rate}} + \underbrace{\underbrace{\frac{m}{m\chi^{LF} + (1-m)}}_{\text{digital-unit spillover multiplier}} \underbrace{\left[\frac{\alpha + (1-\alpha)\tau^{-\sigma}}{\alpha + (1-\alpha)\tau^{1-\sigma}}(1-\varphi^{LF}) + \varphi^{LF}\right](1-\Theta_L^{LF})^{\eta}}_{\text{manufacturing data feedback rate}}}_{\text{bidirectional cross-sector externalities}}, \tag{5}$$

where the manufacturing R&D share $\varphi \equiv \psi_i^M / Y_i^M \in (0,1)$, the digital labor share $\Theta_L \equiv L_i^D/(L_i^D + L_i^M) \in (0,1)$, and the technology ratio $\chi \equiv Z_i^D / Z_i^M > 1$ (the digital technology lead) take laissez-faire steady-state values φ^{LF}, Θ_L^{LF}, and χ^{LF} that satisfy

$$\varphi^{LF} = \frac{\phi(\sigma-1)}{\sigma}, \tag{6}$$

$$\Theta_L^{LF} = \frac{\beta[1-\phi(\sigma-1)/\sigma]}{1-\phi(\sigma-1)\beta/\sigma}, \tag{7}$$

$$m\chi^{LF} + (1-m) = \frac{\kappa^D (\boldsymbol{\Phi}^{LF})^{\xi} \left(\frac{\bar{L}}{2}\right)^{\eta\xi} \frac{\bar{H}}{2}}{(\kappa^M)^{\frac{1}{1-\phi}} (\varphi^{LF})^{\frac{\phi}{1-\phi}} \left(\frac{(1-\Theta_L^{LF})\bar{L}}{2}\right)^{\frac{\phi\eta}{1-\phi}}}. \tag{8}$$

In Eq. (5), the first term on the right-hand side captures data generated by digital consumption. The second term captures the bidirectional cross-sector externalities, given by the interaction of a digital-unit spillover multiplier and a manufacturing data feedback rate. The digital-unit spillover multiplier equals the digital spillover share, $m\chi^{LF}/[m\chi^{LF}+(1-m)]$, divided by the technology ratio χ^{LF}, which converts the manufacturing contribution into units commensurate with the digital data rate. The manufacturing data feedback rate aggregates consumption data, which varies with the iceberg cost τ, and R&D data. When no production line adopts digital technology ($m \to 0^+$), both cross-sector channels shut down and growth depends solely on the digital sector's own data. Eq. (7) determines the equilibrium digital labor share Θ_L^{LF}. A higher R&D share φ^{LF} absorbs more manufacturing output as an internally produced R&D input, expanding gross output and labor demand in manufacturing and thereby lowering Θ_L^{LF}. Eq. (8) characterizes the equilibrium technology ratio χ^{LF}. It rises with the effective data intensity Φ^{LF}, as richer data accelerates digital innovation, and falls with the R&D share φ^{LF}, as manufacturing technology catches up.

The economy with the digital services and manufacturing sectors reveals the growth effect of the bidirectional externality mechanism, which we formalize in the following proposition.

Proposition 1 (*Bidirectional Cross-Sector Externalities and Endogenous Growth*)**.** *The input–output linkages between the digital services and manufacturing sectors create bidirectional cross-sector externalities, which comprise the digital technology spillover and the manufacturing data feedback. Define the growth premium*

$$\Delta g^{LF}(m) \equiv g^{LF}(m) - \lim_{m\to 0^+} g^{LF}(m),$$

where $\lim_{m\to 0^+} g^{LF}(m) = \kappa^D(\Theta_L^{LF})^{\eta\xi}(\bar{L}/2)^{\eta\xi}\bar{H}/2 - 1$ *is the limiting growth rate as the two sectors become technologically independent. For all* $m \in (0, \bar{m})$, $\Delta g^{LF}(m) > 0$ *and* $d\Delta g^{LF}(m)/dm > 0$. *The bidirectional cross-sector externalities generate a positive growth premium that is increasing in the manufacturing sector's digital adaptability.*

Proof. See Online Appendix B.

On the BGP, the lifetime utility of the representative consumer in region i decomposes into a level effect and a growth effect:

$$U_i^{LF} = \frac{1+\rho}{\rho}u_i^{LF}(t{=}1) + \frac{1+\rho}{\rho^2}\ln(1+g^{LF}), \tag{9}$$

where initial-period utility is given by

$$u_i^{LF}(t{=}1) = \ln\left[(\kappa^M)^{\frac{1}{1-\phi}}(\chi^{LF})^{\beta}(\Theta_L^{LF})^{\eta\beta}(1-\Theta_L^{LF})^{\eta(1-\beta)+\frac{\phi\eta}{1-\phi}}(\varphi^{LF})^{\frac{\phi}{1-\phi}}(1-\varphi^{LF})^{1-\beta}(\bar{L}/2)^{\frac{\eta}{1-\phi}}\left[\alpha+(1-\alpha)\tau^{1-\sigma}\right]^{-\frac{1-\beta}{1-\sigma}}\right]. \tag{10}$$

The level effect captures the welfare contribution of the initial consumption allocation, determined by the technology ratio χ^{LF}, the sectoral labor allocation Θ_L^{LF}, and the manufacturing R&D share φ^{LF}. The growth effect captures the welfare contribution of sustained consumption growth, amplified by an additional factor of $1/\rho$ relative to the level effect. Aggregate welfare is

$$\mathcal{W}^{LF} \equiv \sum_{i\in\{A,B\}} U_i^{LF} = \frac{2(1+\rho)}{\rho}u^{LF}(t{=}1) + \frac{2(1+\rho)}{\rho^2}\ln(1+g^{LF}).$$

4. Fiscal competition and efficiency

This section introduces fiscal instruments and fiscal competition into the framework. It begins with the efficiency of the laissez-faire equilibrium relative to the First-Best allocation, and then analyzes decentralized fiscal competition between local governments.

4.1. First-Best optimum and laissez-faire inefficiency

Private agents do not internalize the bidirectional externalities between the digital services and manufacturing sectors. To evaluate the efficiency of the laissez-faire equilibrium, we introduce a social planner who directly allocates resources across regions and sectors.

Definition 2 (*First-Best Allocation*)**.** The First-Best (FB) allocation consists of a symmetric pair $(\Theta_L^{FB}, \varphi^{FB})$ of the digital labor share and the manufacturing R&D share that maximizes aggregate welfare

$$\max_{\Theta_L,\varphi} \quad \mathcal{W}(\Theta_L,\varphi) = \frac{2(1+\rho)}{\rho}u(t{=}1;\Theta_L,\varphi) + \frac{2(1+\rho)}{\rho^2}\ln\big(1+g(\Theta_L,\varphi)\big),$$

subject to:

(i) **Symmetry:** Both regions receive identical (Θ_L,φ), with $L_A = L_B = \bar{L}/2$ and $H_A^D = H_B^D = \bar{H}/2$.

(ii) **Equilibrium:** Given (Θ_L,φ), the equilibrium conditions in Eqs. (4), (5), and (8) determine $(\Phi(\Theta_L,\varphi), \chi(\Theta_L,\varphi), g(\Theta_L,\varphi))$, and the initial-period utility $u(t{=}1;\Theta_L,\varphi)$ follows from Eq. (10).

The social planner's first-order conditions at $(\Theta_L^{FB}, \varphi^{FB})$ are

$$\frac{\partial \mathcal{W}}{\partial \Theta_L} \propto \eta \underbrace{\left[\frac{\beta}{\Theta_L} - \frac{1-\beta}{1-\Theta_L}\right]}_{\text{labor allocation}} - \underbrace{\left[1 - \frac{\beta[m\chi + (1-m)]}{m\chi}\right] \frac{\eta\phi}{(1-\phi)(1-\Theta_L)}}_{\text{net initial technology}} + \underbrace{\left[\frac{\beta[m\chi + (1-m)]}{m\chi} + \frac{1}{\rho}\right] \frac{\xi}{\Phi} \frac{\partial \Phi}{\partial \Theta_L}}_{\text{net data externality}} = 0, \tag{11}$$

$$\frac{\partial \mathcal{W}}{\partial \varphi} \propto \underbrace{-\frac{1-\beta}{1-\varphi}}_{\text{consumption cost}} + \underbrace{\left[1 - \frac{\beta[m\chi + (1-m)]}{m\chi}\right] \frac{\phi}{(1-\phi)\varphi}}_{\text{net initial technology}} + \underbrace{\left[\frac{\beta[m\chi + (1-m)]}{m\chi} + \frac{1}{\rho}\right] \frac{\xi}{\Phi} \frac{\partial \Phi}{\partial \varphi}}_{\text{net data externality}} = 0. \tag{12}$$

Eq. (11) decomposes the social return to digital labor into three terms. The labor-allocation term, the trade-off in direct production scale between the two sectors, measures the net marginal output return of reallocating labor from manufacturing to the digital sector. The net initial-technology term embodies the trade-off in the two sectors' initial technology levels: manufacturing's technology $Z^M(t{=}1)$ falls, while the digital technology lead $\chi = Z^D/Z^M$ widens. Withdrawing labor from manufacturing shrinks its R&D outlay ψ^M and hence $Z^M(t{=}1)$, which lowers initial consumption with unit elasticity, and simultaneously widens χ, whose social value is the χ-coefficient $\beta[m\chi + (1-m)]/(m\chi)$. The term therefore carries the sign of one minus this χ-coefficient. The net data externality term, which decentralized agents fail to internalize, collects the gain in the effective data intensity Φ from expanding the digital sector. This gain raises both the initial level of the digital technology lead χ and the balanced growth rate, the latter weighted by the present-value multiplier $1/\rho$.

Eq. (12) decomposes the social return to manufacturing R&D investment into the same three terms. The negative consumption-cost term represents the direct resource diversion, as allocating more manufacturing revenue to R&D investment reduces consumption. The net initial-technology term embodies the trade-off in the two sectors' initial technology levels, with the directions reversed relative to Eq. (11): manufacturing's technology $Z^M(t{=}1)$ rises, while the digital technology lead χ narrows. R&D investment raises $Z^M(t{=}1)$, which increases initial consumption with unit elasticity, and simultaneously narrows χ. The term therefore enters with the opposite sign and again carries the sign of one minus this χ-coefficient. The net data externality term is positive because higher manufacturing R&D investment raises the effective data intensity Φ, both through the manufacturing data feedback rate and, by lowering χ, through the digital-unit spillover multiplier of Eq. (5). The higher Φ in turn lifts the initial level of the digital technology lead and the growth rate.

In the economically reasonable range $m \in (0, \bar{m})$,[15] we compare the decentralized laissez-faire allocation $(\Theta_L^{LF}, \varphi^{LF})$ with the First-Best allocation $(\Theta_L^{FB}, \varphi^{FB})$ that internalizes the cross-sector externalities, and establish the resulting inefficiency in the following proposition.

Proposition 2 (*Externalities Invalidate Laissez-Faire Efficiency*). *The laissez-faire equilibrium is Pareto-inefficient. The digital technology spillover externality and the manufacturing data feedback externality jointly imply*

(i) $\Theta_L^{LF} < \Theta_L^{FB}$*: laissez-faire under-allocates labor to the digital sector relative to the First-Best allocation;*
(ii) $\varphi^{LF} \lesseqgtr \varphi^{FB}$*: laissez-faire may under- or over-invest in manufacturing R&D, depending on whether the data feedback externality (raising the effective data intensity* Φ*) outweighs the digital spillover externality (narrowing the digital technology lead* χ*);*
(iii) $\mathcal{W}^{LF} < \mathcal{W}^{FB}$*: laissez-faire welfare is strictly below First-Best welfare.*

Proof. See Online Appendix C.

Proposition 2 identifies laissez-faire's inefficiency rooted in the bidirectional cross-sector externalities, as private agents internalize neither the digital technology spillover nor the manufacturing data feedback. The labor allocation determines the relative production scale of the digital services and manufacturing sectors. When these externalities are internalized, expanding the digital services sector both widens the digital technology lead, which pulls up technology in both sectors, and strengthens the self-reinforcing growth effect. Expanding the manufacturing sector instead narrows the digital technology lead; its self-reinforcing growth contribution, bounded by the manufacturing sector's digital adaptability, is weaker than that of allocating the same labor to the digital sector. The efficient allocation therefore devotes more labor to the digital services sector. In other words, laissez-faire under-allocates labor to the digital sector relative to the First-Best allocation.

Furthermore, the manufacturing R&D share determines the internal allocation of output between current consumption and technology accumulation. The two externalities associated with this allocation pull in opposite directions, which is why the sign of $\varphi^{FB} - \varphi^{LF}$ is uncertain. On the one hand, higher manufacturing R&D investment strengthens the data feedback externality. R&D investment and consumption generate data on the same footing, and both raise the manufacturing data feedback rate. R&D investment, however, further strengthens the effective data intensity by raising the digital-unit spillover multiplier. On the other

[15] Specifically, $\bar{m} \in \left(0, \min\{0.5,\ \mathcal{Q}(\Theta_L^{LF})\}\right)$, where $\mathcal{Q}(\Theta_L) \equiv \Lambda(1-\phi)\Theta_L^{(\eta-1)(1+\xi)}(1-\Theta_L)^{1-\eta/(1-\phi)}\left[1-\phi(1-\Theta_L)\right]^{\xi}$, and $\Lambda \equiv \kappa^D(\bar{H}/2)(\kappa^M)^{-1/(1-\phi)}(\bar{L}/2)^{\eta\xi-\phi\eta/(1-\phi)}$ collects the parameters of Eq. (8) that are independent of Φ, Θ_L, and φ. The first bound ensures the manufacturing sector retains a sufficiently autonomous technological base and an independent capacity for its own technological progress. The second bound secures $\partial\Phi/\partial\Theta_L|_{\Theta_L^{LF}} > 0$, so that expanding the digital sector raises the effective data intensity at the laissez-faire allocation. Under the baseline parameters of Table 3 and throughout the perturbation range, $\mathcal{Q}(\Theta_L^{LF})$ exceeds one, so the restriction reduces to $\bar{m} \in (0, 0.5)$.

hand, higher manufacturing R&D investment weakens the digital spillover externality. Improving manufacturing's own technological position narrows the digital technology lead, so fewer digital advances diffuse into manufacturing, which dampens the self-reinforcing growth effect. Laissez-faire therefore under-invests in manufacturing R&D relative to the First-Best allocation when the data feedback externality dominates at the margin and over-invests when the digital spillover externality dominates.

Together, the under-provision of digital labor and the wedge in manufacturing R&D investment leave welfare under laissez-faire strictly below First-Best welfare. This inefficiency motivates the government intervention analyzed below.

4.2. Fiscal instruments and First-Best implementation

Given that laissez-faire is Pareto-inefficient, we now introduce government fiscal intervention. Regional governments deploy three fiscal instruments specific to the digital economy: a digital output subsidy $s_i^D \geq 0$ that promotes digital sector expansion, a manufacturing R&D data subsidy $s_i^{MR} \geq 0$ that rewards the data generated by non-digital sector investment, and a manufacturing tax rate $t_i^M \in [0,1)$ that finances these subsidies under a balanced budget. The digital output subsidy augments digital producers' revenue, so that a digital firm in region i receives $(1+s_i^D)p_i^D$ per unit of output, while the R&D data subsidy lowers the manufacturing firm's effective cost to $(1-s_i^{MR})\,p_i^M$ per unit of R&D.[16] The manufacturing tax is levied on producers at rate t_i^M on output, so the firm retains only the fraction $(1-t_i^M)$ of gross revenue.

Given the fiscal instruments, the government budget constraint requires the manufacturing tax to finance both subsidies, $t_i^M\, p_i^M Y_i^M = s_i^D\, p_i^D Y_i^D + s_i^{MR}\, p_i^M \psi_i^M$. Solving for the equilibrium tax rate as a function of the subsidies (s_i^D, s_i^{MR}) gives

$$t_i^M = \frac{(1-s_i^{MR})\,\beta s_i^D - \left[\beta s_i^D - (1-\beta)s_i^{MR}\right]\phi(\sigma-1)/\sigma}{(1-s_i^{MR})(1-\beta) - \left[\beta s_i^D - (1-\beta)s_i^{MR}\right]\phi(\sigma-1)/\sigma}. \tag{13}$$

The digital output subsidy sets the digital labor share at its policy-adjusted level

$$\Theta_L(s_i^D) = \frac{(1+s_i^D)\beta[1-\phi(\sigma-1)/\sigma]}{1-\phi(\sigma-1)\beta(1+s_i^D)/\sigma}, \tag{14}$$

and the manufacturing tax and the R&D data subsidy jointly set the R&D share at its policy-adjusted level

$$\varphi(s_i^D, s_i^{MR}) = \frac{\phi(\sigma-1)(1-t_i^M)}{\sigma(1-s_i^{MR})} = \frac{(1-\beta)-\beta s_i^D}{(1-s_i^{MR})(1-\beta)\,\sigma/[\phi(\sigma-1)] - \left[\beta s_i^D - (1-\beta)s_i^{MR}\right]}. \tag{15}$$

Eqs. (14) and (15) admit a sequential implementation: the digital output subsidy s_i^D governs the digital labor share, while s_i^D together with the manufacturing R&D data subsidy s_i^{MR} governs the R&D share. To reach the First-Best allocation $(\Theta_L^{FB}, \varphi^{FB})$, we invert Eq. (14) at $\Theta_L(s_i^{D,FB}) = \Theta_L^{FB}$ and Eq. (15) at $\varphi(s_i^{D,FB}, s_i^{MR,FB}) = \varphi^{FB}$, which yields

$$s_i^{D,FB} = \frac{\Theta_L^{FB}}{\beta\left[1-\varphi^{LF}(1-\Theta_L^{FB})\right]} - 1 \;\in\; \left(0, (1-\beta)/\beta\right), \tag{16}$$

and

$$s_i^{MR,FB} = \frac{(1-\beta)\left(\varphi^{FB}-\varphi^{LF}\right) + \beta\varphi^{LF} s_i^{D,FB}\left(1-\varphi^{FB}\right)}{\varphi^{FB}(1-\beta)(1-\varphi^{LF})} \;\in (0,1) \;\text{ if }\; \varphi^{FB} > \varphi(s_i^{D,FB}, 0). \tag{17}$$

Both subsidies in Eqs. (16) and (17) correct the inefficiencies established in Proposition 2. By part (i), laissez-faire under-allocates labor to the digital sector relative to the First-Best allocation, $\Theta_L^{LF} < \Theta_L^{FB}$. A positive digital output subsidy corrects this under-allocation and reallocates labor to the digital sector. By part (ii), laissez-faire under-invests in manufacturing R&D when the data feedback externality, which raises the effective data intensity Φ, outweighs the digital spillover externality, which narrows the digital technology lead χ. In the case $\varphi(s_i^{D,FB}, 0) < \varphi^{FB}$, a positive manufacturing R&D data subsidy then corrects the under-investment by paying R&D for the data supplied to digital innovation. The opposite case $\varphi(s_i^{D,FB}, 0) > \varphi^{FB}$ would turn the corrective instrument from a subsidy into a tax, $s_i^{MR} < 0$. A tax levied specifically on manufacturing research has few real-world counterparts in either advanced or emerging economies. Fiscal systems support manufacturing R&D investment through tax credits and direct grants rather than penalize it, and a government that taxed research would be working against the objective of long-term development. We therefore do not pursue the correction of over-investment when $\varphi(s_i^{D,FB}, 0) > \varphi^{FB}$.

4.3. Tournament competition and Nash equilibrium

The preceding subsection shows that effective fiscal instruments can attain First-Best welfare. This subsection asks whether decentralized tournament competition can serve as an alternative mechanism to achieve substantial welfare gains. A large literature on China's promotion tournament establishes that, within a system combining political centralization with economic decentralization, local officials are evaluated and promoted on the basis of relative economic performance (Maskin et al., 2000;

[16] The subsidy s_i^{MR} applies at a uniform rate to all manufacturing R&D investment, so the government need not identify which R&D investment generates usable data. As Eq. (3) shows, only the digitally adopting share of manufacturing activity generates data; that share determines how high the uniform rate must be set to correct the externality. The government chooses the level of the instrument, not its structure.

Li and Zhou, 2005; Xu, 2011). The existing literature models this as a weighted combination of the official's own-region welfare and a yardstick term that rewards outperforming peer jurisdictions in GDP growth (Li et al., 2019; Fang et al., 2025). The growth rate serves as the primary tournament metric because, as a relative performance measure, it filters out common external shocks and thereby isolates individual officials' policy effort (Maskin et al., 2000).

Following this approach, the central government is the designer of the tournament, setting the competition intensity that regional governments take as given; competition induces regional governments to supply fiscal instruments. Each regional government serves a finite tenure of T periods and chooses its subsidies (s_i^D, s_i^{MR}) to maximize a composite objective that combines own-region welfare with relative growth performance against the rival region.

Definition 3 (*Nash Equilibrium*)**.** The Nash equilibrium (Nash) is a symmetric subsidy pair $(s^{D,Nash}, s^{MR,Nash})$ such that each regional government maximizes

$$\max_{s_i^D, s_i^{MR}} \mathcal{N}_i(s_i^D, s_i^{MR}) = (1-\lambda)\sum_{t=1}^{T}\frac{u_i(t)}{(1+\rho)^{t-1}} + \lambda\left[g_i - g_j\right] = (1-\lambda)\left[\Gamma_1(T)u_i(t{=}1) + \Gamma_2(T)\ln(1+g_i)\right] + \lambda\left[g_i - g_j\right], \tag{18}$$

where $\lambda \in (0,1)$ is the tournament competition intensity and

$$\Gamma_1(T) \equiv \sum_{t=1}^{T}\frac{1}{(1+\rho)^{t-1}}, \qquad \Gamma_2(T) \equiv \sum_{t=1}^{T}\frac{t-1}{(1+\rho)^{t-1}},$$

subject to:

(i) **Budget balance:** The manufacturing tax rate $t_i^M \in [0,1)$ finances the subsidies every period, yielding Eq. (13).

(ii) **Equilibrium:** Given the subsidies s_i^D and s_i^{MR}, private agents then optimize as in Definition 1; the policy-adjusted allocations $(\Theta_L(s_i^D), \varphi(s_i^D, s_i^{MR}))$ follow from Eqs. (14) and (15); and the equilibrium conditions in Eqs. (4), (5), and (8) determine $(\Phi(\Theta_L, \varphi), \chi(\Theta_L, \varphi), g(\Theta_L, \varphi))$.

(iii) **Best response:** Each regional government simultaneously chooses its subsidies (s_i^D, s_i^{MR}) to maximize Eq. (18), taking the rival's (s_j^D, s_j^{MR}) as given. The response of factor grabbing and cross-region technology spillovers to the subsidies enters the objective through the relative growth performance against the rival, and not through the evaluation of own-region welfare.

As $\lambda \to 0^+$, a regional government cares only about local welfare over its finite tenure; as $\lambda \to 1^-$, it cares only about relative growth performance against its rival. The tournament term $\lambda(g_i - g_j)$ then measures the gap between the local region's growth and that of its rival.

Differentiating the tournament objective Eq. (18) with respect to s_i^D and s_i^{MR}, we derive the two marginal conditions:

$$\frac{\partial \mathcal{N}_i}{\partial s_i^D} = \Bigg\{ \underbrace{\sum_{x\in\{\Theta_L,\varphi\}}\left[(1-\lambda)\Gamma_1(T)\frac{\partial u_i(t{=}1)}{\partial x_i} + \left((1-\lambda)\frac{\Gamma_2(T)}{1+g_i}+\lambda\right)\frac{\partial g_i}{\partial x_i}\right]_{L_i,H_i^D,\chi_{ji}}\frac{\partial x_i}{\partial s_i^D}}_{\substack{\text{within-region policy}\\(\lesssim 0)}} + \underbrace{2\lambda\left(\frac{\partial g_i}{\partial L_i}\frac{\partial L_i}{\partial s_i^D} + \frac{\partial g_i}{\partial H_i^D}\frac{\partial H_i^D}{\partial s_i^D}\right)}_{\substack{\text{factor grabbing}\\(>0)}} + \underbrace{\lambda\left[\frac{\partial g_i}{\partial \chi_{ji}}\frac{\partial \chi_{ji}}{\partial s_i^D} - \frac{\partial g_j}{\partial \chi_{ij}}\frac{\partial \chi_{ij}}{\partial s_i^D}\right]}_{\substack{\text{cross-region spillover}\\(<0)}} = 0, \tag{19}$$

$$\frac{\partial \mathcal{N}_i}{\partial s_i^{MR}} = \Bigg\{ \underbrace{\left[(1-\lambda)\Gamma_1(T)\frac{\partial u_i(t{=}1)}{\partial \varphi_i} + \left((1-\lambda)\frac{\Gamma_2(T)}{1+g_i}+\lambda\right)\frac{\partial g_i}{\partial \varphi_i}\right]\frac{\partial \varphi_i}{\partial s_i^{MR}}}_{\substack{\text{within-region policy}\\(\lesssim 0)}} + \underbrace{\lambda\left[\frac{\partial g_i}{\partial \chi_{ji}}\frac{\partial \chi_{ji}}{\partial s_i^{MR}} - \frac{\partial g_j}{\partial \chi_{ij}}\frac{\partial \chi_{ij}}{\partial s_i^{MR}}\right]}_{\substack{\text{cross-region spillover}\\(>0)}} = 0, \tag{20}$$

where $\chi_{ji} \equiv Z_j^D/Z_i^M$ and $\chi_{ij} \equiv Z_i^D/Z_j^M$ are the cross-region technology ratios.

Eq. (19) decomposes the marginal value of the digital output subsidy into three effects. First, the within-region policy effect operates at the pre-deviation factor allocations. The digital output subsidy raises the digital labor share ($x = \Theta_L$), while the manufacturing tax that finances it lowers the R&D share ($x = \varphi$). Both policy margins reach growth through the effective data intensity but pull in opposite directions, so their net contribution is of indeterminate sign. Second, the factor-grabbing effect is the tournament-driven strategic term and is positive. The digital output subsidy expands the region's digital sector and draws in mobile factors, especially the digital talent on which innovation depends. This expansion strengthens the self-reinforcing growth effect of the bidirectional cross-sector externalities, raising regional growth. Because the factor pools are fixed, the inflow both raises the region's own growth rate and lowers the rival's, so the two movements double the effect on the growth differential. Third, the cross-region spillover effect is negative, which strengthens with the intensity υ. Because digital technology spills over across regions,

a digital output subsidy that lifts region i's own digital frontier also lifts the rival's manufacturing pre-R&D baseline technology, so part of the growth gain accrues to the rival and the growth differential narrows. Taken together, the factor-grabbing effect and the cross-region spillover effect both scale with λ, so a higher tournament competition intensity raises the equilibrium digital output subsidy whenever factor grabbing outweighs the cross-region spillover.[17]

Eq. (20) shows that the manufacturing R&D data subsidy reaches the tournament objective through the within-region policy effect and the cross-region spillover effect. The latter effect is positive. The subsidy directs resources into manufacturing R&D, so the region's frontier digital technology stands lower relative to both its own and the rival's manufacturing technology. Less of the region's digital advance therefore accrues to the rival, and the cross-region spillover widens the growth differential.

Tracing the Nash equilibrium as the tournament competition intensity varies yields the following proposition.

Proposition 3 (*Welfare in Tournament Competition Intensity*)**.** *Tournament competition intensity shapes the Nash equilibrium subsidies and welfare as stated below:*

(i) The Nash equilibrium subsidies $s^{D,Nash}(\lambda)$ *and* $s^{MR,Nash}(\lambda)$ *are increasing in the tournament competition intensity* λ.

(ii) The Nash equilibrium welfare $\mathcal{W}^{Nash}\left(s^{D,Nash}(\lambda), s^{MR,Nash}(\lambda)\right)$ *is inverted-U-shaped in* λ*:* $d\mathcal{W}^{Nash}/d\lambda > 0$ *for* $\lambda \in (0, \lambda^{peak})$ *("good competition") and* $d\mathcal{W}^{Nash}/d\lambda < 0$ *for* $\lambda \in (\lambda^{peak}, 1)$ *("bad competition"), where* $\lambda^{peak} \in (0,1)$ *maximizes* $\mathcal{W}^{Nash}$.

Proof. See Online Appendix D.

The inverted-U pattern reflects a trade-off between externality correction and over-subsidization. The laissez-faire allocation does not internalize the bidirectional cross-sector externalities, which weakens the self-reinforcing growth. Officials serving finite tenures discount future growth more heavily than the social planner does, and the tournament competition over relative growth serves as a substitute mechanism that raises both subsidy instruments. The tournament thereby strengthens the incentive to correct the two externalities and to sustain self-reinforcing growth. When tournament competition intensity is low, this externality-correcting effect dominates, so a stronger tournament is "good competition" and welfare rises. At the peak intensity λ^{peak}, the Nash subsidy pair $\left(s^{D,Nash}(\lambda^{peak}), s^{MR,Nash}(\lambda^{peak})\right)$ lies closest to the First-Best pair $\left(s^{D,FB}, s^{MR,FB}\right)$. The welfare it induces comes closest to First-Best welfare, so decentralized competition attains the best outcome the tournament can deliver. Beyond this threshold, a stronger tournament moves the subsidy pair $\left(s^{D,Nash}(\lambda), s^{MR,Nash}(\lambda)\right)$ away from $\left(s^{D,FB}, s^{MR,FB}\right)$ into over-subsidization, and the tournament turns into "bad competition". Resources are then reallocated toward the digital sector beyond the social optimum, and welfare declines.

Furthermore, stronger digital adaptability in manufacturing raises the laissez-faire self-reinforcing growth, as Proposition 1 shows. Regional governments therefore have a stronger incentive to promote digital growth even without tournament competition, and the scope for welfare-improving intervention narrows. As manufacturing becomes more digitally adaptable, the externality correction from tournament competition shrinks, and its marginal benefit meets the marginal loss from over-subsidization at a lower intensity. In other words, an economy with a more digitally adaptable manufacturing sector grows more on endogenous forces, gains less from government intervention, and warrants a milder tournament.[18]

5. Quantitative analyses

This section calibrates the model to the Chinese macroeconomy. The analysis first compares welfare across the laissez-faire and First-Best allocations, and further characterizes the inverted-U welfare pattern as tournament competition intensity varies.

5.1. Calibration

Table 3 reports the baseline calibration to the Chinese economy, with regions modeled as cities. The parameters draw on consensus estimates from the literature, recent Chinese macroeconomic statistics,[19] or internal calibration matching the model to a set of Chinese empirical targets.

Households, government, and endowments. The annual discount factor in macroeconomic models typically falls in the range 0.96–0.99, corresponding to a discount rate of 0.01–0.04 (Kydland and Prescott, 1982; Smets and Wouters, 2003; Christiano et al., 2005; Song et al., 2011). We set $\rho = 0.03$, which is a moderate choice within this range. The government tenure is $T = 5$ years, corresponding to the de jure term of Chinese local government officials, and determines the finite-horizon coefficients $\Gamma_1(T)$ and $\Gamma_2(T)$ in the Nash objective. At $T = 5$ and $\rho = 0.03$, $\Gamma_1(5) = 4.72$ and $\Gamma_2(5) = 9.16$, yielding a myopia ratio $\Gamma_2(5)/\Gamma_1(5) = 1.94$ compared

[17] The negative net inter-regional effect estimated at the manufacturing firm level in Section 2 corroborates the dominance of the factor-grabbing effect.

[18] Online Appendix F.4 relaxes the regional symmetry assumption in the benchmark model and allows the two regions to differ in their initial technology levels. Asymmetry amplifies over-subsidization, since the lagging region subsidizes more aggressively, and it adds a misallocation of factors across the two regions. Therefore, the welfare cost of decentralized fiscal competition exceeds the symmetric level.

[19] We draw primarily on the 2021–2025 statistical releases. Several digital-economy aggregates, especially the industrial digital-penetration rate, have entered official statistics only in recent years, so earlier releases do not report them on a comparable basis.

Table 3
Baseline parameter calibration.

Symbol	Description	Value	Source/Target
Panel A: Households, government, and endowments			
ρ	Discount rate	0.03	Literature range 0.01–0.04
T	Government tenure (years)	5	De jure term of local officials
$\bar{L}$	Total regular labor	200	Normalization
$\bar{H}$	Total digital talent	2	1% of the regular labor
Panel B: Production technology and innovation			
η	Labor output elasticity	0.50	Bai and Qian (2010)
ϕ	Manufacturing R&D technology elasticity	0.15	Hall and Mairesse (1995) and Kancs and Siliverstovs (2016)
ξ	Data elasticity	0.06	Jones and Tonetti (2020)
υ	Cross-region technology spillover intensity	0.333	Keller (2002)
Panel C: Trade and market structure			
σ	CES elasticity of substitution	5.0	Simonovska and Waugh (2014)
α	Home-bias parameter	0.70	Tombe and Zhu (2019)
τ	Iceberg transport cost	1.71	Tombe and Zhu (2019)
Panel D: Internally calibrated parameters			
β	Digital expenditure share	0.162	Jointly matched to:
m	Manufacturing digital adaptability	0.142	$\{p^D Y^D/(p^M Y^M) = 0.17,$
κ^D	Digital innovation efficiency	0.917	$m\chi^{LF}/(m\chi^{LF} + 1 - m) = 0.23,$
κ^M	Manufacturing R&D efficiency	0.906	$g^{LF} = 1\%,\ \chi^{LF} = 1.8\}$

Notes: The calibration treats cities as regions. The parameters draw on consensus estimates from the literature, recent Chinese macroeconomic statistics, or internal calibration matching the model to a set of Chinese empirical targets. The four targets in Panel D pair each model object with a Chinese counterpart. The output ratio $p^D Y^D/(p^M Y^M)$ matches ICT services value added relative to manufacturing value added, the digital spillover share $m\chi^{LF}/(m\chi^{LF} + 1 - m)$ matches the industrial digital-penetration rate, the growth rate g^{LF} matches the growth attributable to digital innovation, and the technology ratio χ^{LF} matches the labor productivity of the ICT sector relative to the economy-wide average.

with the infinite-horizon ratio $1/\rho = 33.3$. Total labor supply is normalized to $\bar{L} = 200$, so that each region's labor endowment is $\bar{L}/2 = 100$. Total digital talent is set to $\bar{H} = 2$, implying that digital specialists account for 1% of the regular labor.[20]

Production technology and innovation. The labor output elasticity is $\eta = 0.50$. We take the estimate of Bai and Qian (2010), who report that China's labor share is approximately 0.50. The manufacturing R&D technology elasticity is $\phi = 0.15$. Hall and Mairesse (1995) and Kancs and Siliverstovs (2016) estimate that the elasticity of productivity with respect to R&D is approximately 0.15, so that 15% of manufacturing technology improvement comes from endogenous R&D investment. The data elasticity is $\xi = 0.06$. We follow Jones and Tonetti (2020), who set the data elasticity at 0.06 by drawing on both data's expenditure share in GDP and the pace at which machine-learning error rates fall with data. The cross-region technology spillover intensity is $\upsilon = 0.333$. Keller (2002) estimates that technology spillovers halve over a distance of about 1200 km, and the mean distance across all of China's cities is about 1200 km. At that distance the cross-region digital technology spillover is half as strong as the local spillover, giving $\upsilon = 0.5/(1 + 0.5) \approx 0.333$.

Trade and market structure. The CES elasticity of substitution is $\sigma = 5.0$, implying a constant markup of $5/4 = 1.25$. Simonovska and Waugh (2014) use cross-country price data to estimate a trade elasticity of approximately 4, implying $\sigma = 5$ under the standard Armington framework where the trade elasticity equals $\sigma - 1$. Similarly, Tombe and Zhu (2019) employ the same trade elasticity of 4 in their study of China's inter-provincial trade, and we follow this convention for inter-city trade. The home-bias parameter and iceberg transport cost are $(\alpha, \tau) = (0.70, 1.71)$. Tombe and Zhu (2019) estimate China's inter-provincial home spending shares in the range 0.623–0.787 and iceberg transport costs in the range 1.71–2.89. We set $\alpha = 0.70$ and take the lower bound $\tau = 1.71$, given the lower trade frictions in inter-city trade relative to inter-provincial trade.

Internally calibrated parameters. The digital expenditure share β, the manufacturing sector's digital adaptability m, the digital innovation efficiency κ^D, and the manufacturing R&D efficiency κ^M are calibrated internally to match Chinese evidence. We set the four jointly by requiring the laissez-faire equilibrium to reproduce four empirical targets observed in recent years. The first target is the ratio of information and communication technology (ICT) services value added to manufacturing value added, which averages about 0.17 (National Bureau of Statistics of China) and corresponds to $p^D Y^D/(p^M Y^M)$. The second target is the industrial digital-penetration rate of about 23% (China Academy of Information and Communications Technology), whose model counterpart is the share $m\chi^{LF}/(m\chi^{LF} + 1 - m)$ of the digital spillover in the manufacturing baseline technology. The third target is the growth rate $g^{LF} = 1\%$. China's real GDP grows about 5% per year (National Bureau of Statistics of China), and the core digital industries where digital innovation originates account for about one-fifth of the digital economy (China Academy of Information and Communications Technology). The fourth target is the technology ratio $\chi^{LF} = 1.8$, which equals the labor productivity of the ICT sector relative to

[20] Under a narrow, occupation-based measure, employment in ICT services is about 0.68% of China's total employment. Under a broad measure of the entire digital-related workforce, the ratio is about 4.25%. We employ a conservative value of 1%, close to the narrow measure, since digital talent in the model refers to the innovation-oriented specialists who create digital technology rather than the full digital-related workforce.

the economy-wide average (García-Herrero and Xu, 2018). Taken together, the four targets jointly determine $\beta = 0.162$, $m = 0.142$, $\kappa^D = 0.917$, and $\kappa^M = 0.906$.[21]

5.2. Quantitative results

5.2.1. Welfare cost measurement

This subsection compares equilibrium outcomes under laissez-faire and tournament competition against the First-Best allocation. To measure welfare gaps, we define the consumption-equivalent welfare of an allocation alloc $\in \{LF, Nash\}$ relative to the First-Best allocation as the scalar $\Omega^{\text{alloc}} \in (0, 1]$ that solves $\mathcal{W}^{\text{alloc}} = \mathcal{W}^{FB} + \frac{2(1+\rho)}{\rho} \ln \Omega^{\text{alloc}}$, i.e.,

$$\Omega^{\text{alloc}} \equiv \exp\left(\frac{\rho}{2(1+\rho)} \left(\mathcal{W}^{\text{alloc}} - \mathcal{W}^{FB} \right) \right).$$

Thus Ω^{alloc} is the factor by which First-Best aggregate consumption must be permanently scaled to deliver the same welfare as the chosen allocation, with the First-Best welfare normalized to $\Omega^{FB} = 1$ by construction. The complement $1 - \Omega^{\text{alloc}}$ is the welfare loss expressed as the percentage reduction in consumption. Because $\mathcal{W}$ decomposes additively into a level component $\frac{2(1+\rho)}{\rho} u(t{=}1)$ and a growth component $\frac{2(1+\rho)}{\rho^2} \ln(1+g)$, the welfare gap can be traced to differences in initial consumption (level) and in the balanced growth rate (growth). Applying the same construction to each component of $\mathcal{W}^{\text{alloc}} - \mathcal{W}^{FB}$ separately yields a level factor and a growth factor,

$$\Omega^{\text{alloc}}_{\text{level}} \equiv \exp\left(u^{\text{alloc}}(t{=}1) - u^{FB}(t{=}1) \right), \qquad \Omega^{\text{alloc}}_{\text{growth}} \equiv \left(\frac{1 + g^{\text{alloc}}}{1 + g^{FB}} \right)^{1/\rho},$$

where the two factors recover the total measure multiplicatively, $\Omega^{\text{alloc}} = \Omega^{\text{alloc}}_{\text{level}} \, \Omega^{\text{alloc}}_{\text{growth}}$.

5.2.2. Laissez-faire versus the First-Best allocation

Fig. 2 compares the laissez-faire equilibrium with the First-Best allocation across the range of the manufacturing sector's digital adaptability $m \in (0, 0.5)$. Panel (a) plots the consumption-equivalent welfare Ω^{LF} together with its level and growth factors, measured against the First-Best welfare $\Omega^{FB} \equiv 1$. Ω^{LF} lies below one throughout and rises monotonically with m, because the laissez-faire self-reinforcing growth strengthens with the manufacturing sector's digital adaptability. The level–growth decomposition is instructive. The level factor $\Omega^{LF}_{\text{level}}$ exceeds one throughout, while the growth factor $\Omega^{LF}_{\text{growth}}$ lies well below one, reflecting that laissez-faire fails to internalize the bidirectional cross-sector externalities and to fully realize the self-reinforcing growth gains: the welfare cost of laissez-faire is essentially a growth cost, partly offset by higher initial consumption.

Panel (b) plots the (Θ_L, φ) allocations behind these welfare measures, each expressed as the ratio of the laissez-faire to the First-Best value. The digital labor ratio $\Theta_L^{LF}/\Theta_L^{FB}$ lies far below one throughout, so laissez-faire under-allocates labor to the digital sector, as Proposition 2 establishes. The manufacturing R&D share ratio $\varphi^{LF}/\varphi^{FB}$ falls with m and crosses one within the range, so laissez-faire moves from over-investing to under-investing in manufacturing R&D as m rises. Because Θ_L^{LF} and φ^{LF} are independent of m, the two ratios in fact trace the First-Best allocation itself, with Θ_L^{FB} falling and φ^{FB} rising in m. Across both panels, the welfare gap $1 - \Omega^{LF}$ narrows: the more adaptable the manufacturing sector, the stronger the growth incentive that arises endogenously under laissez-faire, and the narrower the scope for welfare-improving intervention to correct the externality.

Panels (c) and (d) decompose First-Best and laissez-faire welfare into the level component $\frac{2(1+\rho)}{\rho} u(t{=}1)$ and the growth component $\frac{2(1+\rho)}{\rho^2} \ln(1+g)$, both on the left axis, together with total welfare (right axis). Under both allocations the growth component rises with m, consistent with the growth premium of Proposition 1. The First-Best allocation runs lower in level but higher in growth than laissez-faire, and the growth gain dominates, so that $\mathcal{W}^{FB} > \mathcal{W}^{LF}$.

5.2.3. Tournament competition

Fig. 3 traces the Nash equilibrium of decentralized tournament competition as the competition intensity $\lambda \in (0, 1)$ varies. Panel (a) plots the two Nash subsidies at the calibrated m, each normalized by its First-Best implementation level, $s^{D,FB}$ and $s^{MR,FB}$. Both ratios rise in λ and cross one within the range, so a sufficiently intense tournament pushes each instrument above its First-Best level. The manufacturing R&D data subsidy sits at its lower bound of zero over an initial stretch of low λ, where the laissez-faire manufacturing R&D share already exceeds what tournament competition warrants: its growth payoff falls short of its immediate cost in the tournament objective. Panel (b) decomposes the Nash equilibrium into its level and growth components at the calibrated m. The level component falls, since stronger competition reallocates resources toward the digital sector and depresses initial consumption, while the growth component rises as the digital sector expands and the self-reinforcing growth effect strengthens. Total welfare is inverted-U-shaped, which is the net outcome of these two opposing forces.

[21] We assess robustness by perturbing each of fourteen quantities by ±15% from its baseline value. The fourteen consist of the ten exogenous parameters and the four target moments of Table 3. Online Appendix E reports the protocol and the resulting envelopes. Every qualitative conclusion of the quantitative analysis that follows survives all twenty-eight perturbations. The welfare ranking across allocations, the growth premium of Proposition 1, the under-provision of digital activity established in Proposition 2, and the inverted-U relationship in Proposition 3 all hold in every perturbed economy. We further assess how sensitive the magnitudes are to each perturbation and find them equally stable. The optimal tournament competition intensity and the peak welfare attained at that intensity are the most stable objects in the exercise.

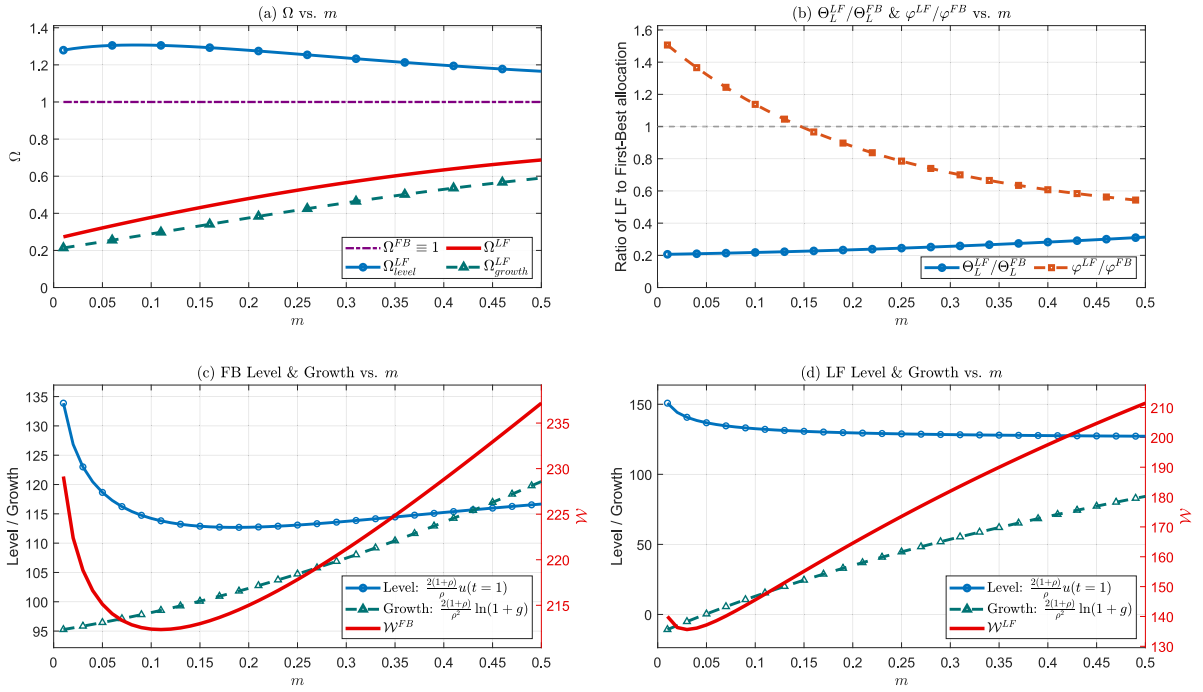


Fig. 2. Laissez-faire versus the First-Best allocation.
Notes: All panels use the baseline calibration and plot outcomes as functions of $m \in (0, 0.5)$. Panel (a): consumption-equivalent welfare Ω^{LF} (red solid) with its level factor $\Omega^{LF}_{\text{level}}$ (blue solid) and growth factor $\Omega^{LF}_{\text{growth}}$ (teal dashed), against the First-Best welfare $\Omega^{FB} \equiv 1$ (purple dash-dotted); $\Omega^{LF} = \Omega^{LF}_{\text{level}}\,\Omega^{LF}_{\text{growth}}$, and $1 - \Omega^{LF}$ measures the permanent consumption loss of laissez-faire relative to the First-Best allocation. Panel (b): ratios of the laissez-faire to the First-Best allocation, $\Theta_L^{LF}/\Theta_L^{FB}$ (blue solid) and $\varphi^{LF}/\varphi^{FB}$ (orange dashed); the gray dashed line marks a ratio of one. Panels (c)–(d): decomposition of First-Best and laissez-faire welfare into the level component $\frac{2(1+\rho)}{\rho}u(t{=}1)$ (blue solid) and the growth component $\frac{2(1+\rho)}{\rho^2}\ln(1+g)$ (teal dashed), both on the left axis, together with welfare $\mathcal{W} = \text{Level} + \text{Growth}$ (red solid) on the right axis. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Panel (c) plots the consumption-equivalent welfare $\Omega^{Nash}(s^{D,Nash}, s^{MR,Nash})$ and its single-instrument counterpart $\Omega(s^{D,Nash})$ at the calibrated m, together with the laissez-faire level Ω^{LF}. The bidirectional cross-sector externalities that laissez-faire fails to correct leave considerable scope for government intervention. The digital output subsidy yields $\Omega(s^{D,Nash})$, which already achieves a substantial welfare gain, and the manufacturing R&D data subsidy delivers a complementary improvement. The curve $\Omega^{Nash}(s^{D,Nash}, s^{MR,Nash})$ peaks at λ^{peak}, where tournament competition closes almost the whole laissez-faire welfare gap. For $\lambda < \lambda^{peak}$ ("good competition"), moderate competition corrects part of the bidirectional cross-sector externalities and pushes welfare above the laissez-faire level; for $\lambda > \lambda^{peak}$ ("bad competition"), excessive competition drives subsidies beyond the social optimum into over-subsidization, and welfare declines, consistent with Proposition 3.

Panel (d) plots λ^{peak} against the manufacturing sector's digital adaptability m. The peak decreases monotonically in m. Stronger digital adaptability in manufacturing narrows the welfare gap left for competition to correct. A milder tournament therefore suffices to come closest to First-Best welfare. As an economy's manufacturing sector becomes more digitally adaptable, the institutional design of intergovernmental competition must be recalibrated. Incentives that were welfare-improving at an early stage of digital development may become welfare-destroying later.

6. Conclusion

This paper examines whether decentralized fiscal competition can correct the bidirectional cross-sector externalities between the digital services and manufacturing sectors. We develop a dynamic two-region spatial general equilibrium model in which frontier digital technology spills over to manufacturing, while manufacturing activity generates data that feeds back into digital innovation. The resulting self-reinforcing growth effect strengthens with the manufacturing sector's digital adaptability. Laissez-faire under-allocates resources to the digital services sector and is Pareto-inefficient. A digital output subsidy and a manufacturing R&D data subsidy can jointly correct these externalities and implement the First-Best allocation. We further introduce tournament competition into the decentralized economy. The welfare consequences exhibit an inverted-U pattern in tournament competition intensity. Moderate competition partially corrects the externalities and raises allocative efficiency, while excessive competition leads to over-subsidization. The optimal tournament competition intensity decreases as manufacturing becomes more digitally adaptable.

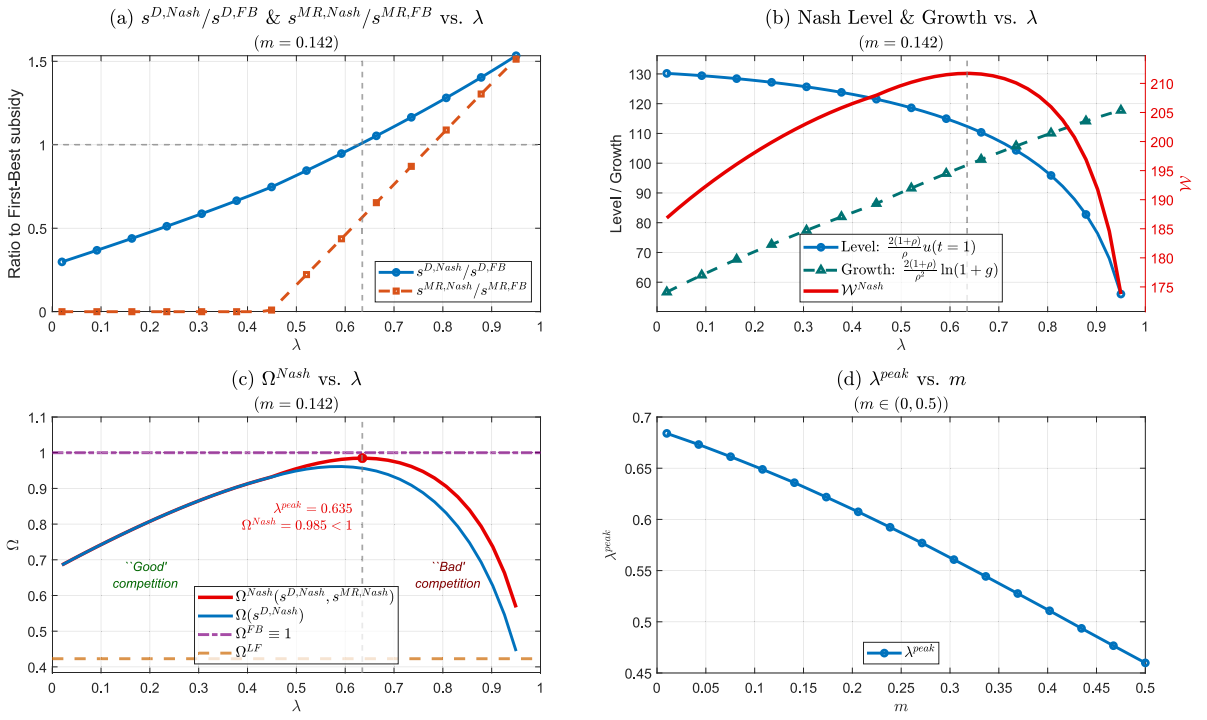


Fig. 3. Tournament competition.

Notes: All panels use the baseline calibration. Panels (a)–(c) plot outcomes as functions of $\lambda \in (0, 1)$ at the calibrated m, and Panel (d) as a function of $m \in (0, 0.5)$. Panel (a): digital output subsidy $s^{D,Nash}$ (blue solid) and manufacturing R&D data subsidy $s^{MR,Nash}$ (orange dashed), each relative to its First-Best implementation level ($s^{D,FB}$ and $s^{MR,FB}$); the horizontal gray dashed line marks a ratio of one, and the vertical gray dashed line marks λ^{peak}. Panel (b): decomposition into the level component $\frac{2(1+\rho)}{\rho}u(t{=}1)$ (blue solid) and the growth component $\frac{2(1+\rho)}{\rho^2}\ln(1+g)$ (teal dashed), both on the left axis, together with welfare $\mathcal{W}^{Nash} = \text{Level} + \text{Growth}$ (red solid) on the right axis. Panel (c): consumption-equivalent welfare $\Omega^{Nash}(s^{D,Nash}, s^{MR,Nash})$ (red solid) and its single-instrument counterpart $\Omega(s^{D,Nash})$ (blue solid), against the laissez-faire welfare Ω^{LF} (orange dashed) and the First-Best welfare $\Omega^{FB} \equiv 1$ (purple dash-dotted), with the peak of Ω^{Nash} marked at λ^{peak}; $\lambda < \lambda^{peak}$ corresponds to "good competition" (under-subsidized) and $\lambda > \lambda^{peak}$ to "bad competition" (over-subsidized). Panel (d): optimal tournament competition intensity λ^{peak} (blue solid). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

These results carry implications for the design of intergovernmental fiscal institutions in the digital economy. First, subsidies to the digital economy are warranted as corrective instruments for market failures. This provides a welfare-theoretic rationale for initiatives such as China's "Digital China" strategy, the European Union's Digital Decade Policy Programme, and the US CHIPS and Science Act. These initiatives serve not merely as industrial upgrading policy, but as a correction of a systematic under-provision of digital activity. Second, the non-monotonic welfare response to tournament competition intensity implies that intergovernmental competition should balance externality correction against over-subsidization. Policymakers should preserve moderate competitive incentives while establishing safeguards against excessive fiscal rivalry. As digital development proceeds or the inter-regional economic landscape evolves, the competition intensity should be recalibrated accordingly. Third, the framework applies to an economic union, where each member state sets its own fiscal instruments and coordination operates at the union level. Fiscal policy coordinated across member states can correct market failures and accelerate the union's digital transformation. More broadly, intergovernmental fiscal institutions should harness the corrective potential of decentralized competition while preventing it from overshooting into welfare-reducing territory.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Yan Liu reports his role as a Guest Editor for the *European Economic Review*. Given that role, Yan Liu had no involvement in the peer review of this article and had no access to information regarding its peer review. Full responsibility for the editorial process for this article was delegated to another journal editor.

The other authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.euroecorev.2026.105496.

Data availability

Data will be made available on request.

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