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Rural E-commerce and County Economic Development in China

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Abstract

With the proliferation of information and communication technology in rural areas, rural e-commerce has gradually become a new economic phenomenon in China. Using the national rural e-commerce comprehensive demonstration policy as a quasi-natural experiment, this study examines the causal linkage between rural e-commerce and county-level economic development in China. Its findings, which draw on county-level panel data from 2011 to 2018, indicate that the policy had a positive effect on the county-level economy in China, resulting in an overall increase in county GDP by 3.5 percent (0.7 percent annually). Our analysis further shows that the impact of the policy differed along the region and human capital dimensions. Further analysis reveals that industrial structure and nonagricultural employment were the main channels for the policy to exert a county-level economic impact. Infrastructure improvement in China also plays an important role. The findings emphasize the importance of advancing e-commerce in rural areas to stimulate county-level economic development.

Keywords: county economy, e-commerce, quasi-natural experiment, rural China
JEL codes: D04, H0, Q0

I. Introduction

The popularization of information and communication technology (ICT), particularly the extensive use of the Internet and intelligent phones, has become increasingly important

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in countries' social and economic development (Jensen, 2007; Deichmann et al., 2016; Hjort and Poulsen, 2019). The adoption of e-commerce is recognized as an effective way to narrow urban–rural disparities and achieve the goal of rural revitalization, as it has a radical effect on economic development (Aker, 2010; Liu et al., 2015; Zhang et al., 2018). E-commerce in rural China boomed during the 2010s and has substantially affected the livelihood of rural residents (Qi et al., 2019). This is likely because rural e-commerce expands markets to the countryside and helps increase the income of rural dwellers. The Chinese government has realized the important role of rural e-commerce and has adopted it as a tool for local economic development. For instance, the national rural e-commerce comprehensive demonstration (NREC) policy, a concrete national project that focuses on the subsidization of poverty-stricken zones to burgeon e-commerce, was enacted in 2014. The impacts of the proliferation of rural e-commerce in China are exemplified by comprehensive policy demonstration and the surge in rural e-commerce and its latent capacity for social-economic development.

With the proliferation of ICT in the rural areas of the developing world, rural e-commerce has gradually become a new economic phenomenon, not only in China but also in Mexico (Marlen et al., 2020), India (Lele and Goswami, 2017), Turkey (Yaşlak et al., 2021), and other developing countries. In addition to China, many countries have introduced policies to encourage the use of ICT to promote agricultural and rural development. For example, the UK and the European Union have implemented the Digital Village Program (Roberts et al., 2017), and in the developing world, countries such as Iran and India, have implemented the Rural ICT Center Program (Niavand and Nia, 2017). The expansion of rural e-commerce has received significant attention from scholars and policymakers in developed countries since the popularization of ICT in the 1990s (Mueller, 2001). This attention was followed by a rapidly growing body of literature focusing on Chinese rural e-commerce since the 2010s (Zhang et al., 2018).

The literature on China's rural e-commerce follows two main themes. The first theme examines how e-commerce clusters form and evolve, and what influences the adoption of e-commerce in rural areas. A great many of these empirical studies have investigated decisive factors regarding the evolution of the Taobao villages (Leong et al., 2016; Lin, 2019), which are associated with entrepreneurship, social innovation, supply networks, and Internet use (Zeng and Guo, 2016a, b; Wei et al., 2019; Ma et al., 2020).[1] For instance, Zeng and Guo (2016a, b) adopted the case study method to highlight

[1]Taobao villages are villages where the number of active online stores exceeds the number of local households by 10 percent and where annual e-commerce transactions exceeds RMB10 million.

that e-commerce associations played a pivotal role in the evolution of Taobao villages. Zeng et al. (2019) used survey data to test the intermediary effect of acquaintance societies and social networks in rural e-commerce development. Lin (2019) studied the impact of e-commerce and population migration on the social spatial transformation of Taobao village and found that ICT infrastructure and social networks constituted the basis of rural e-commerce development. Further, regional inequality was introduced in the research on China's rural e-commerce development (Zhu et al., 2016). In summary, based on case studies or descriptive studies with restricted data, most scholars have investigated the current circumstances, development modes, existing issues, and policy implications of rural e-commerce development in China (Lin et al., 2016; Tang and Zhu, 2020).

The second expanding theme in the literature concerns the influences of e-commerce applications on social and economic gains in rural China. Of the studies that considered the relationship between e-commerce and economic gain, most found that e-commerce played an important role in enhancing farmers' income and economic gains, poverty alleviation, and the promotion of balanced growth in the city and countryside. For instance, Zeng et al. (2019) used survey data to examine the impact of e-commerce adoption on household income in rural China and found that the income of the households that adopted e-commerce in agricultural product sales was significantly higher than that of their counterparts. This echoes Luo and Niu (2019), who further confirmed that the adoption of rural e-commerce increased household revenue, and Li et al. (2021), who found that the income of e-commerce adopters was significantly higher than that of nonadopters, and the considerable increase in sales revenue was one of the main contributors to such large income gains. However, there are also some contradictory findings. For instance, Couture et al. (2021), using a survey based on microdata regarding household and store prices supplemented by transaction records from a large Chinese village firm's internal database, found that farmers did not gain many economic benefits in the stochastic expansion of Taobao's coverage through Alibaba's Rural Taobao Program. This is mainly because the benefits brought by e-commerce are driven by reductions in the cost of retail consumption rather than increases in household income.

China's strategy of using e-commerce as a tool to boost rural development has been an important source of inspiration for other developing countries (Lele and Goswami, 2017). Despite the inconsistent conclusions, most existing studies – including those stated above – utilized data sets from the level of Taobao villages and households. Taobao villages are typical cases of villages that adopt e-commerce in rural China, but they are not representative, and such studies ignore the traits of non-Taobao villages. To learn

how the benefits from rural e-commerce are distributed to rural households, we must first examine whether rural e-commerce boosts economic growth at a more macro level. However, the impact of e-commerce on the overall growth of the regional economy and its related mechanisms have not been studied fully (Wang et al., 2021). To date, there is no consensus about whether – and if so, to what extent – the development of rural e-commerce positively affects county-level economies, and little is known about whether and how e-commerce is associated with China's poverty alleviation and rural revitalization strategies.

This study is novel in several respects. First, it uses the NREC policy as a quasi-natural experiment to assess the impact of e-commerce on county economic development. Drawing on the variation in policy timing across counties, we adopted the difference-in-differences (DID) approach to examine the casual relationship between this policy implementation and county economies. This approach can better solve endogeneity problems and greatly enhance the reliability of empirical results. We focused on the county level because it is a basic unit of China's macro-economic system. Due to the enormous population of counties in China and the pressure of rural poverty alleviation, county-level economic development has become a priority for Chinese policymakers. Counties account for 70 percent of the total population, but county GDP accounts for only 41 percent of the country's overall GDP. This study is among the first to investigate whether the NREC policy has stimulated local economic growth by enhancing the development of rural areas.

Second, unlike most similar studies that use household- and village-level survey data, this study uses a county-level panel dataset. Our analysis combined the information on the NREC policy with a novel dataset from a significant number of official sources. The data covers 2,084 counties in 28 provinces of China between 2011 and 2018. They include comprehensive information about GDP, fiscal expenditure, and output for each industry. The changes involved in becoming e-commerce demonstration counties are also included. Such detailed panel data allow for a thorough inspection of changes in outcomes before and after the NREC policy.

Third, this study not only examines the extent to which the NREC policy has affected counties but also investigates why this could occur (mechanisms) and how it differs across several dimensions (heterogeneous effects). This helps fill the gap in development theory regarding how new technology (e-commerce) contributes to the economic development of developing countries. The theoretical and empirical research conducted in this study may have certain implications for the development of county-level e-commerce and the policy formulation of industrial structures. It may also cause other countries dealing with poverty to rethink how to utilize rural e-commerce as a tool to lift more people out of extreme poverty.

To investigate the impact of the NREC policy, we used DID methods. The biggest challenge was to ensure the effectiveness of the DID methods, which depended on the assumption that non-e-commerce demonstration counties and those that later became e-commerce demonstration counties would have a common trend in comparison with those that became e-commerce demonstration counties earlier in the absence of the NREC policy. To verify this assumption and identify the causality between the NREC and county economic growth accurately, we carried out a placebo test by randomly assigning e-commerce demonstration counties, and we applied an event study to evaluate year-wise variation in the outcome variables before and after the NREC policy, with a 6-year time window.

We obtained three major findings. First, the NREC policy increased the GDP of a county by an average of 3.5 percent, suggesting that the annual growth rate increased by 0.7 percent. This finding suggests that the NREC policy had a positive impact on county economies. Second, the results of the heterogeneous analysis show that the effect of this policy was regionally different along the dimensions of the region and human capital. Third, the industrial structure changed, and nonagricultural employment in e-commerce demonstration counties increased after the NREC policy, which, in turn, may have influenced economic performance positively. These results demonstrate that industrial structure and nonagricultural employment were the main channels for the NREC policy to exert a county-level economic impact.

The rest of the study is arranged as follows. Section II briefly introduces the NREC policy and outlines the policy background. Section III introduces the identification strategies and the data explicitly, followed by the major empirical findings in Section IV. Section V shows the potential mechanism underlying the NREC policy impact. Section VI concludes.

II. Background

In China, although rural e-commerce did not start until the late 1990s, it boomed during the 2010s. In the early 2010s, the Chinese central government proposed the strategy of promoting rural e-commerce to reduce poverty, aiming to lower poverty steadily by introducing e-commerce in poverty-stricken zones. The Chinese government hoped to help farmers improve their revenue and win the battle against poverty through the development of rural e-commerce. In this context, the Ministry of Finance and the Ministry of Commerce jointly issued *Conducting a Comprehensive Demonstration of E-commerce in Rural Areas*. This corresponded to a national-level program dedicated to funding distressed areas to develop e-commerce for the first time in July 2014, thus

starting the implementation of a comprehensive policy demonstration for e-commerce in rural China. The progress of the policy is shown in Table A1 in the Appendix, and the main contents of the policy in 2014 are shown in Table A2 in the Appendix.

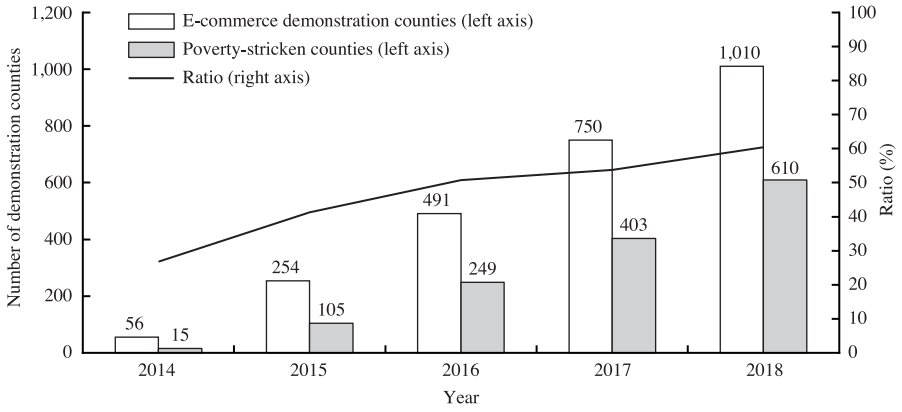
The NREC policy is based on resource endowments and market demand, and its key indicators of selection are logistics foundations, network platforms, characteristic industries, and development levels. In accordance with the policy, rural comprehensive demonstration counties initiating e-commerce were selected to examine the influence of e-commerce on the rural economy and to determine if it could promote sustainable economic development. As the e-commerce demonstration counties were approved by the Poverty Alleviation Office of the State Council and were recognized as suitable for the application of rural e-commerce for poverty reduction, becoming an e-commerce demonstration county meant that the county could be supported via various national and provincial governmental policies and financial funds. Each demonstration county could receive about RMB20 million of central financial support.

The government directed special funds to three areas. Regarding the first area, e-commerce demonstration counties could use e-commerce's cross-temporal characteristics to reduce information asymmetry and develop online supply chains. For the second area, e-commerce demonstration counties promoted the establishment of e-commerce-focused public service centers, e-commerce service stations, and e-commerce industrial parks by policy support that provides preferential access to resources. With the establishment of service centers, e-commerce gradually moves into deep poverty-stricken areas, which opens up rural circulation channels to promote the development of county economies. Concerning the third area, e-commerce demonstration counties can use special funds to develop Taobao villages, promote the prosperity of the industry, and make themselves important rural Internet providers to drive employment. In addition, e-commerce training centers should be established to support college students returning to their hometowns to start their own businesses, carry out the demonstration effect of e-commerce, focus on cultivating farmers' e-commerce skills, and promote county economic development. In short, by being dedicated to promoting the upward trend of agricultural products, improving the rural public service facility system, and carrying out e-commerce training, e-commerce demonstration counties have a role in promoting the counties' economic development.

Figure 1 shows the number of counties that became e-commerce demonstration counties from 2014 to 2018. By 2018, more than 1,010 counties across 22 provinces had become e-commerce demonstration counties. Specifically, the number of funded national-level poverty-stricken counties increased from 249 in 2016 to 610 in 2018, which means they accounted for more than 50 percent of the total funded counties every year (Figure 2).

With the high-speed popularization of Internet access and the stable progress of logistics infrastructure construction, the 56 demonstration counties in 2014 were distributed mainly over the eastern region, including Jiangsu and Hebei provinces, among others. To alleviate rural poverty and revitalize the stagnant rural economy (Li, 2017), comprehensive demonstration work began to move to poverty-stricken areas in 2016. From 2016 to 2018, demonstration counties were mainly concentrated in the central and western regions.

Figure 1. Number of poverty-stricken counties and total e-commerce demonstration counties in China



Sources: Authors' calculation based on data from the Ministry of Commerce.

Note: The calculation is based on the List of National Key Counties for Poverty Alleviation and Development.

According to preliminary calculations, the NREC policy has supported 1,016 demonstration counties in five years, and the central capital investment is RMB20 million per county. By the end of 2018, the central government invested RMB20.32 billion in total, and local governments provided no less than 20 percent of the total funds. We therefore conservatively estimate that from 2014 to the end of 2018, the central and local governments invested no less than RMB24.384 billion in the construction of rural e-commerce. According to the planning by the Market Construction Department of the Ministry of Commerce, the NREC policy will last until 2022 and will cover more than 2,500 counties across the country, with a total investment of more than RMB60 billion. The NREC policy has become the most widely implemented and strongest policy in the field of digital village construction (Tang et al., 2020). From 2014, online retail sales in rural areas began to increase considerably and have been expanding annually. Specifically, they increased from RMB180 billion to RMB1,370 billion between 2014 and 2018; this is a six-fold increase, with an average annual growth rate of 66 percent.

III. Data and empirical strategy

1. Data source

To examine the impact of the NREC policy, we constructed a panel dataset obtained from various official statistical publications with detailed social-economic information at the county level between 2011 and 2018.

The *China County Statistical Yearbook* (NBS, 2012−2019) reflects the social and economic development of China's counties comprehensively and contains data on the overall state and comprehensive information related to the economy, agriculture, industry, education, health, and social security, among others, of more than 2,000 county units in the country. This allowed us to obtain most of the variables required, including county-level GDP, population, the added value of primary industry, the added value of secondary industry, public financial expenditure, the end-of-year loan balance of financial institutions, number of middle-school students in school, number of fixed-line telephone users, and other indicators. Finally, in the chosen period (2011–2018), renamed areas or counties (cities) that changed to districts were regarded as the same unit.

The list of national comprehensive demonstration counties for e-commerce in rural areas from 2014 to 2018 was compiled by the authors using the Ministry of Commerce website.[2] Poverty-stricken counties were drawn from the *List of National Key Counties for Poverty Alleviation and Development* issued by the State Council's Poverty Alleviation and Development Office in 2012.

2. Estimation strategy

To examine the effect of the NREC policy on the county-level economy, we utilized time and geographic variations in the gradual involvement policy since 2011. We collected and collated the county panel data of 2,084 counties in 28 provinces of China from 2011 to 2018, including 1,010 national e-commerce comprehensive demonstration counties in rural areas. Within this sample, 610 poor counties were selected as demonstration counties, accounting for 93.98 percent of all poor counties in the sample. Specifically, the DID technique compares the outcome of counties before and after they became demonstration counties with that of counties that were not demonstration counties during the same period.

[2]Available from: http://www.mofcom.gov.cn/article/zt_dzswjnc/lanmufive/201705/20170502572784.shtml (online; cited August 2023), http://scjss.mofcom.gov.cn/article/cx/201708/20170802630135.shtml (online; cited August 2023), and http://www.mofcom.gov.cn/article/tongjiziliao/sjtj/jcktj/201809/20180902790215.shtml (online; cited August 2023).

The baseline DID estimation is as follows:

$$Y_{it} = \alpha_i + \delta_t + \sigma EC_{it} + \beta \boldsymbol{X}_{it} + \varepsilon_{it}, \quad (1)$$

where i indicates county and t indicates year; Y_{it} denotes the logarithm of GDP and other outcome variables; α_i denotes the county fixed effects, controls for the time-invariant factors that might affect the county-level GDP and other outcomes; δ_t represents the year fixed effects; $\boldsymbol{X}_{it}$ consists other control variables that change across counties and over time, including agricultural development level, industrial structure, government scale, financial development level, human capital level, infrastructure level, and land area per capita; and ε_{it} is a county time-varying error distributed independently of α_i and δ_t.

EC_{it} is the main independent variable of interest, indicating the status of each county i in year t. Specifically, $EC_{it} = Treatment_i \times Post_{it}$, where $Treatment_i = 1$ if county i became a demonstration county during the sample period, and 0 otherwise. $Post_{it}$ is a post-treatment indicator, equal to 1 if $t \geqslant t_{i0}$ (where t_{i0} is the year county i became a demonstration county), and 0 otherwise. We clustered the standard errors at the county level to address the potential issue of serial correlation and heteroskedasticity.

In the estimation of DID, we were concerned that the selection of the demonstration counties was likely to be endogenous, which would largely bias the impact of the NREC policy. To rule out this concern, we followed a tactic used by Li et al. (2016). We experimented with two specifications, which increasingly allowed more flexibility in the estimation. First, supposing that the impact of $\boldsymbol{X}_{it}$ on Y_{it} follows specific time tendencies, the control variables $\boldsymbol{X}_{it}$ interact with a third-order polynomial function of time in Equation (2). Second, to further control for the time impacts of $\boldsymbol{X}_{it}$ on Y_{it}, $\boldsymbol{X}_{it}$ also interacts with the year dummy δ_t. This produces the following augmented DID specification:

$$Y_{it} = \alpha_i + \delta_t + \sigma EC_{it} + \theta(\boldsymbol{X} \times f(t)) + \varepsilon_{it}, \quad (2)$$

where $f(t)$ represents a third-order polynomial function of t or δ_t.

To further check our identifying assumption, we conducted a few other tests, as explained in Section IV. 4, including a placebo test with randomly assigned county status and a test with alternative measurements.

3. Descriptive statistics

Detailed variable definitions and descriptive statistics of the relevant variables are presented in Table 1. As the main variable of interest, the proportion of counties selected as e-commerce demonstration counties was 0.163 on average during the observed period. This increased from 0.027 in 2014 to 0.478 in 2018. During this period, the average

GDP was RMB156.934 billion, and GDP per capita was RMB38,100. For comparative purposes, we also show the growth rate of GDP and GDP per capita, which were 7.3 percent and 8 percent, respectively. As for the composition of GDP, primary industry accounted for a lower proportion than secondary industry. The government scale was 0.292, which means that the contribution of public finance expenditure to GDP was relatively high. The financial development level, defined as the proportion of financial institutions' loan balance of GDP, was fairly high (0.622). The human capital level of the county was only 0.119, which indicates that the proportion of middle school students in the total population was relatively low. The ICT infrastructure level of the county was only 0.107,

Table 1. Descriptive statistics

Variables	Variable definition	Mean	Standard deviation	Data coverage
GDP	GDP (RMB billion)	156.934	146.081	2011–2018
GDP per capita	GDP per capita (RMB10,000 per capita)	3.810	5.139	2011–2018
GDP growth	Growth rate of GDP	0.073	0.142	2012–2018
GDP per capita growth	Growth rate of GDP per capita	0.080	0.183	2012–2018
EC	$EC_{it} = Treatment_i \times Post_t$, $Treatment_i$ is the dummy variable of the selected demonstration county, and $Post_t$ is the time dummy.	0.163	0.369	2011–2018
Agricultural development level	Ratio of the added value of primary industry of GDP (%)	0.193	0.099	2011–2018
Industrial structure	Ratio of the added value of secondary industry of GDP (%)	0.433	0.143	2011–2018
Tertiary industry development level	Ratio of the added value of tertiary industry of GDP (%)	0.370	0.102	2011–2018
Nonagricultural employment	Number of nonagricultural jobs (10,000 per capita)	14.910	16.026	2013–2018
Government scale	Proportion of public finance expenditure of GDP (%)	0.292	0.225	2011–2018
Financial development level	Proportion of loan balance of financial institutions of GDP (%)	0.622	0.315	2011–2018
Human capital level	Proportion of middle school students in the total population (%)	0.119	0.038	2011–2018
ICT infrastructure level	Number of fixed-line telephone users per capita	0.107	0.072	2011–2018
Land area per capita	Land area per capita (100 m^2)	2.035	4.241	2011–2018
IEVH	Dummy variable for the Information Entering Village and Household project	0.130	0.336	2011–2018
Highway mileage	Highway mileage (km)	1,810.395	1,127.053	2011–2018

Notes: All variables represent county-level information. We follow Brandt and Holz (2006) and Li et al. (2016) and ensure that all monetary values are deflated using the provincial price deflators with Beijing as the base province and 2010 as the base year.

which indicates that the coverage of ICT infrastructure was still relatively low. However, this may also be due to data limitations and the inability to obtain further indicators representing ICT infrastructure. Land area per capita, which is an indicator of the area of the county, was 203.5 square meters.

The sample was further partitioned into treatment and control groups and the summary statistics are shown separately in Table 2. This yielded several insights. First, the average GDP of the treatment group is RMB101.272 billion, which is much lower than that of the control group. This result may not indicate a positive relationship between the NREC policy and county-level economic growth. A causal analysis is required to draw a more decisive conclusion, which is the key point of the next section. However, it could be linked to the concern raised above that the counties with lower GDP may be more likely to be selected for the program. We ruled out this concern in the next section. In contrast, the growth rate of GDP in the treatment group is much higher than that of the control group. Second, the treatment and control groups also differ considerably in agricultural development level, industrial structure, tertiary industry, government scale, financial development level, human capital level, and land area per capita. There are also significant differences in nonagricultural employment and ICT infrastructure level. For example, in the counties that were selected as e-commerce demonstration counties, the proportion of the secondary and tertiary industries is higher than that in the control group.

Table 2. Mean differences in characteristics between the control and treatment groups

Variables	Treatment	Control	Difference
GDP	101.272	208.696	–107.424***
GDP per capita	2.733	4.812	−2.079***
GDP growth	0.083	0.064	0.019***
GDP per capita growth	0.089	0.071	0.017***
Agricultural development level	0.220	0.167	0.053***
Industrial structure	0.399	0.464	0.064***
Tertiary industry	0.375	0.365	0.010***
Nonagricultural employment	11.104	18.456	–7.352***
Government scale	0.372	0.217	0.155***
Financial development level	0.644	0.602	0.042***
Human capital level	0.120	0.118	0.002***
ICT infrastructure level	0.087	0.125	–0.039***
Land area per capita	2.245	1.838	0.407***

Note: *** represents significance at the 1 percent level. For the definitions of variables, see Table 1.

IV. Empirical results

1. Estimates of difference-in-differences models

Table 3 reports the main estimation results. There is a significant positive correlation between the NREC policy and the logarithm of GDP. Column (1) of Table 3 shows the results when only the influence effect variable EC of the NREC policy is taken as the explanatory variable under the fixed effects of controlled areas and time. To further verify this relationship, we added control variables in column (2) of Table 3, and the coefficient of the EC variable is still significantly positive. This suggests that the NREC policy has stimulated the economic development of the selected counties.

Table 3. Effect of e-commerce on county economy based on the difference-in-differences method

	lnGDP					ln(GDP per capita)	GDP growth	GDP per capita growth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EC	0.043***	0.055***	0.038***	0.035***	0.035***	0.033***	0.031***	0.019**
	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.005)	(0.007)
DVM	4.615	4.615	4.615	4.615	4.615	10.290	0.073	0.079
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Control variables × Time	No	No	Yes	No	No	No	No	No
Control variables × $Time^2$	No	No	Yes	No	No	No	No	No
Control variables × $Time^3$	No	No	Yes	No	No	No	No	No
Control variables × Year dummy	No	No	No	Yes	Yes	No	No	No
IEVH	No	No	No	No	Yes	No	No	No
ln(one-year lagged GDP)	No	No	No	No	No	No	Yes	No
ln(one-year lagged GDP per capita)	No	No	No	No	No	No	No	Yes
Adjusted R^2	0.975	0.986	0.986	0.988	0.988	0.947	0.566	0.467
Year coverage			2011–2018			2011–2018	2012–2018	2012–2018
Number of clusters	2,074	2,074	2,074	2,074	2,074	2,074	2,059	2,059
Observations	15,078	15,078	15,078	15,078	15,078	15,078	12,930	12,928

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. Control variables include the agricultural development level, industrial structure, government scale, financial development level, human capital level, infrastructure level, and land area per capita. We clustered the standard errors in parentheses at the county level. For the definitions of variables, see Table 1. IEVH refers to another policy, Information Entering Villages and Households, which was implemented simultaneously. DVM, the mean of dependent variables; EC, the variable of an e-commerce demonstration county; FE, fixed effects.

The results that allow interactions between flexible time functions and control variables, as in Equation (2), are reported in columns (3) and (4). Specifically, column (3) reports the interactions between the control variables and a third-order polynomial function of time, and column (4) reports the interactions between the control variables and year dummies. The coefficients of interest (EC) remain positive and significant in these two specifications.

2. Other reforms

One of the biggest concerns in the study is the confounding effect of policy reforms, other than NREC, that took place during the same time period. For instance, in addition to the NREC policy, another policy that was implemented at the same time is the Information Entering Villages and Households (IEVH) project. This project aims to create village-level information service capabilities to meet farmers' needs regarding production, and other key information. The project also aims to use modern information technology to boost rural areas and support agriculture, vigorously improve farmers' ability to obtain information so they can increase their income, and provide support for accelerating the promotion of agricultural modernization and the integration of rural and urban development.

Consistent with the deployment requirements of *Deepening rural reform to accelerate agricultural modernization* (known as *No. 1 Central Document* for 2014), the Ministry of Agriculture designated 10 provinces, including Beijing and Liaoning, and 22 counties, to implement pilot IEVH projects. In 2015, the pilot IEVH projects were expanded. First, the initial batch of 10 pilot provinces, with the 22 pilot counties, had fully completed the project and then at least five pilot counties were added for each province. Second, 10 more provinces with pilot IEVH projects were added, and at least two pilot counties were determined for each new province. By the end of 2018, 13 provinces had already begun to implement whole-province promotion of IEVH projects.

These simultaneous reforms led to concerns that the estimated NREC effect may simply have been caused by the IEVH project if the IEVH project had a positive impact on county-level economic development and the NREC policy was applied in an IEVH county. To isolate the influence of the NREC policy, we controlled for a new variable by collecting information on whether the government of a specific county launched an IEVH project. This allowed us to identify the discrepancy in the development between NREC and non-NREC counties that have the same IEVH project status. As presented in column (5) of Table 3, the coefficient on the NREC policy is still significant and positive. This result suggests that the estimated NREC effect is independent of the IEVH project's effect.

3. Economic magnitude

To further understand the economic magnitude of the impact of the NREC policy, we used the estimation in column (4) of Table 3 and found that about 3.5 percent higher GDP is predicted for e-commerce demonstration counties. With a sample period of 2011–2018 and the beginning of the NREC policy in 2014, the estimated average treatment effect covers five years. That is to say, the 3.5 percent increase in GDP stemming from the e-commerce demonstration county policy can be translated into an approximately 0.7 percent increase annually.

In addition to the year-based calculation, we also measured the economic magnitude by comparing the estimates with the mean value of the outcome variable. As the main outcome of interest, the mean value of the logarithm of GDP from 2011–2018 was 4.615. This suggests that the NREC policy increased the logarithm of GDP by 0.76 percent relative to the sample mean.

4. Heterogeneous effects

(1) Regional level

While the above results show that the NREC policy has a positive impact on county economic development, this may differ along some dimensions. For instance, it is possible that counties with excellent socio-economic conditions may not have the same benefits from the NREC policy. To examine this heterogeneity, we first considered the differences by region. We partitioned the sample into western, central, and eastern regions and investigated the impact for each of them, respectively. The results in Table 4 indicate that, overall, the NREC policy positively impacts the economic development of various regions, but there is obvious regional heterogeneity. We found that the impacts of NREC policy in both the eastern and central regions were relatively large (4.9 and 5.0 percent, respectively). The reasons for this phenomenon may be that in relatively developed areas (e.g., the eastern region), the development conditions of county e-commerce are better, and it is easier to benefit from e-commerce activities. In the central and western regions, the government has provided greater support for e-commerce development, enabling poor counties to benefit from e-commerce activities and reduce poverty. The central region may also benefit from e-commerce activities and the positive externalities of the eastern region. Although the western region has policy support as well, in comparison, the promotion of e-commerce policies is still relatively limited. This is potentially because, as the region with the lowest level of economic performance, the economic foundation of the western region is relatively weak, the local infrastructure (e.g. roads) is relatively underdeveloped, and the majority of young labor migrates to the eastern region. All of these are potential causes for a smaller impact of NREC (4.4 percent) in

the west. We compared the differences between the EC coefficients across heterogeneous influencing factors, finding that the difference in the EC coefficient between central and western regions is significant at the level of 10 percent. The results remained robust if we included the interactions between the control variables and flexible time functions/time fixed effects (Tables A3 and A4 in the Appendix), which suggests more significant regional differences.

Table 4. Heterogeneity analysis of e-commerce's economic effect at the regional level (2011–2018)

Dependent variable: lnGDP	Eastern	Central	Western
	(1)	(2)	(3)
EC	0.049***	0.050***	0.044***
	(0.009)	(0.006)	(0.007)
DVM	5.232	4.784	4.119
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Adjusted R^2	0.985	0.985	0.981
Number of clusters	540	613	902
Observations	3,920	4,641	6,480
Differences			
Eastern versus central		–0.001	
Eastern versus western		0.004	
Central versus western		0.006*	

Notes: *** and * represent significance at the 1 and 10 percent levels, respectively. All variables represent county-level information. The control variables are the same as Table 3. DVM, the mean of dependent variables; EC, the variable of an e-commerce demonstration county; FE, fixed effects.

(2) Population size and human capital

In this section, we examined how the impact of NREC policy on economic performance differed by county population and human capital. We divided the sample into two groups for each of these two dimensions, according to the mean of population and human capital variables in each region from 2011 to 2018. We then compared the heterogeneous effects between the counties with a large population with their counterparts that have a small population in columns (1)–(2) of Table 5 and between the counties with a higher level of human capital with their counterparts in columns (4)–(5) of Table 5. The coefficient of the large population group is higher than that of the small population group, and the difference of the EC coefficients across these two subgroups is significant at the 1 percent level, indicating that the population has a significant positive regulatory impact on promoting economic growth. In other words, the richer the local human resources, the more helpful the NREC is in promoting economic development. It is also found that, in the counties with a higher level of human capital, the impact of NREC

policy is larger compared to their counterparts. The difference of the EC coefficients across subgroups is also significant at the 1 percent level. This indicates the important role of human capital in economic growth, which is in line with human capital theory (Mamuneas et al., 2006). The results of the interactions between the control variables and flexible time functions are presented in Tables A5 and A6 in the Appendix. The results still reveal the importance of human capital in economic development.

Table 5. Heterogeneity analysis of e-commerce's economic effect by influencing factors (2011–2018)

Dependent variable: lnGDP	Small population	Large population	Difference	Low human capital	High human capital	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
EC	0.039***	0.083***	0.043***	0.038***	0.064***	0.026***
	(0.006)	(0.006)		(0.006)	(0.007)	
DVM	4.132	5.356		4.686	4.533	
County FE	Yes	Yes		Yes	Yes	
Year FE	Yes	Yes		Yes	Yes	
Control variables	Yes	Yes		Yes	Yes	
Adjusted R^2	0.974	0.973		0.981	0.986	
Number of clusters	1,206	818		1,254	1,134	
Observations	8,613	5,918		7,749	6,522	

Notes: *** represents significance at the 1 percent level. All variables represent county-level information. The control variables are the same as Table 3. DVM, the mean of dependent variables; EC, the variable of an e-commerce demonstration county; FE, fixed effects.

5. Robustness check

To address concerns about the identification strategy that corroborated the findings, we implemented a series of robustness checks.

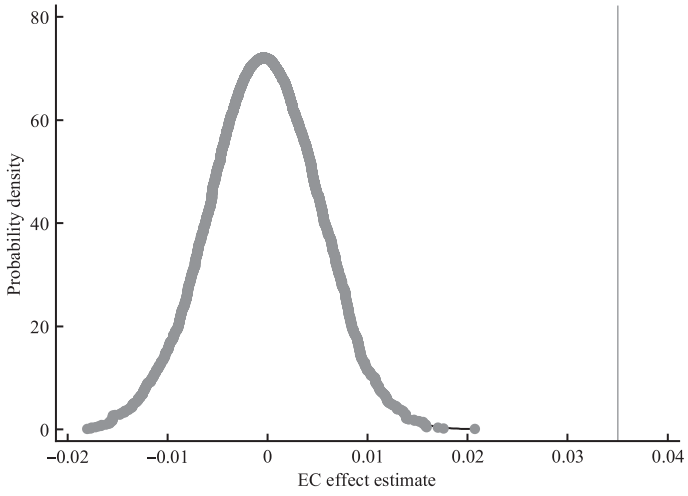
(1) Randomly generated demonstration county status

We first conducted a placebo test by stochastically assigning e-commerce demonstration counties to examine whether there was selection bias and whether the unobserved variables would affect the impacts (La Ferrara et al., 2012; Li et al., 2016). Table A1 in the Appendix indicates that the e-commerce demonstration county policy had been applied for five years. Keeping in mind the requirement of the DID technique regarding the period coverage of the e-commerce demonstration county policy, we randomly selected five years from 2012 to 2017 and assigned counties as the treatment group at random in each year without replacement. For instance, consider that t_1, …, t_5 are five representative years randomly selected from 2012 to 2017. Next, at t_1, 56 counties were randomly selected from all 1,010 counties and designated as demonstration counties.

At t_2, 198 counties were stochastically selected from the remainder as demonstration counties. This stochastic selection process continued until t_5, where the final 260 out of all 1,010 counties were selected as demonstration counties. We conducted a placebo DID estimation using these false treatment variables combined with the specification in column (4) of Table 3. Considering the stochastic generation process of demonstration counties, the false treatment variables should produce no significant estimation, and their magnitudes should approach zero; otherwise, it would indicate a specified error DID estimation. This process was repeated 500 times to improve the identification power of this placebo test.

Figure 2 illustrates the distribution of estimates for 500 runs, and the vertical line in the figure indicates the baseline estimate of 0.035 in column (4) of Table 3. The distribution of randomly assigned estimates is close to zero, and the standard deviation of the estimates is 0.006, indicating that the randomly assigned demonstration county policy makes no difference. Simultaneously, the baseline estimate lies outside the whole distribution. Take together, these observations show that the significantly positive effect of the NREC policy on the county economy was not caused by unobserved factors.

Figure 2. Estimated effects from falsification test



Source: Authors' calculation based on data from the *China County Statistical Yearbook* (NBS, 2012−2019).

Notes: The distribution of estimates from random assignments is –0.00035 and the standard deviation of the estimates is 0.00553. The EC effect represents the influence of the NREC policy on county economic development.

(2) Other proxies for economic development

We were concerned that GDP would not represent economic development well for some counties with low GDP and small populations. To ensure that we had the best measures of economic development, we replaced GDP with three other indicators, including the logarithm of per capita GDP, the annual growth rate of GDP, and the annual growth rate of per capita GDP in columns (6)–(8) of Table 3, respectively. Following Barro (2015), we also controlled for the lagged GDP and lagged per capita GDP (expressed in logarithms) for the purpose of conditional convergence. All results in these three columns show positive and significant coefficients, confirming that the counties benefited economically from the NREC policy. Specifically, columns (6)–(8) of Table 3 show that the NREC policy increased the logarithm of per capita GDP, the annual growth rate of GDP, and the annual growth rate of per capita GDP by approximately 3.3, 3.1, and 1.9 percent, respectively.

(3) Event study application

To verify the assumption that non-e-commerce demonstration counties and those that later became e-commerce demonstration counties would have a common trend in comparison with those that became e-commerce demonstration counties earlier (in the absence of the NREC policy), we followed Jacobson et al. (1993) and adopted an event study to examine the year-wise variation in the outcome variable before and after the NREC policy:

$$y_{it} = \alpha_i + \beta_k \sum_{k \geq -4}^{3+} D_{t_{i0}+k} + \delta_t \boldsymbol{X} + \delta_t + \varepsilon_{it}, \tag{3}$$

the dummy variables $D_{t_{i0}+k}$ denote year-wise variation around the NREC policy, indicating whether $t - t_{i0} = k$, when $k = -4, -3, -2, -1, 0, 1, 2$, and 3+. t_{i0} is the year when the county i became an e-commerce demonstration county. For instance, if the county i carried out its NREC policy in 2016, $k = -1$ when $t = 2015$, and $k = -2$ when $t = 2014$. Note that $k = -4$ denotes 4 or more years before the t_{i0}, which is considered as the omitted category, suggesting that the post-treatment effects are relative to the period four or more years prior to the start of the policy. Put differently, β_k evaluates the impact of the e-commerce demonstration county policy k years after its implementation, supposing that the policy impacts the economy up to 4 years before the project. It also includes the interaction terms between the control variables $\boldsymbol{X}$ and year fixed effects to more flexibly illustrate the difference in county economic performance between the demonstration and nondemonstration counties.

The results of the event study are shown in Table 6. We found that the three coefficients on the pre-treatment status were insignificant, indicating that demonstration

and nondemonstration counties followed similar time tendencies at least 3 years prior to the adoption of the NREC policy. In contrast, right after the adoption of the NREC policy, the coefficients became positive and statistically significant. Combined, these results indicate that with the introduction of the NREC policy, the difference in the outcome variable between demonstration and nondemonstration counties – which had identical time trends before the NREC policy – became larger.

Table 6. Results based on the event study (2011–2018)

	lnGDP
$k = -4$	−0.015**
	(0.006)
$k = -3$	−0.008
	(0.007)
$k = -2$	−0.001
	(0.007)
$k = -1$	0.010
	(0.007)
$k = 0$	0.017**
	(0.007)
$k = 1$	0.022***
	(0.007)
DVM	4.615
County FE	Yes
Year FE	Yes
Control variables × Year dummy	Yes
Adjust R^2	0.988
Number of clusters	2,074
Observations	15,078

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. All variables represent county-level information. We clustered the standard errors in parentheses at the county level. The control variables are the same as in Table 3. $k = -4$ evaluates the impact of the e-commerce demonstration county policy four years after its implementation, and so on down the list. DVM, the mean of dependent variables; FE, fixed effects.

(4) Other robustness tests

We considered the possible bias caused by the short implementation times of some experimental samples. The sample time interval was from 2011 to 2018, and the effective period of policy implementation was 3 to 4 years. The short period of policy implementation for regions selected as demonstration counties in 2018 may lead to the underestimation of economic growth. We thus re-estimated the model by excluding regions selected as demonstration counties in 2018. The results are shown in Table A7

in the Appendix, which still suggests a significantly positive effect. We also eliminated the selected demonstration counties in both 2017 and 2018, and the results remained positive with a larger magnitude.

Although the conditions for the use of the DID method and the regression results of the model were tested in the above series, there may still have been a problem of self-selection of the experimental group samples. Self-selection in this context would mean that higher level policymakers, represented by the provincial-level commercial authorities, prefer to choose counties with better development conditions as policy test points, which leads to biased estimates. This study therefore re-used the propensity score matching (PSM)–DID method for estimation to obtain robust results.

First, the propensity score was estimated using the logit model. The equation is expressed as follows:

$$\text{logit}\left(Treatment_i = 1\right) = \alpha_i + \beta \boldsymbol{X}_{it} + \varepsilon_i. \tag{4}$$

The definition of *Treatment* is the same as above – that is, whether the sample is a dummy variable of the experimental group – and $\boldsymbol{X}_{it}$ are the control variables used in the DID model mentioned above. We used various matching methods to construct different control groups based on the propensity scores obtained in the logit estimation. Nearest neighbor matching (1–5 matching) is a common matching method. The PSM–DID method must pass balancing and common support tests to ensure matching quality. This study therefore used the nearest neighbor matching (5) method for matching, and simultaneously performed the above two tests. The relevant test results are illustrated in Figure A1 in the Appendix. After matching, the deviation between the experimental and control groups is significantly reduced, and the sample basically satisfies the common support hypothesis. After excluding samples that reject the hypothesis of common support, we applied the DID method to re-evaluate the effect of the policy on the county economy. The regression results in Table A8 in the Appendix indicate that the coefficient of the EC variable is still significantly positive. The model estimation results in this study should therefore be robust.

6. Further discussion

In 2016, the NREC policy began to tilt towards poverty-stricken areas to alleviate rural poverty and revitalize the stagnant rural economy. In this section, we regress all samples from poor counties to check whether the NREC policy has achieved this goal and show the results in columns (1)–(5) of Table 7. The coefficient of the EC variable is also positive and statistically significant in columns (1) and (2) of Table 7. The adoption of this policy increased the size of the economy of poor counties by 2.4 percent. This

result reflects the economic growth effect of e-commerce in poverty-stricken areas, thus providing indirect evidence to support the poverty alleviation capabilities of e-commerce development. Considering extensive differences by industry, the results show that the NREC policy has a positive and significant influence only on tertiary industry development, whereas its impact on industrial structure is negative, which is contrary to the above analysis. In other words, the policy's significant positive impact on the county economy in poor areas is mainly driven by tertiary industry.

Table 7. Impact of e-commerce on industry economy in poor counties (2011–2018)

	lnGDP		Agricultural development level	Industrial structure	Tertiary industry development level
	(1)	(2)	(3)	(4)	(5)
EC	0.017*	0.024***	0.001	−0.007**	0.004**
	(0.010)	(0.008)	(0.001)	(0.003)	(0.002)
DVM	3.887	3.897	0.236	0.373	0.383
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Control variables	No	Yes	Yes	Yes	Yes
Adjusted R^2	0.966	0.979	0.918	0.883	0.873
Number of clusters	812	812	805	805	805
Observations	5,521	5,521	5,593	5,593	5,593

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. All variables represent county-level information. We clustered the standard errors (shown in parentheses) at the county level. The control variables are the same as in Table 3. DVM, the mean of dependent variables; EC, the variable of an e-commerce demonstration county; FE, fixed effects.

Table A9 in the Appendix further shows whether the effects for poverty-stricken areas also differ across regions. The coefficients of the EC variable in the central and western regions are significantly positive, and the coefficient of the EC variable in the eastern region is negative but insignificant. This shows that the NREC policy has aided the economic growth of poverty-stricken counties overall. However, there is an obvious regional heterogeneity in the impact effect. The reason for this phenomenon may be that the government has given greater support to e-commerce development, enabling poor counties in the western region to benefit from e-commerce activities and reduce poverty by promoting e-commerce.

In view of the above heterogeneous analysis, we found that the county population and human capital influence the effect of policy implementation. In this section, the analyses of poor counties show different results in columns (1)–(6) of Table A10 in the Appendix, namely that the population had no significant regulatory influence on

promoting economic growth in poor counties. However, human capital had a significant and positive regulatory impact on promoting economic development; the higher the level of human capital, the stronger the local e-commerce application ability and the more conducive it is to economic growth. In general, the left-behind population in poverty-stricken counties is aging very much. Counties' economic development also depends on the quality of the population rather than the population size alone. The inflow of young talent is therefore essential for the development of poverty-stricken counties.

V. Mechanism analysis

In this section, we illustrate the potential mechanisms through which the NREC policy has positive impacts on economic performance. Our main explanation is that the NREC policy improves counties' economies by promoting adjustment of their industrial structure and attracting nonagricultural employment. In this section, we probe alternative explanations and discuss the potential channels.[3]

1. Alternative explanation: National rural e-commerce comprehensive demonstration policy's impact on county industrial structure

A potential alternative explanation for county economic growth is that the NREC policy may promote the development of primary, secondary, and tertiary industries, resulting in the adjustment of industrial structures.

To test this hypothesis, we used the same identification strategy as in Section III and focused on three economy-related outcomes: the logarithms of the output values of the primary, secondary, and tertiary industries. The regression results are presented in Table 8. We found that there was a statistically significant and positive correlation between the NREC policy and the logarithms of the output values of the primary, secondary, and tertiary industries. This finding suggests that the NREC policy may have stimulated the development of the primary, secondary, and tertiary industries in the affected counties, suggesting that this hypothesis is supported.

Making further efforts to explore the effect of the NREC policy on county industrial structure, we focused on three outcomes: the proportion of GDP of the output values of the primary, secondary, and tertiary industries. The regression results are listed in Table 9. We found obvious heterogeneity in the effect of the NREC policy on the these industries. Specifically, the NREC policy had a positive and significant influence on the development of the secondary industry, while its impact on primary and tertiary

[3]Following Depetris-Chauvin et al. (2020), we continue to include the interaction term EC (*treatment* × *post*).

industries was negative. In other words, the significant positive impacts of the policy on county economies were driven mainly by secondary industry.

Table 8. Impact of e-commerce on the output value of industries: Difference-in-differences model estimation (2011–2018)

Dependent variable: ln(Output value)	Primary industry	Secondary industry	Tertiary industry
	(1)	(2)	(3)
EC	0.057***	0.045***	0.025***
	(0.007)	(0.012)	(0.010)
DVM	12.066	13.006	12.859
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Adjusted R^2	0.982	0.974	0.956
Number of clusters	2,015	2,016	2,015
Observations	14,585	14,586	14,532

Notes: *** represents significance at the 1 percent level. All variables represent county-level information. The control variables are the same as in Table 3. DVM, the mean of dependent variables; EC, the variable of an e-commerce demonstration county; FE, fixed effects.

Table 9. Impact of e-commerce on the proportion of industry output value (2011–2018)

Dependent variable: Output value proportion of GDP	Agricultural development level	Industrial structure	Tertiary industry development level
	(1)	(2)	(3)
EC	−0.002	0.006**	−0.006***
	(0.001)	(0.002)	(0.002)
DVM	0.192	0.437	0.367
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Adjusted R^2	0.937	0.892	0.853
Number of clusters	2,015	2,016	2,015
Observations	14,682	14,683	14,682

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. All variables represent county-level information. The control variables are the same as in Table 3. DVM, the mean of dependent variables; EC, the variable of an e-commerce demonstration county; FE, fixed effects.

2. Alternative explanation: National rural e-commerce comprehensive demonstration policy's impact on nonagricultural employment

We examined how the NREC policy affected employment to understand better the channels through which the NREC policy could help accelerate the growth of county-level economies,. We examined the impacts of the NREC policy on three

outcomes: logarithms of nonagricultural employment and employment in secondary and tertiary industries. The regression results are listed in Table 10. We found that there was a statistically significant and positive correlation between NREC policy and nonagricultural employment. Specifically, the policy's significant and positive impact on nonagricultural employment was driven mainly by employment in secondary industry.

Table 10. Impact of e-commerce on nonagricultural employment (2013–2018)

Dependent variable: ln(Nonagricultural employment)	Nonagricultural industry	Secondary industry	Tertiary industry
	(1)	(2)	(3)
EC	0.024*	0.055***	0.012
	(0.012)	(0.018)	(0.014)
DVM	2.199	1.285	1.593
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control	Yes	Yes	Yes
Adjusted R^2	0.938	0.925	0.923
Number of clusters	2,000	2,000	2,001
Observations	11,472	11,474	11,477

Notes: *** and * represent significance at the 1 and 10 percent levels, respectively. All variables represent county-level information. The control variables are the same as in Table 3. DVM, the mean of dependent variables; EC, the variable of an e-commerce demonstration county; FE, fixed effects.

3. Intermediary effect

In this section, we employed the intermediary effect model to estimate the mediating role played by industrial structure and nonagricultural employment between the NREC policy and the county-level economy. The estimated model is as follows:

$$Y_{it} = \alpha_i + \delta_t + a_{it} EC_{it} + \beta_1 \boldsymbol{X}_{it} + \varepsilon_{it}, \tag{5}$$

$$M_{it} = \alpha_i + \delta_t + c_{it} EC_{it} + \beta_2 \boldsymbol{X}_{it} + \upsilon_{it}, \tag{6}$$

$$Y_{it} = \alpha_i + \delta_t + d_{it} EC_{it} + \beta_3 \boldsymbol{X}_{it} + e_{it} M_{it} + \eta_{it}, \tag{7}$$

where M_{it} represents the mediation variable, including industrial structure and nonagricultural employment. ε_{it}, υ_{it}, and η_{it} are error terms. After completing the regression estimation of the three equations, the regression coefficients were analyzed according to the following steps. First, the coefficient was tested. If it was significant, we continued to the second step; otherwise, the mediating effect test ended. Second, we tested the coefficients *c* and *e* in turn. If they were all significant, this would mean that at least part of the influence of *EC* on *Y* was realized through the intermediary variable *M*. If at least one of them was not significant, we could not draw a conclusion and hence went

to the fourth step. The third step was to test the coefficient *d*. If it was not significant, this would mean that the effect of *EC* on *Y* was completely mediated by *M*; otherwise, it would mean that it was only partially mediated. The fourth step was to perform the Sobel test, and the test statistic was $z = \hat{c}\hat{e} / S_{ce}$; $S_{ce} = \sqrt{\hat{c}^2 S_e^2 + \hat{e}^2 S_c^2}$, where S_e and S_c are the standard errors of the estimated coefficients $\hat{e}$ and $\hat{c}$, respectively. If the *z* statistic test result was significant, the mediating effect of *M* was significant, and the test ended.

The results of investigating the intermediary effects of industrial structure and nonagricultural employment between the NREC policy and county economic variables are shown in columns (1)–(6) of Table 11. Columns (1) and (4) reflect the regression results of the first step, including the logarithm of GDP as the dependent variable, and e-commerce demonstration counties as the core independent variable, excluding the intermediary variables. The results show that the coefficients for the e-commerce demonstration counties were all significant, and the intermediary effect test could be continued to obtain the corresponding empirical results. Columns (2) and (5) show the regression results of the second step, with the intermediary variable as the dependent variable, the e-commerce demonstration county as the core independent variable, and other control variables. The results show that the e-commerce model county coefficient was positive and significant. Combining columns (2) and (5) with columns (3) and (6), we can see that at least part of the effect of the NREC policy on the county's economy was achieved through intermediary variables.

Table 11. Test for the mechanism analysis

	lnGDP	Industrial structure	lnGDP	lnGDP	Nonagricultural employment	lnGDP
	(1)	(2)	(3)	(4)	(5)	(6)
EC	0.059***	0.007***	0.056***	0.055***	0.024***	0.048***
	(0.004)	(0.002)	(0.004)	(0.006)	(0.012)	(0.006)
Industrial structure			0.525***			
			(0.023)			
Nonagricultural employment						0.026***
						(0.006)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	15,059	15,079	15,079	15,078	11,472	11,763
F statistics	409.99***	57.60***	425.81***	648.84***	31.78***	355***
Adjusted R^2	0.983	0.887	0.983	0.986	0.938	0.989
z statistics			0.004***			0.001**
			(0.001)			(0.000)

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. All variables represent county-level information. The control variables are the same as in Table 3. EC, the variable of an e-commerce demonstration county; FE, fixed effects.

4. Further explanation

Based on the above analysis, we believe that industrial restructuring and improvement of nonagricultural employment are the main channels through which the NREC policy exerts influence on the regional economy. In this section, we further investigate how the NREC policy created these impacts on industrial restructuring and nonagricultural employment. As part of the trend of vigorously promoting rural e-commerce development, *Implementation of the Strategy of Rural Revitalization* (known as *No. 1 Central Document* for 2018) proposed promoting infrastructure construction strongly for rural e-commerce development. Governments at all levels and all sectors of society jointly promote the construction of rural infrastructure, the upgrade of e-commerce infrastructure, increased capital and technology investment, and improvement in e-commerce support services, as well as the development of rural modernization.

According to the comprehensive demonstration policy of rural e-commerce, each demonstration county can obtain RMB20 million in funding for the construction and transformation of county-level e-commerce centers and village-level e-commerce service sites, the establishment of a three-level logistics distribution mechanism, brand cultivation and quality assurance system construction, and rural e-commerce training. Local governments must take measures actively to promote the construction of county infrastructure, realize "express delivery to the countryside," and solve the "last mile" problem faced by many countries in participating in e-commerce activities.

In terms of road transportation, the scale of county road networks has continued to expand, which facilitates rural residents' travel and goods transportation. The results of examining the relationship between NREC policies and highway mileage variables are shown in Table 12. We found a significant positive correlation between the NREC

Table 12. Impact of e-commerce on the county road networks (2011–2018)

	Highway mileage	Highway mileage	ln(Highway mileage)
	(1)	(2)	(3)
EC	67.054**	58.845*	0.019
	(32.070)	(32.878)	(0.013)
DVM	1,810.395	1,810.395	7.339
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control variables	No	Yes	Yes
Adjusted R^2	0.919	0.910	0.920
Number of clusters	736	733	733
Observations	5,684	5,614	5,614

Notes: ** and * represent significance at the 5 and 10 percent levels, respectively. All variables represent county-level information. The control variables are the same as in Table 3. DVM, the mean of dependent variables; EC, the variable of an e-commerce demonstration county; FE, fixed effects.

policy and highway mileage. Specifically, the policy had a significant positive influence on highway mileage, which demonstrates that in the short term, the policy's impact on county economies may be due to the e-commerce policy promoting short-term infrastructure improvement and that the urgent need for nonagricultural labor quickly promoted the development of secondary industry.

VI. Conclusions

The NREC policy is a novel government policy aimed at promoting rural economies and reducing rural poverty by introducing e-commerce to rural areas. The policy aims to optimize the environment of e-commerce development in rural areas so that more rural areas can be digitally empowered and use e-commerce more effectively. This helps to reduce transaction costs, expand the market scale, and promote industrial development, which all help to achieve economic growth.

To investigate the relationship between e-commerce development and a county's economy and to evaluate the actual effect of the NREC policy accurately, we conducted a large and systematic empirical analysis using panel data for 2,084 counties in 28 provinces in China from 2011 to 2018. Our empirical analyses show that the NREC policy increased the average county economy size by approximately 3.5 percent. However, the impact of this policy was regionally heterogeneous, and population size and human capital affected the implementation effect.

We examined several other results to understand the potential mechanisms at work. First, we found that the NREC policy promoted the development of primary, secondary, and tertiary industries. Our findings show that the policy's significant positive impact on the county-level economy was driven mainly by secondary industry. Second, we presented evidence that the NREC policy had a significant and positive influence on nonagricultural employment. We concluded that industrial restructuring and the improvement of nonagricultural employment were the main channels through which the NREC policy exerted a regional economic impact. We further found that these two channels were also linked to short-term infrastructure improvement in China.

Our study provides the first quantitative evaluation of the NREC policy. It has important policy implications due to its ambitious scale and the huge cost of running the project. More generally, our results indicate that the NREC policy can enhance the county-level economy significantly, which may contribute to China's rural development appreciably in the long term. As China has completely eliminated absolute poverty, it is not only important for China to rethink whether and how e-commerce could be a new engine for social-economic transformation in a new era but it is also insightful for other

developing countries to reconsider whether and how this type of e-commerce policy could be applied as a tool of poverty reduction. However, this study has not thoroughly investigated the impact of NREC policy on the rural–urban disparities and the welfare of the most vulnerable groups. This can be a valuable undertaking for future research.

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Appendix

Figure A1. Balancing test and the common support of propensity scores

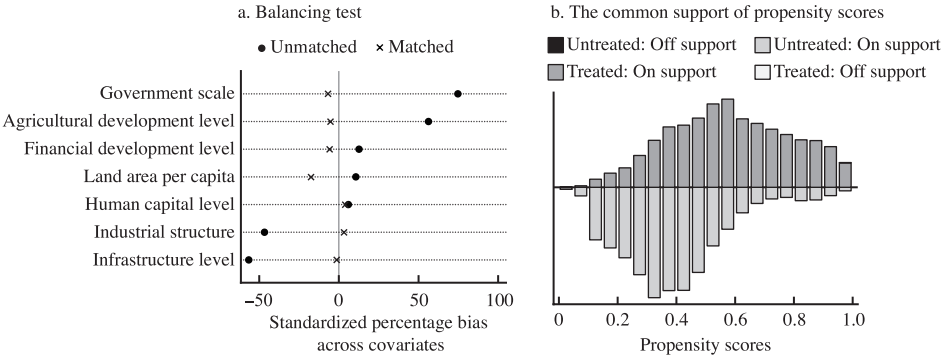

Table A1. Number of counties that became demonstration counties

Year	Number of demonstration counties
2011	0
2012	0
2013	0
2014	56
2015	198
2016	237
2017	259
2018	260
Total	1,010

Source: The data were compiled by the authors based on the Ministry of Commerce website (http://www.mofcom.gov.cn/).

Table A2. Main content of national rural e-commerce comprehensive demonstration policy (2014)

Development goals	In general, (i) create models of e-commerce demonstration; (ii) promote rural economic development; (iii) promote urbanization; (iv) increase the commodity rate of agricultural products; and (v) facilitate the production and life of farmers.
	In terms of specific requirements, (i) the average annual growth of e-commerce transaction volume should not be less than 30 percent; (ii) the logistics costs of e-commerce have been reduced; and (iii) the modernization level of rural circulation has been significantly improved.
Specific tasks	(i) Improve the supporting service system for rural e-commerce, including integrating existing circulation resources and improving the rural logistics distribution system; (ii) expand the application fields of rural e-commerce, including improving the two-way circulation of industrial products to the countryside and agricultural products to the city, supporting youth and college students to start e-commerce entrepreneurship, expanding the sales channels of agricultural products, and promoting the organization and standardization of agricultural production; (iii) improve the application ability of rural e-commerce, including strengthening the promotion of e-commerce knowledge and training relevant practitioners; and (iv) improve the development environment of rural e-commerce, including the establishment of favorable fiscal and financial policy systems.
Financial support	The central government supports each demonstration county with RMB20 million funds and local (province, city, and county) supporting funds.[4]
Financial support priorities	(i) Support the construction and transformation of rural e-commerce distribution and comprehensive service websites; and (ii) support the development of rural e-commerce training.

Source: The data were compiled by the authors based on the Ministry of Commerce website (http://www.mofcom.gov.cn/).

[4]The amount is not specified in the notification document, but it is reflected in the implementation measures of various regions. The amount varies slightly in different years and regions.

Table A3. Heterogeneity analysis of e-commerce's economic effect at the regional level (2011–2018)

Dependent variable: lnGDP	Eastern	Central	Western
	(1)	(2)	(3)
EC	0.016*	0.032***	0.029***
	(0.009)	(0.007)	(0.007)
DVM	5.232	4.784	4.119
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Control variables × Time	Yes	Yes	Yes
Control variables × Time^2	Yes	Yes	Yes
Control variables × Time^3	Yes	Yes	Yes
Adjusted R^2	0.986	0.985	0.983
Number of clusters	540	613	902
Observations	3,920	4,641	6,480
		Differences	
Eastern versus central		−0.016***	
Eastern versus western		−0.012**	
Central versus western		0.003	

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. All variables represent county-level information. The control variables are the same as in Table 3. DVM, the mean of dependent variables; EC, the variable of an e-commerce demonstration county; FE, fixed effects.

Table A4. Heterogeneity analysis of e-commerce's economic effect at the regional level (2011–2018)

Dependent variable: lnGDP	Eastern	Central	Western
	(1)	(2)	(3)
EC	0.012	0.032***	0.023***
	(0.008)	(0.006)	(0.006)
DVM	5.232	4.784	4.119
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Controls × Year dummy	Yes	Yes	Yes
Adjusted R^2	0.988	0.987	0.984
Number of clusters	540	613	902
Observations	3,920	4,641	6,480
		Differences	
Eastern versus central		−0.020***	
Eastern versus western		−0.011***	
Central versus western		0.009**	

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. All variables represent county-level information. The control variables are the same as in Table 3. DVM, the mean of dependent variables; EC, the variable of an e-commerce demonstration county; FE, fixed effects.

Table A5. Heterogeneity analysis of e-commerce's economic effect by influencing factors (2011–2018)

Dependent variable: lnGDP	Small population	Large population	Difference	Low human capital	High human capital	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
EC	0.026***	0.026***	0.001	0.019***	0.031***	0.012**
	(0.006)	(0.007)		(0.007)	(0.007)	
DVM	4.132	5.356		4.686	4.533	
County FE	Yes	Yes		Yes	Yes	
Year FE	Yes	Yes		Yes	Yes	
Control variables	Yes	Yes		Yes	Yes	
Control variables × Time	Yes	Yes		Yes	Yes	
Control variables × $Time^2$	Yes	Yes		Yes	Yes	
Control variables × $Time^3$	Yes	Yes		Yes	Yes	
Adjusted R^2	0.973	0.976		0.981	0.986	
Number of clusters	1,206	818		1,254	1,134	
Observations	8,613	5,918		7,749	6,522	

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. All variables represent county-level information. The control variables are the same as in Table 3. DVM, the mean of dependent variables; EC, the variable of an e-commerce demonstration county; FE, fixed effects.

Table A6. Heterogeneity analysis of e-commerce's economic effect by influencing factors (2011–2018)

Dependent variable: lnGDP	Small population	Large population	Difference	Low human capital	High human capital	Difference
	(1)	(2)	(3)	(6)	(5)	(6)
EC	0.015**	0.022***	0.007*	0.012*	0.023***	0.011**
	(0.006)	(0.006)		(0.007)	(0.007)	
DVM	4.132	5.356		4.686	4.533	
County FE	Yes	Yes		Yes	Yes	
Year FE	Yes	Yes		Yes	Yes	
Control variables	Yes	Yes		Yes	Yes	
Control variables × Year dummy	Yes	Yes		Yes	Yes	
Adjusted R^2	0.977	0.980		0.983	0.988	
Number of clusters	1,206	818		1,254	1,134	
Observations	8,613	5,918		7,749	6,522	

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. All variables represent county-level information. The control variables are the same as in Table 3. DVM, the mean of dependent variables; EC, the variable of an e-commerce demonstration county; FE, fixed effects.

Table A7. Robustness test I (2011–2018)

Dependent variable: lnGDP	Entire sample		Poor counties	
	Excluding 2018 pilot	Excluding 2018 and 2017 pilot	Excluding 2018 pilot	Excluding 2018 and 2017 pilot
	(1)	(2)	(3)	(4)
EC	0.062***	0.063***	0.030***	0.051***
	(0.007)	(0.009)	(0.009)	(0.012)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Adjusted R^2	0.987	0.997	0.983	0.985
Number of clusters	1,824	1,569	584	352
Observations	1,3243	1,1381	3,899	2,279

Notes: *** represents significance at the 1 percent level. All variables represent county-level information. The control variables are the same as in Table 3. EC, the variable of an e-commerce demonstration county; FE, fixed effects.

Table A8. Robustness test II (2011–2018)

	lnGDP		ln(GDP per capita)	
	Nei-1	Nei-5	Nei-1	Nei-5
	(1)	(2)	(3)	(4)
EC	0.051***	0.055***	0.037***	0.032***
	(0.004)	(0.004)	(0.005)	(0.005)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Adjusted R^2	0.986	0.986	0.955	0.953
Number of clusters	2,005	2,055	2,005	2,055
Observations	14,627	15,055	14,627	15,055

Notes: *** represents significance at the 1 percent levels, respectively. All variables represent county-level information. The control variables are the same as in Table 3. Nei-1 and Nei-5 represent the nearest neighbor matching (1) method and the nearest neighbor matching (5) method, respectively. EC, the variable of an e-commerce demonstration county; FE, fixed effects.

Table A9. Heterogeneity analysis (I) of e-commerce's economic effect in poor counties (2011–2018)

Dependent variable: lnGDP	Eastern	Central	Western
	(1)	(2)	(3)
EC	−0.009	0.021***	0.030***
	(0.014)	(0.008)	(0.009)
DVM	4.152	4.357	3.674
County FE	Yes	Yes	Yes

(Continued on the next page)

(Table A9 continued)

Dependent variable: lnGDP	Eastern	Central	Western
	(1)	(2)	(3)
Year FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Adjusted R^2	0.984	0.985	0.974
Number of clusters	50	211	544
Observations	354	1,551	3,606
	Differences		
Eastern versus central		−0.029***	
Eastern versus western		−0.039***	
Central versus western		−0.009**	

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. All variables represent county-level information. The control variables are the same as in Table 3. DVM, the mean of dependent variables; EC, the variable of an e-commerce demonstration county; FE, fixed effects.

Table A10. Heterogeneity analysis (II) of e-commerce's economic effect in poor counties (2011–2018)

Dependent variable: lnGDP	Small population	Large population	Difference	Low human capital	High human capital	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
EC	−0.006	−0.001	0.004	−0.027**	0.020***	0.048***
	(0.009)	(0.009)		(0.011)	(0.010)	
DVM	3.606	4.740		3.977	3.829	
County FE	Yes	Yes		Yes	Yes	
Year FE	Yes	Yes		Yes	Yes	
Control variables	Yes	Yes		Yes	Yes	
Adjusted R^2	0.963	0.970		0.971	0.981	
Number of clusters	549	201		403	473	
Observations	3,669	1,409		2,328	2,628	

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. All variables represent county-level information. The control variables are the same as in Table 3. DVM, the mean of dependent variables; EC, the variable of an e-commerce demonstration county; FE, fixed effects.

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