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Article

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DEVELOPMENT ECONOMICS | RESEARCH ARTICLE

The impact of the digital economy on the cost of living of the population: Evidence from 160 cities in China

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Abstract: The cost of living has shown a gradual upward trend in recent years, which has seriously impacted the quality of life and well-being of residents. This study empirically examines the impact of the digital economy on residents' cost of living and the mechanisms behind it by measuring the digital economy and cost of living indicators in 160 cities in China from 2010 to 2020. The results show that the digital economy can significantly reduce the cost of living for the population. The "marginal effect" of the digital economy on the cost of living is found to be non-linearly decreasing as the level of the digital economy increases, and the more severe the air pollution, the weaker the impact of the digital economy on the cost of living, using a threshold variable of the digital economy and air pollution. Finally, the analysis of mechanisms shows that environmental regulation and healthcare are important ways in which the digital economy can play a role in reducing the cost of living for the population. Meanwhile, this study reveals the intrinsic link between the digital economy and the cost of living, which is important for alleviating the cost of living and enhancing people's well-being.

Subjects: Asian Economics; Chinese Economics; Religion & Economics

Keywords: digital economy; cost of living; threshold model; air pollution

1. Introduction

The 2022 Worldwide Cost of Living Survey (WCOL) shows that average prices in the world's mega-cities rose to 8.1% (measured in local currency) in the previous year. The direct consequence of rising prices is an increase in the cost of living for residents and a loss of life satisfaction. In recent years, China's household cost of living index has also been on the rise, and there are significant differences between different income groups (Song et al., 2020). Energy, family childcare, house prices, city size, ageing and household size all contribute to an increase in the cost of living for residents. And an increase in the cost of living can have a negative impact on population migration, quality of life, urbanisation and labour migration. Therefore, paying attention to the cost of living is of great practical significance in meeting the growing needs of the people for a better life. The China Internet Development Report (2021) shows that the market size of China's digital economy will be RMB 39.2 trillion in 2020, accounting for 38.6% of GDP, with the total digital economy ranking second in the world. Through the identification, selection, filtering, storage and use of big data, the digital economy enables the rapid and optimal allocation and regeneration of resources, significantly reducing transaction costs. So, can the digital economy reduce the cost of living for residents?

There are two branches of the literature that are closely related to the study of this paper. One is the literature related to the digital economy. Studies have found that the digital economy can significantly drive green total factor productivity (Gao et al., 2022; Q. Liu et al., 2022) and green progress by upgrading industrial structures and alleviating factor allocation distortions (J. Zhou et al., 2023). This green technological advancement, thanks to the spillover and sharing nature of the digital economy, will become a core kinetic energy to fuel the low-carbon development of enterprises Li et al., 2023) and usher in new opportunities for the green and low-carbon transformation and development of cities (Yang et al., 2023). The development of the digital economy also helps to promote regional innovation efficiency and coordinated regional economic development (S. Xu & Pei, 2023) and has an apparent spatial spillover effect in that the development of the digital economy in the region inhibits the improvement of innovation efficiency in neighboring regions (Wen & Niu, 2023). Indeed, the digital economy has a positive impact on the daily lives of the population. The study found that the digital economy has a positive impact on rural environmental governance (Cheng & Wang, 2023), urban-rural income gap (Meng, 2023), urban-rural factor allocation (Man et al., 2023), consumption (Y. Zhang et al., 2023), employment quality (Valenduc, 2019) and income (Bongomin et al., 2023) all have a significant positive contribution effect. The second is the literature relating to the cost of living. Studies have found that the cost of living for urban households in China is rising and varies between groups with different income levels (B. Wang & Qian, 2020). Among them, the cost of living for the elderly is 1.9 times higher than the per capita cost of living for households (L. Xu et al., 2011). The high cost of living, represented by house prices, is not conducive to life satisfaction (L. Zhang et al., 2012), and an increase in population density directly contributes to an increase in the cost of living for residents (Y. Chen et al., 2012). Changes in the structure of consumer preferences are usually perceived to be higher than consumers' actual cost of living, and the extent of this substitution bias depends on the choice of the base period (Wu, 2014). It is easy to see that the cost of living for Chinese residents has tended to rise over time, and this can cause a lack of life satisfaction and is not conducive to happiness.

In summary, scholars' research on the digital economy has focused on innovation, total factor productivity, low-carbon urban development, economic growth, and people's livelihoods. On the other hand, scholars' research on the cost of living has focused on measuring cost-of-living indicators, trends, and life satisfaction. However, only some scholars have studied the impact of the digital economy on the cost of living from its perspective. In fact, the digital economy is booming, permeating all aspects of residents' lives, and is inevitably linked to their daily lives. Studies have found that the digital economy can break through spatial and temporal constraints, helping residents quickly capture the information they need to complete transactions at a lower cost (H. Xu et al., 2020). New technologies such as big data and cloud computing can provide an optimal path to the matching problem in the economic market (Jing & Sun, 2019). The digital economy has enabled interoperability and sharing of resources, bringing significant changes and convenience to residents' lifestyles. The digital economy has changed the previous pattern of a unidirectional supply of goods to a two-way exchange flow between supply and demand (J. T. Guo & Luo, 2016). The result will enable households to consume food, clothing, housing, transport, education, and healthcare at lower prices. Through this perspective, this paper attempts to explore how the digital economy affects the cost of living of the population based on a completed analytical framework. Moreover, by choosing the city level as the regional target, the paper can study the impact of the digital economy on the cost of living in a more usual manner.

Precisely, this paper measures the level of development of the digital economy in 160 cities in China from 2010 to 2020, considering the unique attributes of the digital economy, and uses various econometric methods to examine the impact of the digital economy on the cost of living. The findings show that the digital economy significantly reduces residents' living costs. At the same time, the digital economy shows a non-linearly decreasing "marginal effect" on the cost of living, namely, the higher the level of the digital economy, the weaker the effect on the cost of

living. These findings hold when historical data is selected as the instrumental variable and robustness tests are conducted.

1.1. The marginal contributions of this paper

First, it provides a more comprehensive measure of the digital economy at the city level based on the existing literature and enables an in-depth exploration of the impact of the digital economy on the cost of living. Second, the paper introduces air pollution into the model and explores how the external environment may affect the relationship between the digital economy and the cost of living. Third, there needs to be more literature on the impact of the digital economy on the cost of living. To a certain extent, this paper enriches and deepens the existing literature. The remainder of the article is organized as follows: Section 2 presents the theoretical analysis and research hypotheses; Section 3 presents the research design; Section 4 presents the empirical analysis of the impact of the digital economy on the cost of living; Section 5 presents the robustness tests; Section 6 presents the conclusions and policy recommendations; and Section 7 presents future research and limitations.

2. Theoretical analysis and research hypothesis

2.1. Mechanisms of the impact of the digital economy on the cost of living of the population

Consumption inequality exists in the daily lives of residents (D. Zhao et al., 2017), and factors such as regional differences, spatial price differences, and price increases are important contributors to consumption inequality (J. Liu & Chen, 2021; Song et al., 2020; L. F. Zhou & Zhang, 2019). Consumption inequality can cause the cost of living to rise for the population. The digital economy, on the other hand, can reduce the cost of living for residents by reducing regional differences (S. P. Wang et al., 2022), breaking through spatial and temporal constraints, reducing information search costs and sharing costs (Jin & Shi, 2022), and optimizing resource allocation (Xing et al., 2021) to complete transactions at a lower cost. The digital economy can also reduce the production costs of goods (Bai & Yu, 2021) through technological innovation (X. S. Li et al., 2022), improving the efficiency of the industrial division of labour and collaboration (Jiang & Jin, 2022), and increasing the efficiency of corporate labour production (Cai et al., 2021), thus enabling consumers to purchase household goods at relatively low prices. In addition, the digital economy can promote green and high-quality urban development (Sun et al., 2022) to reduce the cost of living for residents. Specifically, the digital economy has improved the efficiency of the green economy by optimizing the industrial structure, promoting technological innovation, and deepening marketization through digital industrialization and digitization of industries (Q. Liu et al., 2022), thereby improving the quality of the environment for the population and reducing the additional costs that residents need to spend to cope with environmental pollution. The digital economy can also effectively reduce the cost of access to market information for individuals, alleviating information asymmetries in disadvantaged areas (Jensen, 2007), as well as information and credit constraints for low-income groups, thus avoiding higher costs for residents. The digital economy can bring convenience to people's consumption, travel, and living environment, allowing residents to access it at a lower cost, thus reducing the cost of living for households and individuals. In view of this, the following hypothesis is proposed in this paper:

Hypothesis 1: The digital economy can significantly reduce the cost of living for residents.

2.2. The non-linear impact of the digital economy on the cost of living for residents

The digital economy can reduce consumption inequalities, regional disparities, breakthrough time and space constraints, and improve the information asymmetries faced by the population. The digital economy can also optimise the allocation of resources, reduce production costs, enhance the intensity of regulation on the environment, and promote the green development of the economy in various direct and indirect ways to reduce the cost of living for residents. However, the digital economy is unlikely to sustainably reduce the cost of living for the population through

these direct or indirect factors. In other words, the "marginal effect" of the digital economy on the cost of living of the population is perhaps non-linear and decreasing. On the one hand, it is because, with the wide application of the digital economy, factors such as poor information, resource allocation, living environment and production up-front are improved. The role of the digital economy on the cost of living will weaken; on the other hand, many factors affect the cost of living of residents, such as consumption habits, regional culture, foreign trade (B. Wang & Qian, 2020), geopolitics (J. P. Chen & Huang, 2014), import tariffs, air pollution (Zeng et al., 2015), foreign direct investment, level of infrastructure and other factors. The digital economy, on the other hand, is only a subset that affects the cost of living of the population. Given this, the following hypothesis is proposed.

Hypothesis 2: The "marginal effect" of the digital economy on the cost of living of the population is non-linear and decreasing.

2.3. Analysis of the mechanisms by which air pollution affects the cost of living of the population

There is also a strong correlation between air pollution and the cost of living for residents, and this effect may affect the relationship between the digital economy and the cost of living. First, there is an increase in health costs. Air pollution negatively affects people's health, including respiratory and cardiovascular diseases (Beelen et al., 2014). When air quality deteriorates, people must spend more money to deal with health problems, such as buying air purifiers, medical expenses, etc. This can increase people's living costs and offset the convenience of the digital economy. Second, there is an increase in the waste of resources. Severe air pollution can lead to environmental degradation and affect the efficient use of resources (Mohsin et al., 2019). For example, in highly polluted areas, people may need to consume more energy to clean the air or to meet their living needs, which can increase energy consumption and the associated costs. In this way, the digital economy's energy and resource efficiency benefits are offset. Third, the quality of life is reduced. Air pollution hurts people's quality of life, such as reduced outdoor time and restricted travel (Frank et al., 2019). This may result in people not being able to fully enjoy the conveniences and entertainment offered by the digital economy, thus reducing the cost of living reduction effect of the digital economy. In summary, severe air pollution increases health costs and wastes resources. It reduces the quality of life, which in turn reduces the effect of the digital economy on reducing the cost of living. In view of this, this paper proposes hypothesis 3.

Hypothesis 3: The worse the air pollution, the weaker the digital economy's effect in reducing the population's cost of living.

3. Model setting and variable description

3.1. Basic model setting

To test the digital economy's impact on the population's cost of living, the following fixed effects model was first constructed:

$$CLI_{it} = \alpha_0 + \beta_1 Dige_{it} + \beta_j \sum X_{it} + \lambda_i + \eta_t + \varepsilon_{it} \quad (1)$$

In equation (1), CLI_{it} denotes the cost of living of the residents of prefecture i in year t. $Dige_{it}$ denotes the level of the digital economy in the prefecture$i$ in year t. X_{it} is a set of control variables, mainly the level of infrastructure (*inf*), foreign direct investment (*fdi*), regional economic level (*rel*), local fiscal expenditure (*gov*), the natural population growth rate (*nat*), and the level of internet penetration (*int*). λ_i is the regional individual effect, η_t is the time effect, and ε_{it} is the residual term. In all regression analyses, individual fixed effects and time-fixed effects were controlled for. This is because the fixed effects are set to some extent to avoid bias in the estimation results caused by omitted variables. To avoid endogeneity issues, historical data on post and telecommunications for

each prefecture-level city in 1984 was used as the digital economy's instrumental variable (*ph*), drawing on Huang et al. (2019). Other control variables were kept consistent with the above.

3.2. Threshold model setting

To verify whether there is a threshold model for the digital economy on quality of life and whether it is affected by air pollution, the article uses the digital economy (*Dige*) and air pollution (*AP*) as threshold variables, and the threshold model is constructed as follows:

$$CLI_{it} = \alpha_0 + \theta_1 Dige_{it} \times I(Dige \le \gamma_1) + \theta_2 Dige_{it} \times I(Dige > \gamma_1) + \beta_j \sum X_{it} + \lambda_i + \eta_t + \varepsilon_{it} \quad (2)$$

$$CLI_{it} = \alpha_0 + \theta_1 Dige_{it} \times I(AP \le \gamma_2) + \theta_2 Dige_{it} \times I(AP > \gamma_2) + \beta_j \sum X_{it} + \lambda_i + \eta_t + \varepsilon_{it} \quad (3)$$

Where, CLI_{it} denotes the cost of living of the residents of prefecture *i* in year *t*. $Dige_{it}$ denotes the level of the digital economy in the prefecture*i* in year *t*. X_{it} is a set of control variables consistent with the previous section. In equation (2), the digital economy *(Dige*) is both the main effect and the threshold variable. In equation (3), air pollution (*AP*) is the threshold variable and is expressed as the PM2.5 concentration value. γ_1 and γ_2 are the magnitudes of the thresholds, λ_i is the regional individual effect, η_t is the time effect, ε_{it} is the residual term, and θ_1 and θ_2 are the coefficients of the threshold model estimates. $I(\cdot)$is the indicative function, satisfying the condition in parentheses, then $I = 1$, otherwise $I = 0$. Equations (2) and (3) consider a single-threshold model, which can be extended to a multi-threshold model by steps such as the measurement test of the sample.

3.3. Variable descriptions and measures

3.3.1. Cost of living levels

The cost of living is a measure of the impact on consumer welfare of external shocks and the resulting adjustments in consumption habits. In cost of living index measures defined by utility levels, it is often necessary to consider the effect of the form of the expenditure function or consumer demand preferences. However, the form of the expenditure function and the level of utility of the consumer is generally difficult to observe directly, as it is shown. And, as consumers face changes in the relative prices of products at different times, then the share of expenditure and the quantity consumed will also change. In addition, there is no micro-database that effectively calculates the cost of living. Referring to previous literature, the total consumer price index is used to reflect the cost of living of the population. To some extent, the CPI is a better indicator of the cost of living index (Fan & Song, 2014; Lee & Argente, 2015; B. Wang & Qian, 2020).

3.3.2. Measurement of the level of the digital economy

Drawing on T. Zhao et al. (2020), five indicators were used: Internet penetration rate, number of Internet-related employees, Internet-related output, number of mobile Internet users, and digital financial inclusion development. The above five indicators relate to the actual content: the number of Internet users per 100 people, the proportion of computer services and software employees, the total number of telecommunications services per capita, the number of mobile phone users per 100 people, and the China Digital Inclusive Finance Index. Table 1 shows the corresponding indicator levels and specifics. The above five indicators were dimensioned using principal component analysis to obtain the Digital Economy Index (*Dige*).

3.3.3. Control variables

To analyze the digital economy's impact more fully on the population's cost of living, it is also necessary to set control variables that impact the cost of living. In order to more comprehensively analyze the impact of the digital economy on the cost of living of the population, this paper sets control variables affecting the cost of living after referring to Gao, Li, and Yu (2022) and Li, Gao, and

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Table 1. Digital economy indicator measurement system

Tier 1 indicators	Tier 2 indicators	Tier 3 indicators	Indicator attributes
Digital economy composite development index	Internet penetration rate	Internet users per 100 population	+
	Number of Internet-related employees	Percentage of employees in computer services and software	+
	Internet-related outputs	Total telecommunications services per capita	+
	Number of mobile internet users	Mobile phone subscribers per 100 population	+
	Digital Inclusive Finance Development	China Digital Inclusive Finance Index	+

Li (2023).The details are as follows: infrastructure level (*inf*), measured in kilometers of main urban roads per person; foreign direct investment (*fdi*), expressed as the ratio of actual foreign investment used in the year to regional GDP; regional economic level *(rel*), expressed as real GDP per capita; local general budget expenditure (*gov*); natural population growth rate (*nat*), expressed as the difference between the birth rate and the death rate (*gov*); and Internet penetration (*int*), expressed as the number of households with Internet broadband access. In this case, infrastructure, regional economic level, local fiscal expenditure, and internet penetration are treated as natural logarithms.

3.4. Data sources and descriptive statistics

The study was conducted for 160 prefecture-level cities in China for the period 2010–2020, using balanced panel data. The data for the relevant indicators used to calculate the digital economy were obtained from the China Urban Statistical Yearbook. Digital inclusive finance, on the other hand, comes from a joint compilation by the Ant Financial Services Group and the Digital Finance Research Centre of Peking University (F. Guo et al., 2020). The General Consumer Price Index, infrastructure, foreign direct investment, local budgetary expenditure in the first budget, natural population growth rate and internet penetration can also be obtained from the statistical yearbooks of each city. Data on PM2.5 concentration values were sourced from the Atmospheric Composition Analysis Group at Dalhousie University, Canada. See Table 2 for specific descriptive statistics on the data involved. Using balanced panel data, the study was conducted for 160 prefecture-level cities in China from 2010–2020. The data for the relevant indicators used to calculate the digital economy were obtained from the China Urban Statistical Yearbook. Digital inclusive finance, on the other hand, comes from a joint compilation by the Ant Financial Services Group and the Digital Finance Research Centre of Peking University (F. Guo et al., 2020). The General Consumer Price Index, infrastructure, foreign direct investment, local budgetary expenditure in the first budget, natural population growth rate, and internet penetration can also be obtained from the statistical yearbooks of each city. Data on PM2.5 concentration values were sourced from the Atmospheric Composition Analysis Group at Dalhousie University, Canada. See Table 2 for specific descriptive statistics on the data involved.

4. Empirical analysis of the impact of the digital economy on the cost of living

4.1. Baseline regression results

Table 3 reports the results of linear estimates of the digital economy's impact on the population's cost of living. Only the core explanatory variable digital economy is added in column (1), and control variables are progressively added in columns (2)-(4). The regression results above all control for time and area fixed effects, avoiding the bias in the estimation results caused by

Table 2. Descriptive statistics

Variable name	Meaning of variables	Sample size	Mean	SD	Min	Max
CLI	Cost of living index	1760	102.5109	1.2287	95.9	106.8
Dige	Digital economy	1760	0.6066	0.0511	0.5008	0.9558
inf	Infrastructure	1760	0.9016	0.2266	−0.2319	1.6317
fdi	Foreign direct investment	1760	0.0196	0.0229	1.8106	0.3722
rel	Regional economic level	1760	2.3744	0.0648	2.2008	2.5708
gov	Financial expenditure	1760	15.0333	0.7866	11.7111	18.2405
nat	Natural population growth rate	1760	4.8699	3.2221	−9.9000	9.4900
int	Internet popularity	1760	4.5106	1.0473	1.3863	7.7249
PM2.5	Concentration values of PM2.5	1760	44.5524	15.2874	17.9306	106.1613
ph	Historical data on post and telecommunications	1760	8.6026	1.1989	5.7893	12.7611

omitted variables as much as possible. As seen in Table 3, the estimated coefficients for the core explanatory variable Digital Economy (*Dige*) are negative, and all pass the 1% confidence level, indicating that the digital economy can significantly reduce the cost of living for the population. In addition, the estimated coefficient on the core explanatory variable, the digital economy, remains significantly negative after the gradual inclusion of the control variables, indicating robust results. Hypothesis 1 is confirmed.

It is worth noting that the spread of infrastructure, foreign direct investment, and the internet has helped to ease the cost of living for residents. The possible reason for this is that infrastructure and FDI have conveniently changed the way of life, the way of travel, and the living environment of the population. The spread of the internet has empowered residents to capture information from the outside world quickly and facilitated the widespread use of internet platforms and digital payments, allowing residents to purchase goods at a lower cost. However, increased local fiscal spending and population growth raise the cost of living for residents. This may be because fiscal expansion causes a crowding-out effect on consumption and drives inflation, further leading to an increase in the cost of living. The increase in household size also leads to additional living costs such as food, clothing, housing, and transportation.

4.2. Threshold model regression results

The panel threshold models constructed according to equations (2) and (3) include the digital economy (*Dige*) and air pollution (*AP*) as threshold variables, respectively, and analyze the heterogeneous impact of the digital economy on the cost of living of residents. Referring to Wang (2015), this study estimated separate econometric models for the single threshold model, the double threshold model, and the triple threshold model to determine the number of threshold values for the threshold variables. Moreover, this paper uses the bootstrap method to calculate the asymptotic distribution of the statistics for each model and to test the significance of the threshold effects.

The estimation results of the threshold model constructed for equation (2) are shown in columns (1) and (2) of Table 4. In addition, this paper also refers to Gao, Li, Li, et al. (2022) and Li, Gao, and Shi (2023) and conducts LR tests related to the threshold model to enhance the credibility of the threshold regression results. The LR tests for columns (1) and (2) are shown in Figures 1 and 2. It was found that there are two thresholds of 0.6018 and 0.6661 in equation (2), making the impact of the digital economy on the cost of living non-linear. The regression coefficient for the digital economy is −10.7149 when the level of the digital economy is below 0.6018, −10.1479 when the

Table 3. Digital economy base regression

	(1)	(2)	(3)	(4)
Dige	−6.8578*** (2.6086)	−6.0450*** (2.2175)	−6.0457*** (2.2058)	−5.8755*** (2.1192)
inf		−0.3378*** (0.1134)	−0.3349*** (0.1164)	−0.3037*** (0.1132)
fdi		−3.9330*** (1.4183)	−4.1272*** (1.4138)	−3.9135*** (1.3747)
rel			−0.0118 (0.1623)	0.0391 (0.1673)
gov			0.2400* (0.1356)	0.2353* (0.1371)
nat				0.0171* (0.0098)
int				−0.1865** (0.0880)
con	107.0924*** (1.4620)	107.5571*** (1.3983)	104.2318*** (2.9876)	104.2081*** (3.0320)
Control variables	No	Yes	Yes	Yes
Individual effects	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes
N	1760	1760	1760	1760
r2	0.7335	0.7419	0.7424	0.7447

Notes: Standard errors are clustered at the prefecture level and are shown in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

digital economy is greater than 0.6018 and below 0.6661, and −9.1491 when the digital economy is greater than 0.6661. In addition, all of the above regression coefficients pass the 1% confidence level, implying that the digital economy can significantly reduce living standards. However, as the level of development of the digital economy increases, the impact of the digital economy on alleviating the cost of living of the population diminishes. Column (1) yields a similar conclusion, indicating robust results. Hypothesis 2 is proved.

The estimation results of the threshold model constructed for equation (3) are shown in columns (3) and (4) of Table 4. Column (4) is treated as a control variable based on column (3). The corresponding LR tests are shown in Figures 3 and 4. For column (4), when the PM2.5 concentration value is lower than 79.8657, the regression coefficient of the digital economy is −5.6739 and significant at a 1% confidence level; when the PM2.5 concentration value is greater than 79.8657, the regression coefficient of the digital economy is −4.4563 and significant at 1% confidence level. This suggests that as air pollution becomes progressively more severe, the impact of the digital economy on the cost of living is diminished. Column (3) also yields similar results, indicating that the conclusion is reliable. Hypothesis 3 is proved.

5. Robustness tests

5.1. Endogeneity test

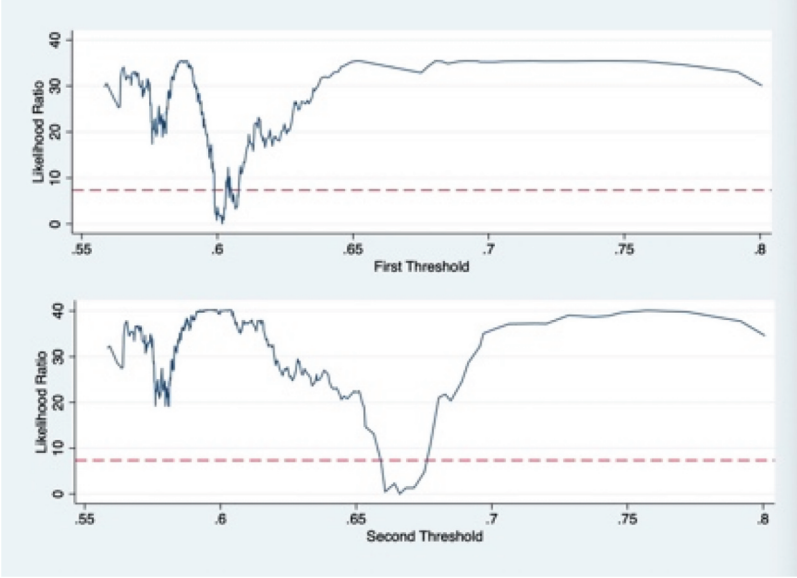
As the factors affecting the cost of living are complex, although this paper has controlled for factors as far as possible, there may be some hard-to-observe factors that can significantly impact the cost of living. To avoid endogeneity problems caused by omitted variables, historical data on post and telecommunications for 160 prefectures in 1984 were selected as instrumental variables for the digital economy indicator, drawing on Huang's approach (Huang et al., 2019). On the one hand, the impact of traditional telecommunication facilities on the cost of living will diminish as the frequency of use decreases, satisfying exclusivity; on the other hand, the Internet as

Table 4. Threshold model tests and estimation results

	(1)	(2)	(3)	(4)
$Dige<\gamma_1$	−12.2947*** (3.3232)	−10.7149*** (2.8616)		
$\gamma_1 < Dige < \gamma_2$	−11.7020*** (3.2229)	−10.1479*** (2.7663)		
$\gamma_2 < Dige$	−10.5051*** (2.9575)	−9.1491*** (2.5274)		
$\gamma_3 < PM_{2.5}$			−6.6614*** (2.5275)	−5.6739*** (2.0608)
$PM_{2.5} > Accessisdenied$			−5.4433** (2.5629)	−4.4563** (2.1020)
Constant	110.3381*** (1.9275)	106.0134*** (3.1030)	107.1201*** (1.4783)	103.7908*** (3.0581)
Single F statistic	108.61***	83.66***	105.80***	81.59***
Single P-value	0.0000	0.0133	0.0000	0.0000
Double P-value	0.0033	0.0000		
Control variables	Yes	Yes	Yes	Yes
Individual effects	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes
N	1760	1760	1760	1760
r2	0.6630	0.6749	0.6573	0.6719

Notes: Standard errors are clustered at the prefecture level and are shown in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Figure 1. LR test for regression in column (1) of Table 4.



a subsequent development of traditional communication facilities, the historical telecommunication infrastructure of the region will have an impact on the application of Internet technology in the future, in terms of usage habits, telecommunication infrastructure, and other factors. In addition, it should be noted that the historical data on post and telecommunications for the 160 prefectures selected are cross-sectional data that cannot be directly applied to the econometric regression of the panel data. Therefore, referring to T. Zhao et al. (2020), a variable that changes over time is introduced to construct the instrumental panel variable. That is, the number of

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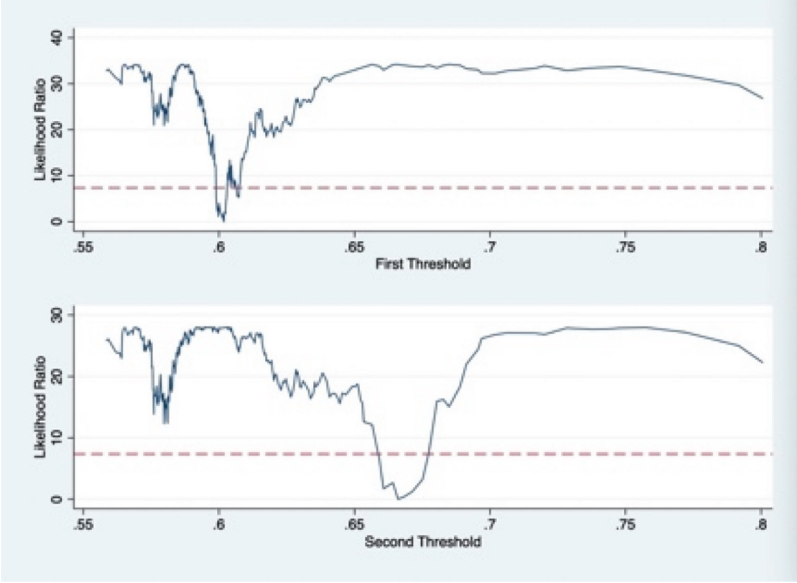
Figure 2. LR test for regression in column (2) of Table 4.



telephone sets per 10,000 people in 1984 for each of the 160 prefecture-level cities was multiplied by the number of national Internet users in the previous year as an instrumental variable for the digital economy indicator for that prefecture. The regression results are shown in Table 5.

The results in the sub-thermal columns (1) and (2) of Table 5 shows that the digital economy's impact on the population's cost of living still holds after accounting for endogeneity. In terms of weak instrumental variable identification, the Wald F statistic is greater than the critical value at the 10% level of the Stock-Yogo weak identification test, indicating that there is no weak instrumental variable problem. Overall, the selection of a cross-sectional term between the number of telephones in each prefecture and the number of Internet users nationwide in 1984 as an instrumental variable is effective in avoiding endogeneity problems caused by omitted variables. It also indicates the reliability of the regression results underlying this paper.

Figure 3. LR test for regression in column (3) of Table 4.

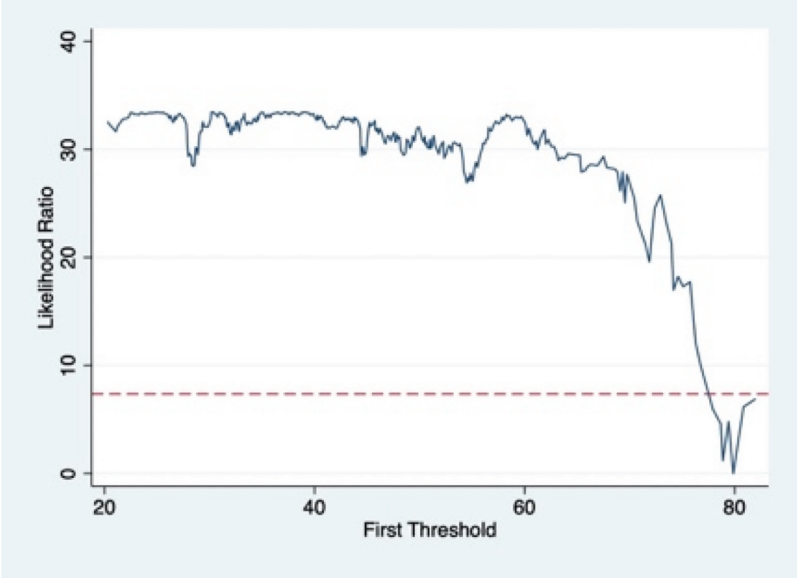


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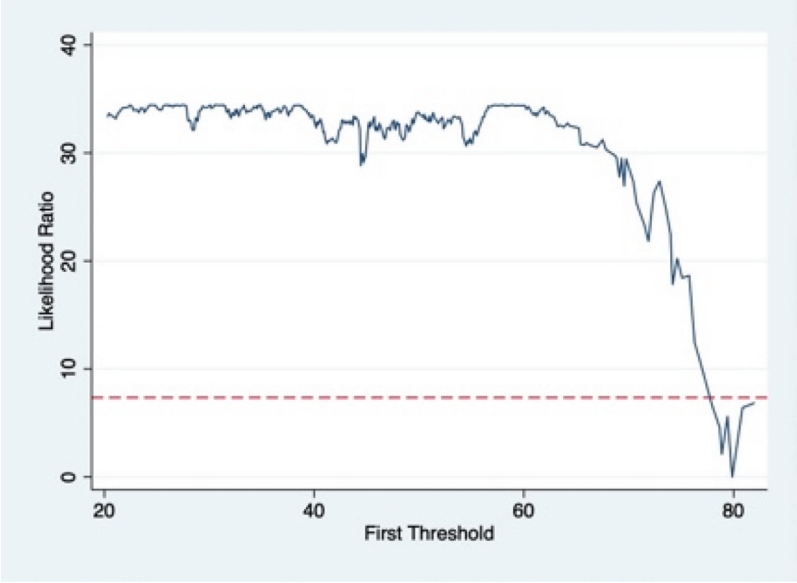
Figure 4. LR test for regression in column (1) of Table 4.



5.2. Robustness tests for the digital economy

To further test the reliability of the regression results of the benchmark model, this paper conducts robustness tests in the following aspects. First, the measurement of the digital economy is changed. Specifically, the measure of the digital economy is changed from the principal component analysis method to the entropy method for measurement and applied to the benchmark model, as shown in column (1) of Table 6. It can be seen that the regression coefficient in column (1) is significantly negative, indicating that the underlying regression results remain reliable after changing the measure of the digital economy. Second, drawing on Zhang et al. (2019), robustness tests were conducted by controlling for variables lagged by one period, which helped to mitigate endogeneity issues due to potential two-way causality. The specific results are presented in column (2) of Table 6. The regression coefficient of *Dige* is significantly negative, indicating that the regression results remain robust after lagging all control variables by one period. Third, 2011–2020 is divided into two time periods, 2011–2015 and 2016–2020, for robustness testing. This division is because the first official definition of the digital economy in China was the G20 Digital Economy Development and Cooperation Initiative released at the G20 Summit in Hangzhou in 2016. Since then, the digital economy has appeared in large numbers in various local government documents, accelerating its development. The specific regression results are shown in columns (3) and (4) of Table 6. It is easy to see that the regression coefficients for columns (3) and (4) are significantly negative, again indicating the reliability of this paper's underlying regressions. However, the regression results for column (3) are more significant than column (4), suggesting that the digital economy significantly reduced the cost of living in 2011–2015. This may be because 2011–2015 was a period of rapid development of the digital economy when many emerging technologies and platforms began to emerge and become widely used. At this stage, the maturity and penetration of the digital economy are relatively low, but its potential and innovation are high. As a result, the digital economy may have a more pronounced effect on reducing the cost of living. Overall, the regression results in this paper remain consistent with those of the previous benchmark model and 2SLS after considering changing the measurement of the digital economy, controlling for the one-period lag of the variables, and dividing two different periods, indicating robust results.

5.3. Robustness tests for threshold models

The digital economy measured by the entropy method continues to be applied to detect threshold models. In addition, this study replaces *PM2.5* with Air Quality Index (*AQI*) and *PM10* concentration

Table 5. Endogeneity test

	(1)	(2)
digital	−7.5665*** (2.0121)	
ph		8.5407*** (1.4807)
con	105.0695*** (2.7236)	0.4749*** (0.1369)
F Statistic Value		33.4682
Control variables	Yes	Yes
Individual effects	Yes	Yes
Time effect	Yes	Yes
N	1760	1760
r2	0.7438	0.7981

Notes: Standard errors are clustered at the prefecture level and are shown in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 6. Robustness tests for the baseline regressions

	(1) CLI	(2) CLI	(3) 2011–2015	(4) 2016–2020
Dige	−2.6638** (1.2068)	−6.6627** (2.2805)	−11.1545*** (3.5989)	−1.0174* (1.2047)
con	100.7457*** (2.5898)	109.1738*** (3.6100)	109.9822*** (8.9497)	95.9339*** (2.5898)
Control variables	Yes	Yes	Yes	Yes
Individual effects	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes
N	1760	1600	1760	1760
r2	0.7325	0.7424	0.7328	0.7540

Notes: Standard errors are clustered at the prefecture level and are shown in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

values for the threshold model of air pollution. The *AQI* and *PM10* data were obtained from the China Air Quality Online Analysis Platform (Wang, 2021) as the platform only provides monthly data for 2014 and beyond; the data used in columns (3) and (4) span from 2014–2020. Referring to Wang et al. (2021), the monthly *AQI* and PM10 data of prefecture-level cities were converted into annual means using arithmetic and applied to model (3). The specific regression results are shown in Table 7. Column (1) shows the regression results for the digital economy threshold model. Columns (2) and (3) show the regression results for air pollution as a threshold variable. Overall, the regression findings from the robustness tests of the threshold models remain consistent with the previous section, indicating that the findings are robust.

6. Analysis of intermediary effects

The next step is also to answer what are the pathways through which the digital economy contributes to the cost of living of the population. Research has shown that the digital economy can provide advanced detection and data analysis techniques to help detect and manage environmental pollution (Luo et al., 2022). Through digital technology, governments and businesses can get a more accurate picture of environmental conditions and develop more effective environmental regulation policies. Strict environmental regulations can reduce sources of pollution, improve air quality and water quality, and reduce health problems and costs associated with environmental pollution for people. In addition, the development of the digital economy has enabled the

Table 7. Robustness tests for the threshold model

	(1)	(2)	(3)
Dige <Threshold	−5.0558*** (1.6270)		
Threshold < Dige	−2.9969** (1.1574)		
AQI<Threshold		−4.1230** (1.5986)	
Threshold <AQI		−3.4609** (1.5960)	
PM10<Threshold			−3.9813** (1.6239)
Threshold<PM10			−2.8661* (1.6254)
con	101.1723*** (2.5298)	101.8973*** (3.6139)	101.1543*** (3.6623)
Single F statistic	85.64***	42.64***	41.31***
P Value	0.0167	0.0033	0.0000
Control variables	Yes	Yes	Yes
Individual effects	Yes	Yes	Yes
Time effect	Yes	Yes	Yes
N	1760	1120	1120
r2	0.6660	0.3953	0.4063

Notes: Standard errors are clustered at the prefecture level and are shown in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

healthcare industry to use technologies such as big data analytics and artificial intelligence to improve healthcare. For example, telemedicine technology can make communication between doctors and patients easier and reduce the cost and time of medical care for patients. Digital technology can also improve the accuracy and efficiency of medical diagnosis and treatment, reduce the incidence of medical errors, and reduce medical costs and hospital stays. The digital economy can theoretically reduce the cost of living for residents through environmental regulation and the level of healthcare. In terms of empirical testing, following the approach of Jiang Jiang (2022), in order to avoid the controversy regarding the mediating effect, this paper only adopts regression analysis on the effect of the digital economy on environmental regulation and medical level, while the effect of environmental regulation and medical level on the cost of living is analysed theoretically, where the theoretical analysis is explained in detail at the beginning of this paragraph.

In terms of environmental regulation (*ER*), the frequency of words related to "environmental protection" in local government work reports as a proportion of the total number of words in the local government reports is used as a proxy variable for environmental governance, following Deng et al. (2019). To verify that the development of the digital economy can reduce the cost of living through environmental regulation, environmental regulation is used as the explanatory variable, the digital economy is used as the explanatory variable, and the other control variables remain the same as in the previous section. The regression results are shown in columns (1) and (2) of Table 8. The regression coefficients for the digital economy are all significantly positive at the 5% confidence level, indicating that the digital economy can reduce residents' living costs through environmental regulation.

Regarding healthcare levels (*HL*), the number of healthcare beds per 10,000 people is used to measure the region's healthcare level. Studies show that the digital economy helps improve the healthcare system and the healthcare protection system (H. Li & Zhao, 2023). By promoting the

Table 8. Intermediary effects regression results

	(2) *ER*	(3) *ER*	(4) *HL*	(5) *HL*
Dige	0.0046** (0.0020)	0.0037** (0.0017)	0.9781* (0.5019)	0.8017** (0.3935)
con	0.0003 (0.0011)	0.0005 (0.0056)	2.5620*** (0.2855)	0.7474 (0.7342)
Control variables	No	Yes	No	Yes
Individual effects	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes
N	1760	1760	1760	1760
r2	0.3627	0.3813	0.9088	0.9160

Notes: Standard errors are clustered at the prefecture level and are shown in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

integration of digital resources with essential public services such as healthcare, the digital economy promotes the balanced development of healthcare services and the digitization of healthcare. A well-developed healthcare system and services can enable residents to seek medical treatment close to their homes, alleviate the problems of complex and expensive access to medical care, and reduce or eliminate non-essential medical expenses. Therefore, to verify that the digital economy can reduce residents' cost of living by improving healthcare, the same approach as environmental regulation is adopted here, and the results are presented in columns (3) and (4) of Table 8. The regression coefficients for the digital economy are significant, at least at the 10% confidence level, indicating that the digital economy can mitigate the cost of living of the population by enhancing the level of physical healthcare.

7. Conclusions and policy implications

7.1. Conclusions

Using data from 160 prefectures as a sample, the digital economy's impact on residents' cost of living is explored using a fixed utility model, a two-stage least squares model, and a panel threshold model. The study found that the digital economy can significantly reduce the cost of living for residents and has become an important factor in reducing the cost of living, improving their welfare and well-being in the new era. This finding still holds after a series of endogeneity and robustness tests, including the introduction of instrumental variables. Secondly, the impact of the digital economy on the cost of living shows a non-linear trend of diminishing "marginal effects". As the level of the digital economy increases, the extent to which the digital economy reduces the cost of living decreases. Third, air pollution can undermine the ability of the digital economy to reduce the cost of living. This is because air pollution can raise the cost of the additional payments that residents have to make for the anti-pollution measures, they take to deal with environmental pollution. Fourth, the digital economy reduces the cost of living through environmental regulation and improved healthcare, i.e., environmental regulation and healthcare are the channels through which the digital economy affects the cost of living.

7.2. Policy implications

Based on the above findings, the following policy recommendations are made:

The first is to promote the development of the digital economy. The government should promote the development of the digital economy, including providing support for innovation and entrepreneurship, strengthening digital infrastructure, and promoting the application of digital technology. By upgrading the digital economy, the effect of reducing the cost of living can be further enhanced.

The second is to formulate environmental protection policies. The government should increase its efforts to combat environmental pollution, formulate and implement strict environmental protection policies and reduce air pollution. This will help reduce the additional costs that residents have to pay to cope with environmental pollution, thus enhancing the ability of the digital economy to reduce the cost of living.

The third is to provide environmentally friendly solutions for the digital economy. The government can encourage environmentally friendly solutions in developing the digital economy, such as applying green energy and technological innovations for energy conservation and emission reduction. These solutions can reduce the cost of living while reducing the negative impact on the environment.

The fourth is to provide education and training for residents. The government can enhance education and training for residents on the digital economy and improve their knowledge and application. This will help residents to utilise the opportunities of the digital economy better, reduce the cost of living, and enjoy the benefits of the digital economy.

These policy recommendations aim to enhance further the cost of living reduction effect of the digital economy and reduce the debilitating effect of air pollution on the digital economy. Through these measures, the welfare and well-being of residents can be promoted, and the more significant benefits of the digital economy for residents in the new era can be realised.

8. Future research and limitations

Research on the digital economy currently focuses on total factor efficiency, economic growth, and the environment. However, research on the digital economy regarding people's well-being still needs more research. Therefore, this paper will focus more on what impact the digital economy brings to people's lives in future research and whether it will improve people's life satisfaction and happiness. These are all areas that need further research in the future. In fact, some things could be improved in this paper. For example, in terms of constructing indicators for the cost of living in this paper, the cost of living should be a comprehensive indicator, and the factors it contains are complex and varied. According to the classical definition of Konus (1939), calculating the cost of living needs to involve people's consumption utility. However, the utility of people's consumption is difficult to measure and is more of a perception. At the same time, measuring the cost of living also implies the need for a micro-database associated with it, which has yet to be established in our country in a working way.

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