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Identifying the Spatiotemporal Differences and Driving Forces of Residents' Consumption at the Provincial Level in the Context of the Digital Economy

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Abstract: The digital economy has become a new form of the economy. Based on data from the *China Year Book* from 2012 to 2020, this paper characterizes China's spatial differences in regional consumption expenditure in the context of the digital economy. We utilize the GIS spatial analysis technique, ESDA, Geodetector, and other spatial econometric tools to reveal the spatiotemporal evolution patterns and driving mechanism of residents' consumption development in the context of the digital economy for 31 provinces in China and propose differentiated policy suggestions for residents' consumption development against the background of the digital economy in China, creating a reference for decision making on residents' consumption in China. The findings show that, first, provincial residents' consumption expenditures appear to decrease on a gradient from eastern to central and western China, showing extreme polarization and spatial aggregation. Second, the power of the seven driving factors of residents' consumption varies widely across time; the driving factors representing the digital economy can reduce the regional differences in residents' consumption. On the other hand, non-digital economic factors increase the spatial difference. Third, two digital economic factors play the most important roles in the interaction effect in most years.

Keywords: digital economy; residents' consumption expenditure; spatiotemporal differences; driving factors; geodetector

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Citation: Wei, Q.; Wang, C.; Yao, C.; Wang, D.; Sun, Z. Identifying the Spatiotemporal Differences and Driving Forces of Residents' Consumption at the Provincial Level in the Context of the Digital Economy. *Sustainability* **2022**, *14*, 14227. https://doi.org/10.3390/su142114227

Academic Editors: Lucia Porcu and Nuria Rodríguez-Priego

Received: 7 August 2022
Accepted: 19 October 2022
Published: 31 October 2022

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1. Introduction

1.1. Background

Consumption is considered the central process of the economy in economic theory [1]. Residents' consumption consists of the goods and services used by individual households or the community to satisfy their individual or collective needs or wants. Residents' consumption refers to the extent to which resources meet the needs of people's survival, development, and enjoyment in the consumption process of physical products and services [2,3].

The contribution rate of residents' consumption expenditure to economic growth in 2019 was 57.76% [4], which exceeded the sum of the contributions of investment and export. Consumption has increasingly become an important means to promote economic growth. Conforming to the development trend of consumption, further tapping consumption potential, and continuously expanding consumption demand are important conditions for maintaining the sustained and healthy development of China's economy and for improving people's quality of life.

The term digital economy was first mentioned in Japan and proposed by Don Tapscott in 1995 [5]; it is driven by the convergence of information, computing, and communication, which lead to the extensive growth of e-commerce, new competitive strategies, and changes in business processes and organizational structures [6]. With the appearance of the digital

economy, scholars have proposed new definitions and characteristics for it. For instance, the digital economy is a special economic form, and its nature is that goods and services are digital trade-in forms [7]. A digital economy is an economy in which the production, sales, and consumption of goods and services depend on the network of electronic means based on an intermediary information flow [8]. It is an economy that operates through digital technology, including technical facilities, and e-commerce [9]. The digital economy's key resource is information, a series of economic and social activities carried out by people through the Internet and related technologies [8,10]. Compared to agriculture, industry, and other industries, the digital economy is an emerging industry [11], and owing to its short development period, the digital economy system is not perfect [12]. The OECD (2020) defined the digital economy as all economic activities that are based on or through the application of digital input for their enhancement [13]. With the transformation from the traditional economy to the digital economy, how the digital economy affects residents' consumption in China has become an important topic. The digital economy is an economic model succeeding the agricultural economy and industrial economy, with the network as the carrier, digital information as the element, online service as the model, and sharing economy as the direction [14].

At present, the digital economy has penetrated all fields of society, causing major changes in the economic environment and form. By 2020, the scale of China's digital economy had reached CNY 39.2 trillion, and the proportion of the GDP jumped from 27% in 2015 to 38.6% in 2020 [15]. In the first half of 2021, the online retail sales of physical goods reached CNY 5026.3 billion, a year-on-year increase of 18.7%, accounting for 23.7% of the total retail sales of social consumer goods [16]. It can be seen that the digital economy is comprehensively reconstructing the development mode and pattern of China's economy. Therefore, strengthening the research on the effect of the digital economy on residents' consumption expenditure and unearthing the trends and laws of consumption development are important ways to promote the sustainable growth of consumption. It has important theoretical and practical significance for revealing the internal mechanism of the digital economy on residents' consumption [17].

1.2. Literature Review

Some scholars have studied the impact of the digital economy on household consumption from different perspectives, such as its impact on upgrading household consumption and consumption structure [18–22], consumer behavior [23–26], consumption level, circulation field [4,27], and upgrading the industrial structure [28]. Some studies have focused on the influence of the digital economy on demand and consumption [2,29–35], business models [36–39], and background characteristics of the digital economy [40,41]. As for how the digital economy influences residents' consumption, it leads to changes in the quality, content, price, and accurate matching of residents' consumption [14,24,42]; the Internet eliminates the problem of asymmetric consumption information and accelerates the upgrading of residents' consumption [4,18,40,43,44]. The changes in consumer psychological demand, consumer motivation, and consumption mentality are the internal causes of the changes in the characteristics of residents' consumption behavior against the background of the digital economy [32,37,45]. The resident network under the digital economy is more inclined to geographical space and cost saving, and online consumption produces a community effect [35,46,47].

The spatial effect is an important concern of many scholars, and this paper comments on the relevant literature from two aspects: the research subject and research methods.

In terms of the subject of spatial effect, research in this area is still in its infancy. Some scholars have used panel data to explore the impact and spatial effects of the development of digital finance on residents' consumption [48,49]. The empirical results have shown that there is a significant spatial spillover effect on residents' consumption. Digital finance can promote residents' consumption levels in this region, and there is also a significant positive spillover effect [50–52]. Zhang and Tu (2017) [53] empirically studied the differen-

tial impact of Internet finance and the development of various fields on Chinese residents' consumption behavior and structure. Tan, Li, and Zhu (2022) found that Internet penetration significantly reduced the degree of regional consumption differences in China [54]. Their results indicate that Internet penetration can narrow the regional consumption gap by alleviating the degree of income differences and reducing the consumer price index. This inhibitory effect showed distinct heterogeneity owing to different income levels, geographical distribution, and development characteristics. Wang (2022) analyzed the spatial autocorrelation between the digital economy and consumption upgrading, further discussing the spatial agglomeration characteristics of consumption upgrading; the results indicate that there is an obvious spatial autocorrelation between the digital economy and consumption upgrading [55]. Wei (2022) analyzed the topological characteristics and driving factors of provincial residents' consumption spatial spillover network. The results show that the spatial spillover network has the characteristics of neighborhood spillover and club convergence; moreover, spatial adjacency, residents' disposable income, urbanization level, consumer credit, and consumption environment similarity have significant driving effects on the spillover correlation of the consumption level [56]. Xu (2021) theoretically analyzed the role of digital economic development in influencing residents' consumption inequality and empirically examined the cracking effect of digital economic development on regional consumption inequality by using the dynamic panel model. The research discovered that the development of the digital economy has different cracking effects on consumption inequality in different regions [47]. Shen (2020) empirically tested the promotion effect of "Internet + retail" on consumption upgrading and its regional differences. The research found that "Internet + retail" has a significant positive effect on the scale and quality of consumption in the Yangtze River delta, and there are also significant regional differences [57]. Li and Huang (2022) empirically examined the direct impact of the digital economy on service consumption and the spatial spillover effect by using the spatial Durbin model. The research showed that the development of the digital economy can not only promote the growth of local residents' service consumption expenditure, but also have a significant positive spatial spillover effect on residents' service consumption expenditure in neighboring areas [58]. Hu (2020) studied the logical mechanism of the impact of mobile payment on Chinese residents' consumption. It was found that mobile payment can reduce the transaction costs of consumers, ease the mobility constraints of residents, and reduce the psychological loss of consumers when they pay; it can then improve the consumption intention and stimulate residents' consumption. The research results also show that mobile payment has a positive pull effect on the total consumption expenditure of Chinese residents, and the impact of mobile payment on the consumption of Chinese residents is heterogeneous in different regions, on different income levels, and at different ages [59]. Jiao and Sun (2021) used the extended linear expenditure model (ELES) to measure consumption upgrading and explored the link between digital economic development and consumption upgrading. The research found that digital economic development plays a leading role in promoting consumption upgrading; the development of the digital economy realizes consumption upgrading by improving residents' ability to cope with risks, alleviating their current liquidity constraints, and improving network-based convenient services. Moreover, the development of the digital economy has a positive spatial spillover effect on consumption upgrading, and both the direct effect and the total effect are positive [44]. Based on the essential function of consumer finance, Ma and Han (2017) analyzed the impact of Internet consumer finance on the consumption behavior of urban residents in China. The research results show that the generation and development of the Internet consumer finance model can positively promote the consumption behavior of urban residents in China; moreover, there are regional differences in the impact of Internet consumer finance on the consumption behavior of urban residents in China [60].

In terms of experimental methods, previous studies have used many mainstream ones such as: the fixed effect model [57,58,61], system GMM [44,47,54,62], quantile and intermediary effect model [48,55], simultaneous equation model and OLS [55,59], static

and dynamic panel GMM method [60,61], propensity score matching [2,59], ELES model and dynamic spatial Durbin model [44,51], gravity center analysis, spatial autocorrelation analysis [55], spatial panel measurement, geographically weighted regression [50], the spatiotemporal double fixed effect spatial Durbin model [52], VAR model and complex network analysis method [56], and the Thiel index and dynamic panel model [47,58], etc.

However, there are gaps in the existing relevant literature. First, most empirical studies merely emphasize the spatial effect of the digital economy's impact on residents' consumption, while ignoring the analysis of spatiotemporal evolution, which is limited and challenging when reflecting the characteristics and internal mechanism of the spatiotemporal difference in an intuitive and accurate way. In the actual operation of the social economy, the digital economy itself has the characteristics of crossing region and time, so a spatiotemporal analysis must be supplemented. Second, most existing studies on the impacts of residents' consumption differentiation are based on traditional statistical methods, which cannot demonstrate and explain the complex spatiotemporal impacts, for instance, when many driving factors have the effect of interaction enhancement. This paper fills the research gap by combining the spatial and temporal evolution of residents' consumption in the context of the digital economy using a nonlinear statistical method. Therefore, we selected the panel data of 31 provinces in China from 2012 to 2020 and used Moran's *I* and Geodetector to empirically analyze the spatiotemporal effect produced by the process of residents' consumption led by the digital economy, so as to provide a reference for the coordinated development of the regional economy.

Accordingly, this paper focuses on the following issues: (1) What spatiotemporal patterns and effects on residents' consumption development against the background of the digital economy at the provincial level in China can be found by mining features of residents' consumption expenditure? (2) What are the driving factors affecting residents' consumption in the context of the digital economy? What are the driving factors of interaction? How do their driving mechanisms perform? (3) How do we provide differentiated policy suggestions for effective delivery of residents' consumption in the context of the digital economy at the provincial level in China based on the two findings above?

1.3. Research Methods and Paper Organization

To resolve these questions, the research consisted of five steps. Step 1 involved the research question, where the research objectives and problems of this paper were put forward and confirmed based on the background analysis and literature review. Step 2 concerned the study area, variables selection, and data processing. Step 3 dealt with research methods, where the spatial cluster, global Moran's *I*, and local Moran's *I* of residents' consumption at the provincial level were calculated by Stata 16, ArcGIS 10.2, and Python 3.7. Step 4 was the analysis of the results, where the spatiotemporal characteristics of residents' consumption were reflected by spatial differentiation analysis, spatial cluster analysis, and spatial autocorrelation analysis. The driving factors of residents' consumption were calculated by Geodetector based on its factor detection, ecological detection, and interaction detection methods. Step 5 presented our conclusions and suggestions, where the conclusions were drawn based on results, and policy recommendations put forward on optimizing the development of residents' consumption according to the analysis of different regions.

The remainder of our paper is organized as follows. Section 2 demonstrates the study area and data source. Section 3 explains variable selection, research models, and methods. Section 4 analyzes the data and explores the spatial differences in residents' consumption using global and local spatial autocorrelation analysis with scatter plots. Section 5 analyzes the driving factors of spatial differences in residents' consumption using Geodetector. Finally, Section 6 concludes the paper and proposes policy implications.

2. Study Area and Data Source

2.1. Study Area

The study in this paper covered 31 provinces and municipalities directly under the central government and autonomous regions in mainland China, excluding Taiwan, Hong Kong, and Macau (see Figure 1).



Figure 1. Study Area.

2.2. Data Sources

To ensure the unity of the analysis data, this paper used 31 provincial panel data from 2012 to 2020 as the research sample (except for insufficient data in Hong Kong, Macao, and Taiwan). The data were taken from the *China Statistical Yearbook* and *China Regional Financial Operation Report*. The data for a few years were filled by extrapolation or interpolation of adjacent years. The data quality was high, so the calculated value was reliable. The variable data in this paper were obtained directly by using public statistical data or simple operations.

2.3. Residents' Consumption Distribution

Residents' consumption in China's provinces has grown from 2012 to 2019, with a national average growth rate of 8.5%. However, under the effects of COVID-19, residents' consumption experienced a decline in 2020, with a national average growth rate of −1.6% in that year (see Figure 2).

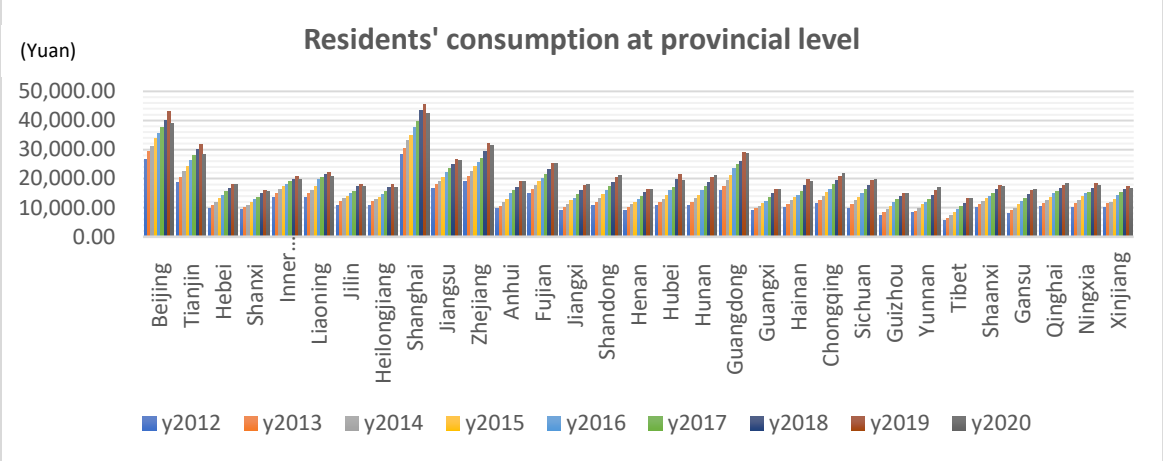


Figure 2. Bar chart of residents' consumption at the provincial level.

Using the Jenks natural breaks classification (a data classification method designed to optimize the arrangement of a set of values into "natural" classes), the provincial residents' consumption data were divided into four levels. From the perspective of spatial distribution, the distribution of provincial residents' consumption was generally characterized by high levels in the eastern coastal areas and low levels in the central and western regions. In 2012, the distribution was more balanced than in subsequent years. From 2014 to 2018, most provinces in the eastern region remained at the same level, while Inner Mongolia, Hebei, Henan, Jiangxi, and Shaanxi in the central region declined. The level of consumption in Xinjiang also declined from 2018. In 2020, influenced by COVID-19, the levels of Heilongjiang, Jilin, Qinghai, and Ningxia also decreased (see Figure 3).

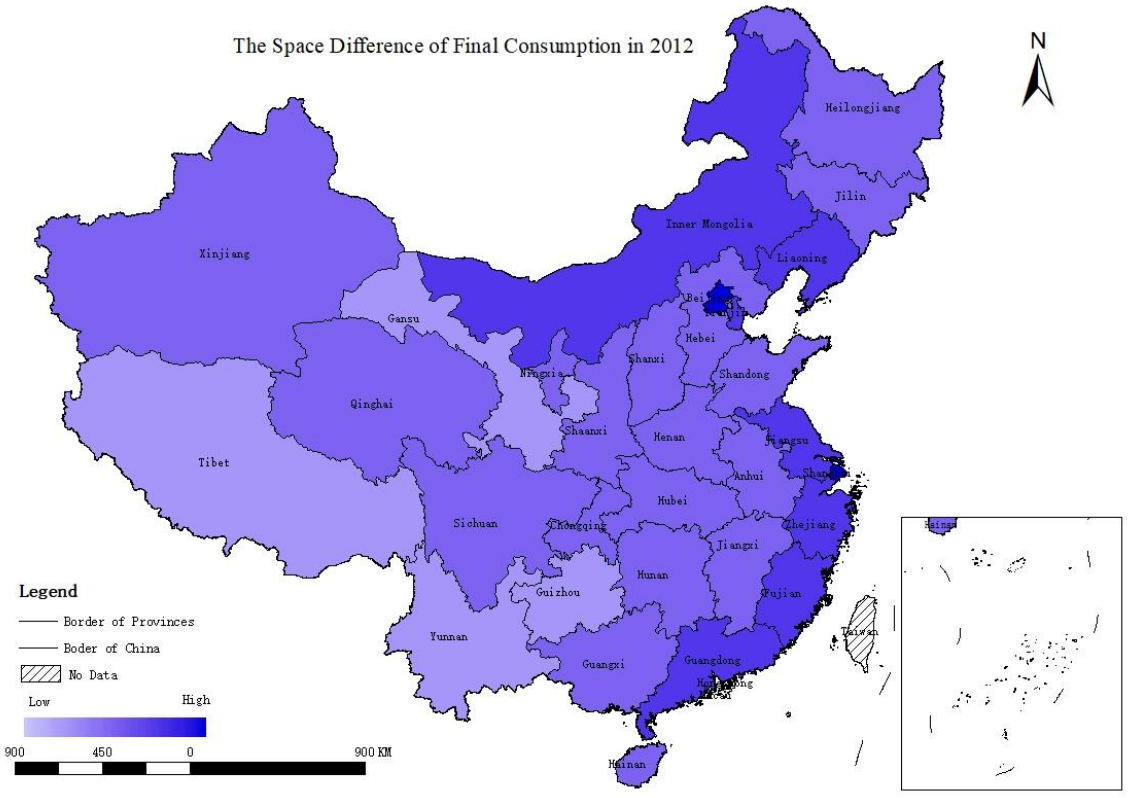


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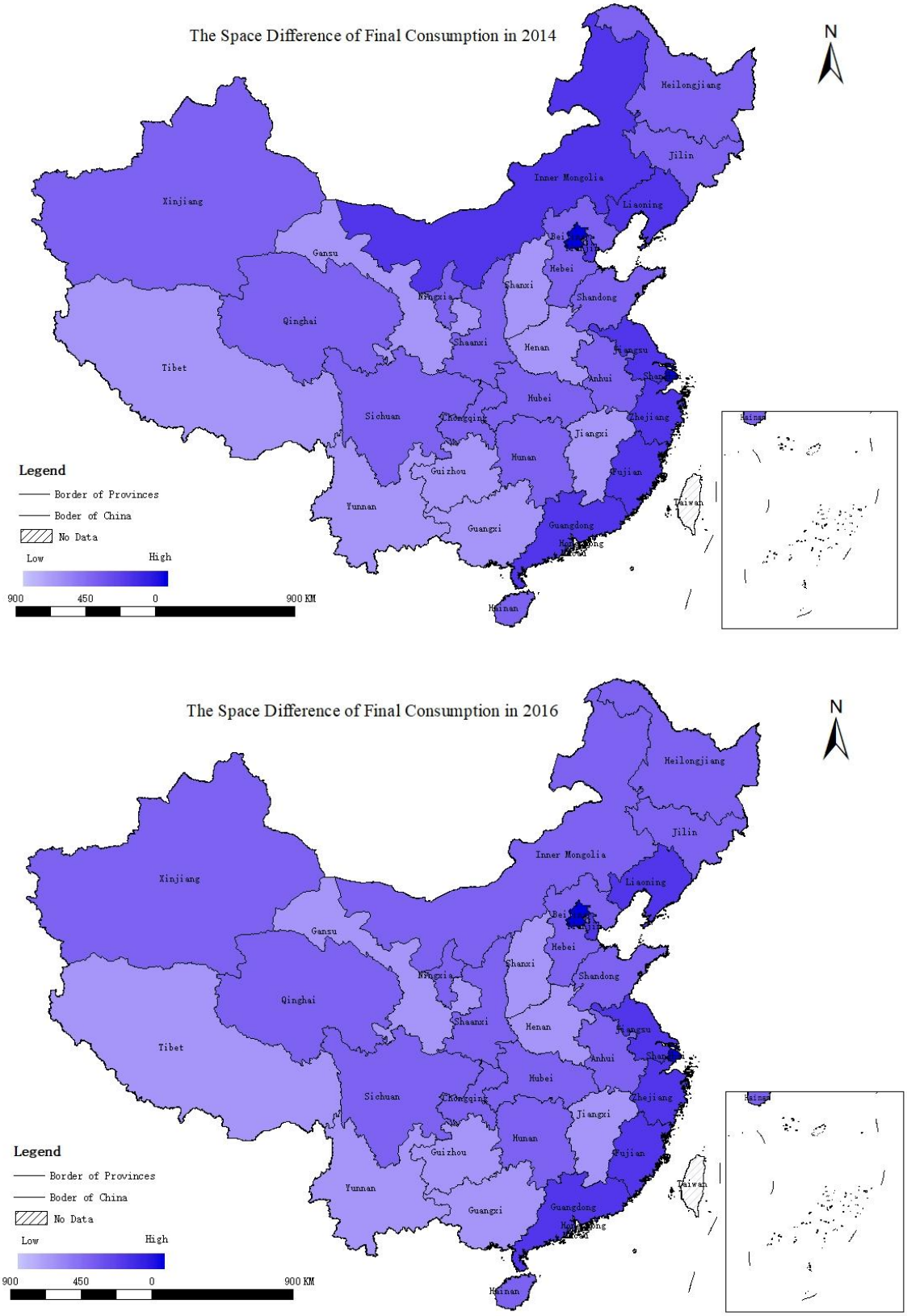


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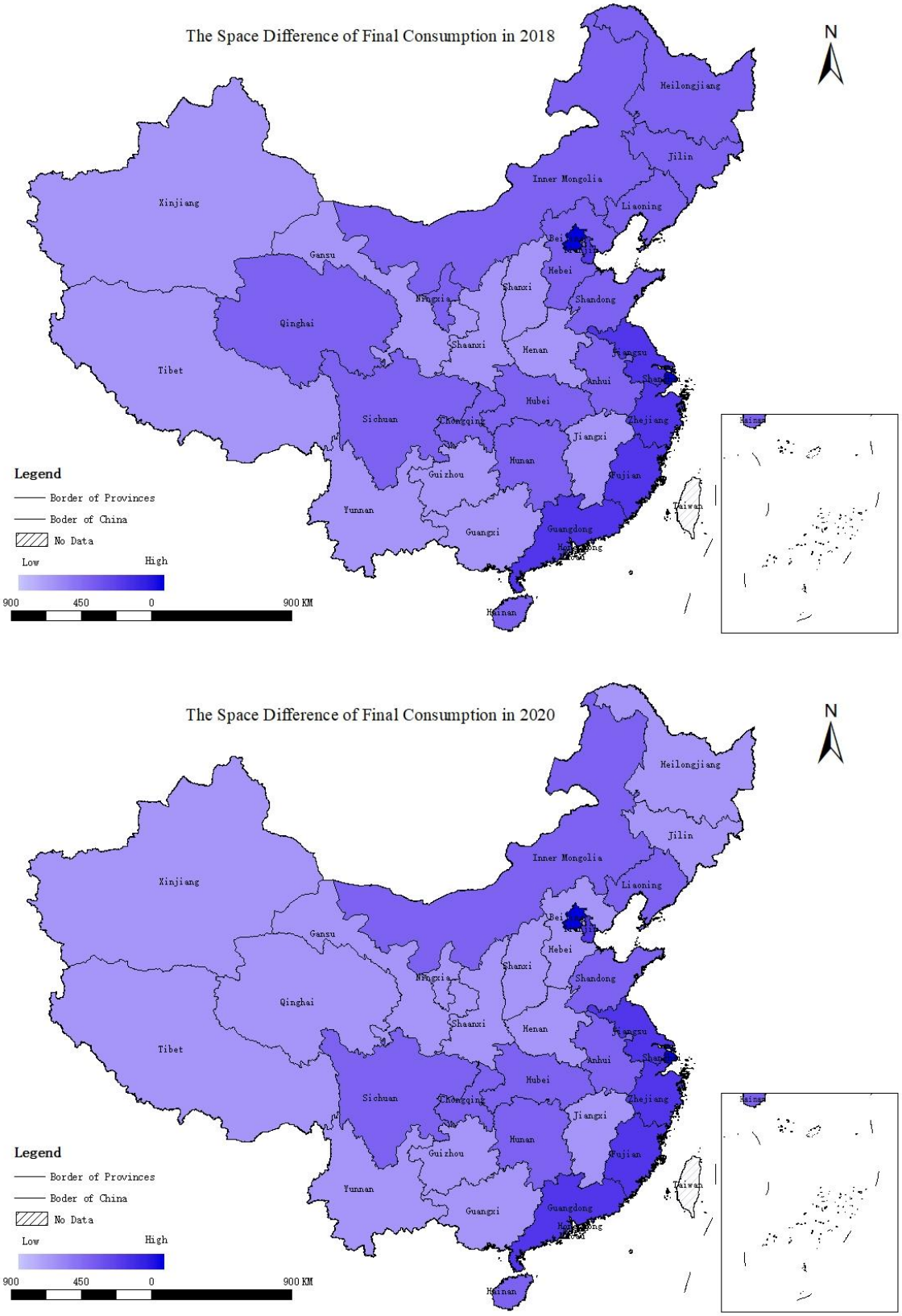


Figure 3. Residents' consumption distribution at the provincial level.

3. Model Setting

3.1. Variable Selection

With the development of China's economy, both residents' income and consumption expenditure have grown [63]. According to Keynes' absolute income theory [1] and the life cycle hypothesis income consumption theory [2] regarding residents' income level, urbanization affects residents' consumption decisions to varying degrees. Many empirical studies have been carried out on the impact of per capita disposable income [4,64–66], per capita GDP [4,67,68], and urbanization level [4,48,65,66,69] on residents' consumption using Chinese data.

In addition, according to this theory, under normal circumstances, the rise of online shopping platforms, the rise of post and telecommunications business volumes, and the popularity of mobile phones in the total demand function have shifted the consumption field of domestic residents from physical stores to e-commerce platforms [70]. The popularizing rate of mobile phones is a measure of the popularity of smart phones [71]. With the continuous strengthening of the functions of smart phones and the significant improvement of the Internet speed of smart phones [55], the number of Chinese Internet users using mobile phones to surf the Internet and the proportion of mobile phones available to surf the Internet have reached a high proportion, indicating that mobile phones have become the mainstream way to navigate the Internet [72]. As an important indicator of the application level of the digital economy in the field of consumption [73], the per capita post and telecommunications business volume has the advantages of strong data consistency and easy access [18]. According to the above considerations and referring to some papers, this paper selected the mobile phone penetration rate [21,44,47,55–60,72] and per capita post and telecommunications business volume [18,73,74] to measure the level of the digital economy.

The development of digital payment has changed the payment methods of residents in their daily lives. The changes in consumption fields and payment methods have not only affected consumers' consumption ideas [75], but also made digital consumer finance grow and develop rapidly. Compared with traditional consumer finance, the personal digital consumer credit model is more flexible and diverse and more popular with consumers [76–78]. Personal digital consumer credit weakens the credit constraints of residents and enables them to complete cross-period consumption through mobile terminals [79,80], which plays a positive role in improving residents' consumption levels [60,77]. In order to study the impact of personal digital consumption credit on various consumer expenditures of residents, this paper selected the payment subindex of the Peking University Digital Inclusive Financial Index to express the digital payment level (DP) and used the credit subindex of the Peking University Digital Inclusive Financial Index to express the personal digital consumption credit level (dicc) [80].

With reference to these papers, we know the variables mentioned above all have an important impact on residents' consumption. However, in most articles, variables representing the digital economy and variables representing the non-digital economy are studied separately, and few works of literature combine them for comparative study, which made it difficult for us to determine the difference and the impact characteristics of the variables between digital economy factors and non-digital economy factors in residents' consumption. Therefore, the seven variables related to residents' consumption were finally screened through exploratory spatial data analysis (ESDA) (see Table 1), including four variables representing the digital economy (*mpr*, *pcptv*, *dp*, *dicc*) and three non-digital economy variables (*pgdp*, *ul*, *pdci*), so that we could analyze and compare digital economic variables with non-digital economic variables. This paper applied the per capita residents' consumption of each province as the proxy of residents' consumption (Y).

Table 1. Driving factors of provincial consumption expenditure.

Variable Type	Variable Name	Description	Computation
Dependent Variable	*Y*	residents' consumption expenditure	per capita residents' consumption of each province in China
Independent Variable	*pgdp*	per capita GDP	regional GDP/total population at the end of the year
	ul	urbanization level	the proportion of the urban population at year end = urban population at year end/total population at year end
	pdci	per capita disposable income	–
	mpr	mobile phone penetration rate	–
	pcptv	post and telecommunications services per capita	total post and telecommunications services/regional population at year end
	dp	digital payment level	using the payment subindex of the Peking University Digital Financial Inclusion Index [80]
	dicc	digital finance individual consumption credit level	using the credit sub-index of the Peking University Digital Financial Inclusion Index [80]

3.2. Global Spatial Autocorrelation Model

Global Moran's *I* identified the overall spatial dependence of residents' consumption in each province within the study area.

Moran's *I* is considered the most common method to obtain quantitative results and to explore the spatial autocorrelation among samples [81]. Moran's *I* has been widely applied to examine spatial patterns, such as clustered, dispersed, or random distribution. The global spatial autocorrelation is mainly used to measure whether there are aggregation characteristics of residents' consumption expenditure at the provincial level. It is measured by Moran's *I*. The calculation formula is as follows:

$$I = \frac{n \times \sum_{i=1}^{n} \sum_{j \neq 1}^{n} W_{ij}(x_i - \overline{x})(x_i - \overline{x})}{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}\right) \times \sum_{i=1}^{n} (x_i - \overline{x})^2} \quad (1)$$

where *I* is Moran's *I*, $n = 31$, X_i and X_j represents the per capita consumption expenditure of i and j, $\overline{x}$ represents the average of each province, $(x_i - \overline{x})(x_i - \overline{x})$ represents the similarity of the per capita consumption expenditure of province i and j, and W_{ij} is the position weight matrix of provincial elements i and j. If $W_{ij} = 1$, then province i and j are contiguous, else if $W_{ij} = 0$, they are not contiguous. The contiguity-based method is applied to identify the weight matrix. The value of Moran's *I* ranges from -1 to 1, and positive (negative) values indicated positive (negative) spatial autocorrelation.

3.3. Local Spatial Autocorrelation Model

Local Moran's *I* can reflect the local spatial autocorrelation of residents' consumption in provinces of China; local spatial autocorrelation can measure whether the similar value (high or low value) of provincial residents' consumption expenditure has agglomeration in local space. A Moran scatter diagram is used for analysis, and the calculation formula of local Moran's *I* is as follows:

$$I_i = \frac{(x_i - \overline{x})}{m_0} \sum_{j} W_{ij}(x_j - \overline{x}) \quad (2)$$

where x_i is the average per capita consumption expenditure of the ith province, and $\overline{x}$ is the average per capita consumption expenditure of the 31 provinces. The sum of j includes all neighbors of province i. If $I_i > 0$, this indicates the spatial agglomeration of provinces with similar consumption expenditure in a region; if $I_i < 0$, this indicates the spatial agglomeration of provinces with different consumption expenditure in a certain region. The Moran scatter diagram is often used to analyze local spatial instability, representing four types of local spatial relationships between a province and its surrounding provinces, which are H–H, L–H, L–L, and H–L. H–H (High–High) means that provinces with high consumption expenditure are mainly surrounded by provinces with high consumption expenditure. L–H (Low–High) means that provinces with low consumption expenditure are mainly surrounded by provinces with high consumption expenditure. L–L (Low–Low) means that provinces with low consumption expenditure are mainly surrounded by provinces with low consumption expenditure. H–L (High–Low) means that provinces with high consumption expenditure are mainly surrounded by provinces with low consumption expenditure.

3.4. Geodetector

Geodetector is a set of statistical methods to reveal spatial difference and its driving force. This method can detect both numerical data and qualitative data. It is widely used in the evolution of geographical element patterns and regional spatial differences [82]. Its core idea is based on the assumption that if an independent variable has an important impact on a dependent variable, the spatial distribution of the independent variable and the dependent variable should be similar [62,83]. The Geodetector model does not need a linear hypothesis, is collinear-immune to multiple independent variables, and can accurately identify the bi-factor interaction [83,84]. The judgment of the relationship between dependent variables with a small sample size and influencing factors is more reliable than the classical linear regression model, especially when the sample size is less than 30. At the same time, it can detect the global driving force (the independent variable corresponding to the maximum q-value) [85]. It can also detect local driving forces in different regions. In addition, Geodetector detects the real interaction between the two variables, not limited to the multiplicative interaction specified in advance by econometrics [82]. In this paper, factor detector, interaction detector, and risk detector in Geodetector [82] are used for the analysis.

3.4.1. Factor Detector

Factors can impose significant impacts on the specific area when the geographical aspects have significant consistency, making them the driving forces for the region. In this case, factor detection is used to measure the spatial difference in residents' consumption in provinces and the degree of explanation of various driving factors of the spatial difference in consumption. It is measured by the q-value, and the calculation formula is as follows:

$$q = 1 - \frac{1}{N\sigma^2} \sum_{h-1}^{L} N_h \sigma_h^2. \tag{3}$$

In Equation (4), q is the explanation degree of the driving factor for the spatial difference in residents' consumption at the provincial level; $N = 31$; σ^2 is the discrete variance of residents' consumption expenditure in each province; N_h and σ_h^2 are the number and variance of sub-level regions, respectively; and L is the stratification of factor X. $q \in [0, 1]$, the greater the value of q, the more significant the difference in residents' consumption among provinces. When $q = 1$, a certain factor completely controls the spatial difference in the consumption of the provincial residents; when $q = 0$, it means that a certain factor does not affect the spatial difference in the consumption expenditure. For instance, assuming that both the driving factors X_1 and X_2 have a significant impact on residents' consumption (Y), if the q-value of X_1 is greater than the q-value of X_2, then it is said that the driving

force of X_1 is greater than that of X_2, namely, X_1 can promote more spatial difference in residents' consumption than X_2.

3.4.2. Ecological Detector

Ecological detection is used to compare the influence of two factors X_1 and X_2 on the spatial distribution of the attribute Y. The ecological detector mainly identifies the impact difference between two factors. In order to detect which factor tends to be the most significant of the various effects, it is measured by the F statistic:

$$F = \frac{N_{X1}(N_{x2} - 1)\sum_{h=1}^{L1} N_h \sigma_h^2}{N_{X2}(N_{x1} - 1)\sum_{h=1}^{L2} N_h \sigma_h^2} \quad (4)$$

where N_{X1} and N_{X2} represent the sample size of two factors X_1 and X_2, respectively; L_1 and L_2 represent the number of layers of variables X_1 and X_2, respectively. Where the null hypothesis H_0: $\sum_{h=1}^{L1} N_h \sigma_h^2 = \sum_{h=1}^{L2} N_h \sigma_h^2$, if H_0 is rejected at the significance level of α, it indicates that there is a significant difference in the influence of two factors X_1 and X_2 on the provincial spatial distribution of consumption expenditure.

3.4.3. Interaction Detection

Interaction detection is used to quantitatively express the joint action relationship between two driving factors of the spatial difference in residents' consumption. With driving factor X_m, X_n after the interaction, several situations may occur:

(1) If $q(X_m \cap X_n) < min(X_m, X_n)$, the interaction of X_m and X_n decreases nonlinearly;
(2) If $min(X_m, X_n) q(X_m \cap X_n) < max(X_m, X_n)$, X_m, X_n is single-factor nonlinear weakening;
(3) If $q(X_m \cap X_n) > max(X_m, X_n)$, X_m and X_n are bi-factor enhancement;
(4) If $q(X_m \cap X_n) = q(X_m) + q(X_n)$, X_m, X_n are independent of each other;
(5) If $q(X_m \cap X_n) > q(X_m) + q(X_n)$, the interaction of X_m and X_n is enhanced nonlinearly.

The general identification method of interaction is to add the product term of two factors to the regression model to test its statistical significance. However, the interaction of two factors is not necessarily a multiplication relationship. By calculating and comparing the q-value of every single factor and the q-value after the superposition of two factors, the Geodetector can judge whether there is an interaction between the two factors, as well as the strength, direction, linearity, or nonlinearity of the interaction. The superposition of two factors includes both multiplication and other relationships. As long as there is a relationship, it can be tested.

4. Residents' Consumption Spatial Difference

4.1. Global Spatial Autocorrelation Analysis

To understand the dynamics of the spatial structure of consumption, this paper took data every two years from panel data from 2012 to 2020 to show and analyze the evolution law of per capita consumption spatial structure.

Using Stata 16.0 to conduct global spatial autocorrelation analysis on the per capita consumption expenditure, it can be seen in Table 1 that the Moran's I in each year was greater than zero, which passed the significance test (Z-value 1.65, p-value 0.01). It was inferred that there was a positive spatial correlation in China's consumption expenditure, and there was H–H (High–High) and L–L (Low–Low) spatial agglomeration in space; that is, provinces with high consumption expenditure were adjacent in space, and provinces with low consumption expenditure were also adjacent in space. From the perspective of the timeline, although Moran's I has changed in the past nine years, the fluctuation range was small, which indicates that the inter-provincial differences in China's residents' consumption had little annual change (see Table 2).

Table 2. Moran's *I* of the provincial residents' consumption expenditure from 2012 to 2020.

Year	Moran's *I*	*Z*-Value	*p*-Value
2012	0.321	3.159	0.001
2014	0.311	3.066	0.001
2016	0.297	2.927	0.002
2018	0.315	3.117	0.001
2020	0.326	3.178	0.001

4.2. Local Spatial Autocorrelation Analysis

Moran scatter diagrams of local spatial autocorrelation were drawn by Stata10.6, and all of them passed the significance test of 0.01. The 31 provinces were classified into four types: H–H, L–L, L–H, and H–L (Figure 4). It can be seen that residents' consumption showed prominent spillover and lock-in effects, with the economically developed eastern regions of Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, and Fujian being high-value aggregation regions, while most of northern, northwestern, and northeastern China were low-value aggregation regions in a relatively solidified pattern. Inner Mongolia, Liaoning, Guangdong, and Chongqing were "star" regions with higher resident consumption than their neighboring provinces, while Hebei, Jilin, Heilongjiang, Anhui, Jiangxi, and Hainan were "collapse" regions with a lower level than other nearby provinces. Specifically, in 2012, L–H regions included Hebei, Jilin, Heilongjiang, Anhui, Jiangxi, and Hainan, and L–L regions included Shanxi, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. H–L regions included Inner Mongolia, Liaoning, and Guangdong, while H–H regions included Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, and Fujian. In 2016, the H–L regions shrank, with a reduction of Heilongjiang, and then shrank again in 2020, with a reduction of Jilin. In 2016, the L–L regions expanded, with the addition of Heilongjiang, and expanded again, with the addition of Inner Mongolia in 2018 and Jilin in 2020. The H–L regions shrank, with a reduction of Inner Mongolia in 2018, and Chongqing replaced Inner Mongolia in H–L regions in 2020, while the H–H regions remained stable. In 2019, Fujian was further added to the H–H regions, and Ningxia turned into a part of the L–L regions. Only Jiangxi and Hainan were left in the L–H regions, while Sichuan remained an H–L region.

On the whole, Chinese residents' consumption presented a spatial pattern of "high in the east and low in the central and western regions", with slight changes over the past nine years. Nearly 60% of the provinces were concentrated in L–L regions, indicating that China's residents' consumption was still at a relatively low level overall.

As seen in Table 3, the spatial average autocorrelation coefficient of residents' consumption decreased year by year since 2012 and increased rapidly after hitting the bottom in 2016. By 2020, it exceeded 2012. The spatial correlation of residents' consumption as a whole showed a V-shape, first decreasing and then increasing.

Table 3. Moran's *I* scatter chart data statistics of provincial residents' consumption expenditure from 2012 to 2018.

Year	Quadrant I High–High (H–H)	Quadrant II Low–High (L–H)	Quadrant III Low–Low (L–L)	Quadrant IV High–Low (H–L)
2012	6	6	16	3
2014	6	6	16	3
2016	6	5	17	3
2018	6	5	18	2
2020	6	4	19	2

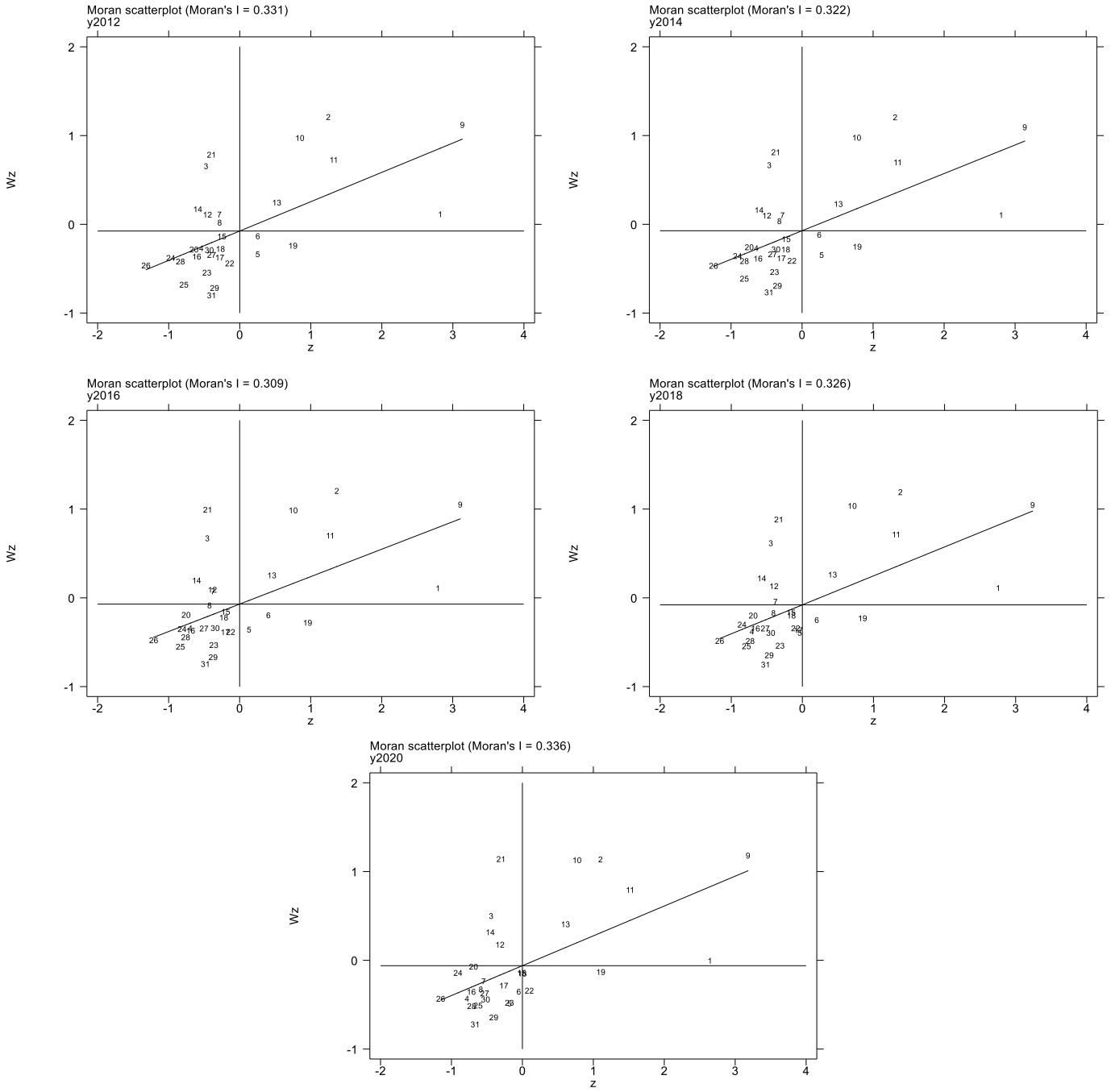


Figure 4. Moran's *I* scatterplot of the per capita consumption in each stage. The figures represent provinces, and the numbering sequence is arranged acccording to the panel data of each province from the National Bureau of Statistics, China.

5. Driving Factors of Residents' Consumption Spatial Differences

5.1. Factor Detection Analysis

The Geodetector analysis must discretize the independent variables. After the sample data are standardized, the independent variables are classified by the natural breakpoint method, and then the factors of the independent variables and dependent variables are detected.

The results are shown in Table 4. It can be seen that from 2012 to 2020, the seven driving factors had explanatory power for the spatial differences in residents' consumption expenditure. From the global average value for 2012 to 2020, the order of the factors'

explanatory power was per capita disposable income (*pdci*), per capita GDP (*pgdp*), urbanization level (*ul*), per capita post and telecommunications business volume (*pcptv*), mobile phone penetration rate (*mpr*), personal digital consumption credit level (*dicc*), and digital payment level (*dp*). From the perspective of the timeline, the leading driving factors of the five years were consistent. The factor with the strongest explanatory power was per capita disposable income (*pdci*), and the *q*-value over the years was above 0.76. The explanatory power of the per capita postal and telecommunications business volume (*pcptv*) on the spatial differences in consumer expenditure has decreased since 2016. The explanatory power of the urbanization level (*ul*) on the spatial differences in consumer expenditure increased first and then decreased. The per capita GDP (*pgdp*) has generally risen. The explanatory power of the personal digital consumption credit level (*dicc*) experienced a process of first being stable, then enhanced, and then weakened, and the others were relatively stable. Before 2016, the regions with high per capita postal and telecommunications business volume were all economically developed regions; because they were affected by the differences in regional economy, this factor's spatial difference was larger. After 2016, owing to the rapid development of online shopping, the per capita postal and telecommunications business volume in all provinces of the country rapidly increased, so this factor's impact on spatial differences has been rapidly reduced.

Table 4. Factor detection analysis results in the driving factors of residents' consumption.

NO.	Description	Variable		2012	2014	2016	2018	2020	Avg.
1	Per capita GDP	*pgdp*	*q* *p*	0.7690 0.000	0.7593 0.000	0.7218 0.000	0.8229 0.000	0.7972 0.000	0.7722
2	Urbanization level	*ul*	*q* *p*	0.7358 0.000	0.7106 0.000	0.7412 0.000	0.7064 0.000	0.7220 0.000	0.7296
3	Per capita disposable income	*pdci*	*q* *p*	0.8383 0.000	0.8378 0.000	0.7633 0.000	0.7857 0.000	0.8674 0.000	0.8322
4	Mobile phone penetration rate	*mpr*	*q* *p*	0.6514 0.000	0.6480 0.000	0.6501 0.000	0.4367 0.0359	0.7060 0.0039	0.6132
5	Per capita post and telecommunications business volume	*pcptv*	*q* *p*	0.8021 0.000	0.7998 0.000	0.7123 0.000	0.4145 0.0450	0.5290 0.0173	0.6562
6	Digital payment level	*dp*	*q* *p*	0.4881 0.0116	0.4862 0.0114	0.4438 0.0077	0.4070 0.0126	0.5786 0.000	0.4807
7	Personal digital credit level	*dicc*	*q* *p*	0.5334 0.0034	0.5046 0.0070	0.4993 0.0077	0.5202 0.0030	0.5754 0.000	0.5237

The digital payment level (*dp*) had the weakest explanatory power for the spatial differences in residents' consumption expenditure, indicating that, as a single factor, the digital payment level (*dp*) had the least effect on the regional differences in residents' consumption. The personal digital credit level (*dicc*) and mobile phone penetration rate (*mpr*) were slightly stronger. On the whole, these indicators representing the digital economy tended to reduce the regional differences in residents' consumption. The reason may be that the digital economy can break through regional restrictions relatively easily, resulting in small spatial differences. Table 5 shows the ranking order of the single factor's driving forces.

Table 5. The ranking order of the single factor's driving forces.

Year	Ranking Order												
2012	*pdci*	>	*pcptv*	>	*pgdp*	>	*ul*	>	*mpr*	>	*dicc*	>	*dp*
2014	*pdci*	>	*pcptv*	>	*pgdp*	>	*ul*	>	*mpr*	>	*dicc*	>	*dp*
2016	*pdci*	>	*ul*	>	*pgdp*	>	*pcptv*	>	*mpr*	>	*dicc*	>	*dp*
2018	*pgdp*	>	*pdci*	>	*ul*	>	*dicc*	>	*mpr*	>	*pcptv*	>	*dp*
2020	*pdci*	>	*pgdp*	>	*ul*	>	*mpr*	>	*dp*	>	*dicc*	>	*pcptv*
Avg.	*pdci*	>	*pgdp*	>	*ul*	>	*pcptv*	>	*mpr*	>	*dicc*	>	*dp*

5.2. Ecological Detection Results and Analysis

The results of ecological detection (Tables 6–10) show that, in 2012 and 2014, there were significant differences between per capita disposable income (*pdci*) and urbanization rate (*ul*), and per capita post and telecommunications business volume (*pcptv*) and mobile phone penetration rate (*mpr*) in the spatial distribution of residents' consumption expenditure. Most other factors made no significant difference in the spatial distribution of residents' consumption expenditure. In 2016 and 2018, there was no significant difference among all factors in the spatial distribution of household consumption expenditure. In 2020, only the per capita disposable income (*pdci*) and urbanization rate (*ul*) made significant differences in the spatial distribution of residents' consumption expenditure.

Table 6. Ecological detection results of residents' consumption at the provincial level in China in 2012.

2012	***pgdp***	***ul***	***pdci***	***mpr***	***pcptv***	***dp***	***dicc***
pgdp							
ul	*N*						
pdci	*N*	*Y*					
mpr	*N*	*N*	*N*				
pcptv	*N*	*N*	*N*	*Y*			
dp	*N*	*N*	*N*	*N*	*N*		
dicc	*N*	*N*	*N*	*N*	*N*	*N*	

Y indicates that there is a significant difference in the importance of the two independent variables to the dependent variables; *N* indicates that there is no significant difference in the importance of the two independent variables to the dependent variable (the same below).

Table 7. Ecological detection results of residents' consumption at the provincial level in China in 2014.

2014	***pgdp***	***ul***	***pdci***	***mpr***	***pcptv***	***dp***	***dicc***
pgdp							
ul	*N*						
pdci	*N*	*Y*					
mpr	*N*	*N*	*N*				
pcptv	*N*	*N*	*N*	*Y*			
dp	*N*	*N*	*N*	*N*	*N*		
dicc	*N*	*N*	*N*	*N*	*N*	*N*	

Table 8. Ecological detection results of residents' consumption at the provincial level in China in 2016.

2016	***pgdp***	***ul***	***pdci***	***mpr***	***pcptv***	***dp***	***dicc***
pgdp							
ul	*N*						
pdci	*N*	*N*					
mpr	*N*	*N*	*N*				
pcptv	*N*	*N*	*N*	*N*			
dp	*N*	*N*	*N*	*N*	*N*		
dicc	*N*	*N*	*N*	*N*	*N*	*N*	

Table 9. Ecological detection results of residents' consumption at the provincial level in China in 2018.

2018	***pgdp***	***ul***	***pdci***	***mpr***	***pcptv***	***dp***	***dicc***
pgdp							
ul	*N*						
pdci	*N*	*N*					
mpr	*N*	*N*	*N*				
pcptv	*N*	*N*	*N*	*N*			
dp	*N*	*N*	*N*	*N*	*N*		
dicc	*N*	*N*	*N*	*N*	*N*	*N*	

Table 10. Ecological detection results of residents' consumption at the provincial level in China in 2020.

2020	*pgdp*	*ul*	*pdci*	*mpr*	*pcptv*	*dp*	*dicc*
pgdp							
ul	*N*						
pdci	*N*	*Y*					
mpr	*N*	*N*	*N*				
pcptv	*N*	*N*	*N*	*N*			
dp	*N*	*N*	*N*	*N*	*N*		
dicc	*N*	*N*	*N*	*N*	*N*	*N*	

5.3. Interaction Detection and Analysis

Figure 5 shows the analysis results of the interaction detection. It can be seen that the *q*-value of the seven driving factors increased significantly after the interaction of two factors. After the interaction of the factors, they all showed the bi-factor enhancement effects, and there was no independence or weakening. The typical ones were digital payment level (*dp*), personal digital credit level (*dicc*), mobile phone penetration rate (*mpr*), and per capita post and telecommunications volume (*pcptv*). In most years, these factors alone had relatively low explanatory power over the spatial differences in consumption expenditure. Digital payment level (*dp*), personal digital credit level (*dicc*), and mobile phone penetration rate (*mpr*) were between 0.4 to 0.6, and the per capita post and telecommunications business volume (*pcptv*) was also around 0.4 at the lowest. However, after they interacted with other variables, the *q*-value increased greatly—about 1.5 times in many cases or even more than twice in some cases—showing strong explanatory power. The same significant increase also occurred at the level of urbanization (*ul*); after the interaction between per capita disposable income (*pdci*) and per capita GDP (*pgdp*) and other variables, the interaction value was larger, but the increase in the bi-factor enhancement effect was generally smaller.

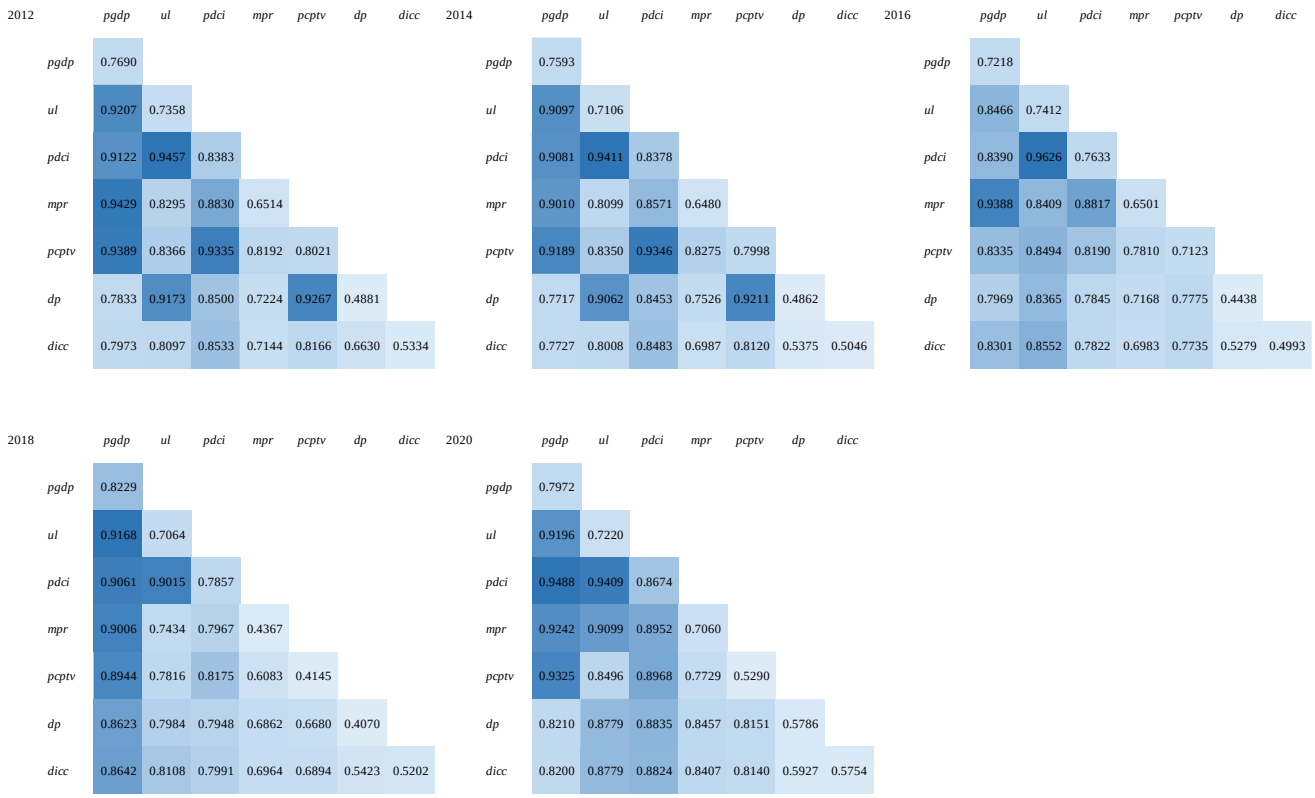


Figure 5. Interaction detection results of the driving factors of residents' consumption at the provincial level.

In Figure 6, we can see the growth rate of the explanatory power of factor interaction. By year, the top five growth rates of the explanatory power of factor interaction in 2012 were *dp* ∩ *pcptv*, *dp* ∩ *ul*, *dp* ∩ *pdci*, *dicc* ∩ *pdci*, and *dicc* ∩ *pcptv*. The top five growth rates in the explanatory power of factor interaction in 2014 were *dp* ∩ *pcptv*, *dp* ∩ *ul*, *dp* ∩ *pdci*, *dicc* ∩ *pdci*, and *dicc* ∩ *pcptv*. The top five growth rates in the explanatory power of factor interaction in 2016 were *dp* ∩ *ul*, *dp* ∩ *pgdp*, *dp* ∩ *pdci*, *dp* ∩ *pcptv*, and *dicc* ∩ *ul*. In 2018, *pcptv* ∩ *pgdp*, *dp* ∩ *pgdp*, *mpr* ∩ *pgdp*, and *pcptv* ∩ *pdci* accounted for the top five growth rates in their explanatory power of the interaction. The top five increases in the explanatory power of interaction in 2020 were *pcptv* ∩ *pgdp*, *pcptv* ∩ *pdci*, *pcptv* ∩ *ul*, *dicc* ∩ *pdci*, and *dp* ∩ *pdci*. We noted that the interaction factors of *mpr*, *pcptv*, *dp*, and *dicc*, which represent the indicators of the digital economy, improved residents' consumption expenditure after interacting with other variables. We also noted that Chinese residents' consumption expenditure was affected by many factors affecting digital economy indicators.

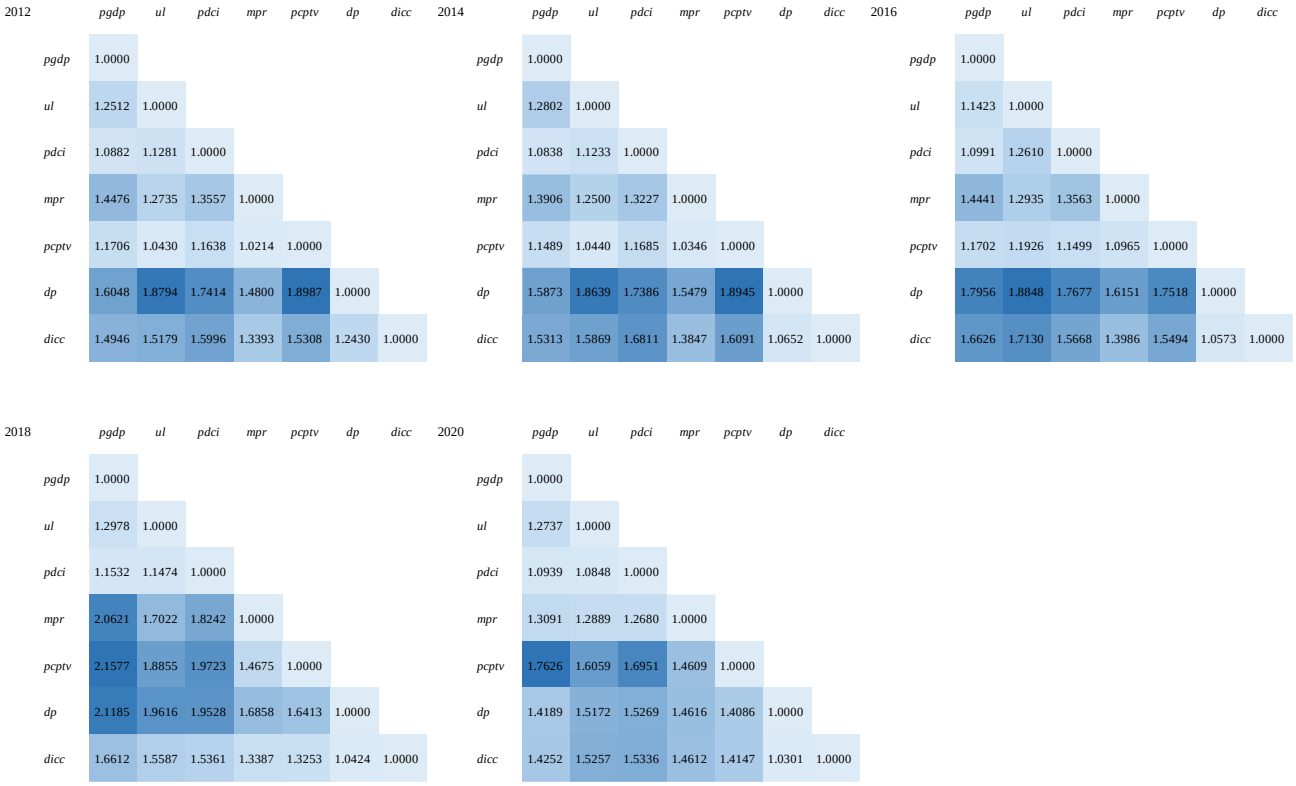


Figure 6. The rate of increase in interaction detection results of the driving factors.

5.4. Comprehensive Analysis of Driving Force Factors

Based on the results of factor detection and ecological detection, we conducted a comprehensive analysis as follows. First, in general, per capita disposable income (*pdci*), per capita GDP (*pgdp*), and urbanization level (*ul*) were the core driving factors for the spatial differences in provincial residents' consumption. Second, before 2016, per capita disposable income (*pdci*) and per capita post and telecommunications business volume (*pcptv*) were the primary influencing factors affecting the spatial differences in residents' consumption expenditure. After 2016, the per capita post and telecommunications business volume (*pcptv*) was no longer primary influencing factor, and the factors that directly affected residents' consumption expenditure changed to per capita disposable income (*pdci*), per capita GDP (*pgdp*), and urbanization level (*ul*). Third, before 2016, the level of urbanization (*ul*) and mobile phone penetration rate (*mpr*) were the main secondary influencing factors on the spatial differences in residents' consumption expenditure. In 2016, the per capita post and telecommunications business volume (*pcptv*) dropped to a secondary influencing factor. After 2018, the main secondary driving factor was the mobile

phone penetration rate (*mpr*). Fourth, personal digital credit level (*dicc*) and digital payment level (*dp*) were the third-level influencing factors of the spatial differences in provincial residents' consumption expenditure for most years and had little impact on the spatial differences in residents' consumption expenditure.

The driving forces of digital economic variables and non-digital economic variables on residents' consumption were different in different years. The degree to which core factors, important factors, and auxiliary factors of residents' consumption changed was also different in the research period, which indicated that the driving mechanism of residents' consumption against the background of the digital economy had diversified characteristics, which can provide a reference for the optimization of residents' consumption policies in different development stages of China. Among all the driving forces, on average, the non-digital economy variables—per capita disposable income, per capita GDP, and urbanization level—exerted the top three greatest forces on the spatial differences in residents' consumption, indicating that the traditional economic indicators still occupy a crucial position for residents' consumption, which echoes many papers' findings [4,64–67]. Since they had obvious regional disparities, this indicated that traditional economy variables can lead to greater spatial differences in residents' consumption, which is not conducive to balanced development of residents' consumption among regions.

The driving forces of the four digital economy variables were weaker than the other three variables, on average. Among the driving forces of the four variables, according to the factor detection results, there were significant differences in the acting forces of different factors, with the simultaneous presence of stability factors and fluctuation factors. Per capita post and telecommunications business volume was the factor with the largest fluctuation; in 2012 and 2014, it was the second strongest driving force among all the factors, but after 2014, it fell dramatically to become the weakest driving force in 2020. The reason was that, in 2012 and 2014, the digital economy was not yet prosperous throughout the country, only developing rapidly in some developed regions (Shanghai, Jiangsu, Zhejiang, etc.). This created significant regional disparities, so this variable's driving force for the spatial difference in residents' consumption was significantly strong in these years. However, from 2016, with the rapidly developing post and telecommunications digital economy nationwide, this business quickly broke through the geographical disparities and become more balanced among provinces. Thus, it became the driving factor of the smallest spatial difference until 2020. Among the driving factors of the digital economy, mobile phone penetration rate, digital payment level, and personal digital credit level were stability factors; their driving forces were relatively stable during the nine years. Mobile phone penetration rate represented the infrastructure of the digital economy, digital payment level stood for the consumption method, and personal digital credit level represented the degree of release of consumption constraints in the digital economy. The mobile phone penetration rate had a stronger correlation with the regional economy, so its driving force for spatial difference was greater than the other two driving factors. The driving factors of digital payment level and personal digital credit level were that they are both online services and have better territorial penetration; when users access the Internet, the two services can help them permeate any province, so their driving force for spatial differences in residents' consumption was much smaller, indicating they are very conducive to the regional balance of residents' consumption.

6. Conclusions and Recommendations

6.1. Conclusions

With panel data from 31 provinces in China from 2012 to 2020, this paper performed spatial autocorrelation and utilized Geodetector to analyze the driving factors of spatial differences in consumer spending against the background of the digital economy. The main conclusions are as follows:

(1) Residents' consumption expenditure at the provincial level in China has a positive spatial correlation, showing a spatial pattern of "high in the east and low in the

middle and west"; the inter-annual variation in the inter-provincial differences in residents' consumption expenditure is small, and the spatial dependence is mainly L–L agglomeration.

(2) From the average value of the overall stage, the single-factor driving force of the four factors representing the digital economy on the spatial differences in residents' consumption expenditure is lower than the digital economic factors, indicating that in terms of a single factor, the digital economic factors are beneficial to reducing the regional differences in residents' consumption; in other words, they are good for the balance of residents' consumption among all provinces because they can break through regional limitations.

(3) All of the factor pairs are bi-factor-enhanced. In terms of the average value of the overall stage, the interaction values of non-digital economic factors are larger, indicating that non-digital economic factors greatly increase the spatial differences in residents' consumption and enlarge the regional imbalance in residents' consumption after interacting with other factors, while the four factors representing the digital economy improve residents' consumption expenditure after interacting with other factors.

6.2. Policy Recommendations

Based on the above results, to effectively reduce the regional imbalance in residents' consumption in China and promote the coordinated development of the regional economy, the following suggestions are put forward: (1) From the perspective of non-digital economic driving factors, the urbanization level, per capita GDP, and per capita disposable income should be further increased. These factors play a huge role in the development of Chinese residents' consumption; in particular, the improvement of the urbanization level has a significant impact on the development level of residents' consumption. (2) From the perspective of the driving factors of the digital economy, in terms of regions, the southeast is economically developed, and residents' consumption is relatively high, while residents' consumption in the central and western regions is relatively low; therefore, it is necessary to increase the input of digital economic elements to effectively promote resident's consumption across the country and to balance development. It is necessary to further promote the development of the mobile phone penetration rate, per capita post and telecommunications business volume, digital payment level, and digital consumer credit level, not only in the central and western regions, but also in the eastern regions. These factors play an increasingly significant role in promoting balance in residents' consumption and reducing regional differences in residents' consumption. (3) According to the interactive enhancement effect of non-digital factors and digital factors, the non-digital economic factors and digital economic factors should develop in a coordinated way to promote the rapid development of residents' consumption. (4) We should deepen regional cooperation, strengthen regional connections, and further enhance the level of the digital economy in the eastern coastal area and the central-western regions. We should also establish a digital economy coastal cooperation pilot zone, give full play to the digital economy capabilities of the eastern region, drive the development of the digital economy in the central and western regions, and then promote the balanced development of residents' consumption. (5) Governments should introduce various support policies according to local conditions and promote the development of various elements of the digital economy in the central and western regions, to encourage the balanced development of residents' consumption in the region and the entire country.

6.3. Limitations and Future Work

Due to time constraints, this paper did not conduct a detailed study on the specific indicators in the digital economy and the allocation of economic characteristics in different regions. This will be studied in future work to determine what specific factors in the

digital economy are more suitable for specific regions and to propose more targeted policy recommendations to improve residents' consumption expenditure in each region.

Author Contributions: Conceptualization, Q.W.; Data curation, Z.S.; Funding acquisition, C.Y.; Investigation, D.W.; Methodology, D.W.; Project administration, C.W.; Resources, Z.S.; Supervision, C.W.; Writing—original draft, Q.W.; Writing—review & editing, C.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by 1. Beijing Social Science Fund [20GLB028]; 2. Beijing Municipal Universities Basic Research Funds, Capital University of Economics and Business [ZD202105]; 3. General Research Project of Humanities and Social Sciences in Colleges and Universities of Henan Province [2023-ZZJH-085]. The APC was funded by [20GLB028, ZD202105].

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All the data are from the National Bureau of Statistics of China, http://www.stats.gov.cn/ (accessed on 1 May 2022).

Acknowledgments: We would like to thank the support of the following funds: 1. Beijing Social Science Fund (20GLB028); 2. The Capital University of Economics and Business Special Fund for Basic Scientific Research in Beijing's Universities (ZD202105); 3. General research project of Humanities and Social Sciences in Colleges and Universities of Henan Province (2023-ZZJH-085). We would also like to thank the team members of the Complex System Simulation Team of the School of Management Engineering, Capital University of Economics and Business, for their support and help with the professional software.

Conflicts of Interest: The authors declare no conflict of interest.

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