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The Impact of Agricultural Industry Agglomeration in Sichuan Province on Agricultural Carbon Emissions

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Abstract. This article utilizes panel data from 2005 to 2020, covering 21 cities in Sichuan Province, to empirically examine the relationship between agricultural industry concentration and carbon emissions. The findings reveal a clear inverted U-shaped relationship between agricultural industry agglomeration and carbon emissions. This relationship also exhibits temporal lag and regional disparities. In Sichuan Province, the link between agricultural industry agglomeration and carbon emissions follows this inverted U-shaped pattern, emphasizing the need for a comprehensive understanding of agglomeration's role in shaping emissions.Carbon emissions in agriculture display strong temporal path dependence, underscoring the importance of timely policies for carbon reduction. Local governments should adapt their strategies to regional peculiarities, promoting the growth of local agricultural industries through increased scale and agglomeration. A well-planned distribution of agricultural industries across regions is essential for sustainable development.

1 Introduction

In September of the year 2020, China unveiled its ambitious dual carbon objectives: attaining a "carbon peak" by the year 2030 and subsequently achieving "carbon neutrality" by 2060. This strategic vision is poised to mitigate carbon emissions through the means of technological advancement, innovation, optimization of industrial structures, and the promotion of a lifestyle rooted in low-carbon principles, green ethics, and environmental sustainability.

In conclusion, the trajectory of agricultural industry agglomeration is marked by distinct phases, each yielding its own set of impacts on agricultural carbon emissions. It is a matter of profound debate whether agricultural industry agglomeration, with its multifaceted implications, ultimately exerts a beneficial or detrimental influence on the trajectory of agricultural carbon emissions.

2 Literature review

To sift through the existing literature, we embark on our scholarly voyage by commencing with an exploration of agricultural carbon emissions themselves. The focal points of this inquiry encompass the realm of agricultural carbon emission accounting and its distinctive attributes.

Initially, agricultural carbon emission accounting revolved around six pivotal facets: fertilization, pesticides, agricultural film, diesel consumption, irrigation, and tillage [1,2]. This approach predominantly concentrated on the agricultural land's utilization within the farming milieu. However, as research endeavors evolved, the accounting paradigm broadened its scope. A burgeoning corpus of research now encompasses a comprehensive array of agricultural carbon sources, encompassing facets like agricultural land usage, the planting industry, livestock and poultry husbandry, among others [3,4].

Turning our gaze to the characterization of agricultural carbon emissions, the research terrain shifts to encompass an exploration of their spatiotemporal evolution characteristics [5-8], spatial spillover effects [9-11], threshold attributes [12, 13], structural traits [14-15], and convergence phenomena [17,18].

2.1 The study hypothesis proposes

Based on the combing of the existing literature, the following hypothesis is proposed in order to make a better conclusion.

Hypothesis 1: Agricultural industrial agglomeration has an impact on agricultural carbon emissions by producing agglomeration effects such as scale effect, technology effect, structure effect, social effect and cumulative effect.That is, the relationship between agricultural industry agglomeration and agricultural carbon emission is "inverted u type".

Hypothesis 2: Agricultural carbon emissions may have a certain time path dependence, that is, the agricultural carbon emissions in the early stage may have an impact on the later stage.

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3 Data

3.1 Variable selection

This feat is achieved by the multiplication of the carbon emissions of each individual source by their corresponding carbon emission coefficients, which are, in turn, judiciously summed. Hence, the most current methodology embraced within this discourse predicates itself upon the ensuing blueprint:

$$C = \sum g_i \varepsilon_i \quad (1)$$

In this paradigm, the symbol "C" assumes the mantle of representation for the overarching edifice of total agricultural carbon emissions. "G," on the other hand, stands as the venerable envoy, bearing the imprints of emissions emanating from each discrete carbon source. Meanwhile, the Greek letter "ε," with its intrinsic symbolism, serves as the custodian of the carbon emission coefficients, deftly charting the course for each unique carbon source enmeshed in this intricate narrative of environmental reckoning.

3.2 Independent Variables (lq)

The independent variable denoted as 'lq' signifies the agricultural industrial agglomeration index, a parameter of significant relevance.

$$lq_{ij} = (k_{ij} / k_i) / (k_j / k) \quad (2)$$

The symbols "k_{ij}" and "k_i" denote the provincial agricultural output value and the regional output value for the i-th province, respectively. Correspondingly, "k_j" and "k" represent the national agricultural output value and the national GDP, respectively. It is noteworthy that the magnitude of "lq_{ij}" directly mirrors the degree of agglomeration within the agricultural industry.

3.3 Control variables

Agricultural carbon emission intensity, rural per capita net income (*inc*), agricultural industrial structure (*struc*), agricultural mechanization level (*ma*), planting industry structure (*pis*), animal husbandry industrial structure (*ais*), and industrialization level (*il*) may engage in intricate, mutually causal relationships, giving rise to endogenous dynamics. Consequently, these variables are incorporated as control factors, thereby enhancing the precision and robustness of our analytical model.

Notably, the level of urbanization (*ur*) is ascertained by quantifying the proportion of the regional non-agricultural population to the total population. Additionally, we gauge regional economic development by evaluating the unchanged gross domestic product (GDP) per capita at year-end relative to the total population. The agricultural mechanization level (*mach*) is characterized by the cumulative horsepower of agricultural machinery employed, while the structural composition of industry (*struc*) is elucidated by the ratio of total agricultural output value to the aggregate output value encompassing agriculture, forestry, animal husbandry, and fisheries.

3.4 The empirical model

$$\ln c_{it} = a + a_1 \ln c_{it-1} + \beta_1 lq_{it} + \beta_2 lq_{it}{}^2 + control + \varepsilon_{it} \quad (3)$$

Esteemed scholars of yore delved into the intricate realm of the "inverted U"-shaped association between the aggregation of the agricultural industry and the emanation of agricultural carbon emissions. They did so by invoking the venerable Environmental Kuznets Curve framework, adorning it with the primary (*lq*) and secondary (lq^2) terms of the agricultural industry.

3.5 Data sources

The wellspring of our original dataset finds its origins in an array of venerable tomes, including the provincial statistical yearbooks, "China Statistical Yearbook," "China Rural Statistical Yearbook," and the locally cherished "Sichuan Provincial Statistical Yearbook." Further insights were gleaned from the venerable annals of various city and state-level statistical compendia.

4 Methodology

4.1 Descriptive statistics of the variables

Table 1. Descriptive statistics of the variables

N	mean	sd	min	max
336	256.8	188.5	10.38	857.1
336	1.194	0.603	0.0383	3.317
336	0.522	0.0872	0.317	0.740
336	0.512	0.152	0.233	0.896
336	7,550	5,559	1,374	33,195
336	0.556	0.276	0.132	1.416
336	0.361	0.0851	0.112	0.574
336	0.308	0.0895	0.105	0.581
336	0.172	0.172	0.0161	2.344

Upon an attentive perusal of Table 1, it becomes evident that a tapestry of variables, including the degree of agricultural industrial agglomeration, the echelons of agricultural mechanization, the tier of regional economic development, and the dispersion gradient of per capita net income in rural areas, manifests with an air of magnitude.

4.2 Unit root inspection

To circumvent the specter of pseudoregression, we diligently subjected the dataset to rigorous scrutiny. Employing the discerning LLC test and the venerable Fisher-ADF test, we embarked on a quest to ascertain the stability of the sequence.

Table 2. Root in unit and co-integration tests for variables

variable	LLC checkout	The Fisher-ADF test	conclusion
lncit	0.0000	0.5122	non-stationary
Δlncit	0.0480	0.0000	steady
lq	0.0135	0.5084	non-stationary
Δlq	0.0000	0.0000	steady
lq2	O.0045	0.9919	non-stationary
Δlq2	0.0000	0.0000	steady
lninc	0.6222	0.9785	non-stationary

Δlninc	0.0000	0.0000	steady
il	0.9956	0.6427	non-stationary
Δil	0.0000	0.0000	steady
ais	0.3003	0.6037	non-stationary
Δais	0.0000	0.0000	steady
pis	0.9858	0.8303	non-stationary
Δpis	0.0000	0.0000	steady
ur	0.0013	0.07959	non-stationary
Δur	0.0000	0.0000	steady
struc	0.0000	0.0162	steady
Δstruc	0.0000	0.0000	steady
KAO-MDF	0.0000		Correlation exists
KAO-DF	0.0000		Correlation exists
KAO-ADF	0.0000		Correlation exists

Intriguingly, As shown in Table 2, our inquiry into co-integration, as gauged by the outcomes of the KAO-MDF, KAO-DF, and KAO-ADF tests, has yielded noteworthy results. It is with a degree of statistical significance, set at the conventional 5% threshold, that we decisively reject the null hypothesis, thus affirming the presence of a co-integration nexus interlinking these variables.

4.3 Panel estimation results

Table 3. panel estimation results

	fixed effect (fe)	stochastic effect (re)	System gmm two-step
	lnc	lnc	lnc
l.lnc			0.9991***
			(49.5319)
lq	0.4757***	0.7020***	0.1732**
	(4.8164)	(6.7845)	(2.4693)
lq2	-0.0557**	-0.1105***	-0.0461**
	(-2.1534)	(-4.0333)	(-2.3743)
lninc	0.8334***	0.3311***	-0.0768
	(7.9792)	(5.8090)	(-0.9415)
lnma	0.1620***	0.2021***	0.0281
	(4.7575)	(5.7755)	(1.5167)
il	1.1810***	1.6651***	-0.0895
	(7.0438)	(10.1173)	(-0.5184)
ais	1.0037***	0.7712***	-0.4340**
	(3.8908)	(2.9600)	(-2.2491)
pis	-0.2892***	-0.4307***	-0.0261
	(-5.0865)	(-7.2249)	(-0.5670)
ur	0.3013	0.1159	0.5364*
	(1.3606)	(0.5517)	(1.8865)
struc	0.1173	0.1516	0.0724
	(0.4857)	(0.6451)	(0.3006)
_cons	-2.6952***	1.0252**	0.4792
	(-3.2953)	(1.9771)	(0.5990)
N	600	600	570
R2	0.755	0.734	
AR(1)[P]			-3.53[0.000]
AR(2)[P]			-1.45[0.147]
Hasen[p]			18.25[0.148]
symmetry axis			2.1730

In accordance with the findings in Table 3, with the inclusion of a lagged term in the dependent variable within our empirical model, a crucial transformation unfolds. It imparts a nuanced complexion to our modeling, rendering the residuals no longer strictly exogenous and homoscedastic in nature. In such circumstances, the instrumental variable method emerges as the more fitting and judicious approach to estimation. Simultaneously, recognizing the potential interplay between agricultural carbon emission intensity, our core explanatory variables, and the regional level of economic development, we have opted to employ the Systematic Generalized Method of Moments (GMM) to skillfully navigate the endogeneity lurking within our equation.

4.4 Five-point sample estimation results

This division neatly segregates them into two distinctive echelons: the echelon of heightened Agricultural Industrial Concentration (aq ≥ 1.194) and the echelon marked by diminished Agricultural Industrial Concentration (aq < 1.194). Within the lofty stratum of agricultural industrial concentration, a cadre of nine cities emerges, collectively constituting a compendium of 176 meticulously observed instances.

Table 4. Results of the sample systematic GMM test

Variables	High cluster group	Low cluster group
	(1)	(2)
	lnc	lnc
L.lnc	0.8550***	0.9705***
	(8.8504)	(33.3249)
lq	0.0433	0.2768**
	(0.4061)	(2.9125)
lq2	-0.0035	-0.0809***
	(-0.1799)	(-2.9806)
struc	0.2385	-0.2329
	(1.1494)	(-1.2629)
ur	-0.4132	0.5104
	(-0.9053)	(1.6499)
lninc	0.2042	-0.0819
	(1.1848)	(-0.9436)
lnma	0.0542	0.0152
	(0.8984)	(0.8590)
il	0.3721	0.0483
	(0.9227)	(0.2776)
ais	0.4134	-0.5536***
	(1.3165)	(-3.3001)
pis	0.1951	-0.0716***
	(1.2615)	(-2.9679)
N	247	304
AR(1)[P]	-2.45[0.014]	-2.63[0.009]
AR(2)[P]	-0.65[0.513]	-1.53[0.125]
Hansen[P]	27.37[0.159]	20.22[0.164]

Table 4 displays the statistical distribution of survey responses.Through the application of systematic generalized method of moments (SYS-GMM) testing on our samples, we discern a dichotomy within the realm of agricultural industry agglomeration. In one echelon, we observe a salient positivity, while in the secondary echelon, a discernible negativism manifests. However, it is crucial to underscore that this relationship acquires its significance solely within the sphere of low concentration. This observation vividly illuminates the nuanced interplay between agricultural industry agglomeration and agricultural carbon emissions, characterized by a heterogeneous, inverted U-shaped curve.

5 Discussion and Implication

From a Sichuan Province vantage point, a conspicuous "inverted U-shaped relationship" manifests between agricultural industrial agglomeration and agricultural carbon emissions, thus validating Hypothesis 1. This empirical validation underscores the imperative of a nuanced grasp of agricultural industrial agglomeration's role in shaping agricultural carbon emissions. It further accentuates the necessity for region-specific, timely policy formulations.

Temporal entwinements exert a profound influence on agricultural carbon emission intensity. The echoes of heightened agricultural carbon emission intensity in the antecedent period resonate through time, casting a shadow upon subsequent periods, thereby corroborating Hypothesis 2. This underscores the exigency for temporal considerations in addressing carbon fixation and reduction within Sichuan Province's agricultural sector.

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