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Smart Cities Are More Populous: Evidence from China

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Abstract: This paper examines whether the widespread adoption of digital technologies in cities has increased attractiveness. Based on China's smart-city construction (SCC), a pilot program aimed at promoting applications of digital technologies in cities, this paper finds that SCC has led to a higher urban population growth in smart cities in China. Two potential channels are suggested by mechanism analysis: improved ecological environment resulting from digital governance with respect to pollution and green production; essential digital information provided by internet users. Specifically, relying on difference-in-differences analysis, the results reveal that, from 2005 to 2017, SCC in China led to approximately 4.4% higher urban population growth in smart cities relative to non-smart cities. In particular, evidence from migrant survey data suggests that smart cities are more favorable destinations for distant migrants, and migrants with higher educational attainment and income. Our findings highlight the importance of digitalization in urban development.

Keywords: smart city; urban population; difference-in-differences analysis; urban environment; internet

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1. Introduction

The widespread diffusion of internet-based information communication technologies (ICT) has profoundly impacted city governance, thereby leading to higher energy efficiency [1], green production [2], and sustainable development [3]. On the other hand, the spatial effect of these digital technologies has attracted extensive discussion. Digital technology has revolutionized the methods and the cost of information transmission, enabling a massive amount of information to be accessed without time and distance constraints. In light of this, early literature hypothesized that the anti-spatial feature of digital technologies might weaken the need for agglomeration, thereby leading to "the end of geography" [4], "the death of distance" [5], and "the death of cities" [6]. Additionally, empirical evidence showed that ICT has led to more dispersed city structures [7] and more decentralized manufacturing [8]. Other literature, however, casts doubt on the assertion that emerging ICT applications will cancel out the importance of agglomeration. Morgan [9] pointed out that transferring tacit knowledge via the internet is difficult, raising the significance of physical proximity in innovation. Craig et al. [10] demonstrated the complementary role of ICT in cities; moreover, the transportation cost for physical commodities also makes the death of distance a premature notion [11].

With the rapid development and wide application of ICT in modern society, an examination of the agglomeration impact of such technologies is warranted. Existing literature regarding the spatial effect of ICT, however, mainly concentrates on the agglomeration of infrastructure, knowledge, and industry in a city [10,12–19] while ignoring the indispensable role of agglomeration, people. In other words, the following question remains unanswered: does the widespread adoption of ICT in a city impact population agglomeration? This paper aims to fill this knowledge gap using evidence from a populous and digitalized country, China. Specifically, smart-city construction (SCC) in China, which aims to promote the application of ICT in cities, is used to examine the impact.

China has experienced severe environmental pollution for decades. As of 2015, the average $PM_{2.5}$ concentration value in China was five times higher than WHO recommendations and over 80% of Chinese cities have a value three times higher than the air quality guidelines' threshold [1]. Pollution is accountable for large population outflow from urban areas in China [20–23]. However, empowered by the ICT, the SCC alleviates pollution through optimized energy consumption [1], and the effect of technological and allocation innovation [24]. The resulting improvement in the urban ecological environment can potentially reduce population outflow from smart cities. On the other hand, in the 21st century, the internet has been extensively used by Chinese people. As of 2017, the number and the penetration rate of internet users in China ranked first globally [2], which were 0.72 billion and 55.8%, respectively [3]. Furthermore, data show that social media and instant messaging tools, such as Weibo and QQ, are the most popular applications, and 93% of internet users utilize these applications to maintain and expand their social networks [4]; in other words, the internet has become a major source of information for people in China and has led to a series of social changes, such as higher divorce rates [25], lower life satisfaction [26], and a sex revolution [27]. Accordingly, because smart cities enable access to the internet at lower costs [28] and play the role of an information hub [29], such cities offer an advantage in terms of providing essential information, e.g., related to income, job opportunities, and education availability to potential migrants through the internet.

In light of the above, this paper attempts to explore the relationship between the SCC and population agglomeration, that is, whether or not the wide-ranging ICT applications in cities are responsible for urban population growth. To this end, using a panel dataset for 2005–2017 that covers 157 prefecture-level cities, this paper empirically examines the impact of the SCC on urban population growth. The difference-in-differences model is employed because the SCC in China can be considered a quasi-natural experiment; robustness checks are performed to alleviate endogenous concerns regarding selection issues, common trend assumptions, and pre-treatment trends. This paper also uses the mediating effect model to test whether the SCC contributes to urban population growth through the effect of urban environment improvement and internet diffusion. In addition, based on the digital divide theories, this paper further inspects the micro impact of the SCC on migrants, using the China migrants' dynamic survey.

This study contributes to the literature in several respects. First, this paper provides a marginal contribution to the discussion on the impacts of digital technologies on urban agglomeration, shedding new light on this critical issue. Second, the findings advance the literature on the importance of ICT in urban development [16,30–32], extending it to the urban population and further highlighting the complementary role of the ICT in cities. Third, this paper complements studies on the impact of smart city policies on the urban ecological environment and the ICT infrastructure [1,33–35], demonstrating that promoting an ecological environment and internet use makes smart cities more attractive to migrants, hence adding to the literature on the interplay of SCC, the ecological environment, ICT, and the population. Finally, from an empirical standpoint, this paper provides a robust examination of the population agglomeration effect of SCC, employing a rigorous difference-in-differences framework to yield accurate and reliable results.

The rest of the paper is organized as follows. Section 2 provides background and presents the hypothesis. Section 3 includes a detailed description of data, variables, and empirical models. Section 4 presents empirical results and corresponding analyses. Section 5 provides discussions. Section 6 concludes the paper and offers policy suggestions.

2. Background and Hypotheses

2.1. Brief Description of the Smart City and Its Application in China

The smart city has in-depth applications of ICT, such as the Internet of Things (IoT). Connected by the internet, IoT systems monitor different aspects of the smart city (e.g., the environment, energy, and transportation), providing essential information to the smart city government and residents. Information regarding the environment enables the city administration to perform optimized pollution control so as to improve environment quality while maintaining desired production levels. Furthermore, the abundant ICT resources in the smart city lower the internet's connection cost, and the procedure to access information familiarizes smart-city residents with the internet as a method of information gathering and sharing, making them active users of the internet. In practice, smart city projects conform to the smart city concept. "Smart Country 2015", implemented by the Singapore government, aimed to connect individuals, enterprises, and the government via the internet; "U-Korea" launched in Korea was intended to enhance internet availability, digitalize the cities, and improve environmental quality; "I-Japan" implemented in Japan focused on the application of IoT in e-governance and education.

China is also a keen pioneer of SCC. Since 2010, the Chinese government issued a series of policies regarding the introduction and specification of the smart city. The policies aimed to promote ICT application in cities in seven spheres: infrastructure, construction, livability, management, service, industry, and economy. Subsequently, in 2012, the Chinese Ministry of Housing and Urban–Rural Development announced the first list of national pilots for SCC, consisting of 3 town-level regions, 50 county-level regions, and 37 prefecture-level regions. In the following two years, 200 additional regions were selected as national smart-city pilots in the second and third batches of pilots. As the pilots of the SCC, these three batches of pilot regions received government funds from the central government for smart city construction; meanwhile, each pilot batch was given a three-year construction period to implement the policy targets. In 2017, according to the report on the Nineteenth National Congress of the Communist Party of China, the Chinese government had already invested over 500 billion yuan in SCC. As of 2019, 271 prefectural cities in China were undertaking SCC [5]. In light of the above, the construction of smart cities will significantly influence every aspect of China's economy through the application of new-generation ICT.

2.2. Literature Review and Hypotheses

2.2.1. Literature of Smart Cities

Literature regarding smart cities can be categorized into two strands. The first strand of the literature demonstrates that a smart city is a city with an upgraded ICT level. Although the definition of the smart city varies in the literature [36], there is a consensus that the implementation of a smart city will strongly promote the level of ICT applications in a city. When the term "smart city" was first introduced in the 1990s, research was focused on how ICT could be designed and integrated into the city [37]. In practice, through reliance on state-of-the-art information technologies—e.g., monitoring sensors, the IoT, and big data—ICT is designed to merge into aspects of a city's critical infrastructure, such as transportation, energy supply, and waste management [28,33,38].

The second strand of the literature shows that these ICT upgrades, in turn, alleviate environmental issues in smart cities and enhance residents' connections to the internet. Specifically, the smart city benefits the urban environment in three respects: First, the smart city enhances energy efficiency to alleviate pollution. Theoretically, the IoT and big data enable the city administration to optimize the operation of the city, such as its transportation and production, leading to optimal energy consumption and, hence, lower pollution [39]. By analyzing 251 cities in China, Yu and Zhang [1] empirically confirm that the smart city has higher energy efficiency and fewer environmental issues than non-smart cities. Second, the smart city can directly monitor pollutants, which helps reduce pollution. Sensors with optical and pressure systems can visualize and simulate pollution, which assists city operations in waste processing and recycling [40,41]. Third, the smart city promotes innovations for pro-environmental technologies, reducing pollution. Chu et al. [35] show that the smart city decreases urban pollution levels through innovations in green technologies and resource allocation in China. Furthermore, ubiquitous ICT in the smart city provides network infrastructure to residents while enabling them to adapt internet to their lives [42,43]; moreover, the smart city enhances the ICT experience for the residents and empowers them to utilize internet services through multiple devices connected to the

ICT infrastructure [44]; Schaffers et al. [45] shows that the smart city facilitates citizens' skills in using information technologies by encouraging them to participate in IoT projects through the internet.

2.2.2. Environment Effect and Population Outflow from Cities

Cities with poor environment can experience a decrease in population due to population outflow. According to Rosen–Roback's urban spatial equilibrium theory [46,47], the spatial mobility of labor is affected by urban amenities; hence, the urban environment, an essential factor affecting the well-being of the residents, doubtless plays an important role in determining whether residents would stay or leave a city. On the one hand, with rapid development in industrialization and urbanization, developing countries such as China enjoy the economic benefit of expanding cities. On the other hand, urban areas in developing countries suffer from severe pollution issues. For example, using an air quality index, Liu and Yu [21] show that the majority of Chinese cities have poor air quality; further, it has been reported that half a million people die in India every year due to air pollution [6]. Studies also confirm that urban pollution exerts a negative influence on residents' health. Pollution is harmful to the residents' physical well-being because it contributes to health problems such as stroke and cancer; in particular, air pollution is highly associated with respiratory and cardiovascular disease [48], increased infant mortality rates [49], and decreasing worker productivity [50]. From a mental health perspective, the deterioration of the urban ecological environment, such as air quality, can negatively impact an individual's mental health and significantly decrease residents' subjective well-being [51–53].

Migration decision-making involves analysis of costs and returns [54], and the returns in terms of health outweigh the cost of migration for many people; in other words, for physical and mental health reasons, more families are choosing to move out of cities with severe pollution. Tiebout [55] proposes a "voting with one's feet" theory that families would migrate to a community with desired public goods. Based on this theory, economists find empirical evidence that people do "vote with their feet" on environmental quality. Areas with increased pollutant emissions have undergone a 9% population decline [56]; additionally, using a Baidu search index of the keyword "migration", Qin and Zhu [57] find that for every 100 point increase in the air quality index, the frequency of searching for "migration" will increase by 4.8%, which reflects that air pollution increases people's willingness to out-migrate; Heblich et al. [58] also illustrate that coal pollution leads to a persistent population outflow from industrial cities for families that can afford the cost of moving. Furthermore, polluted cities are not attractive destinations for migrants. Chen et al. [23] show that an increase in air pollution can increase the outflow of residents from a county by 50%; migrants in a polluted city are less likely to settle down and more likely to re-migrate [21].

2.2.3. Internet Effect and Population Inflow to Cities

In the digital era, a city with more internet users has advantages in attracting potential migrants by providing them with essential information. Information concerning the destination, such as income, job opportunities, and education availability, is indispensable to migration decision-making. Lack of accessibility to such information will inhibit migration and hence lower the migration rate [59]. Before the digital era, migrants gathered information mainly from narrow personal networks and, consequently, their choice of destination was constrained. Boyd [60] points out that the social network from kinship, friendship, and community is essential for immigration to industrial countries. Limited by information availability, migrants tend to move to places where their relatives or friends live, who can serve as a sufficient source of information [61]. However, in the digital era, ICT has enormously reshaped ways of communication and forms of social networks. As a backbone of ICT, the internet can transfer information at light speed while lowering the cost of information in search and transportation [62]. In this context, digital platforms that build on ICT play an increasingly significant role in maintaining and expanding social networks. Shah et al. [63] find that the internet has a growing number of users, especially among the young generation. Additionally, the internet has been widely used for information collection or relationship maintenance through online applications such as instant messaging tools or digital social media [64,65]. The frequent usage of the internet, in turn, expands interpersonal connection [66], social networking [67], and social connectivity with strangers [68]; Goggin [69] also shows that this phenomenon persists in mobile social networks.

The above studies showed that the internet enlarges the source and the scope of the information, which complements the traditional social network. Conversely, these changes impose an influence on population inflow to a city. Through digital platforms, the internet provides potential migrants with a wide range of information, such as housing prices [70], job opportunities [71], and education [72]. Consequently, the abundant information on the internet can extend the choice of migration destination; in other words, instead of moving to places where acquaintances or relatives live [60,61], migrants will choose a place where the information is abundant. Empirical evidence shows that the use of the internet decreases information friction and enhances information flow; as a result, the internet promotes domestic migration over even greater distances than before [72–74]. Winkler [75] finds that the increase in internet adoption enhances within-country migration whilst inhibiting immigration.

2.2.4. Hypotheses

The above literature suggests that SCC can potentially promote population growth in cities through the environment effect and the internet effect. Specifically, empowered by ICT-based technologies, SCC can positively impact the urban ecological environment through pollution governance and green production. Consequently, residents of a smart city are less likely to leave the city because of urban environmental issues than those of a non-smart city. Second, through internet, smart cities can provide more information than conventional cities to potential migrants. This is because SCC reduces the cost of internet connectivity, fostering more active internet users; conversely, these users provide potential migrants with abundant information regarding smart cities on the internet, thus making smart cities more attractive to potential migrants.

It is important to note that ICT breaks the geographical barrier of communication. Kraut et al. [64] argue that the internet facilitates distant communication; in particular, digital social media such as Facebook empowers distant interpersonal relationships [67]. In this regard, by disseminating more information on the internet, smart cities could potentially promote distant migration. Furthermore, although the internet is a rich source of information, the ability to acquire information from the source is greatly differentiated according to digital divides. The first-level digital divide generally exists among low-income populations because they have insufficient financial means to sustain or even establish a connection to the internet [76,77]. Additionally, education plays an important role in collecting digital information. Pruulmann-Vengerfeldt [78] points out that people with lower education attainment suffer a second-level digital divide because they lack the skills to operate the internet; people with lower education levels mainly use the internet for entertainment [79]. Therefore, migrants with lower income and educational attainment are less likely to be attracted by smart cities. Based on the above analyses, this paper proposes the following three hypotheses:

Hypothesis 1. *The urban population level (UPL)—urban population and its growth rate—is higher in smart cities.*

Hypothesis 2. *Smart cities experience higher UPL, which can be attributed to the improvement in the urban environment and the increase in internet users.*

Hypothesis 3. *Smart cities are more attractive to distant migrants and migrants with higher income and educational attainment.*

3. Methodology

3.1. Data Sources

Covering 156 prefecture cities in China, the dataset used in this study comprises panel data extracted from the China Urban Statistics Yearbook, China Regional Economic Statistics Yearbook, CEIC database, and EPS database. Our sample starts in 2005 due to numerous missing variables in earlier years. It is important to note that the last batch of national smart city pilots was issued in 2014 with a 3-year construction period. As the smart city program ended in 2017, we cannot identify whether a non-pilot city began to receive national funds for SCC in the subsequent years; therefore, we ended our sample in 2017, which also circumvented the impact of COVID-19 on domestic migration. It is important to note that our study focuses on domestic migration because of the nature of the available population data, which only includes residents holding Chinese citizenship.

In addition, a unique micro dataset from the China Migrants Dynamic Survey (CMDS) in 2017 is extracted to explore the micro impact of the SCC on the migrants. Conducted by the Migrant Population Service Center of the National Health Commission of China, the CMDS is an annual survey covering 31 provinces and including 200,000 households in mainland China. The purpose of the CMDS is to obtain essential information about migrants in China, such as their education and income. After including only the migrants whose migration date is after 2012 and whose age ranges from 18 to 60 years, the sample in this study contains 77,305 observations.

3.2. Variable Selection

3.2.1. Outcome Variables

The outcome variable, UPL, includes 2 indicators: Pop measures the population of usual residents in the city, the unit of which is 10^4 individuals; $lnPop$ reflects population growth. These variables offset the effect of natural population growth by deducting the number of births and adding the number of deaths. In addition, changes in population could be caused by the shift of the area in the administrative division; thus, urban population density (10^4 individuals/km^2), $Densi$, and its growth rate, $lnDensi$, are used as alternative measurements for the UPL to take into account the dynamics in the city administrative area and to verify the robustness of the baseline results.

3.2.2. Explanatory Variable

A dummy variable serves as the explanatory variable, indicating whether a city is selected as a pilot for the SCC and whether the time is after the beginning of the SCC. Since 2012, the Chinese Ministry of Housing and Urban–Rural Development has initiated a program for smart-city construction, aiming to enhance ICT applications in a growing group of smart-city pilots (SCPs). The program can be seen as a quasi-natural experiment, allowing for the adoption of the difference-in-differences strategy to explore the effect of the SCC on urban population growth. It should be noted that, as the dataset ends in 2017, the policy impact of pilots from 2013 and 2014 may be less pronounced given a 3-year implementation. Therefore, we only include prefectural pilots introduced in 2012 to reveal the long-run impact of the SCC. Additionally, this study focuses on prefecture-level cities owing to data availability: the treatment group contains 34 prefecture cities where the whole city administration area was listed in national pilots in 2012; the control group includes 122 prefecture cities where the whole city administration area was never included in national smart city pilots during the SCC; that is, these cities never implemented or benefited from the SCC program. Figure 1 shows the geographical distribution of sample cities. In summary, the variable takes a value of one for observations within which the city is a pilot and the year is after 2012, and a value of zero otherwise.

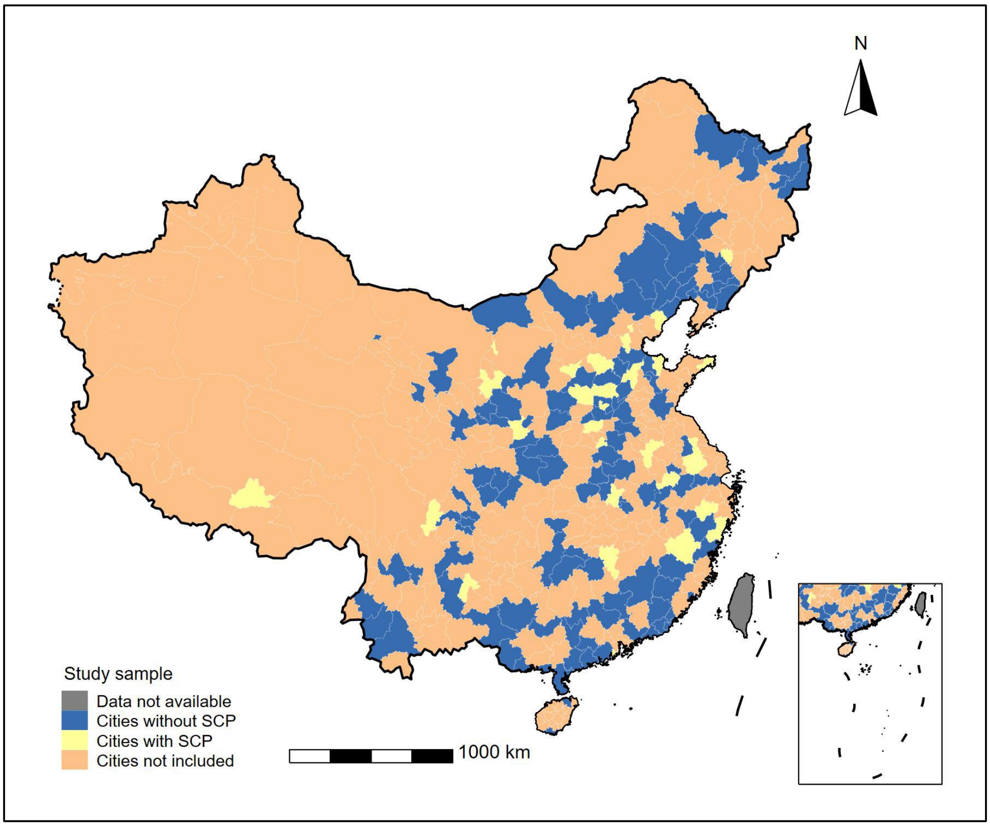

Figure 1. Geographical distribution of the sample.

3.2.3. Selection Concerns

An important prerequisite for an effective quasi-natural experiment is the randomness in the selection of the treatment group; in other words, to precisely identify the causal relationship between SCC and the urban population, the SCPs should be chosen randomly regardless of city characteristics, such as economic performance and population. If the SCPs are randomly selected, the explanatory variable is strongly exogenous, avoiding endogenous bias in estimation. To best alleviate selection concerns, this paper adopts two approaches. First, the mean trends for the variables of interest, the urban population, population density, internet user, and SO_2 levels, are plotted in Figure 2. As shown in subfigures (A) and (B), before SCC starts, the growth of the urban population and density show a parallel trend between the SCPs and the control groups. Subfigures (C) and (D) also illustrate parallel trends in SO_2 and internet users. These parallel trends imply that the selection of the SCPs is random regarding the variables of interest; otherwise, the trends are unlikely to be parallel before SCC initiation. Furthermore, after 2012, divergence of growth sets in for all variables, implying that the SCC is accountable for the differences between the groups.

Second, referring to Jia [80], this paper performs linear probability regressions to check whether the probability of being selected as a pilot differs between the cities in the sample, given their characteristics in 2011; the results are reported in Table 1. Column (1) shows that an advantage in population does not increase the probability. Column (2) further indicates that the characteristics of a city, such as economic performance and residents' income, are of no importance in pilot selection. In column (3), the inherent characteristics of a city are also considered; that is, two dummy variables, SEZ and RC, indicating whether a city is a special economic zone and regional capital, respectively, are included in the regression; insignificant coefficients give credit to the randomness in the SCP selection.

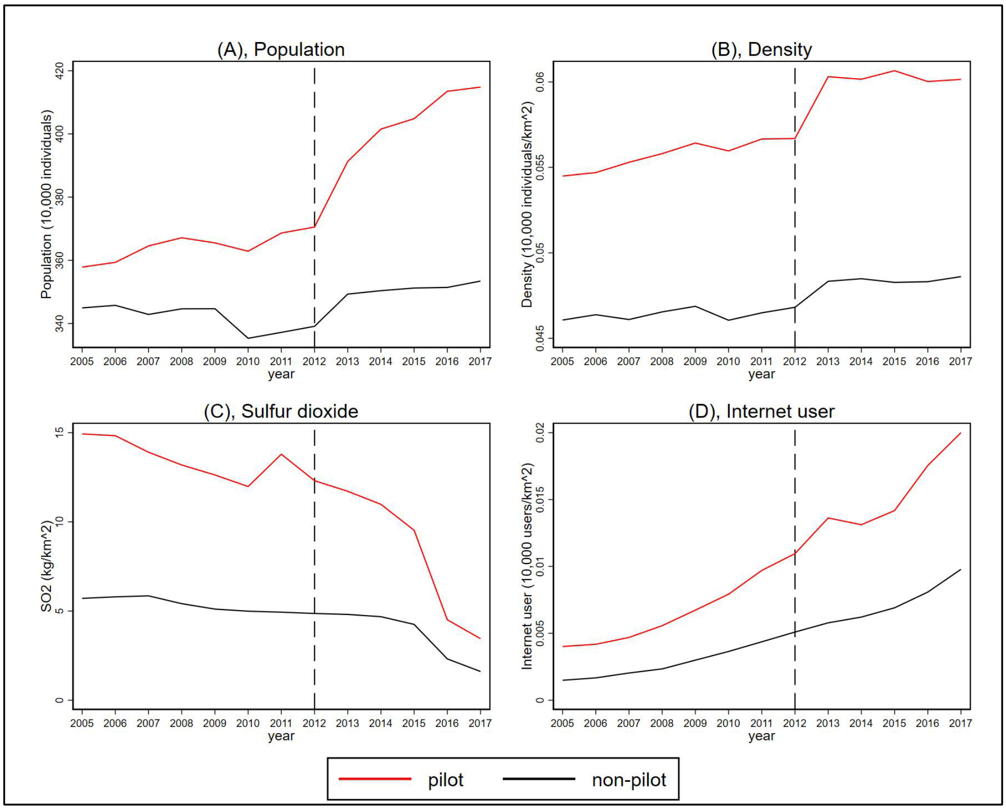

Figure 2. Trends of mean values for: (**A**), number of usual residents; (**B**), the density of usual residents; (**C**), intensity of sulfur dioxide; (**D**), number of internet users.

Table 1. Selection concerns.

	SCP		
	(1)	**(2)**	**(3)**
Population	1.26×10^{-4}	-3.06×10^{-4}	-2.28×10^{-4}
	(0.000)	(0.000)	(0.000)
Gdp		8.97×10^{-5}	9.58×10^{-5}
		(0.000)	(0.000)
Income		0.074	0.084
		(0.054)	(0.054)
Busers		0.002	0.001
		(0.002)	(0.002)
Musers		−0.000	−0.000
		(0.000)	(0.000)
SO_2		0.008	0.007
		(0.006)	(0.006)
$PM_{2.5}$		0.008	0.010
		(0.006)	(0.006)
SEZ			−0.175
			(0.292)
RC			0.290
			(0.249)
Observations	156	156	156
R^2	0.004	0.277	0.295

Note: The values represent the regression coefficients of explanatory variables; standard errors are in parentheses. SO_2 represents sulfur dioxide; $PM_{2.5}$ denotes particulate 2.5; Buser denotes broadband internet user; Muser denotes mobile phone user. SEZ denotes whether a city is a special economic zone; RC denotes whether a city is a regional capital.

3.2.4. Control Variables

Several factors that affect the city population are selected as control variables. Housing price (Hprice; unit: 10^4 RMB/m^2) is considered because housing expenses are essential in labor location choices [81]. Referring to Black and Henderson [82], the influence of local GDP performance (Ln_gdp) and the average income of the working population (Income; unit: 10^4 CNY) are considered. The total area of the road (Road; unit: 10^6km^2) is selected because developed road systems lower transportation costs, thereby facilitating agglomeration [83]. Because an increase in higher education institutions leads to population growth [84], the natural logarithm of the number of universities (Ln_university) is controlled for. Public services are important for the choice of labor location [85]; therefore, the area of green land (Grland; unit 10^3 km^2) and natural logarithms of the number of hospitals (Ln_hospital) are included.

3.3. Empirical Models

3.3.1. Benchmark Model

This paper aims to investigate the impact of SCC on the urban population. To better estimate the impact without bias due to the endogeneity problem, the DID method is employed. The model is as follows.

$$UPL_{it} = \alpha_0 + \alpha_1 SCP_{it} + \gamma \boldsymbol{X}_{it} + \mu_i + \tau_t + \varepsilon_{it} \tag{1}$$

where i indexes cities and t indexes time periods. The outcome variable, UPL_{it}, is the urban population level. The explanatory variable SCP_{it} is a dummy variable equal to 1 if city i is a smart city pilot and time t is greater than 2012, and 0 if not. Found in previous literature, $\boldsymbol{X}_{it}$ is a vector of control variables that can affect city population. μ_i and τ_t are city fixed effect and year fixed effect, respectively. ε_{it} is the error term. Coefficient α_1 measures the average population growth in smart cities relative to non-smart cities in the post-construction periods.

3.3.2. Robustness Check Models

Validation of the common trends assumption is a crucial part of the DID strategy [86]. In other words, the effectiveness of the identification depends on an important assumption that population trends for the SCP and the non-SCP cities are parallel before the initiation of the SCC. Referring to the event study specification [87], the model for validating the parallel trend is given as follows.

$$UPL_{it} = \beta_0 + \sum_{p \in P} \beta_p D_{ip} + \gamma \boldsymbol{X}_{it} + \mu_i + \tau_t + \varepsilon_{it} \tag{2}$$

where p indexes the number of periods from the start of the SCC, which takes values in the set $P = \{-5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5\}$, and $p = -1$ serves as a comparison group. The values in P are $t \in \{2005, 2006, 2007\}, t \in \{2008\}, t \in \{2009\}, t \in \{2010\}, t \in \{2011\}$, $t \in \{2012\}, t \in \{2013\}, t \in \{2014\}, t \in \{2015\}, t \in \{2016\}$, and $t \in \{2017\}$, respectively. D_{ip} is a dummy variable denoting whether city i is a city of the SCP at period p. The common trend assumption holds true if coefficients for periods before the SCC are insignificant.

The quasi-experiment identification framework requires randomness in the selection of the treatment and control groups. However, the inherent variability of the cities in terms of their political and economic status could interfere with the choice of the SCP group and consequently weaken the exogeneity of the explanatory variable. An interaction variable is introduced into Equation (1) to mitigate further the possible endogenous bias caused by the selection issue and take into account the pre-treatment trend. The model is specified as follows.

$$UPL_{it} = \beta_0 + \beta_1 SCP_{it} + S_i * T + \gamma \boldsymbol{X}_{it} + \mu_i + \tau_t + \varepsilon_{it} \tag{3}$$

where S_{it} is a dummy variable taking a value of 1 if city i is a special economic district or a regional capital, and 0 otherwise; T represents a time trend.

3.3.3. Mechanism Models

The SCC comprehensively upgrades the ICT infrastructure and applications in the cities, and the impact of these upgrades on population agglomeration is twofold. First, applications of ICT technologies decrease urban pollution, making smart cities more ecologically friendly, which positively impacts the growth of the urban population. Second, the SCC fosters active internet usage among the residents in smart cities, which, in turn, increases the popularity of the smart cities on social media and provides job opportunities online, attracting potential migrants who search for information over the internet on the smart cities. To identify these potential channels, we employ a widely used two-step procedure [88,89]. The model is given as follows.

First step:

$$Chann_{it}^{k}(Env_{it}, Nuser_{it}) = \phi_0 + \phi_1^k SCP_{it} + \gamma \mathbf{X}_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (4)$$

Second step:

$$UPL_{it} = \rho_0 + \rho_1 SCP_{it} + \rho_2^k Chann_{it}^{k}(Env_{it}, Nuser_{it}) + \gamma \mathbf{X}_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (5)$$

where $Nuser_{it}$ and Env_{it} are the mechanism variables, denoting the internet users and the environment, respectively. $Nuser_{it}$ was measured by the density of broadband internet users (Buser; unit: 10^4 users/km^2), because the higher the number of internet users in a city, the higher the popularity of the city on social media. Additionally, the density of mobile phone users (Muser; unit: 10^4 users/km^2) was considered, given that mobile networks are an irreplaceable component of the internet. Because air quality is the most direct indicator of the well-being of the urban environment, following [35,90], SO_2 (unit: kg/km^2) and PM 2.5 (unit: µg/km^2), variables measuring the intensity of air pollutants, are selected as measures for Env_{it}. In the first step, we examine the relationship between SCC and a mechanism variable. Given the significant relationship, in the second step, we include the mechanism variable as a covariate in baseline Equation (1), and a channel is verified when the ρ_1 in Equation (5) is lower than the baseline coefficient α_1 in terms of significance or magnitude.

3.3.4. Heterogeneity Analysis Model

On the one hand, the SCC increases the speed and range of information flow, enhancing the accessibility of information to potential migrants at distant locations, thus encouraging migration from farther away. On the other hand, digital divides restrict the reach of online information to low-income or uneducated individuals; consequently, the impact of the SCC on migration varies among different migrant cohorts. To explore the heterogeneous effects of the SCC, a logit model that estimates the CMDS dataset is constructed as follows:

$$Choice_i = \beta_0 + \beta_1 H(Edu_i, Inc_i, Dist_i) + \gamma \mathbf{X}_i + \varepsilon_i \quad (6)$$

where i indexes migrants. $Choice_i$ is a dummy variable (SCP) that is set to 1 if the destination of migration is a smart city and 0 otherwise. Edu_i measures the education level of the respondent ranging from 1 "elementary school" to 5 "graduate school"; Inc_i represents the monthly income of the migrant from 1 "low income" to 3 "high income"; $Dist_i$ denotes the migration range on a scale of 1 to 3, where 1 = "migration within a city," 2 = "migration between cities," and 3 = "migration between provinces."

4. Results

4.1. Baseline Results

Table 2 reports the results of the estimation using Equation (1). The standard errors are clustered at the city level in columns (2) and (5), and at the province level in columns (3) and (6). Columns (2) and (3) show that the urban population is significantly higher in the smart cities at the 1% level. This difference in the UPL, however, can be biased by the inequality of the population at the beginning of the SCC; therefore, an alternative independent variable, the natural logarithm of the population, is used to measure the population growth caused by the SCC. Columns (5) and (6) indicate that the SCC leads to population growth by 4.4% in the SCP compared with that in its control group, which implies a positive role of the SCC in urban population agglomeration; therefore, hypothesis 1 is validated. Additionally, the results of the coefficients for control variables mostly conform to the previous literature; that is, housing price, GDP performance, public infrastructure, and public services positively affect population growth.

Table 2. Impact of SCC on urban population level.

	Pop			**Log (Pop)**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
SCP	30.088 ***	19.976 ***	19.976 ***	0.061 ***	0.044 ***	0.044 ***
	(3.738)	(3.855)	(3.753)	(0.010)	(0.011)	(0.012)
Hprice		38.388 ***	38.388 ***		0.120 ***	0.120 ***
		(9.343)	(11.473)		(0.028)	(0.033)
Income		−1.925	−1.925		−0.007	−0.007
		(1.606)	(1.901)		(0.005)	(0.006)
Ln_gdp		15.076 ***	15.076 **		0.067 ***	0.067 ***
		(4.573)	(7.346)		(0.016)	(0.022)
Road		1.099 ***	1.099 ***		0.002 ***	0.002 ***
		(0.245)	(0.251)		(0.001)	(0.001)
Ln_University		2.525 ***	2.525 ***		0.001	0.001
		(0.563)	(0.487)		(0.001)	(0.001)
Grland		22.137 ***	22.137 ***		0.063 ***	0.063 ***
		(5.029)	(5.039)		(0.019)	(0.019)
Ln_Hospital		9.259 ***	9.259 ***		0.025 ***	0.025 **
		(2.411)	(2.776)		(0.010)	(0.012)
Control	No	Yes	Yes	No	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City cluster	No	Yes	No	No	Yes	No
Province cluster	No	No	Yes	No	No	Yes
Observations	2028	2028	2028	2028	2028	2028
R^2	0.090	0.172	0.172	0.078	0.119	0.119

Note: The values represent the regression coefficients of explanatory variables; standard errors are in parentheses; ** and *** denote significance at the 5%, and 1% levels, respectively.

4.2. Robustness Check

Several robustness checks were performed to verify baseline results' robustness, which are presented in Table 3. First, alternative measurements for the UPL were used to re-estimate Equation (1). Population density was used to cancel out the influence of changes in city administrative area on population growth and the result in column (1) indicates a 4.3% growth of population density for the SCP. Furthermore, referring to [91], an index of night-time light intensity is constructed as a proxy for the UPL and column (2) indicates that the conclusion of the baseline result remains unchanged.

Table 3. Robustness checks.

	Log (Densi)	Log (Light)	Log (Pop)		
					PSM-DID
	(1)	(2)	(3)	(4)	(5)
SCP	0.043 ***	0.084 **		0.040 ***	0.046 ***
	(0.009)	(0.037)		(0.010)	(0.011)
Pre_5			−0.023		
			(0.025)		
Pre_4			−0.016		
			(0.025)		
Pre_3			−0.002		
			(0.025)		
Pre_2			−0.004		
			(0.025)		
Current			−0.002		
			(0.025)		
Post_1			0.028		
			(0.025)		
Post_2			0.032		
			(0.025)		
Post_3			0.037		
			(0.025)		
Post_4			0.079 ***		
			(0.025)		
Post_5			0.079 ***		
			(0.025)		
Control	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	2028	2028	2028	1584	2028
R^2	0.0513	0.649	0.127	0.0770	0.130

Note: The values represent the regression coefficients of explanatory variables; standard errors are in parentheses; ** and *** denote significance at the 5%, and 1% levels, respectively.

Second, the parallel trend, an important prerequisite of the DID analysis, was examined by estimating Equation (2). As shown in column (3), coefficients for UPL are insignificant in pre-construction periods. In other words, there is no statistical difference in the UPL between treatment and control groups prior to the SCC; hence, the common trend assumption holds. As illustrated in Figure 3, the impact of the SCC on the UPL takes place during four periods relative to the initiation of the SCC; this lag of policy impact can be explained by a 3-year construction period. Moreover, the divergence continuously remains significant afterward, implying the persistence of the impact.

Third, potential endogeneity issues are considered. Column (4) shows that the coefficient of interest from Equation (3) remains consistent with the baseline result, indicating that the cities' inherent characteristics did not interfere with the selection of the SCP. In addition, inspired by [92], a placebo test simulating pre-treatment trends was carried out. Specifically, a false sample was generated by randomly re-assigning 34 smart city pilots and the initiation of SCC in the 156 cities in the original sample and a year between 2005 and 2017, respectively; subsequently, the sample is estimated by using Equation (1). After repeating the whole procedure 500 times, a sample of coefficients simulating the impact of the false SCC on the UPL is obtained, which can be used to verify whether the effect of population agglomeration is truly due to SCC: in other words, the true estimate of the SCP variable, 0.044, should be statistically different from its simulated counterpart given that the baseline result is robust. As shown in Figure 4, the true estimate is located above 95 percentiles of the CDF of the simulated estimates. It excludes the potential influence of the pre-treatment trends on the baseline result. To further enhance the exogeneity of the DID analysis, the PSM-DID, in which observations that fall out of the assumption of common support are deleted before executing the DID, was employed; a similar result in column (5) verifies the positive relationship between the SCC and the UPL. In conclusion, the above results validate the identification model's effectiveness and confirm the baseline results' robustness.

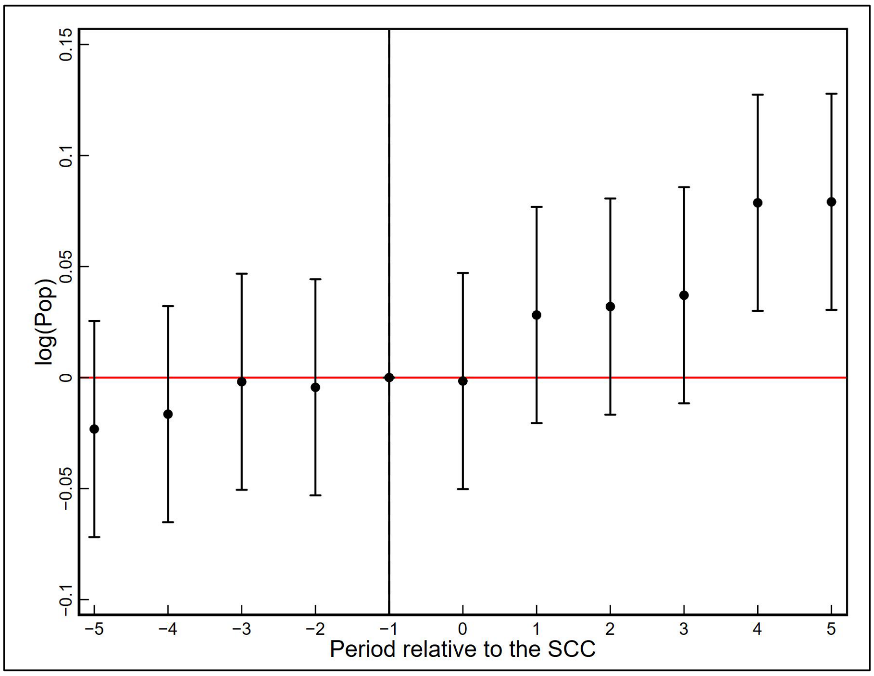

Figure 3. The dynamic impact of the SCC on the UPL. Note: The vertical line measures the estimation coefficient; the horizontal line denotes periods from the beginning of the SCC. Solid points represent the coefficients in column (3) of Table 3; one period before the SCC is selected as a comparison group. Dashed lines show the confidence intervals at 90%.

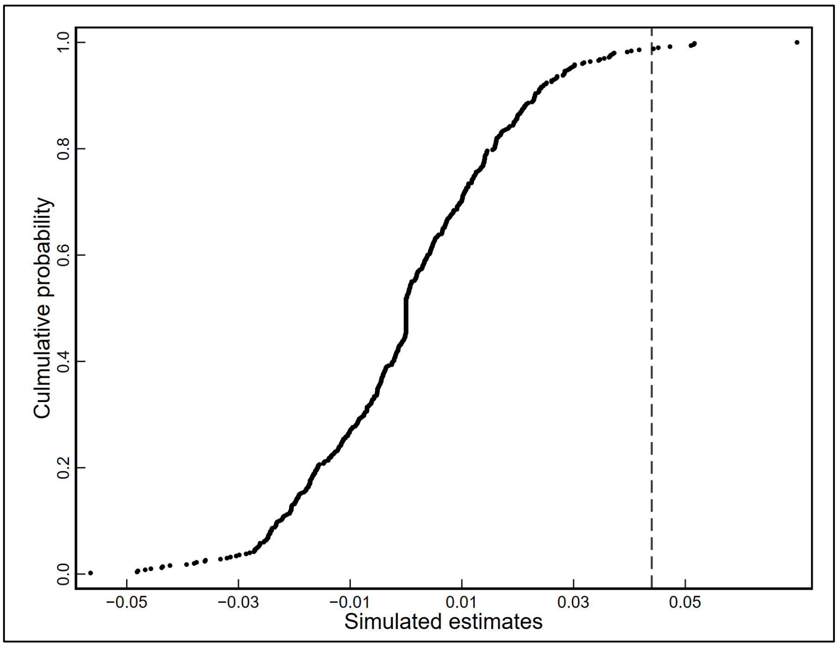

Figure 4. Placebo test for the impact of the SCC on the UPL. Note: This figure plots the CDF of 500 simulations for the regression of the UPL on the SCP. The vertical line indicates probability and the horizontal line measures the estimation coefficients of the SCP; the dashed line represents the baseline result, 0.44. Solid points represent the coefficient for each simulation.

4.3. Mechanisms

Although the positive impact of the SCC on population agglomeration has been confirmed, an important question remains unaddressed: Why is the SCP more attractive to people than "less smart" cities? Exploring the mechanisms is crucial for answering this question, and understanding the impact of the SCC on individuals and economies. Using a two-step procedure, we investigate whether the SCC may impact population agglomeration through the environment and internet effects.

In the first step, we examine the impact of the SCC on the environment and internet users separately. Columns (1) and (2) of Table 4 indicate that the SCC improves the urban ecological environment, consistent with previous research. This phenomenon is probably due to the information-promoting effect of the ICT. Boosted by the ICT, information flows within the SCP benefit the urban environment in two respects. First, knowledge as information can be easily accessed and exchanged, facilitating overall innovation, within which innovation regarding green technologies, such as waste processing, reduces pollution. Second, monitoring data as information in every part of city operation, such as production and transportation, helps the SCP utilize energy and resources efficiently, decreasing the emission of pollutants. Columns (3) and (4) show that the SCC significantly increases the number of network users. A possible explanation for these results is narrower digital divides in the SCP. Upgradation of the internet infrastructure, such as through comprehensive adoption of fiber-optic internet and 4G mobile networks, increases the availability of ICT resources and consequently lowers the cost of connection to the internet, removing the first-level digital divide between potential internet users; moreover, promoting receiving and sharing information over the internet in the SCP familiarizes the residents with the internet and enhances their internet usage skills, alleviating the second-level digital divide between the internet users.

Table 4. First step.

	Environment		**Internet User**	
	SO_2	**$PM_{2.5}$**	**Buser**	**Muser**
	(3)	**(4)**	**(1)**	**(2)**
SCP	−2.728 *** (0.487)	−0.991 ** (0.336)	0.002 *** (0.0004)	0.042 *** (0.011)
Control	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Observations	2028	2028	2028	2028
R^2	0.323	0.199	0.668	0.693

Note: The values represent the regression coefficients of explanatory variables; standard errors are in parentheses; ** and *** denote significance at the 5% and 1% levels, respectively. SO_2 represents sulfur dioxide; $PM_{2.5}$ denotes particulate 2.5; Buser denotes broadband internet user; Muser denotes mobile phone user.

Subsequently, in the second step, we separately include the proxies as a covariate in the baseline model. If the coefficient estimating policy impact is lower than the baseline result with respect to magnitude or significance, a potential channel is suggested. In Table 5, columns (1)–(2) and (3)–(4) investigate the environment effect and the internet effect, respectively. In line with the extant literature, significantly negative coefficients for pollutants imply a negative impact of pollution on population agglomeration; similarly, more network users can lead to higher population growth. By observing coefficients of interest, SCP, we find that the policy impact is lower than the baseline result when the environment effect and internet effect are controlled for. The above results viewed together provide strong support for Hypothesis 2.

Table 5. Second step.

	Environment Effect		Internet Effect	
	(1)	(2)	(3)	(4)
SCP	0.025 *** (0.009)	0.027 *** (0.009)	0.032 *** (0.010)	0.036 *** (0.010)
SO_2	−0.006 *** (0.001)			
$PM_{2.5}$		−0.016 *** (0.002)		
Buser			4.806 *** (0.715)	
Muser				0.153 *** (0.021)
Control	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Observations	2028	2028	2028	2028
R^2	0.163	0.215	0.145	0.145

Note: The values represent the regression coefficients of explanatory variables; standard errors are in parentheses; *** denotes significance at the 1% level. SO_2 represents sulfur dioxide; $PM_{2.5}$ denotes particulate 2.5; Buser denotes broadband internet user; Muser denotes mobile phone user.

There are several possible explanations for these phenomena. First, cities in developing countries, e.g., China, are facing a dilemma between economic development and environmental protection. On the one hand, in seeking to maximize output from industries, cities suffer from pollutants discharged from factories; additionally, rising energy consumption caused by expanding urban scale exacerbates the pollution issues. On the other hand, the deteriorating urban environment pushes residents out of the city. With the assistance of ICT, the SCP, however, can maintain desired production and energy consumption while preserving the environment, which may persuade residents not to leave the city. Consequently, this retaining effect of the environment keeps the SCP, unlike non-smart cities, from losing population. Second, the internet has become a major source of information collection and communication in the digital era; this includes surfing social media, such as Facebook and Weibo, as a way of exploring the news; communicating via instant messaging tools, e.g., Whatsapp and Wechat, to share text, voice, and videos. These digital platforms together form a cyber community where people exchange information. In this regard, the larger the number of internet users in a city, the more likely it is that information regarding the city is disseminated in the cyber community and received by potential migrants; in other words, a growing number of internet users gives the SCP an information advantage over other cities in terms of attracting migrants. Therefore, the increase in internet users creates an attracting effect for the SCP.

5. Discussion

5.1. Heterogeneous Analysis

The above sections show that smart cities are more appealing to migrants due to the internet effect, since smart cities have the advantage of providing potential migrants in the cyber community with essential information. However, the ability to receive this information varies among migrants. Furthermore, the anti-spatial feature of the internet possibly plays a role in migration. As argued in the literature review section, smart cities may be more attractive to distant migrants, and migrants with higher income and education levels. Therefore, to examine this heterogeneity, Equation (6) is estimated with the CMDS dataset and the results are reported in Table 6. Column (2) shows that a one-level increase in distance between the original place and destination causes a 0.555-times higher probability of migrating to the SCP. This result implies that, because the internet breaks the geographical barrier of information transmission, migrants can make migration decisions based on the information concerning a distant smart city, such as job opportunities and the city's natural environment. Columns (3) and (4) reveal a positive relationship between education level and the choice of a smart city as a migration destination, with or without the control variables. Specifically, coefficients in column (4) indicate that, when the education level of migrants increases by one level, the possibility of migrating to the SCP will increase 0.061 times. Similarly, column (6) indicates that an increase in migrants' income leads to a 0.018 times higher probability of choosing the SCP. These phenomena can be consequences of digital divides: migrants with lower income are more likely to suffer from the first-level digital divide, that is, to be unable to acquire or sustain an internet connection; moreover, less-educated migrants struggle with the second-level digital divide, i.e., they lack skills to use the internet and are hence unable to gather essential information even if they are connected to the internet. In other words, the information on the internet is blocked out by the digital divides; consequently, the internet attracting effect of the SCP on these migrants is weaker. The above results verify hypothesis 3 and suggest the attracting effect of the internet.

Table 6. Distance, education, income, and choice of smart cities as destination.

	SCP					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dist	0.440 ***	0.441 ***				
Odds ratio	1.552 ***	1.555 ***				
	(0.011)	(0.011)				
Edu			0.063 ***	0.059 ***		
Odds ratio			1.065 ***	1.061 ***		
			(0.008)	(0.010)		
Inc					0.019 ***	0.018 ***
Odds ratio					1.019 ***	1.018 ***
					(0.002)	(0.002)
Control	No	Yes	No	Yes	No	Yes
Observations	77,305	77,305	77,305	77,305	77,302	77,302
Pseudo-R^2	0.213	0.219	0.082	0.106	0.123	0.164

Note: The values represent the regression coefficients of explanatory variables; standard errors are in parentheses; *** denote significance at the 1% level. Dist denotes migration range of a migrant; Edu denotes education level of a migrant; Inc denotes income level of a migrant.

5.2. Analysis of Benefits

The growth of the population in the city may reshape the labor market. In this regard, Equation (1) is re-estimated to examine the influence of the SCC on employment and Table 7 reports corresponding results. Specifically, the UPL is replaced by the number of overall workers and workers in three sectors: the primary sector, the secondary sector, and the tertiary sector. Column (1) shows that the SCC promotes the growth of the working population in the SCP; additionally, column (4) indicates that the SCC positively affects the growth of employment in the tertiary sector.

In the heterogeneous analysis, we find that the SCP is more attractive to migrants with higher educational attainment and income, which implies that the SCP enjoys superior human capital than the cities in the control group. By using GDP data in the three sectors as the dependent variable and population as the mediation variable, this paper estimates models similar to Equation (1) to investigate further the impact of the disparity in population on GDP growth and results are shown in Table 7. Columns (1)–(4) indicate that the disparity of the population between the SCP and the control group affects the GDP growth. In particular, the growth of the GDP in the tertiary sector is higher in the smart cities, which is consistent with the results for employment growth. In conclusion, the SCC benefits both the employment and the GDP performance of the smart cities, especially in the tertiary sector.

Table 7. Impact of SCC on working population and GDP.

	Panel A: Workers			
	Log (Worker)	**Log (Fworker)**	**Log (Sworker)**	**Log (Tworker)**
	(1)	**(2)**	**(3)**	**(4)**
SCP	0.068 ***	−0.074	0.025	0.032 **
	(0.017)	(0.071)	(0.026)	(0.012)
Observations	2028	2028	2028	2028
R^2	0.468	0.290	0.374	0.575
	Panel B: GDP			
	Log (Gdp)	**Log (Agri)**	**Log (Indus)**	**Log (Comm)**
	(1)	**(2)**	**(3)**	**(4)**
SCP	0.048 **	0.015	0.044 *	0.037 **
	(0.020)	(0.033)	(0.026)	(0.017)
Control	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Observations	2028	2028	2028	2028
R^2	0.886	0.744	0.776	0.919

Note: The values represent the regression coefficients of explanatory variables; standard errors are in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Fworker, Sworker, and Tworker are the number of workers in the primary sector, the secondary sector, and the tertiary sector, respectively. Agri, Indus, and Comm are GDP in in the primary sector, the secondary sector, and the tertiary sector, respectively.

5.3. *Smart Cities and Digitalization during COVID-19*

During the COVID-19 pandemic, frequent lockdowns were enforced to slow down the spread of the virus, strictly prohibiting outdoor activities for city residents. As a result, internet-based services have become important agents for remote working, communication, and entertainment during the pandemic, leading to a higher level of digitalization. An interesting question to be answered is whether smart cities have advantages in facilitating digitalization during the pandemic. To this end, we use prefecture city data from 2020–2022 to examine the difference in internet penetration between smart city pilots and non-pilots. The results are reported in Table 8. Columns (1)–(2) suggest that, during the pandemic, the SCC had a positive and significant impact on mobile internet penetration, while its impact on broadband internet penetration was positive but insignificant. A possible explanation for this phenomenon is that people are inclined to utilize the internet via mobile phones as the smartphone has become more and more versatile in recent years. Overall, the above results imply that the SCC might have played a positive role in enhancing digitalization during COVID-19.

Table 8. Impact of SCC on digitalization during COVID-19.

	Bpen	**Mpen**
	(1)	**(2)**
SCP	0.079	0.669 ***
	(0.190)	(0.193)
Control	Yes	Yes
Year fixed effect	Yes	Yes
Observations	465	467
R^2	0.089	0.221

Note: Standard errors are in parentheses; *** denotes significance at the 1% level. Bpen denotes broadband internet penetration, measured by the ratio of broadband internet users to usual residents; Mpen denotes mobile internet penetration, measured by the ratio of mobile phone users to usual residents.

6. Conclusions

To answer a long-disputed question about whether or not widespread adoption of ICT can offset agglomeration, this paper investigates the relationship between ICT and urban population agglomeration in the context of China's SCC, which aims to enhance ICT applications in cities. The results suggest that, instead of being a substitution for cities, ICT is a complement.

Using the DID method to analyze 156 prefecture-level cities, we provide sound evidence that the SCC significantly promotes urban population growth; widespread ICT adoption in cities is beneficial to population agglomeration. The main driver of this phenomenon is the information flow facilitated by ICT in terms of gathering and sharing. First, digital information flow within smart cities enables pollution governance and green production, which leads to improved urban environmental quality that serves as a force to retain its residents. Second, promoted by internet users, smart cities have an information advantage over non-smart cities in the cyber community; this information flow outside smart cities enables it to attract more potential migrants in the digital era. Furthermore, we show that smart cities are attractive to highly educated and high-income migrants, as digital divides can neutralize the information advantage of smart cities for migrants with lower income and educational attainment. Additionally, migrants from farther distances prefer to select smart cities as their destination because ICT breaks spatial barriers of information diffusion. Finally, the results of the benefit analysis suggest that the uneven growth of population leads to a divergence between the smart cities and the "less smart" cities in terms of employment and GDP performance.

The findings of this paper have several policy implications. First, for cities in developing countries such as China that are beset with severe environmental issues, promoting SCC is a wise choice because it reduces urban pollution and hence keeps cities from losing essential human capital, which plays an indispensable role in sustaining high-quality urban development. Second, public educational institutions should advance the popularization of knowledge regarding internet use, as the internet has become a major source of information in the digital age. Finally, it is important for policymakers to comprehensively promote SCC or similar policies to eliminate the digital divides within a city and between the cities, given that differentiated ICT levels lead to a difference in the urban population growth, and hence disparate regional economic performance, which is harmful to balanced development and can further worsen regional inequality. Future research could include an in-depth analysis of the micro impact of the retaining effect of SCC on city residents, which this study does not perform because of the lack of available data. Furthermore, future discussion advancing the topic to effects on corporations and industry is of interest.

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Conflicts of Interest: The authors declare that they have no conflict of interests.

Abbreviations

CMDS: China Migrants Dynamic Survey. SCC: smart-city construction. SCP: smart city pilot. UPL: urban population level.

Notes

[1] Related report link: https://www.greenpeace.org.cn/pm25-city-ranking-2015/#_ftn1, (accessed on 20 September 2023).

[2] Related report link: https://www.sohu.com/a/211077461_800248, (accessed on 20 September 2023).

[3] Related report link: https://www.cnnic.net.cn/hlwfzyj/hlwxzbg/hlwtjbg/201803/t20180305_70249.htm, (accessed on 14 November 2022).

[4] Related report link: https://www.wangsu.com/report/list/DEVREPORT, (accessed on 23 November 2022).

[5] Related report link: https://www.ndrc.gov.cn/xxgk/jd/wsdwhfz/202005/t20200515_1228150.html, (accessed on 20 September 2023).

[6] Related report link: https://www.washingtonpost.com/news/energy-environment/wp/2016/05/12/who-global-air-pollution-is-worsening-and-poor-countries-are-being-hit-the-hardest/, (accessed on 20 September 2023).

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