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# Bridging the digital divide for resilient cities: Lessons from Chinese prefectures

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A B S T R A C T

Digital infrastructure underpins the urban transition to the digital economy. Using geolocated 4G base-station data for 274 Chinese prefecture-level cities (2014–2022), we construct an intra-urban digital divide index capturing within-city inequality in access to mobile infrastructure (a first-order digital divide) and examine its relationship with employment-based urban economic resilience. Two-way fixed-effects estimates, supported by instrumental-variable, spatial, and quantile analyses, show that greater within-city infrastructure inequality systematically reduces resilience. The adverse effect is stronger in cities with more advanced economic development and digitalization, larger migrant inflows, and a more homogeneous educational composition. This pattern holds in both resistance and recovery episodes, with a larger effect during recovery. Mechanism tests show that unequal digital infrastructure undermines economic resilience by altering firm entry patterns, limiting innovation diffusion, and reducing industrial diversity. As an extension, we proxy a second-order (usage-based) digital divide using within-city inequality in internet engagement and find consistent evidence that digital disparities erode resilience. Spatial models reveal negative spillovers whereby a city's digital fragmentation diminishes the resilience of its neighbors. The results highlight digital equity as resilience infrastructure and motivate place-based, coordinated investments to close intra-urban digital gaps.

## 1. Introduction

The concept of resilience, originally rooted in mechanics, describes a material's capacity to return to its initial state after stress. By extension, urban resilience refers to a city's ability to maintain stability, adapt to disturbances, and recover functionality in the face of systemic shocks (Martin & Sunley, 2015). As urbanization accelerates, cities concentrate populations, capital, and infrastructure, becoming complex socio-ecological systems. These dynamics increase vulnerabilities to economic disruptions, environmental risks, and public health crises. Recognizing these challenges, China formally included the goal of building "resilient cities" in its 2020 national planning agenda.

Existing research shows that cities often recover relatively quickly from natural shocks such as earthquakes or epidemics (Cavallo et al., 2013; Jedwab et al., 2022). Yet disruptions to economic and institutional structures tend to have longer-lasting effects on urban trajectories (Glaeser, 2022). Historical experience illustrates this divergence: the shift from canal-based to maritime trade precipitated Yangzhou's decline and coastal cities' rise during the late Qing dynasty (Cao & Chen, 2022). In more recent decades, advances in digital technologies have transformed Silicon Valley into a global innovation hub, while leaving traditional industrial cities increasingly marginalized. These cases highlight that resilience is shaped not only by physical infrastructure and disaster preparedness but also by deeper structural and technological dynamics.

The global rise of digital technologies, and their evolution into a digital economy, is one such transformative force (Goldfarb & Tucker, 2019). Digital tools enhance forecasting, coordination, and service delivery, thereby improving cities' capacity to respond to risks (Xu et al., 2024). However, their benefits are unevenly distributed, reflecting the persistent "digital divide." The literature identifies three dimensions of this divide (Lythreatis et al., 2022): (1) First-level digital divide centers on inequalities in access to the internet. (2) Second-level digital divide focuses on inequalities in digital skills and online engagement. (3) Third-level digital divide highlights inequalities in outcome (specifically, internet-derived benefits) despite equal access, skills, and online

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behaviors. While national and regional digital divides are well documented, the impacts of intra-urban infrastructure inequality remain insufficiently studied. For instance, Harrison and Heley (2015) reveal how spatial inequalities and governance structures condition regional resilience, suggesting that internal fragmentation within regions profoundly matters. Similarly, Lee et al. (2025) show that Korea's national smart city program highlights the importance of institutional design and inclusiveness for building resilience. Together, these studies indicate that digital infrastructure disparities within cities are likely to have profound effects on resilience, yet this dimension remains underexplored.

This study focuses on the first-level digital divide (inequalities in infrastructure access) by using geolocated data on 4G base stations across Chinese prefecture-level cities. We demonstrate that intra-urban digital divides weaken economic resilience by alternating new firm entry, slowing innovation diffusion, and reducing industrial diversity. The detrimental effect is most pronounced in cities characterized by greater economic development, advanced digitization, larger inflows of migrants, and a more uniform educational background among their residents. Moreover, we find that local digital fragmentation generates negative spillovers, weakening resilience in neighboring cities.

Our contribution is threefold. First, we extend the literature on urban resilience by introducing digital infrastructure inequality rather than digital infrastructure/economy level as a critical determinant. Prior studies emphasize the role of physical infrastructure (Li et al., 2023), governance (Woodruff et al., 2021), and digital economy indicators more broadly (Shen et al., 2025; Xu et al., 2024; Zhang et al., 2024). While the rapid development of the digital economy has generated aggregate growth dividends, its internal unequal distribution also constitutes a potential structural risk. We focus specifically on the digital divide, and our mechanism analysis highlights how inequalities in firm entry, innovation, and industrial diversity channel its effects on resilience. Second, we contribute to measurement by constructing a novel index of intra-urban digital inequality, based on the dispersion of 4G base stations across counties within prefecture-level cities. Existing studies usually examine inter-regional or inter-city divides (Etherington & Jones, 2009; Fiaschi et al., 2018), but to our knowledge, no work has systematically measured digital fragmentation within cities. Third, by documenting negative spillovers across neighboring cities, we emphasize the need for coordinated governance. These findings contribute to global discussions on resilient and inclusive urban development, aligning with the Sustainable Development Goals and the New Urban Agenda.

The remainder of this study is organized as follows: Section 2 reviews the relevant literature on digital divides and urban resilience. Section 3 develops the theoretical framework and hypotheses. Section 4 introduces the data and methods. Section 5 presents the empirical findings and robustness tests. Section 6 provides extended analyses, including mechanisms, spatial effects, and distributional heterogeneity. Section 7 concludes with policy implications and potential avenues for future research.

## 2. Literature review

### 2.1. Research on the digital divide

The rapid diffusion of digital technologies has fundamentally reshaped production, consumption, and social interaction by substantially reducing the costs of information storage, computation, and transmission (Goldfarb & Tucker, 2019). However, the benefits of digitalization have not been evenly distributed, giving rise to persistent and multidimensional inequalities commonly referred to as the "digital divide." Initially, the concept was used to describe disparities in access to information and communication technologies (ICTs), focusing primarily on the first-level divide in physical connectivity (Rogers, 2001). Over time, the notion has been extended to encompass inequalities in digital skills, usage patterns, and socioeconomic outcomes, which are often classified as the second- and third-level digital divides, respectively (Hilbert, 2010; Lythreatis et al., 2022). Building on this progression, the literature has developed a multi-layered analytical framework commonly referred to as the "three-level digital divide." The first-level divide captures inequalities in access to devices and network infrastructure (Sharma et al., 2025), the second-level divide emphasizes differences in digital skills, autonomy of use, and psychological barriers such as motivation and self-efficacy (Luan et al., 2023), while the third-level divide focuses on the unequal distribution of beneficial outcomes derived from internet use across individuals and groups (Nishijima et al., 2017). This framework highlights that the digital divide has evolved from a narrow issue of technical access into a dynamic and cumulative process of "access–capability–outcome" conversion, in which disadvantages at earlier stages tend to translate into persistent inequalities at later stages (Bruno et al., 2023).

At the individual and household levels, digital divides manifest in unequal access to devices, broadband connectivity, and digital competencies, which constrain opportunities in education, employment, entrepreneurship, and civic participation (Hilbert, 2010; Pérez-Morote et al., 2020). These disadvantages tend to accumulate over time, reinforcing income inequality and welfare gaps. Some studies even identify the digital divide as a structural driver of persistent poverty, especially in developing regions (Gebremichael & Jackson, 2006; Yue et al., 2024). Importantly, due to strong network externalities and increasing returns in digital platforms, early disadvantages in digital access may be amplified over time, generating self-reinforcing cycles of exclusion (Park, 2017).

At the regional and national levels, a growing body of empirical research has documented that uneven ICT diffusion contributes to long-term disparities in economic performance, innovation capacity, and industrial upgrading, particularly between urban and rural areas (Liu et al., 2026; Philip et al., 2015; Reveiu et al., 2023; Salemink et al., 2017). Digital infrastructure has been shown to facilitate entrepreneurial opportunity recognition, reduce entry barriers, and stimulate innovation activities. For example, using Global Entrepreneurship Monitor (GEM) survey data, Schade and Schuhmacher (2022) find that higher levels of national digital infrastructure significantly promote entrepreneurial activity by reducing perceived risks and transaction costs. Similarly, Osei (2024), based on data from 28 African countries, demonstrates that improvements in digital infrastructure significantly enhance innovation outputs.

Nevertheless, the spatial distribution of digital infrastructure is often highly uneven, and such imbalances constitute a fundamental source of digital inequality. Empirical evidence from different regions confirms that infrastructure gaps remain substantial across space. In the United States, metropolitan areas exhibit nearly twice the level of telecommunications access compared to non-metropolitan regions (Gabe & Abel, 2002). In Indonesia, regional digital disparities continued to widen between 2010 and 2012, largely driven by differences in infrastructure investment across regions (Sujarwoto & Tampubolon, 2016). In Sub-Saharan Africa, institutional barriers to infrastructure sharing among cross-border telecom operators have led to persistent under-coverage in remote areas (Arakpogun et al., 2020). These studies suggest that infrastructure-led digital divides are not transitional phenomena but may persist without targeted policy intervention.

Two strands of literature are particularly relevant to this study. The first examines the relationship between digital infrastructure development and regional resilience. Cheng et al. (2025) show that the coordinated development of digital infrastructure and digital finance enhances urban resilience by improving resource allocation efficiency and risk-sharing capacity. Shi et al. (2025) construct a composite index of "new infrastructure" at the provincial level, covering information, integrated, and innovation-oriented infrastructure, and find that such investments strengthen economic and social resilience, although they may exert negative environmental effects. These studies, however, primarily focus on the average level of infrastructure development rather than its intra-regional distribution.

The second strand emphasizes that regional disparities in digital infrastructure can exacerbate uneven economic development. de Clercq et al. (2023) find that unequal high-speed broadband coverage across urban and rural areas in the European Union constrains regional economic growth, and that narrowing the access gap can improve overall productivity. Du and Wang (2024), using provincial-level data in China, show that digital infrastructure has a stronger impact on innovation in eastern regions, while insufficient infrastructure in less-developed regions widens interregional innovation gaps. Overall, these findings highlight that not only the level but also the spatial distribution of digital infrastructure matters for economic outcomes.

Despite these advances, existing studies predominantly assess digital inequality at the inter-country, inter-regional, or provincial levels (Etherington & Jones, 2009; Fiaschi et al., 2018; McCann, 2020), while intra-urban digital disparities remain largely overlooked. Yet, substantial heterogeneity in infrastructure provision and digital service accessibility often exists within cities, reflecting historical development patterns, fiscal capacity, and spatial planning policies. Such within-city digital divides may directly affect firms' entry decisions, innovation clustering, and industrial diversification, which are all critical components of urban economic resilience. In this paper, we explicitly focus on the first-level, infrastructure-based digital divide at the intra-urban scale, where unequal access to foundational connectivity can become a binding constraint on higher-order digital participation and economic adjustment. Therefore, examining digital inequality at the intra-urban scale provides a more precise understanding of how digital infrastructure shapes cities' adaptive and recovery capacities, and constitutes the primary focus of this study.

### 2.2. Research on the determinants of urban resilience

Resilience is widely regarded as a key attribute that enables cities to withstand external shocks and sustain long-term economic vitality. Scholars have approached this concept from multiple perspectives. For instance, evolutionary economic geography emphasizes the roles of path dependence and industrial diversification in strengthening resilience (Martin & Sunley, 2015; Simmie & Martin, 2010). In contrast, research in planning and urban studies highlights the importance of governance structures and institutional arrangements in shaping resilient urban systems (Monstadt & Schmidt, 2019; Serbanica & Constantin, 2023; Woodruff et al., 2021).

With the advancement of digital technologies and the acceleration of urban digital transformation, growing attention has been paid to the application of digital tools in urban governance and urban management (Adhvaryu & Mathew, 2025), particularly in the context of emergency management and disaster response. On the one hand, digital technologies enable continuous monitoring and early warning of potential risks. Through the deployment of Internet of Things (IoT) sensors, satellite remote sensing, and big data analytics, urban managers can collect real-time meteorological and geological information, identify emerging risks, and issue timely warnings, thereby improving the precision and effectiveness of disaster prevention (Han & Zang, 2025; Vicari et al., 2019). On the other hand, after shock events occur, digital technologies support information transmission and the restoration of social operations. With the assistance of emergency communication systems, social media platforms, and digital public service interfaces, governments, communities, and residents can remain connected under extreme conditions, coordinate rescue resources, and maintain essential services, which helps reduce social disruption and facilitate recovery (Henman, 2020; Kim et al., 2022). These channels suggest that digital capacity can shape both the immediate shock response and the subsequent recovery trajectory.

Existing empirical studies indicate that the application of digital technologies and the development of the digital economy can contribute to stronger urban resilience. Reveiu et al. (2023), using data from 278 regions in the European Union, find that internet access and computer usage significantly explain differences in labor market resilience. Xu et al. (2024) construct a city-level digital economy index based on internet usage, internet-related employment, telecommunications revenue, number of internet users, and digital financial development, and show that digital economy development enhances urban economic resilience. Wen et al. (2024), using evidence from Chinese cities, further demonstrate that investment in new-type digital infrastructure strengthens economic resilience.

Even so, existing studies tend to emphasize the overall level of digital development, while paying limited attention to the distribution of digital infrastructure within cities. This limitation is noteworthy because overall urban resilience can be constrained by its weakest components (Martin & Sunley, 2015). If digitally disadvantaged neighborhoods face systematically higher information frictions and weaker access to online services, within-city digital gaps may act as bottlenecks that slow reallocation, dampen innovation diffusion, and ultimately constrain aggregate resilience. Unequal access to digital infrastructure within cities may become a critical bottleneck that restricts resilience development and weakens the overall capacity of urban systems to cope with shocks. By addressing this gap, this study builds on existing research and provides new evidence on how intra-urban digital infrastructure inequality affects urban resilience.

## 3. Theoretical framework and research hypothesis

Urban economic resilience depends not only on the level of resources and technologies but also on how equitably they are distributed within a city. In particular, intra-urban digital divides can undermine urban resilience by creating unequal access to key resources, limiting adaptive capacity, and obstructing economic dynamism. In this part, we argue that intra-urban digital divides can reduce urban economic resilience through three distinct but complementary channels. First, by restricting access to digital infrastructure in less connected counties, the divide suppresses new firm entry and generates spatial inequality in entrepreneurial activity. Second, it distorts the geography of innovation by concentrating inventive efforts in digitally advantaged areas, hence limiting spillovers and cross-regional recombination. Third, it compresses industrial diversity by amplifying sectoral concentration, which reduces redundancy and adaptability. These channels are conceptualized as parallel rather than sequential, and we examine each of them separately in the empirical analysis. In addition, digital fragmentation within one city can transmit outward through supply chains and labor markets, generating negative spillovers for neighboring cities. These mechanisms link the spatial distribution of digital infrastructure to the adaptive capacity of urban economies and motivate the hypotheses that follow.

### 3.1. Digital inequality and firm entry inequality

New firm entry contributes to resilience by generating employment, introducing new technologies, and stimulating structural adjustment (Fritsch & Wyrwich, 2018). A broad and spatially dispersed base of entrepreneurial activity increases the likelihood that alternative growth paths can emerge when dominant sectors decline. In this sense, the distribution of firm entry across urban space is a structural attribute that shapes recovery capacity.

However, when digital infrastructure is spatially concentrated, firms in digitally disadvantaged districts face higher information costs, weaker access to online platforms, and greater difficulties in connecting with markets and suppliers. As a result, entrepreneurial activities tend to cluster in digitally advantaged areas, while peripheral districts experience suppressed entry. This generates inequality in firm entry within cities and narrows the effective entrepreneurial base that supports adaptation and recovery.

Existing research often links entrepreneurship and resilience at regional or national levels, yet it rarely considers how intra-urban digital disparities skew the geography of firm entry. For example, studies such as Simmie and Martin (2010) and Fritsch and Wyrwich (2018) explore firm entry in relation to urban resilience, but they often focus on regional patterns without addressing intra-urban disparities. Our framework highlights this mechanism, showing that uneven opportunities within cities can constrain resilience even when aggregate entry rates appear robust. Further empirical studies such as Boschma (2015) and McCann (2020) have shown that entrepreneurial dynamics support employment generation and economic diversification, which are key components of resilience. Our study builds on this, suggesting that digital inequality exacerbates firm entry inequality, limiting entrepreneurial opportunities in disadvantaged urban areas.

### 3.2. Digital inequality and innovation inequality

Innovation enables cities to adapt to shocks by fostering recombination, variety creation, and new growth paths (Martin & Sunley, 2015; Simmie & Martin, 2010). A more spatially inclusive innovation system allows ideas to circulate across districts and promotes diversified experimentation, which strengthens adaptive capacity. Therefore, the internal distribution of innovation activities constitutes an important structural feature of resilient urban economies.

When digital infrastructure is unevenly distributed, innovative activities are more likely to concentrate in digitally advantaged districts that benefit from better connectivity, data access, and collaboration opportunities. In contrast, peripheral areas face higher costs of information exchange and weaker participation in innovation networks. This spatial polarization of innovation limits cross-regional spillovers and reduces system-wide learning capacity, thereby weakening resilience.

While prior studies have largely examined aggregate levels of innovation or R&D intensity, they have paid little attention to how inequalities in innovation opportunities within a city influence resilience. For example, Simmie and Martin (2010) and Boschma (2015) emphasize that spatially diversified innovation systems increase resilience by promoting learning and recombination, yet few studies have investigated how unequal access to innovation within cities might hinder this process. By addressing this overlooked dimension, our study advances the understanding of digital equity as a resilience factor.

### 3.3. Digital inequality and industrial diversity

A diverse industrial base provides resilience against sector-specific shocks and fosters cross-sectoral reallocation (Brown & Greenbaum, 2017; Grabner & Modica, 2022). A diversified industrial structure increases redundancy and allows cities to better absorb sector-specific downturns, making diversity a core structural attribute of resilient economies.

Unequal digital access, however, tends to reinforce the concentration of economic activities in digitally intensive sectors and locations. Firms are more likely to cluster in the same digitally advantaged districts and industries, which strengthens specialization and weakens diversification. Over time, this process compresses industrial diversity and increases vulnerability to structural shocks.

While previous studies emphasize the importance of diversification for resilience, they do not consider how digital fragmentation within a city undermines diversification itself. Studies such as Brown and Greenbaum (2017) have highlighted the importance of industrial diversification for resilience, but they focus primarily on traditional economic sectors, without considering the role of digital infrastructure in fostering or hindering such diversification. Our approach therefore complements existing research by linking intra-urban digital inequality to industrial diversity as a resilience mechanism.

Building on the analysis in the preceding subsections, we propose one main hypothesis and three mechanism-specific hypotheses.

**H1 (Main hypothesis).** Intra-urban digital divides in information infrastructure undermines urban economic resilience.

**H2 (Mechanism).** Greater intra-urban digital inequality reduces resilience by concentrating firm entry in digitally advantaged areas.

**H3 (Mechanism).** Greater intra-urban digital inequality reduces resilience by widening disparities in innovation.

**H4 (Mechanism).** Greater intra-urban digital inequality reduces resilience by lowering industrial diversity.

### 3.4. Extensions: Spillovers and distributional heterogeneity

Cities are embedded in wider regional systems through supply chains, labor markets, and infrastructure networks. Digital fragmentation within one city can therefore create negative spillovers, weakening resilience in neighboring cities by reducing inter-urban connectivity and knowledge flows. Moreover, the effect of digital inequality is likely to be distributionally heterogeneous. It may be particularly harmful where resilience is already low due to structural disadvantages, but it can also constrain advanced cities that rely heavily on seamless digital integration (Giannakis & Bruggeman, 2020; Glaeser, 2022; Wen et al., 2024).

**H5 (Spillovers).** Intra-urban digital inequality in one city reduces the resilience of neighboring cities through negative spillover effects.

**H6. (Distributional heterogeneity):** The adverse effect of intra-urban digital inequality on resilience is more pronounced at both the lower and upper ends of the resilience distribution.

In brief, these hypotheses extend existing research and related journals that highlight the roles of governance, infrastructure, and institutional design in shaping resilience (Serbanica & Constantin, 2023; Woodruff et al., 2021). By shifting attention from aggregate levels to intra-urban inequalities, our study links digital equity to core mechanisms of resilience and clarifies why bridging the digital divide within cities is essential for building resilient urban economies. These theoretical arguments and hypotheses provide the foundation for the empirical analyses that follow, where they will be systematically tested. Fig. 1 presents the theoretical framework of this paper.

## 4. Research design

### 4.1. Data and sample

Our empirical analysis uses a balanced panel of 274 prefecture-level cities in China covering the period 2014–2022, yielding a total of 2466 city–year observations. This timeframe is selected because China's deployment of 4G base stations began in 2014, following the issuance of 4G operating licenses to the three major telecommunications operators by the Ministry of Industry and Information Technology on December 4, 2013, while the latest city-level employment statistics are available only up to 2022. Using prefecture-level cities as the unit of analysis is particularly appropriate, as each prefecture-level jurisdiction integrates

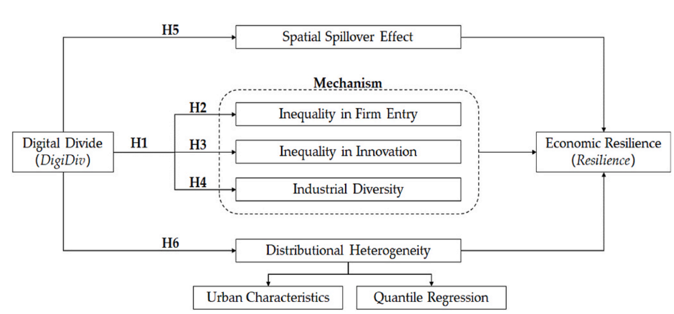


**Fig. 1.** Theoretical framework.

 

an urban core with multiple surrounding counties or county-level cities within a single administrative and economic entity. This institutional structure allows us to capture intra-city variation, which is central to our research question.[1] To maintain a balanced panel, occasional missing values in socioeconomic indicators were interpolated using a linear trend approach, consistent with standard practice in panel-data studies.

We compile data from multiple sources. Geospatial data on 4G base stations are drawn from the OpenCelliD database (https://opencellid.org), which provides point coordinates for each station. These points are spatially joined to official county-level administrative boundaries to count base stations by county and year. Within our 274-city sample, this procedure yields a balanced county–year grid covering 2851 county-level units over 2014–2022; counties remain in the dataset even when no station is matched in a given year (the count is recorded as zero rather than treated as missing). To ensure comparability of spatial units over time, we harmonize county boundaries to a fixed administrative system and apply it consistently across years; any rare reorganizations that would otherwise create breaks in prefecture-level series are handled by excluding the affected units from all years.[2] This matching enables the construction of within-city indicators that reflect dispersion in access to digital infrastructure across counties of the same prefecture-level city. According to the 2022 Statistical Bulletin of Civil Affairs Development released by the Ministry of Civil Affairs, China had 2843 county-level administrative units and 293 prefecture-level cities in 2022. These national totals are reported for context. All county-level units are covered in the original geospatial base-station dataset, which consists of latitude–longitude point records and does not exhibit sample attrition over time during the study period. Details of the digital divide measure are presented in Section 4.2.

City-level socioeconomic information, including employment used to build the resilience outcome, comes from standard statistical yearbooks and bulletins. The employment-based resilience index follows the approach introduced later in Section 4.2, where we define the metric formally and link it to national employment dynamics.

## 4.2. Variables construction

### 4.2.1. Dependent variable: Economic resilience

Following Giannakis and Bruggeman (2020) and Muštra et al. (2023), we measure urban economic resilience from the employment perspective by comparing each city's annual employment dynamics with the national average (see Du et al., 2020, for an operational measurement framework). The underlying idea is that resilience can be understood as the relative ability of a local economy to withstand downturns and to recover, benchmarked against the national trajectory. Similar methods have also been applied in other national contexts, such as Lagravinese (2015) in the study of regional disparities in Italy, which further demonstrates the robustness and transferability of this measurement strategy.

Let $M_{it}$ denote the number of employed persons in city $i$ in year $t$, and let $M_{nt}$ denote the national number of employed persons in year $t$. Resilience is defined as the difference between the city's employment growth rate and the national employment growth rate, normalized by the absolute value of the national employment growth rate, so as to express the city's relative deviation from the national trend in proportional terms:

$$Resilience_{it} = \frac{\left(\frac{M_{i,t}-M_{i,t-1}}{M_{i,t-1}}\right) - \left(\frac{M_{n,t}-M_{n,t-1}}{M_{n,t-1}}\right)}{\left|\frac{M_{n,t}-M_{n,t-1}}{M_{n,t-1}}\right|} \tag{1}$$

This normalization ensures that the indicator captures the percentage deviation of city-level employment growth from the national benchmark, thereby making the measure comparable across years with different macroeconomic conditions. A positive $Resilience_{it}$ value indicates above-national performance in absorbing and recovering from shocks, a negative value indicates below-national resilience, and a value close to zero implies parity with the national pattern. This measure is consistent with the notion that downturns involve a shock phase followed by a recovery phase, both of which are reflected in employment dynamics over time.

It should be noted that economic resilience is a broad concept that can involve resistance, recovery, and longer-run reconfiguration. Our baseline measure, which is constructed from relative employment dynamics, should therefore be read as a parsimonious, outcome-based summary of how a city's labor market performs through shocks, rather than a complete inventory of all resilience dimensions. We focus on employment because it is consistently measured across cities and years and closely tied to the welfare costs of downturns. To make the stage profile more transparent, we complement the baseline analysis with a phased regression exercise that separates periods of resistance and recovery (Section 6.2.3). In addition, our mechanism evidence on entry, innovation, and industrial structure provides complementary information on channels closely related to adaptive capacity.

### 4.2.2. Independent variable: Digital divide

Our core explanatory variable is the intra-urban digital divide, defined as the dispersion of access to digital infrastructure within each prefecture-level city. The use of geocoded base-station data to capture inequality in digital access is well established in the literature. For instance, Hodler and Raschky (2017) employ OpenCellID point-level data to assign cell sites to fine-grained subnational spatial units and construct measures such as cell-site density to reflect uneven diffusion of mobile infrastructure across regions. Building on this approach, our measure explicitly focuses on within-city dispersion of per-capita base-station availability across counties, which directly operationalizes the concept of an intra-urban digital divide. We construct this measure using geospatial data on 4G base stations from the OpenCelliD database, matching point coordinates to county-level administrative boundaries to obtain annual counts ($BaseStations_{cit}$).

Following infrastructure inequality literature, we normalize counts by population to obtain per-capita values, then compute the standard deviation across counties:

$$DigiDiv_{it} = \mathrm{Std.Dev}_{c\in i}\left(\frac{\mathrm{BaseStations}_{cit}}{\mathrm{Population}_{cit}}\right) \tag{2}$$

This formula aligns with similar approaches used to assess spatial imbalances in infrastructure deployment (Lucendo-Monedero et al., 2019; Zhang, Dang, et al., 2021) and complements broader digital divide measurement frameworks that emphasize multi-dimensional and spatial components (Zhou et al., 2024). A higher $DigiDiv_{it}$ value indicates greater inequality in digital infrastructure within a city. This reflects a deliberate focus on distributional disparity, which resonates with our theoretical emphasis on how unequal access shapes innovation, firm entry, and diversity mechanisms.

Fig. 2 shows how the number of 4G base stations in China expanded during our study period. In 2014, only 14 county-level administrative units and 6 prefecture-level cities had at least one recorded 4G base station, whereas by 2022 this number had increased to 2139 county-

[1] In the Chinese administrative hierarchy, a prefecture-level city differs from the concept of a single urban municipality in many other countries. Instead, it is a multi-jurisdictional unit typically including a central urban district together with several surrounding counties or county-level cities. This feature is crucial for our analysis, as our measure of intra-urban digital inequality is constructed across these county-level subunits within each prefecture-level city.

[2] We harmonize county boundaries to a fixed administrative system for the full sample period. For the Laiwu–Jinan reorganization, we exclude the affected units from all years to avoid breaks in prefecture-level series. Appendix Table A1 summarizes county coverage and stability.

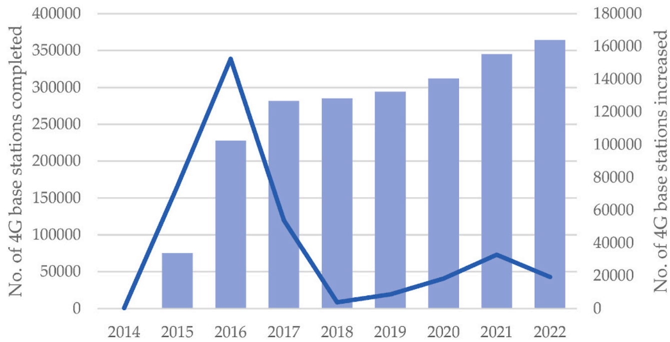


**Fig. 2.** No. of 4G base stations completed (left) and increased (right) in China (2014–2022).
*Note:* This figure illustrates the nationwide expansion of 4G infrastructure during 2014-2022. Our analysis, however, relies on a within-city dispersion measure based on county-level per-capita base station counts.

level units and 272 prefecture-level cities, indicating a dramatic expansion in geographic coverage. The sharp increase after 2016 highlights the rapid pace of deployment, which confirms that our chosen observation period captures a phase of strong growth and sufficient variation for empirical analysis. Since our analysis focuses on the distribution of base stations within each city, this figure is provided only as background information. In the regression models below, we control for year effects to account for overall national trends in base-station construction, while our digital divide index captures the differences across counties within a city based on OpenCelliD data matched to county boundaries.

### 4.2.3. *Control variables*

To account for structural and institutional factors that may confound the relationship between the digital divide and resilience, we include a series of control variables widely used in the urban and regional development literature. Government intervention (*Gov*) is measured as the ratio of general budget expenditure to fiscal revenue, reflecting the degree of fiscal involvement in local economies. Foreign trade dependence (*Trade*) is defined as total imports and exports over GDP, capturing a city's openness to global markets. Financial development (*Fin*) is proxied by the ratio of financial institution loan balances to GDP, indicating the depth of the local financial system. Technology expenditure intensity (*Tech*) is measured as science-related expenditure relative to GDP, representing investment in knowledge and innovation. Finally, industrial structure (*Ind*) is expressed as the share of secondary industry value added in GDP, reflecting the structural composition of the local economy. All variables are constructed from the China City Statistical Yearbooks and related statistical bulletins to ensure consistency and comparability across cities and years.

Table 1 reports the variable definitions and symbols for the dependent variable (*Resilience*), the independent variable (*DigiDiv*), and the control variables. Table 2 presents descriptive statistics (mean, standard deviation, minimum, maximum) for the balanced panel of 274 prefecture-level cities over 2014–2022 (N = 2466 city–years).

**Table 1**
Variable descriptions.

| Type | Name | Symbol | Definition |
|---|---|---|---|
| Dependent | Economic resilience | *Resilience* | Difference between the city's employment growth rate and the national employment growth rate in year $t$ (Eq. (1)). |
| Independent | Digital divide | *DigiDiv* | Standard deviation of county-level per-capita 4G base-station counts within a prefecture-level city (Eq. (2)) |
| Control | Government Intervention | *Gov* | General budget expenditure/ revenue |
| | Foreign Trade | *Trade* | Total imports and exports/GDP |
| | Financial development | *Fin* | Loan balances of financial institutions/GDP |
| | Technology expenditure | *Tech* | Science-related expenditure/GDP |
| | Secondary industry | *Ind* | Share of secondary industry value added/GDP |

**Table 2**
Summary statistics.

| Variable | Obs | Mean | Sd | Min | Max |
|---|---|---|---|---|---|
| *Resilience* | 2466 | −0.1760 | 3.2985 | −6.7148 | 7.3225 |
| *DigiDiv* | 2466 | 1.5400 | 6.0320 | 0.0000 | 126.4433 |
| *Gov* | 2466 | 3.0266 | 1.9329 | 0.9037 | 37.0761 |
| *Trade* | 2466 | 0.1770 | 0.6212 | 0.0004 | 28.3684 |
| *Fin* | 2466 | 1.5877 | 0.7387 | 0.3769 | 20.1002 |
| *Tech* | 2466 | 0.0030 | 0.0030 | 0.0001 | 0.0631 |
| *Ind* | 2466 | 42.8647 | 10.1724 | 11.7058 | 75.5000 |

Notes: $N = 2466$ city–years (balanced panel of 274 prefecture-level cities over 2014–2022). Missing values in socioeconomic indicators were linearly interpolated to ensure panel balance.

### 4.3. *Model setup*

To empirically assess the effect of intra-urban digital divide on economic resilience, we estimate a two-way fixed effects panel model. The specification is as follows,

$$Resilience_{it} = \alpha + \beta DigiDiv_{it} + \boldsymbol{X}\gamma + \lambda_i + \delta_t + \varepsilon_{it} \tag{3}$$

where the dependent variable $Resilience_{it}$ denotes the degree of urban economic resilience in city $i$ at year $t$, measured as in Eq. (1). The core explanatory variable is $DigiDiv_{it}$, the intra-urban digital divide index defined in Eq. (2). $\boldsymbol{X}$ is a vector of control variables introduced in Section 4.2.3. $\alpha$ is the constant term. $\lambda_i$ represents city fixed effects, which account for time-invariant unobservable characteristics such as geography and long-standing institutional differences. $\delta_t$ represents year fixed effects, which capture nationwide shocks and macroeconomic fluctuations that affect all cities simultaneously. The error term $\varepsilon_{it}$ is clustered at the city level to allow for arbitrary heteroskedasticity and serial correlation within cities over time.

The coefficient of interest is $\beta$. A negative value of $\beta$ would indicate that greater intra-urban digital inequality reduces a city's ability to withstand and recover from shocks, whereas a positive value would suggest the opposite. This setup allows us to identify whether disparities in digital infrastructure within cities play a significant role in shaping resilience, after accounting for structural characteristics and common shocks.

## 5. Empirical findings

### 5.1. *Baseline analysis*

Table 3 reports baseline estimates of the relationship between intra-urban digital inequality and economic resilience using a two-way fixed effects specification. In Column (1), where only the digital divide index (*DigiDiv*) is included along with city and year fixed effects, the estimated coefficient is negative and statistically significant (−0.0391, SE = 0.0197, $p < 0.05$). Introducing the full set of controls in Column (2) yields a similar estimate (−0.0445, SE = 0.0193, $p < 0.05$). Column (3) further controls year fixed effects. Column (3), which further incorporates year fixed effects, produces nearly identical results (−0.0420, SE = 0.0207, $p < 0.05$). Overall, the evidence consistently indicates that a wider intra-urban digital divide is associated with lower levels of economic resilience, and the magnitude of the effect proves robust across alternative specifications.

**Table 3**
Baseline regression results: Impact of digital divide on economic resilience.

| | (1) | (2) | (3) |
|---|---|---|---|
| | Resilience | Resilience | Resilience |
| *DigiDiv* | −0.0391** | −0.0445** | −0.0420** |
| | (0.0197) | (0.0193) | (0.0207) |
| Controls | No | Yes | Yes |
| City FE | Yes | Yes | Yes |
| Year FE | Yes | No | Yes |
| Observations | 2466 | 2466 | 2466 |
| Adjusted $R^2$ | 0.161 | 0.169 | 0.169 |

Notes: ***, **, and * denotes statistical significance of 1%, 5% and 10%, respectively. Robust standard errors in parentheses are clustered at the city level.

To quantify the practical importance of the result, we compare the Column (3) estimate with the dispersion of *DigiDiv* reported in Table 2 (standard deviation = 6.0320), The coefficient implies that a one-standard-deviation increase in the digital divide is associated with a decline in resilience of about 0.2533 (= 0.0420 × 6.0320). When benchmarked against the standard deviation of the resilience measure (3.2985), this effect corresponds to roughly 7.68% of a standard deviation, indicating a meaningful magnitude in the urban resilience context.

Overall, the baseline estimates in Table 3 consistently show that a wider intra-urban digital divide significantly undermines economic resilience. This conclusion holds across specifications with progressively stringent controls, including city-level covariates, city and year fixed effects. These findings provide strong support for hypothesis H1 and set the stage for the robustness checks that follow.

### 5.2. Robustness tests

#### 5.2.1. Endogeneity consideration

Although the baseline regressions provide evidence consistent with hypothesis H1, potential endogeneity remains a concern. The relationship between the digital divide and economic resilience may be biased by unobserved factors, such as local government interventions or cultural attributes, which could simultaneously influence both digital infrastructure and resilience outcomes. Reverse causality is also possible if less resilient cities reduce investment in digital networks in response to economic stress. To address these issues, we apply an instrumental variables (IV) approach.

Following Zhang, Liu, and Ding (2021), we construct an IV based on topographic slope to address endogeneity concerns in estimating the effects of intra-urban digital inequality. Data come from the digital elevation model (DEM) provided by the Resource and Environment Science and Data Center, Chinese Academy of Sciences (https://www.resdc.cn/data.aspx?DATAID=284). Using ArcGIS, we compute the average slope at the county level and aggregate to the prefecture level. We then define terrain heterogeneity as the standard deviation of county-level average slopes within each city. This geographic instrument is plausibly exogenous because topography is a natural, historically predetermined factor that influences infrastructure costs but is unlikely to be correlated with contemporary urban socioeconomic conditions. Furthermore, it strongly predicts the placement and density of 4G base stations, as rugged terrain increases deployment costs and results in uneven coverage within cities, thereby satisfying the relevance condition.

To enhance identification and introduce time-varying variation, we create a composite instrument by interacting this time-invariant terrain heterogeneity with a proxy for lagged provincial digital development: the natural logarithm of per capita webpage counts from the previous year. This interaction combines cross-sectional geographic barriers with temporal variation in digital infrastructure momentum. The lagged nature of the digital component and its measurement at the provincial level minimize the potential for direct correlation with city-specific contemporary shocks. By multiplying these two elements, the composite instrument preserves exogeneity, as neither historical provincial digital development nor local topography is directly influenced by current city-level resilience outcomes. At the same time, it enhances predictive power for current digital inequality, thereby supporting a causal interpretation of its effect on urban resilience.

The IV results, reported in Column (1) of Table 4, show that the estimated coefficients of *DigiDiv* remain negative and statistically significant, and their magnitudes are larger than in the baseline OLS, suggesting that baseline estimates may have been attenuated by endogeneity. Diagnostic tests support the validity of the instrument. The Kleibergen–Paap rk *LM* statistic rejects the null of under-identification, indicating sufficient correlation between the instrument and *DigiDiv*. The Kleibergen–Paap rk Wald *F* statistic is above the conventional threshold of 10, alleviating weak-instrument concerns.

#### 5.2.2. Alternative measures

To examine whether our findings are sensitive to variable definitions, we consider alternative measures of both the dependent and independent variables.

(1) Alternative dependent variable

We first recalculate urban economic resilience using GDP rather than employment (*Resilience_new*) as the underlying indicator, following the approach of Martin et al. (2016). This alternative measure compares annual changes in regional GDP with national averages in the same way as the baseline construction. The results, reported in Column (2) of Table 4, show that the coefficient on the digital divide remains negative and significant. Although the magnitude of the effect differs from the employment-based measure, the direction and statistical significance are consistent, indicating that our findings are not driven by a particular operationalization of resilience.

(2) Alternative independent variable

We also construct an alternative digital divide index that accounts for land-use intensity. Instead of calculating per capita base stations, we compute base station density (per built-up area) at the county level and then aggregate the standard deviation across counties within each city.

**Table 4**
Robustness checks: IV strategy and alternative key variables.

| | IV approach | Alternative dependent variable | Alternative independent variable | Excluding early-transition years |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Resilience | Resilience_new | Resilience | Resilience |
| *DigiDiv* | −0.8648*** | −0.0120*** | | −0.0493** |
| | (0.1714) | (0.0039) | | (0.0238) |
| *DigiDiv_new* | | | −0.0659** | |
| | | | (0.0328) | |
| Controls | Yes | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| KP rk Wald *F* statistic | 10.162 [0.002] | | | |
| KP rk *LM* statistic | 2.298 [0.000] | | | |
| Observations | 2430 | 2466 | 2457 | 1644 |
| Adjusted $R^2$ | | 0.205 | 0.171 | 0.100 |

Notes: ***, **, and * denotes statistical significance of 1%, 5% and 10%, respectively. Robust standard errors in parentheses are clustered at the city level.

This operationalization mitigates potential bias from differences in geographic scale and urban form. Column (3) of Table 4 shows that the recalculated variable (*DigiDiv_new*) produces a coefficient of −0.0659, significant at the 5% level. The result is comparable to the baseline specification, confirming that the negative relationship between digital inequality and resilience does not depend on the precise definition of the divide.

#### 5.2.3. *Excluding the early diffusion period*

To ensure the robustness of our findings and to address potential measurement concerns related to the transition across mobile service generations, we perform a robustness check by excluding the years 2014, 2015, and 2016. During this period, the early diffusion of 4G occurred alongside continued reliance on legacy technologies (e.g., 2G/3G), and network build-out may have been accompanied by reconfiguration of coverage and capacity across space, potentially introducing measurement error in capturing the within-city distribution of effective digital access.[3] In particular, when multiple generations coexist, the presence of 4G infrastructure does not necessarily imply uniform effective access for residents, for reasons such as device compatibility, subscription plans, and local rollout priorities. To mitigate the influence of this transitional stage, we focus on the period 2017–2022, when 4G coverage had become substantially broader and the spatial pattern of infrastructure was more mature.

Column (4) of Table 4 shows that the coefficient on the digital divide remains consistent with the benchmark regression and continues to be negative and statistically significant. Overall, excluding the early diffusion years yields similar estimates, suggesting that our main findings are not driven by the initial transition period and are robust to this conservative sample restriction.

#### 5.2.4. *Controlling for potential confounding factors*

Finally, we assess whether the estimated effect of the digital divide is confounded by other concurrent policies or infrastructure characteristics. We include three additional controls: (i) the "Broadband China" pilot policy (*BroadbandChina*), (ii) the National Big Data Comprehensive Pilot Zone (*BigdataCity*), and (iii) urban transport infrastructure measured by road area (*Road*). These variables capture policy interventions and physical infrastructure that could simultaneously shape digital development and resilience.

The results are reported in Columns (1)–(3) of Table 5. Across all specifications, the coefficient on *DigiDiv* remains negative and significant, with magnitudes similar to the baseline. This indicates that the observed relationship is not an artifact of overlapping policy initiatives or infrastructure endowments, but rather reflects a distinct effect of intra-urban digital inequality on resilience.

#### 5.2.5. *High-dimensional fixed effects*

To further address potential omitted variable bias arising from unobserved time−varying provincial shocks, we augment the specification with province−year fixed effects. This high−dimensional fixed effects approach absorbs all province-specific shocks that vary over time, such as heterogeneous policy interventions or province-wide economic cycles (Guimarães & Portugal, 2010).

The results, presented in Column (4) of Table 5, demonstrate that the marginal impact of the digital divide on economic resilience retains both its direction and statistical significance after incorporating province−year fixed effects. This estimate closely aligns in magnitude and sign with the baseline coefficient. The stability of these effects across specifications underscores that our core finding—digital divide exerting a robust negative influence on economic resilience—persists even after rigorously accounting for unobserved time−varying provincial confounders.

#### 5.2.6. *Data trimming*

Extreme values may exert disproportionate influence on regression results. To address this, we trim the top and bottom 5% of the resilience distribution and re-estimate the baseline model. The excluded cities include highly developed metropolitan centers with strong policy advantages at the top end, and remote or resource-constrained areas at the bottom end. These cases represent atypical environments that may bias the estimates.

As reported in Column (5) of Table 5, the coefficient on *DigiDiv* remains negative and statistically significant after trimming. This suggests that our results are not driven by extreme cases, but rather reflect a robust pattern across the broader sample of cities.

## 6. Further analyses

### 6.1. *Channel tests*

Building on the theoretical framework in Section 3, we empirically examine three channels through which intra-urban digital inequality may undermine urban economic resilience.

#### 6.1.1. *Firm entry inequality*

We next test whether digital fragmentation skews the geography of new business formation. Firm entry inequality is measured as the standard deviation of county-level counts of new digital enterprises within each city. Enterprise data are mainly obtained from the National Enterprise Credit Information Publicity System (NECIPS, http://www.gsxt.gov.cn/index.html) and supplemented with Qichacha (http://www.qichacha.com). We consider both all industries and digital-related industries, using panel data on firm counts from county-level registration records. To ensure intra-urban variations are captured, these county-level data were matched to city-year panels, which allows for clear tracking of firm entry inequality within each city over time. For city *i* in year *t*, the inequality in firm entry is measured as the standard deviation of newly registered firm counts across counties:

$$FirmEntry_{it} = \mathrm{Std.Dev}_{c\in i}(FirmNum_{cit}) \tag{4}$$

where $FirmNum_{cit}$ is the number of newly registered firms in county *c* of city *i* in year *t*. Higher values of $FirmEntry_{it}$ indicate greater firm entry inequality.

Empirically, overall new-firm entry shows no clear relationship with *DigiDiv* in Column (1) of Table 6. In contrast, Column (2) indicates a significant and positive association between *DigiDiv* and the dispersion of new digital ventures, implying that digital entrepreneurship opportunities concentrate in a subset of better-connected counties. This pattern restricts broad-based participation in the digital economy and weakens the city's capacity to reallocate activity during shocks, which matches the firm-entry mechanism in Section 3.1.

This evidence is consistent with research linking infrastructure and entrepreneurship formation, where uneven foundational networks differentially lower entry costs and shape the local opportunity set for new firms (Audretsch et al., 2015).

Thus, digital inequality significantly raises the dispersion of new digital firm entry within cities, even when overall entry responses are muted, supporting the mechanism and the associated hypothesis H2 in Section 3.

#### 6.1.2. *Innovation inequality*

We examine whether the digital divide contributes to inequality in innovation. For each county, we compile annual counts of various types of patent applications and aggregate them to the prefecture level. The standard deviation of these patent counts across counties within each

[3] We thank the reviewer for highlighting the possibility that cross-generation technology migration may introduce measurement noise in early years; this motivates the sample restriction reported in Section 5.2.3.

**Table 5**
Robustness checks: Confounding factors, high−dimensional FE and data trimming and confounding factors.

| | Controlling for confounding factors | | | High−dimensional FE | Data trimming |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Resilience | Resilience | Resilience | Resilience | Resilience |
| *DigiDiv* | −0.0415** | −0.0398* | −0.0398* | −0.0425*** | −0.0421** |
| | (0.0208) | (0.0210) | (0.0216) | (0.0153) | (0.0206) |
| *BroadbandChina* | 0.3324 | | | | |
| | (0.5409) | | | | |
| *BigdataCity* | | −0.3483 | | | |
| | | (0.4514) | | | |
| *Road* | | | −0.0106 | | |
| | | | (0.0097) | | |
| Controls | Yes | Yes | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Province × Year FE | No | No | No | Yes | No |
| Observations | 2430 | 2466 | 2333 | 2430 | 2466 |
| Adjusted $R^2$ | 0.227 | 0.169 | 0.178 | 0.227 | 0.169 |

Notes: ***, **, and * denotes statistical significance of 1%, 5% and 10%, respectively. Robust standard errors in parentheses are clustered at the city level.

**Table 6**
Channel tests: Firm entry inequality.

| | (1) | (2) |
|---|---|---|
| | All enterprises | Digital enterprises |
| *DigiDiv* | 0.2786 | 3.8305* |
| | (0.9932) | (2.1853) |
| City FE | Yes | Yes |
| Year FE | Yes | Yes |
| Controls | Yes | Yes |
| Observations | 2466 | 2466 |
| Adjusted $R^2$ | 0.764 | 0.675 |

Notes: ***, **, and * denotes statistical significance of 1%, 5% and 10%, respectively. Robust standard errors in parentheses are clustered at the city level.

prefecture is then calculated to measure the extent of innovation inequality. Patent data are obtained from the China National Intellectual Property Administration, including invention patents, appearance design patents, and utility model patents. As with firm entry inequality, these county-level data were matched to prefecture-year panels, ensuring that intra-city spatial disparities are properly captured and analyzed over time. For each prefecture-level city $i$ in year $t$, the innovation inequality variable is calculated as:

$$Patent_{it} = \mathrm{Std.Dev}_{c\in i}(PatentNum_{cit}) \tag{5}$$

where $PatentNum_{cit}$ represents the total number of patents in county $c$ of city $i$ in year $t$. Higher values of $Patent_{it}$ indicate greater innovation inequality.

Columns (1)–(4) of Table 7 show that higher *DigiDiv* is associated with significantly greater dispersion in patenting across counties, for all patent categories. These estimates indicate that digital fragmentation concentrates knowledge creation in digitally advantaged districts, constrains cross-county spillovers, and weakens recombinant innovation that is crucial for adaptability, which is consistent with the innovation-inequality mechanism proposed in Section 3.

**Table 7**
Channel tests: Inequality in innovation.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | All patents | Invention patents | Appearance design patents | Utility model patents |
| *DigiDiv* | 39.8753*** | 12.4168*** | 12.3699*** | 22.2921*** |
| | (4.7615) | (1.8329) | (3.2302) | (3.2841) |
| City FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |
| Observations | 2466 | 2466 | 2466 | 2466 |
| Adjusted $R^2$ | 0.819 | 0.844 | 0.760 | 0.732 |

Notes: ***, **, and * denotes statistical significance of 1%, 5% and 10%, respectively. Robust standard errors in parentheses are clustered at the city level.

This mechanism aligns with evidence that resilience benefits from diversified and connected innovation systems, whereas excessive spatial concentration limits knowledge exchange and flexibility (Boschma, 2015; Bristow & Healy, 2018). Classic studies on localized knowledge spillovers suggest that the spatial configuration of innovation shapes diffusion and recombination, providing a micro-foundation for the link between digital fragmentation and innovation inequality (Jaffe et al., 1993).

Thus, the findings show that unequal digital infrastructure significantly increases within-city innovation inequality across patent categories, supporting the mechanism in Section 3 and the associated hypothesis H3.

### 6.1.3. Industrial diversity

Finally, we evaluate whether digital divide erodes industrial diversity. We proxy the diversification index (*DIV*) using a Herfindahl-type index constructed from the distribution of sectoral activity; lower diversity corresponds to higher concentration. The index is calculated as:

$$DIV_i = -\sum_{s=1}^{S}\left(e_{is}/e_i\right)\ln\left(e_{is}/e_i\right) \tag{6}$$

where $e_{is}$ denotes the number of enterprises in sector $s$ within city $i$, and $e_i$ represents the total number of enterprises across all sectors in that city. Following China's Industrial Classification System (GB/T 4754–2017), industrial diversity is calculated at both the 1-digit and 2-digit sectoral levels.

Table 8 reports that greater *DigiDiv* is associated with reduced industrial diversity after controlling for city fixed effects, year fixed effects, and the full set of covariates, which echoes the argument in Section 3.3 that resilience depends on variety and the potential for cross-sectoral reallocation. This result is in line with the urban and regional resilience literature that links diversified structures with shock absorption and recovery capacity (Boschma, 2015; Brown & Greenbaum, 2017).

Hence, cities with stronger intra-urban digital inequality exhibit lower industrial diversity, supporting H4 proposed in Section 3.

## 6.2. Extensions

This section extends the baseline analysis along four dimensions to

**Table 8**
Channel tests: Industrial diversity.

| | (1) | (2) |
|---|---|---|
| | 1-digit | 2-digit |
| *DigiDiv* | −0.0008** | −0.0036*** |
| | (0.0003) | (0.0012) |
| City FE | Yes | Yes |
| Year FE | Yes | Yes |
| Controls | Yes | Yes |
| Observations | 2466 | 2466 |
| Adjusted $R^2$ | 0.995 | 0.986 |

Notes: ***, **, and * denotes statistical significance of 1%, 5% and 10%, respectively. Robust standard errors in parentheses are clustered at the city level.

**Table 9**
Spatial regression analysis.

| | (1) | Coefficient interpretation | | |
|---|---|---|---|---|
| | Resilience | Direct effects | Indirect effects | Total effects |
| *DigiDiv* | −0.0394 | −0.0448** | −0.0173** | −0.0622** |
| | (0.0189) | (0.0194) | (0.0076) | (0.0268) |
| $\rho$ | 0.2933*** | | | |
| | (0.0248) | | | |
| City FE | Yes | | | |
| Year FE | Yes | | | |
| Controls | Yes | | | |
| Observations | 2466 | | | |

Notes: ***, **, and * denotes statistical significance of 1%, 5% and 10%, respectively. Robust standard errors in parentheses are clustered at the city level.

provide a more comprehensive investigation of the relationship between digital divide and urban economic resilience. First, we examine potential spatial spillover effects, assessing whether a city's digital divide influences not only its own resilience but also that of neighboring cities. Second, we explore distributional heterogeneity to determine whether the impact varies across cities with different economic, digital, and socio-demographic characteristics. Third, we decompose resilience into distinct phases (resistance and recovery) to analyze how digital divide differentially affects each stage of the resilience process. Finally, we introduce a measure of the second-order digital divide, which captures inequality in the actual usage of digital technologies, to complement our primary access-based indicator. Together, these extensions offer broader and more nuanced evidence on how digital divide shape urban economic resilience.

### 6.2.1. Spillover effects

Hypothesis H5 posits that intra-urban digital inequality has spatial spillover effects, influencing not only local resilience but also the resilience of neighboring cities. Given the interdependence of urban systems through labor mobility, supply chains, and knowledge flows, disparities in one city may weaken regional adaptive capacity, while reducing such disparities could strengthen cross-boundary cooperation (Duranton & Puga, 2004; Graham, 2007).

To test this mechanism, we use a spatial autoregressive (SAR) model with city and year fixed effects:

$$Resilience_{it} = \alpha + \rho \sum_{j=1}^{N} \omega_{ij} Resilience_{it} + \beta DigiDiv_{it} + \boldsymbol{X}\gamma + \lambda_i + \delta_t + \varepsilon_{it} \quad (7)$$

where $\rho$ captures the degree of spatial interdependence across cities. $\omega_{ij}$ is the spatial weight matrix. an $N \times N$ non−negative spatial weight matrix, and $\boldsymbol{X}$ represents the vector of control variables. Following standard practice in spatial econometrics (Anselin, 2003; LeSage & Pace, 2009), we row-normalize the weight matrix and implement a $k$-nearest neighbor scheme with $k = 4$. Because in SAR models the structural coefficient $\beta$ does not directly reflect marginal effects, we compute the direct, indirect (spillover), and total effects based on the partial derivatives of the reduced form. The model is estimated by maximum likelihood (MLE), which provides consistent estimates of both the autoregressive parameter and covariate effects.

The results in Table 9 reveal strong spatial dependence. The direct effect of *DigiDiv* remains negative and statistically significant, consistent with our baseline findings. Importantly, the indirect effect of neighboring cities' digital inequality is also negative and significant, confirming that digital fragmentation generates substantial spillovers. The total effect indicates that aggregate economic losses from digital inequality are about 39% larger when regional spillovers are considered, relative to local effects alone. The positive and significant spatial autoregressive coefficient further supports interdependence in resilience outcomes. These results provide clear support for hypothesis H5: intra-urban digital inequality not only undermines local economic resilience but also exerts negative spillovers on neighboring cities.

### 6.2.2. Distributional heterogeneity

Hypothesis H6 suggests that the effect of intra-urban digital inequality on resilience is not uniform across cities but varies with urban characteristics and positions along the resilience distribution. We evaluate this proposition using grouped regressions by urban characteristics and fixed-effects quantile regressions.

(1) We examine heterogeneity by urban economic development. We proxy the city's general economic development level using the average luminosity from DMSP-OLS nighttime light data (https://www.ncei.noaa.gov). As shown in Panel An of Table 10 (Columns 1–2), the negative effect of *DigiDiv* on resilience is considerably stronger in cities with higher average luminosity. This pattern suggests that the adverse impact of digital division is more pronounced in richer urban areas, possibly due to their greater reliance on and exposure to digital infrastructure disruptions within already complex economic systems (Ma et al., 2012).

We further examine heterogeneity by splitting cities into high and low digital economy groups based on city-level indicators. Panel A of Table 10 (Columns 3–4) shows that the adverse effect of intra-urban digital inequality is markedly stronger in digitally advanced cities (coefficient in the high group $= -0.0493$, $p < 0.10$), while the effect is statistically negligible in the low group. This pattern is theoretically consistent with complementarity and network-externality mechanisms: when the average digital level is high, production, coordination, and knowledge diffusion become more tightly intertwined with digital infrastructure, so fragmentation creates "weak links" that significantly depress urban system performance (Elliott et al., 2022; Jones, 2011). In other words, the same degree of inequality destroys more effective connections where the underlying digital infrastructure is already dense and economically significant.

The result also aligns with evidence that digital infrastructure and adoption raise productivity, connectivity, and resilience potential in principle (Haller & Lyons, 2015; Kim, 2006; Wen et al., 2024; Xu et al., 2024), but that these benefits depend on equitable access (Lythreatis et al., 2022; Reveiu et al., 2023). In digitally advanced settings, unequal access more sharply impedes knowledge recombination and spillovers, which are core ingredients of urban adaptability, because collaborative search and innovation networks increasingly rely on ICT-enabled interactions (Boschma, 2015; Bristow & Healy, 2018; Jaffe et al., 1993; Kaufmann et al., 2003). Overall, Columns (3)–(4) imply that raising the average digital level without closing intra-urban gaps may leave cities more exposed to shocks, precisely because fragmentation undermines the complementarities that make digital systems productive in the first place.

**Table 10**
Distributional heterogeneity: grouped regressions by urban characteristics.

| Panel A: Economic development and digital level | | | | |
|---|---|---|---|---|
| | Economic development | | Digital level | |
| | (1) | (2) | (3) | (4) |
| | High | Low | High | Low |
| *DigiDiv* | −0.0432** | −0.0141 | −0.0493* | 0.0087 |
| | (0.0216) | (0.1539) | (0.0297) | (0.0888) |
| City FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |
| Observations | 1235 | 1219 | 1359 | 1094 |
| Adjusted $R^2$ | 0.211 | 0.171 | 0.250 | 0.055 |
| Panel B: Population migration on economic resilience | | | | |
| | Intra−provincial migration | | Inter−provincial migration | |
| | (1) | (2) | (3) | (4) |
| | High | Low | High | Low |
| *DigiDiv* | −0.0478** | −0.0504 | −0.0479*** | 0.0711 |
| | (0.0195) | (0.1266) | (0.0181) | (0.0853) |
| City FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |
| Observations | 1413 | 1053 | 1224 | 1242 |
| Adjusted $R^2$ | 0.213 | 0.106 | 0.191 | 0.162 |
| Panel C: Educational level on economic resilience | | | | |
| | Years of schooling | | Illiteracy rate | |
| | (1) | (2) | (3) | (4) |
| | High | Low | High | Low |
| *DigiDiv* | −0.0226 | −0.0472*** | 0.0304 | −0.0574*** |
| | (0.0769) | (0.0139) | (0.0511) | (0.0100) |
| City FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |
| Observations | 1215 | 1251 | 1305 | 1161 |
| Adjusted $R^2$ | 0.179 | 0.143 | 0.123 | 0.214 |

Notes: ***, **, and * denotes statistical significance of 1%, 5% and 10%, respectively. Robust standard errors in parentheses are clustered at the city level.

(2) *We consider population migration.* Based on the Seventh National Population Census, we stratify cities by the shares of intra-provincial and inter-provincial migrants. Panel B of Table 10 indicates that the adverse impact of *DigiDiv* intensifies with higher migrant shares for both categories. A plausible interpretation is that mobility increases socio-economic heterogeneity and raises coordination demands; where digital access is uneven, newcomers face barriers to information and services, amplifying vulnerability during shocks (Chan & Buckingham, 2008).

(3) *We assess educational attainment.* We measure educational disparities as the standard deviation of average years of schooling and, alternatively, of illiteracy rates across counties within each city. Panel C of Table 10 shows that *DigiDiv* has more pronounced negative effects in cities with relatively homogeneous educational profiles. Lower diversity in human capital may constrain functional redundancy and reduce the scope for recombination and adaptation, which is in line with arguments that diversified knowledge bases and related variety help strengthen the resilience of regional economies against disturbances (Boschma, 2015; Frenken et al., 2007).

(4) *We study distributional heterogeneity by employing fixed-effects quantile regressions.* These are estimated at the 10th, 25th, 50th, 75th, and 90th conditional quantiles of resilience. Table 11 reveals a U-shaped pattern: effects are small and statistically insignificant around the median, but they become significantly negative in the lower and upper tails. In low-resilience cities, digital inequality compounds structural disadvantages such as limited industrial variety and fiscal fragility; in high-resilience cities, it disrupts cross-cluster knowledge exchange and slows diffusion at the frontier. These results indicate that mean regressions mask heterogeneous responses across the distribution and justify a quantile approach (Koenker, 2004).

**Table 11**
Distributional heterogeneity: Quantile regression analysis.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | q10 | q25 | q50 | q75 | q90 |
| *DigiDiv* | −0.0376*** | −0.0392*** | −0.0322 | −0.0540*** | −0.0567** |
| | (0.0109) | (0.0103) | (0.0636) | (0.0202) | (0.0270) |
| City FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Observations | 2466 | 2466 | 2466 | 2466 | 2466 |
| Adjusted $R^2$ | 0.3144 | 0.3009 | 0.2713 | 0.2804 | 0.3068 |

Notes: ***, **, and * denotes statistical significance of 1%, 5% and 10%, respectively. Robust standard errors in parentheses are clustered at the city level.

#### 6.2.3. Economic resilience across different phases: Resistance and recovery

To better capture the multidimensional nature of economic resilience, we perform a phased regression analysis that divides the response of urban economies into two distinct stages: resistance and recovery. This approach allows us to examine resilience as a dynamic process, from a city's initial ability to withstand shocks, to its speed of recovery and longer-term capacity for structural transformation.

We define resistance phase as the period during which a city experiences employment growth below the 20th percentile of its historical distribution, indicating a vulnerability to economic shocks (*Resistance*). The recovery phase occurs when a city transitions from negative to positive employment growth following the resistance phase, signifying a rebound in economic activity (*Recovery*).

In our analysis, we create interaction terms between *DigiDiv* and these phases (*Resistance* and *Recovery*) to explore how the digital divide influences urban resilience differently during these stages. The regression results, shown in Column (1) of Table 12, reveal that the interaction

**Table 12**
Economic resilience across phases: Interaction terms and second-order digital divide.

| | Interaction terms | Second-order digital divide |
|---|---|---|
| | (1) | (2) |
| | Resilience | Resilience |
| *DigiDiv* | −0.0041 | |
| | (0.0317) | |
| *DigiDiv* × *Resistance* | −0.0149** | |
| | (0.0062) | |
| *Resistance* | −3.3436*** | |
| | (0.0951) | |
| *DigiDiv* × *Recovery* | −0.0374*** | |
| | (0.0108) | |
| *Recovery* | 1.9632*** | |
| | (0.1511) | |
| *DigiDiv_second* | | −0.0493** |
| | | (0.0238) |
| Controls | Yes | Yes |
| City FE | Yes | Yes |
| Year FE | Yes | Yes |
| Observations | 1846 | 1644 |
| Adjusted $R^2$ | 0.510 | 0.100 |

Notes: ***, **, and * denotes statistical significance of 1%, 5% and 10%, respectively. Robust standard errors in parentheses are clustered at the city level.

between *DigiDiv* and the *Resistance* phase is negative and statistically significant, indicating that higher digital inequality during the resistance phase is associated with lower resilience. Similarly, the interaction between *DigiDiv* and the *Recovery* phase is also negative and significant, suggesting that cities with higher levels of digital inequality face slower recovery from economic shocks.

Overall, the results suggest that the digital divide plays a significant role in shaping urban economic resilience, particularly during the recovery phase. This supports the notion that resilience is a dynamic process, influenced by different factors at various stages of shock response. By breaking resilience down into its component phases, we gain a deeper understanding of how digital inequality affects economic recovery and long-term resilience.

#### *6.2.4. Second-order digital divide*

To supplement our primary measure of the digital divide, we introduce an additional indicator that reflects the second-order digital divide—the inequality in the actual usage of digital technologies within cities. While the baseline analysis focuses on access to digital infrastructure (the first-order digital divide), the second-order divide concerns disparities in how individuals engage with digital tools and services. This distinction is important, as disparities in access alone may not fully capture the complexity of digital inequality, especially in terms of how individuals use and benefit from digital technologies.

This concept of a multi-tiered digital divide has been widely discussed in the literature, notably by Wei et al. (2011), who categorize digital divides into three levels: the first-level divide, which pertains to access to ICTs (such as internet connectivity or mobile infrastructure); the second-level divide, which focuses on the usage and engagement with digital tools (such as frequency of internet use); and the third-level divide, which concerns the outcomes individuals or groups derive from internet engagement, such as economic, educational, or social benefits.

For this subsection, we focus on the second-order digital divide, which captures disparities in the frequency of internet usage at the individual level. We measure this inequality using data from the Chinese General Social Survey (CGSS), which includes individual-level survey data spanning 2010–2023. The survey covers a sample of 96,417 individuals from across thirty-one provinces, municipalities, and autonomous regions. To quantify digital usage inequality, we calculate the Gini coefficient of internet usage frequency at the city level, and then match this data with the corresponding city-level panel for the analysis period (2014–2022).

As shown in Column (2) of Table 12, the estimated coefficient for the second-order digital divide is negative and statistically significant, suggesting that cities with greater inequality in digital usage experience lower resilience to economic shocks. The consistency of this result with our primary measure based on 4G base station availability reinforces our conclusions and emphasizes the importance of both access-based and usage-based dimensions of digital inequality in shaping urban economic resilience.

Although this analysis using the second-order digital divide is an extension of our main analysis, it offers important complementary insights into how disparities in digital usage contribute to urban resilience. The results suggest that digital inequality across both access and usage dimensions plays a significant role in determining cities' capacity to withstand and recover from economic shocks.

## 7. Concluding remarks

This study has examined how digital inequality within cities influences their ability to withstand and recover from economic shocks. Using a balanced panel of 274 Chinese prefectures from 2014 to 2022, we found that uneven deployment of 4G infrastructure significantly reduces employment-based resilience when benchmarked against national trajectories. Mechanism analyses revealed that unequal access to digital infrastructure limits opportunities for new firm entry, narrows the geography of innovation, and contributes to more concentrated industrial structures. Spatial regressions confirmed that these effects extend beyond individual cities, generating negative spillovers across neighboring jurisdictions. Heterogeneity tests further showed that the impacts are particularly pronounced in cities with more advanced economic development and digitalization, heavier inflows of migrants, or more homogeneous educational profiles. Taken together, these results suggest that bridging digital divides is not only a matter of equity but also a central pillar of resilient urban development.

Several policy lessons can be drawn from these findings. First, our results show that resilience is weakened by disparities within cities, which suggests that local governments should direct digital investment toward underserved districts instead of pursuing uniform expansion. Second, the heterogeneity analysis indicates that digital inequality exerts a stronger negative impact in digitally advanced cities. This finding stresses the importance of sequencing policies: upgrading digital technology levels alone is insufficient and may even exacerbate vulnerability if gaps persist. Hence, digital expansion strategies should be complemented by targeted measures to ensure equitable access, so that the gains from technological progress are not undermined by unequal distribution. Third, since the analysis demonstrates that digital inequality constrains firm entry and narrows industrial variety, urban planner should develop digital infrastructure jointly with complementary assets such as transport networks and entrepreneurship support systems, in line with studies showing that both infrastructure and related variety are critical for sustaining regional resilience (Audretsch et al., 2015; Boschma, 2015). Fourth, the presence of significant spillover effects across neighboring cities implies that strengthening cross-jurisdictional coordination is essential to prevent localized digital divides from evolving into regional structural constraints, a concern highlighted in research on inter-city spillovers in China (Graham, 2007). Finally, the increased vulnerability of migrant-heavy and educationally homogeneous cities indicates that digital inclusion should be closely integrated with human-capital and social-integration policies, so that connectivity contributes to broadly shared resilience (Boschma, 2015; Frenken et al., 2007).

While the study makes several contributions, it also has limitations. First, our measure of the digital divide relies on 4G base-station locations, which capture supply-side reach but not service quality or household-level usage. Incorporating signal strength, latency, or the expansion of 5G networks would allow a more precise assessment of where digital constraints matter most. Additionally, while we have addressed the first-order (access) and second-order (usage) digital divides, we have not fully explored the third-order divide (Hilbert, 2010; Nishijima et al., 2017), which refers to the unequal outcomes or benefits derived from digital participation. For example, differences in digital skills, online income opportunities, and social participation could play a significant role in determining how the digital divide impacts urban resilience. Incorporating such outcome-based measures would provide a more comprehensive view of how digital inequality interacts with resilience across different layers of urban society. Second, the resilience indicator, following Giannakis and Bruggeman (2020), is based on relative employment dynamics, which reflects the net outcome of shocks and subsequent recovery. However, this aggregate measure does not explicitly distinguish between different phases of resilience, such as resistance, recovery, and reorientation. In the revised manuscript, we introduce a phased regression analysis to address this limitation, breaking down resilience into the resistance and recovery phases. While this extension provides valuable insights into the dynamic nature of resilience, it remains a preliminary effort and there are certainly areas for further refinement. Future research could improve upon this approach by more precisely identifying shock timing and modeling phase-specific responses, which would allow for a clearer understanding of how urban economies adapt and recover over time. Third, the mechanism analysis highlights the roles of innovation, firm entry, and industrial diversity, but other potential channels, such as governance quality and institutional trust, remain outside the scope of this paper and merit closer attention. Fourth, although endogeneity concerns were addressed through instrumental variable estimation and dynamic panel techniques, future work could take advantage of staggered policy implementations, such as broadband pilots or big-data initiatives, as quasi-experiments. Recent methodological advances in staggered difference-in-differences (Callaway & Sant'Anna, 2021) provide promising tools for such designs. Addressing these issues would not only refine measurement but also deepen our understanding of how digital inequalities intersect with broader urban systems.

## CRediT authorship contribution statement

**Shuning Kong:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis. **Zesu Hua:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Yihua Yu:** Writing – review & editing, Validation, Supervision, Conceptualization.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Yihua Yu reports financial support was provided by the National Natural Science Foundation of China and the Ministry of Education of China. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix

The table summarizes the county-level coverage and stability of the 4G base-station data across 2014–2022. In each year, the number of counties remains constant at 2851. The number of counties with non-zero 4G stations gradually increases as infrastructure diffuses. Counties with zero 4G stations in a given year are retained in the dataset.

**Table A1**
County-level coverage and stability of the 4G base-station data (2014–2022).

| Year | County-level units | Counties with non-zero 4G stations | Counties with zero 4G stations (count = zero) |
|---|---|---|---|
| 2014 | 2851 | 14 | 2837 |
| 2015 | 2851 | 35 | 2816 |
| 2016 | 2851 | 109 | 2742 |
| 2017 | 2851 | 210 | 2641 |
| 2018 | 2851 | 453 | 2398 |
| 2019 | 2851 | 889 | 1962 |
| 2020 | 2851 | 1387 | 1464 |
| 2021 | 2851 | 1700 | 1151 |
| 2022 | 2851 | 2089 | 762 |

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