Chapter 8
Effects of Digital Technologies on Renewable Energy Development: Empirical Evidence and Policy Implications from China

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Abstract Despite widespread employment of digital technologies in renewable energy generating, transmitting, distribution, storage, and pricing, there is a lack of empirical investigation into the effects of digital technologies on renewable energy development. In this context, this paper estimates the influence of digital technologies on renewable energy market integration in China. This study conducts a series of regressions based on provincial data from 2003 to 2020 and an index of digital technologies measured with the entropy weight method, and finds that digital technologies have significantly bolstered renewable energy development in China. To analyze how to overcome specific barriers to renewable energy expansion, this paper also examines the case study of Qinghai province, which has the potential to power itself with 100% renewable energy. These findings provide valuable policy guidance for ASEAN countries regarding achieving carbon–neutral energy transitions.

Keywords Digital technologies · Renewable energy · China

JEL Classification Q48 · C13 · C54

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1 Introduction

China aims to hit peak emissions by 2030 and achieve carbon neutrality by 2060. Notwithstanding, given that China is the world's largest emitter of carbon dioxide and that 80% of China's energy comes from fossil fuels, it faces challenges in achieving these goals. From Fig. 1, which shows annual power generation from renewable energy in each province between 2003 and 2020, we see that China has made much progress in using renewable energy over the last two decades. However, to become carbon-neutral, it is crucial that China makes further progress in transitioning to renewable energy, e.g., solar and wind power, and invest in projects that absorb carbon dioxide.

Given that renewable energy, such as solar and wind power, is intermittent, and that the demand side is far removed from suppliers, much of China's renewable energy has gone to waste, particularly solar and wind power in the northwest and hydropower in the southwest. Some 17.1% of total wind generated power was lost in 2017 alone. Although such losses have been reduced since 2019 due to rising energy demand and lower renewable energy prices, much renewable energy is still being wasted at the national level, given its large installed capacity. In the first half of 2021, 12.64 billion KWh wind power and 3.32 billion KWh solar energy was lost.

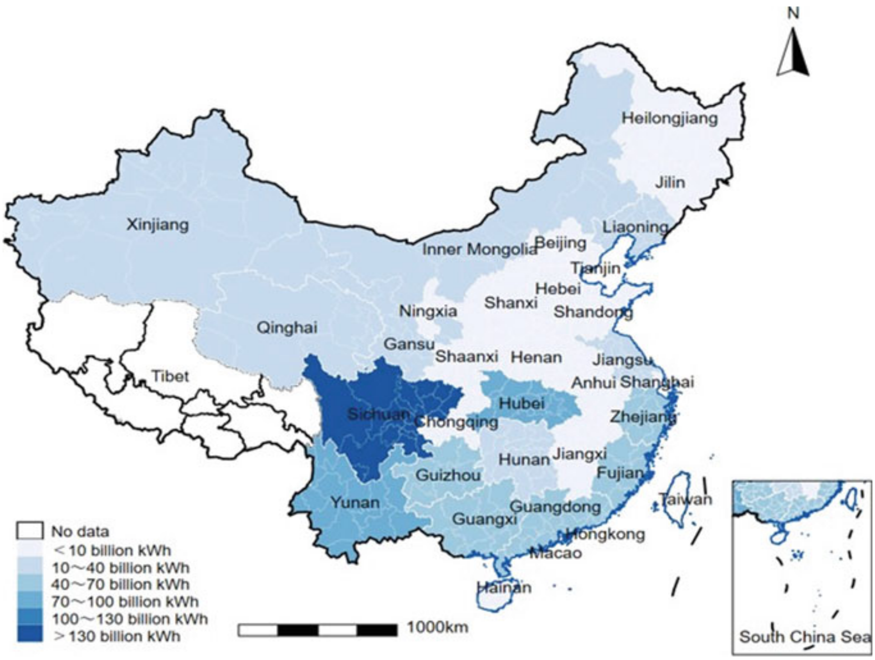

Fig. 1 Renewable power generation in China, 2003–2020

China has taken several measures to address this waste and make renewable power a greater part of the country's energy mix, with digital technology application being crucial. Digital technology has bolstered renewable energy development in many ways, with big data, blockchain, artificial intelligence, fifth-generation (5G) cellular networks, and cloud computing widely used in renewable energy generation, transmission and distribution, storage, and pricing.

The current literature has not paid sufficient attention to the impact of digital technology on renewable energy, however. To date, many studies have looked at the effects of digital technology in terms of social welfare (Shivendu and Zhang 2019), employment (Domini et al. 2021), technological innovation (Feng et al. 2022), factor misallocation (Shen and Zhang 2022), and industrial productivity (Wu and Yu 2022). Notwithstanding, most have analyzed how digital technology transforms the economy overall, ignoring the impact on renewable energy, which plays an important role in energy security, economic growth, and environmental protection (Bhattacharya et al. 2017; Nguyen and Kakinaka 2019). Although literature specializing in renewable energy has explored a number of factors driving renewable energy development, as shown in Sect. 2, literature review, the role of digital technology has not been comprehensively examined. Studies of the relationship between digital technology and energy have mainly investigated the impact of digitization on consumption, with few studies looking at the impact on the supply side of renewable energy.

Accordingly, this study aims to bridge this research gap between renewable energy and digital technology, by empirically estimating how digital technology boosts renewable energy based on evidence from China, and exploring precise mechanisms by which digital technologies facilitate renewable energy. In addition to these estimations and following a heterogeneity analysis of the impact, this paper will take up the case study of Qinghai, a Chinese province that has achieved 100% renewable energy transition for its economy, to further analyze actual steps involved. This paper will then draw on these findings to shed light on how other Chinese provinces and ASEAN member states may find examples of how to achieve their own carbon neutrality goals.

The methodology is as follows. Using Chinese provincial data from 2003 to 2020, we measure China's digital technologies with the entropy weight method and apply the general moment method (GMM) to estimate the impact of said digital technologies on renewable energy development. The results suggest that digital technologies have facilitated renewable energy significantly, through their influence on economic development and industrial structure. The significantly positive relationship between digital technologies and renewable energy development remains robust after a number of robustness checks, including considering spatial spillover of digital technology from neighboring regions and changing the weight of indexes used to calculate the value of digital technologies. The regional heterogeneity analysis reveals that the impact of digital technologies on renewable energy varies across China, with the greatest impact felt in the country's east. This can be explained by such distinctive characteristics as greater digital innovation, more developed market mechanisms, and more efficient administration. These findings, together with Qinghai province's experience of transitioning to 100% renewable energy, provide valuable policy implications for other countries and regions struggling to achieve their own energy transition targets.

The remainder of this paper is organized as follows. Section 2 reviews the literature. Section 3 describes the data used in this study and presents our econometric approaches. Section 4 presents estimation results and tests the mechanisms by which digital technologies affect renewable energy. Section 5 conducts robustness checks and heterogeneity analysis of the primary findings. Section 6 briefly describes experiences in using digital technologies to facilitate renewable energy development in Qinghai province. Section 7 summarizes our main conclusions and provides insights for policy.

2 Literature Review

While many studies examine factors driving renewable energy or the impact of digital technology, there is a lack of investigation into the effects of digital technology on renewable energy development.

2.1 Factors Driving Renewable Energy Development

The literature includes a large number of studies investigating drivers of renewable energy deployment, which find that economic performance and financial development vitally affect renewable energy expansion. Specifically, economic growth rates (Sadorsky 2009a), per capita income (Marques et al. 2010), openness to trade (Omri and Nguyen 2014), FDI inflows (Bhattacharya et al. 2016; Kutan et al. 2018), and economic freedom (Baranes et al. 2017) can positively promote renewable energy demand. Capitalization and growth of stock markets also benefit renewable energy development by financing more clean energy projects and economic activity.

Other factors also affect renewable energy growth, including carbon emissions (Sadorsky 2009b; Marques et al. 2010), oil prices (Sadorsky 2009b; Omri and Nguyen 2014), fossil fuel lobbies, and energy self-sufficiency (Marques et al. 2010). Related polices are fundamental drivers of renewable energy growth, including application of voluntary approaches (Aguirre and Ibikunle 2014). Gozgor et al. (2020) indicate that greater economic globalization promotes renewable energy, while Zheng et al. (2021a, b) find that demand side factors, e.g., consumers' price sensitivity, also closely relates to their support for, and thus overall development of, renewable energy.

Most studies examining renewable energy development determinants are conducted using country-level data, especially from G7 economies (e.g., Sadorsky 2009b), BRICs (e.g., Salim and Rafiq 2012; Kutan et al. 2018), OECD countries (e.g., Gozgor et al. 2020), European countries (e.g., Marques et al. 2010; Baranes et al. 2017), G20 countries (e.g., Bhattacharya et al. 2017), and ASEAN (Association of Southeast Asian Nations) economies (e.g., Nepal and Musibau 2021). Some have examined specific countries, such as China (e.g., Lin et al. 2016; Chen 2018) and Indonesia (e.g., Al-Irsyad et al. 2019).

In sum, while the literature has extensively analyzed factors conducive to renewable energy development from economic, financial, and political perspectives, examination of the role of digital technology is relatively insufficient, despite its extensive employment in generating and using renewable energy. Research on this subject regarding China is particularly limited.

2.2 Impact of Digital Technologies on Energy

More and more studies are paying attention digital technology applications to energy. The International Energy Agency (IEA) (2017) points out that digital technologies, such as smart appliances and shared mobility, improve the safety, productivity, efficiency, and sustainability of energy systems. Digitization has the potential to save some 5% of total annual generation costs in electricity in particular, as operation and maintenance costs can be reduced, energy efficiency of generating plants and grids can be improved, and operational lifetimes of assets can be extended. Thanh et al. (2022) empirically analyze the nexus of digitization and energy security in 27 European countries between 2015 and 2019, finding that promoting digitization is beneficial regarding the acceptability and sustainability of energy security, while deleterious on development. Conversely, energy security positively affects digitization, especially in business and the public sector. Baidya et al. (2021) have reviewed the opportunities, challenges, and future directions for energy digitization.

Overall, in existing literature concerning the impact of digital technologies on energy, the role of digitization in energy demand and consumption has attracted the most attention. Bastida et al. (2019) explore the potential of information and communication technology (ICT)-based interventions in households to decrease electricity usage and suggests that such effects on consumer behavior can reduce household final electricity consumption by 0–5%. Lange et al. (2020) estimate the impact of ICT on energy demand across 28 member states of the European Union. They find that overall digitization increases energy consumption, as physical capital and energy complement each other in ICT, which is energy-intensive, and increased energy efficiency thus pays dividends. Ren et al. (2021) examine the situation in China, and find that the relationship between China's internet development and energy consumption is significantly positive, and that internet development promotes energy consumption scaling through economic growth. Husaini and Lean (2022) study the impact of digitization on total and disaggregated energy consumption in five major ASEAN member states, concluding that digitization reduced such consumption by both metrics. Xu et al. (2022) investigate the effects of digitization on energy and related mechanisms from an international perspective, demonstrating that digitization reduces energy consumption, decreases energy intensity, and optimizes energy structure, by promoting technological innovation, accelerating human capital accumulation, and alleviating industrial structure distortions. Digitization also has greater energy savings in low-income and underdeveloped countries.

A number of analytical studies have examined the application and impact of digital technologies to renewable energy. Strielkowski et al. (2021) focus on strategies employing 5G cellular for optimal demand-side response management in future energy systems with large proportions of renewables. They confirm that effective deployment of faster and more reliable cellular networks would allow faster data transfer and processing, including peer-to-peer energy trade markets, Internet of Vehicles markets, and faster smart metering. Hossain et al. (2016) investigate the role of smart grids in renewable energy, concluding that using smart grids may facilitate efficient use of renewables in turn. Ahl et al. (2019) explore potential challenges of blockchain-based peer-to-peer microgrids, and suggest implications thereof for institutional development. Sharifi et al. (2021) analyze the impact of artificial intelligence on energy post-COVID-19 pandemic, and encourage countries whose economies depend on non-renewable energy to develop solar and wind energy, as renewables can reduce the virus's destructive effects and drive economic prosperity.

In summary, in contrast to the increasingly important role of digital technologies in renewable energy development, only a limited number of qualitative studies have been conducted to-date. The current literature has not paid sufficient attention to quantitative analyses based on historical data. Investigations of precise mechanisms by which digital technology plays its role are also few and far between. This paper will accordingly attempt to bridge this gap by conducting empirical analysis to estimate the impact of digital technologies on China's growth in renewables, and examine the case study of Qinghai province to shed light on how to transition to 100% renewable energy.

3 Data and Methodology

3.1 Description

This section presents sources and statistical descriptions of data. The data used to measure the key explanatory variable, i.e., *Digital Technologies*, was extracted from various yearbooks, including *China Statistical Yearbook*, *China Energy Statistical Yearbook*, *China Electricity Statistical Yearbook*, *China Population and Employment Statistical Yearbook*, and *China Technology Statistical Yearbook*. Information about crude oil prices comes from the U.S. Energy Information Administration (EIA), and that about CO_2 emissions from the Carbon Emission Accounts and Datasets (CEADs). Where values are missing, we select data from provincial yearbooks and adjust to match values selected from the abovementioned yearbooks. We supplement data on broadband access ports, which are absent prior to 2006, by backward projecting using the average annual growth rate of this variable.

Table 1 Descriptive statistics

Variables	Obs	Mean	Std.Er	Max	Min
Renewable energy (10^9 kWh)	540	38.9	54.9	365.4	0
Digital techniques	540	0.148	0.122	0.701	0.008
Economic development (10^9 RMB)	540	1215.7	1184.3	7090	36.1
CO_2 emissions (10^6 tons)	540	269	186	950	16
Environmental regulation (10^6 RMB)	540	1879.51	1878.63	14,000	4.76
Government size (10^6 RMB)	540	22.9	10.7	75.8	8.4
Industrial structure (%)	540	0.984	0.321	1.897	0.191
Urbanization rate (%)	540	0.537	0.145	0.938	0.257
Oil price (USD per barrel)	540	6.119	0.330	6.577	5.476
General technology (10^9 RMB)	540	34.751	51.112	309.849	0.121

We measure the dependent variable, renewable energy development, with the difference in electricity generation between the aggregate and that generated from thermal energy. We measure the key explanatory variable, digital technologies, with several approaches, including the entropy weight method in the main analysis and adjusting the weights of related indexes in the robustness check, as shown in more detail in the following section. Economic development is signified by gross domestic product (GDP) per capita by province. We deflate nominal GDP per capita values by the GDP index, using 1998 as the base year. The proxy variable for environmental regulation is costs incurred responding to environmental pollution, while that for government size is the ratio of government spending to GDP. Industrial structure is measured by the ratio of GDP in secondary sectors to that in tertiary sectors in a given province, while urbanization rate is measured by the ratio of urban to total population in a province. General technology is measured with research and development (R&D) investment. In the following regressions, we use the natural logarithms of renewable energy, economic development, CO_2 emissions, crude oil price and general technology. Table 1 gives the descriptive statistics of each variable.

3.2 *Measurement of Digital Technologies*

This paper applies the entropy weight method (EWM), an important information model, to measure the key explanatory variable, that is, digital technologies. It evaluates values by measuring the degree of differentiation in information. The higher the degree of dispersion of the measured value, the higher the degree of differentiation of the index, and the more information that can be derived. Higher weight should be given to the index, and vice versa. Hence, according to the degree of variation of each index, the information entropy tool can be used to calculate the weight of each index and provide comprehensive evaluation of multiple indexes.

The first step in this method is standardizing measured values. Suppose m indexes and n years are set in the evaluation, and x_{ij} denotes the ith sample in year j. Then the standardized value of $x_{ij,}$ which is recorded as X_{ij}, is calculated as follows:

$$X_{ij} = \frac{x_{ij} - min\{x_i\}}{max\{x_i\} - min\{x_i\}}$$

where $min\{x_i\}$ and $max\{x_i\}$ are the minimum and maximum value of the ith sample in all years, respectively. In this study, six indexes are used, and the attributes of all indexes are positive.

The second step is to calculate the weight of index i in year j, and the calculation is given as:

$$w_{ij} = \frac{X_{ij}}{\sum_{j=1}^{n} X_{ij}}$$

Define the entropy value of the ith index, denoted with E_i, as follows:

$$E_i = \frac{\sum_{j=1}^{n}(w_{ij} \times lnw_{ij})}{lnn}$$

Then the range of the entropy value E_i is between zero and one. Given the calculation method of the ith index's weight W_i, which is shown as:

$$W_i = \frac{1 - E_i}{\sum_{i=1}^{m}(1 - E_i)}$$

Then the evaluation score of index i in year j is $S_{ij} = W_i \times X_{ij}$. Financially, the value of digital techniques, denoted as $Digital_j$, is calculated as:

$$Digital_j = \sum_{i=1}^{m} S_{ij}$$

Table 2 gives the indexes used to calculate the values of digital technologies. In total, we have six indexes, which can be grouped into four categories. This means that we select the indexes from four perspectives, including number of employees, outputs, infrastructure, and investment in related fields. The last two columns display the weight and attribute of each index. It can be seen that indexes classified as outputs and infrastructure are assigned higher weights, especially broadband ports and telecommunications business per capita.

Figure 2 shows the trend of China's adoption of digital technologies from 2003 to 2020, as measured by the EWM. It indicates that overall, the level of China's digital technology adoption rises consistently in this period, and even more prominently after 2010. This is consistent with the fact that China acts as one of the world's leading adopters of digital technologies and is shaping the global digital landscape.

Table 2 Indexes used to calculate the value of digital techniques

Classes	Indexes	Weights	Attributes
Number of employees	Ratio of employees in the ICT industry and other information transmission service industry to aggregate employees	0.190	+
Outputs	Telecom business per capita	0.212	+
	Mobile phone switch capacity	0.133	+
Infrastructure	Long-distance optical cable line length	0.074	+
	Broadband access port of internet	0.229	+
Investment	Investment in fixed assets of the whole society in ICT	0.162	+

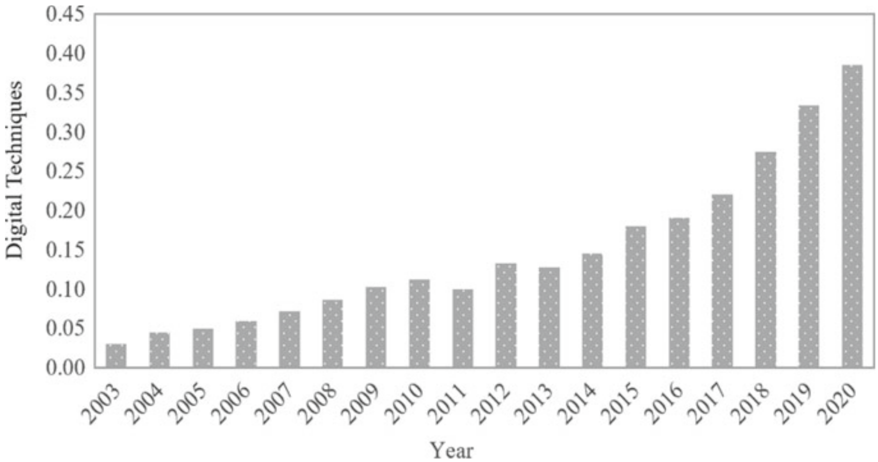

Fig. 2 Trend of digital technology adoption in China, 2003–2020

3.3 *The Econometric Model*

3.3.1 The Baseline Model

In the baseline model, we apply the general method of moments (GMM) that includes a lagged dependent variable as the instrumental variable to deal with the potential endogeneity problem. We specify the model setting as follows:

$$Renew_{it} = \alpha + \beta Renew_{it-1} + \rho Digital_{it} + \delta X_{it} + V_t + \lambda_i + \varepsilon_{it} \tag{1}$$

where $Renew_{it}$ represents the level of renewable energy development of province i in year t,

$Renew_{it-1}$ is the one-period lagged value of the dependent variable, which is used as the instrumental variable to cope with potential endogeneity. $Digital_{it}$ is the variable that captures digital technologies of province i in time t, and ρ is the associated coefficient. X_{it} indicates a vector of control variables, including economic development, CO_2 emissions, environmental regulation, government size, industrial structure, urbanization rate, crude oil price, and general technology level. β and δ denote the coefficients for the instrumental variable and control variables, respectively. ν_t is the year dummy variable that controls the variables that are constant across provinces but vary over time, i.e., time-fixed effects, λ_i is the dummy variable for provinces that controls the unobserved time-invariant individual effect, i.e., individual fixed effects, and ε_{it} is the error term.

3.3.2 The Spatial Durbin Model in Robustness Check

In one robustness check, we use a spatial econometric model to consider the influence of spatial factors on the development of renewable energy. The main reason to use this method is that neighboring regions, which are based on geographical relationships, share common characteristics in such domains as politics, economics, and culture, implying that there are spatial spillover effects among said neighboring regions. To account for these spatial effects, we apply the spatial Durbin model, which includes a spatially lagged dependent variable and spatially lagged explanatory variables, to estimate the effects of digital technologies on renewable energy. The model is set as follows:

$$Renew = \rho Renew + X\beta + WX\theta + \varepsilon \tag{2}$$

where *Renew* is the renewable energy dependent variable, a $(n \times 1)$ vector, where n is the number of observations included in the model. ρ stands for the effect of renewable energy development of a given region's neighboring regions on the renewable energy development of this specific region. W is a $(n \times n)$ matrix of spatial weighting coefficients. X is a $(n \times k)$ matrix of the independent variables. β is a $(k \times 1)$ vector of parameters associated with explanatory variables. θ is the spatial autoregressive coefficient, which reflects the influence of the spatial factors on the dependent variables. ε is a $(n \times 1)$ vector whose elements follow $\varepsilon \sim (0, \sigma^2 I_n)$.

3.3.3 The Mediation Model in Mechanism Tests

To identify and explain the mechanisms that underpin the relationship between renewable energy development and digital technologies, in Sect. 4.2 we run regressions using the following mediation model:

$$Renew_{it} = \alpha_0 + \alpha_1 Renew_{it-1} + \alpha_2 Digital_{it} + \alpha_3 Z_{it} + V_t + \lambda_i + \tau_{it} \tag{3}$$

$$Mediator_{it} = \beta_0 + \beta_1 RMediator_{it-1} + \beta_2 Digital_{it} + \beta_3 Z_{it} + V_t + \lambda_i + \mu_{it} \tag{4}$$

$$\begin{aligned} Renew_{it} = \gamma_0 + \gamma_1 Renew_{it-1} + \gamma_2 Digital_{it} \\ + \gamma_3 Mediator_{it} + \gamma_4 Z_{it} + V_t + \lambda_i + \xi_{it} \end{aligned} \tag{5}$$

where Eq. (3) regresses the dependent variable on the independent variable to confirm that the independent variable is a significant predictor of the dependent variable. Equation (4) regresses the mediator on the independent variable to confirm that the independent variable is a significant predictor of the mediator. If the mediator is not associated with the independent variable, it could not possibly mediate anything. Equation (5) regresses the dependent variable on both the mediator and independent variable to confirm that the mediator is a significant predictor of the dependent variable and that the strength of the coefficient of the previously significant independent variable in the first step is now greatly reduced. Equation (3) is similar to Eq. (1); the only difference is the number of control variables included in X_{it} and Y_{it}. In Eq. (3), some variables in X_{it} are excluded, as they are used as mediators in the mediation model, implying that Eq. (5) runs essentially the same regression as Eq. (1). $Mediator_{it}$ indicates the possible mediator, and in this study, economic development and industrial structure are tested as mediators. τ_{it}, μ_{it} and ξ_{it} are error terms.

4 Results and Discussion

4.1 Preliminary Results

In the baseline specification, we ran the regression with the full sample using the GMM model, and present the estimation results in column (1) of Table 3. For comparison, we also demonstrate the outcomes estimated with the pooled ordinary least square (POLS) model and random effect (RE) model in columns (2) and (3), respectively. We see that the impact of digital technologies on renewable energy development is significantly positive across all model specifications, at least at the five-percent level.

Renewable energy development in the current period is also positively linked to its level in the last period, suggesting that renewable energy increases are path dependent on resource endowments and infrastructure construction. Economic development level, carbon emissions, environmental regulation, and oil price may all significantly promote renewable energy development in the current period, in line with the literature review in Sect. 2. By contrast, there is a negative relationship between renewable energy development level and government size, industrial structure, and urbanization. Given the measurement of these variables, these findings are economically straightforward.

Table 3 Preliminary estimation results

Variables	GMM	POLS	RE
	(1)	(2)	(3)
Digital technologies	3.831**	4.786***	1.313***
	(1.498)	(0.722)	(0.452)
L. Renewable energy	0.613***		
	(0.110)		
Economic development	0.808**	1.351***	– 0.183
	(0.381)	(0.240)	(0.253)
CO_2	0.330**	0.221*	1.084***
	(0.143)	(0.128)	(0.165)
Environmental regulation	0.080*	0.060	0.063
	(0.042)	(0.075)	(0.039)
Government size	– 4.935**	3.618***	0.151
	(2.097)	(0.580)	(0.675)
Industrial structure	– 0.444***	– 0.844***	– 1.156***
	(0.168)	(0.218)	(0.150)
Urbanization	– 2.989**	– 12.263***	0.072
	(1.394)	(0.815)	(1.038)
Oil price	1.914***	0.139	0.055
	(0.603)	(0.156)	(0.081)
General technology	– 0.716***	0.176**	0.294***
	(0.271)	(0.081)	(0.111)
Constant	0.000	4.843***	– 4.738***
	(0.000)	(1.312)	(1.424)
Time fixed effects	Y	N	N
Individual fixed effects	Y	N	Y
Observations	510	540	540
R^2		0.604	0.750
AR(1)	0.000		
AR(2)	0.425		
Sargan test	0.097		

Robust standard errors are in parentheses. *$p < 0.05$, **$p < 0.05$, ***$p < 0.01$. This applies to all following tables as well

4.2 Possible Mechanisms

In this section, we test the potential mechanisms by which digital technologies affect renewable energy development. Considering the established link between GDP and renewable energy consumption (Amri 2017), and the role of industrial policy adjustment in China's energy mix (Liu et al. 2021), we take economic development and industrial structure as mediators in two separate tests, respectively. We test the plausibility of these mechanisms with the mediation model introduced in Sect. 3.3.3, and the associated estimation results are given in Table 4. The third and fourth columns demonstrate the impact mechanism through economic development, and the fifth and sixth columns report the impact channel through industrial structure. Only the estimation results of Eqs. (3) and (4) are presented, as the estimates of Eq. (5) can be found in column (1) of Table 3.

It can be seen that the coefficient of digital technologies in Eq. (5) is smaller than that estimated with Eq. (3), signifying that the presence of the mediator mediates the relationship between digital technologies and renewable energy. The estimation results of Eq. (4) show that the impact of digital technologies on economic development is statistically significant, implying that the changes in digital technologies could predict economic development trends. This is also the case for the impact of digital technologies on industrial structure, as the coefficient of digital technologies in the last column of Table 4 is also statistically significant at the five-percent level.

It is worthwhile to point out that we added the square of digital technologies in the regression of Eq. (4), indicating that the relationship between digital technologies and economic development is non-linear. The estimation results in the third column

Table 4 Possible mechanisms

Variables	Economic development		Industrial structure	
	Equation (3)	Equation (4)	Equation (3)	Equation (4)
Digital technologies	5.539***	– 0.542**	3.999**	– 0.064**
	(1.935)	(0.223)	(1.554)	(0.028)
Square of digital technologies		0.636***		
		(0.244)		
L. Renewable	0.576***		0.676***	
	(0.120)		(0.101)	
L. GDP		0.846***		
		(0.107)		
L. Industrial				1.198***
				(0.067)
Controls	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y
Individual fixed effects	Y	Y	Y	Y
Observations	510	510	510	510
AR(1)	0.000	0.033	0.000	0.000
AR(2)	0.392	0.873	0.398	0.054
Sargan test	0.118	0.188	0.113	0.062

of Table 4 show that the sign for digital technologies is negative and that for its square is positive. This implies a U-shaped relationship between digital technologies and economic development, showing that digital technologies exert first a negative, then a positive impact on GDP per capita. The initial negative impact of digital technologies on GDP can be attributed to the phasing-out effect of the investment in digital technologies. To illustrate, at the very beginning, when the investment in digital technology is insufficiently large, the obvious facilitating effects of digital technologies on economic activities cannot be fully unleashed, as economies of scale have yet to be achieved. Instead, as investment in other areas might be affected due to this phasing-out effect, it makes sense that digital technologies might negatively affect GDP at some time in a given place. Increased adoption of digital technologies will however, drive economies of scale sufficient to exceed the phasing-out effect, generating a net positive impact on the economy.

Likewise, the negative coefficient of digital technologies in the last column of Table 4 implies that digital technologies contribute to industrial structure upgrades, as the value of industrial structure in this study is calculated as the ratio of GDP in secondary sectors to that in tertiary sectors, as shown in Sect. 3. It is possible that digital technologies exert these effects through bolstering human capital and technological innovation, which promote overall industrial structure transitions from conventional industry to high-tech.

5 Robustness Checks and Heterogeneity Analysis

In this section, we conduct a serious of robustness checks on the main findings, including applying a different estimation strategy and changing the measurement of the key explanatory variable, i.e., digital technologies. We also investigate the heterogeneity of digital technologies' effects to enrich discussion about these findings.

5.1 Robustness Checks

5.1.1 Spatial Durbin Model

To capture how spatial factors influence the impact of digital technologies on renewable energy development, in this section we run a regression using the spatial Durbin model. To do this, we first construct the spatial weight matrix, W, using the geographic distance spatial matrix. To illustrate, the value of the element w_{ij} in matrix W is assigned with the inverse of the square of the geographical distance between province i and province j. The estimation results of the spatial Durbin model are displayed in column (1) of Table 5.

Table 5 Robustness checks

Variables	Spatial Durbin model	Change measurement of digital techniques
	(1)	(2)
Digital technologies	2.944***	4.236***
	(0.623)	(1.475)
W. renewable	− 0.154**	
	(0.076)	
L. renewable		0.614***
		(0.115)
Control variables	Y	Y
Time fixed effects	Y	Y
Place fixed effects	Y	Y
Observations	540	510
R^2	0.803	
AR(1)		0.000
AR(2)		0.458
Sargan test		0.100

As can be seen, the coefficient of spatially lagged renewable energy, i.e., *W. renewable*, is − 0.154, significantly negative at the five-percent level, indicating that renewable energy development in a given province is likely to be negatively affected by that in neighboring provinces. This can partly be explained by local protectionism pertaining to market segmentation and political contests in the context of political advancement in China (Zheng et al. 2021a, b). Notwithstanding, the coefficient of digital technologies on renewable energy remains robust in terms of both sign and magnitude, showing that advancement in digital technologies effectively facilitates greater renewable energy development, which is consistent with the findings obtained in the baseline models.

5.1.2 Changing Digital Technology Measurements

To further verify the validity of the above findings, we change digital technology measurements and re-run the regressions in the baseline model. More specifically, we standardize each index used to calculate the value of digital technologies, due to their differences in units, and adjust the weight of these indexes, weighting them all equally. The associated estimation results are given in column (2) of Table 5. We can see that the estimated coefficient of digital techniques is significantly positive at the one-percent level, which is consistent with the estimate in the baseline analysis. While the coefficient increases somewhat, it yet remains robust in terms of both sign and magnitude, indicating the reliability of these findings.

Table 6 Heterogeneity analysis

Variables	Eastern regions	The rest regions
	(1)	(2)
Digital technologies	7.118***	4.733***
	(2.430)	(1.581)
L. renewable	0.562***	0.562***
	(0.119)	(0.119)
Control variables	Y	Y
Time fixed effects	Y	Y
Place fixed effects	Y	Y
Observations	510	510
AR(1)	0.000	0.000
AR(2)	0.424	0.424
Sargan test	0.152	0.152

5.2 Heterogeneity Analysis

This section analyzes the heterogeneous effects of digital technology on renewable energy in terms of regional differences, taking into account the vast disparity in economic and social development across China. While it is well known that eastern China is much more developed in many aspects, disparities between the inland central and western regions have been considerably reduced due to the efforts of China's prominent place-based policy, that is, the Great Western Development Programme that was instituted in 2000 (Jia et al. 2020). Therefore, in the regional heterogeneity analysis, we divide all samples into two groups, one group in the east regions and the others being the rest of the country. The estimates are displayed in Table 6.[1]

As shown in Table 6, the impact of digital technologies on renewable energy is much greater in the eastern areas than is estimated for the rest of the country. This can be explained by the greater digital innovation, more active market mechanism, and more efficient administrative management in advanced technology delivery in the eastern regions (Jia et al. 2020; Zheng et al. 2022).

[1] As we use the interaction of regional dummy variables and digital technology in this analysis, the number of observations is 510 in both columns of Table 6.

6 Case Study: Qinghai Province

6.1 *The Background of Renewable Energy in Qinghai*

Qinghai province in Northwest China is renowned for its renewable energy generation. By the end of 2021, its installed power generation capacity reached 41.14 million kilowatts (KW), of which 25.28 million KW were renewable energy and 37.21 million KW clean energy, accounting for 61.5 and 90.45% of its power generation capacity, respectively. Qinghai thus has the highest proportion of renewable clean energy in its energy supply in China. In the first half of 2022, Qinghai's clean energy power generation reached 42.67 billion kilowatt-hours (kWh), accounting for 84.8% of the province's total power generation, with renewable energy power generation of 21.26 billion kWh, accounting for 42.3%.[2]

Figure 3 shows changes in renewable energy in Qinghai versus the Chinese average between 2003 and 2020. A comparison of histograms shows that power generation from renewable energy in Qinghai remains higher than the national average over most of the past two decades. Only in the period from 2014 to 2017 did Qinghai's renewable energy generation fall relatively below the national average, as renewable energy curtailment during that time was too great. Since then, however, power generation from renewable energy in Qinghai has once more surpassed the national average.

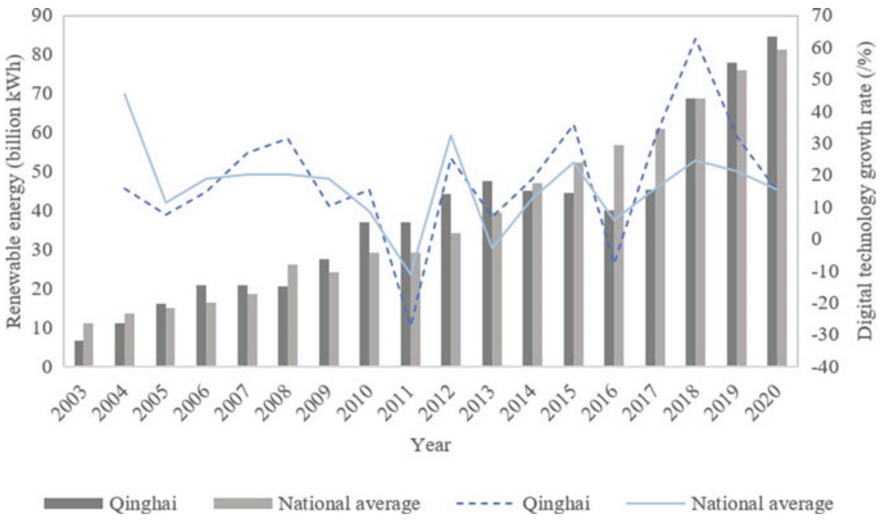

Fig. 3 Renewable energy and digital technology changes between 2003 and 2020 in Qinghai versus the Chinese national average

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[2] See http://qh.news.cn/2022-08/13/c_1128912266.htm.

Based on its outstanding energy infrastructure, Qinghai province has carried out a "Green Power" campaign annually since 2017. In 2017, it successfully ran on 100% renewable energy for seven continuous days, as part of a trial conducted by the State Grid Corporation of China. From June 25 to July 29, 2022, Qinghai conducted a 35-day "Green Power 5 Weeks" campaign, using wind, solar, hydro, and other renewable energy sources, to achieve "zero carbon emissions" in both industrial and residential electricity supply. In the past five years, its cumulative clean power supply was 25.156 billion kWh, reducing coal consumption by 11.43 million tons and CO_2 emissions by 20.58 million tons.

6.2 Applying Digital Technology to Promote Renewable Energy

Since 2017, Qinghai province has carried out an overall assessment of demand potential and grid flexibility for large-scale renewable energy connections, and comprehensively studied optimal power mixes of various energy sources, e.g., wind, solar, hydro, and thermal energy. They have also analyzed optimal dispatching of multi-energy units and maximum power generation of new energy stations. In the process, a number of programs applying digital technology have been launched, including "Software Demonstration for Optimal Annual/Monthly Electricity Generation Scheduling", "Random Optimal Renewable Energy Generation Scheduling System", and "Complementary and Coordinating Dispatching System for Energy Generation from Multiple Power Sources". Qinghai has leveraged digital technology to maximize renewable energy use while effectively reducing dispatching risk and improving its electricity supply system's safety and reliability. Many entities promote these programs, including top universities, companies in energy or related infrastructure construction, and professional associations. Many projects applying cutting-edge digital technology have been put at the top of their research lists, including interaction between providers and end-users, load modes and assessment systems with renewable energy as the main generation source, and the demonstrated interaction between generation and load. In practical work, the following tasks have also become key work, including network-based energy storage, direct current (DC) collection and networking, electricity-carbon collaborative management, and comprehensive energy planning and operation based on industrial zones.

Figure 3, which shows the trend of digital technology growth rates, also shows via the line graphs that digital technology adoption in Qinghai accelerated in 2017 and have significantly exceeded the national level since, although the gap between Qinghai and the national level is unstable in the previous years. Overall, the change of digital technology in Qinghai goes in line with its outstanding performance in renewable energy. To some extent, this reveals that digital technology in Qinghai has considerably facilitated renewable energy development there.

6.3 Barriers and Policy Responses

In China, almost all provinces are trying to apply digital technologies to facilitate expansion renewable energy generation, and Guizhou and Sichuan, two western provinces with extensive renewables, are rapidly building more computing power to drive digital economies and provide digital services to eastern China. In this context, Qinghai faces tremendous challenges from peer provinces. Qinghai has been making many efforts in many ways to deeply integrate digital technology with renewable energy, particularly in improving policy structure and mechanism design, launching key projects, attracting high-level human capital in related fields, and facilitating social capital participation in digital technology.

Regarding improving policy structure and mechanism design, key provincial leaders direct dedicated personnel in developing Qinghai's digital economy. The Digital Economy Development Bureau, a provincial government agency, manages such relevant affairs as confirmation, openness, circulation, transactions, and security data resources. The bureau has established targeted standards and systematic regulations for said digital economic development, and is exploring better coordination across departments and hierarchies. It has also simplified processes for applying for data use among governments and concerned companies.

Qinghai has constructed several data centers, computing infrastructure and national computing hubs in the course of launching key projects, including the National Qinghai-Tibet Plateau Scientific Data Center—Qinghai Branch, Qinghai-Tibet Plateau Ecological Big Data Center, Huawei Big Data Center, and Big Data Centers of the Three Major Telecom Operators. The bureau has taken a number of measures, to stimulate these data centers to release more potential and thereby promote Qinghai's digital economic development, including sharing project resources, taking advantage of counterparts' assistance to reduce poverty, and striving to become a showcase for investment. In particular, two 10-million KW renewable energy bases built by Qinghai are continuously allocating relevant energy to companies inside and outside the province, to promote the reciprocal model of carrying out crucial projects by sharing resources.

Considering that human capital is one of the core elements for digital technology development, Qinghai tries to attract and employ representative talent in computer science, software engineering, artificial intelligence, data science, and electronic engineering. The province has also adopted innovative policies featuring telework and teleconferencing which allow workers to work remotely for Qinghai regardless of where they actually reside.

Qinghai also grasps the emerging characteristics of digital economy and provides preferential policies for social capital participation. The province compensates for its economic development shortcomings by considering its local economic conditions and relevant social capital investment demands.

7 Conclusion

In this paper, we evaluate the role of digital technologies in renewable energy development, based on China's provincial data from 2003 to 2020, by applying the entropy weight method to measure China's digital technology level and employing the GMM estimation approach in the baseline analysis. We also test potential channels through which digital technologies bolster renewable energy growth, in terms of economic development and industrial structure adjustment. We also conduct a series of robustness checks to ensure the validity of our primary findings, using the spatial econometric method to take possible geographical influences into account and handling the influence of the weighting of the indexes used to measure digital technologies. We also conduct a heterogeneity analysis before depicting Qinghai province's particular measures to how achieve 100% renewable energy. The aforementioned primary findings suggest that the application of digital technologies has significantly facilitated renewable energy development in China, an outcome that is robust across a number of model specifications and assessment methods. Digital technologies exert these effects through affecting economic development and adjusting industrial structure. This impact is particularly prominent in the more developed eastern regions where conditions are more conducive to advancement in digital technologies. These conclusions shows that it is plausible to expand renewable energy application by enhancing digital technology. Moreover, to make digital technologies work better in improving renewable energy, it is necessary to ensure conditions suitable for digital innovation, in both market mechanisms and government efficiency.

The Qinghai province case study shows that a place with extensive renewable resources that nonetheless lags significantly in economic development is able to promote renewable energy development with the help of digital technologies, given reasonable policy and mechanism design. Other important factors to consider include emerging characteristics of digital technologies, representative human capital, and social capital investment.

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