Sense of Economic Gain from E-Commerce: Different Effects on Poor and Non-Poor Rural households

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Abstract: *Sense of economic gain of e-commerce participation is an important aspect for evaluating the inclusiveness of e-commerce development. Based on the data of 6,242 rural households collected from the 2017 summer surveys conducted by the China Institute for Rural Studies (CIRS), Tsinghua University, this paper evaluates the effects of e-commerce participation on rural households' sense of economic gain with the propensity score matching (PSM) method, and carries out grouped comparisons between poor and non-poor households. Specifically, the "Self-evaluated income level relative to fellow villagers" measures respondents' sense of economic gain in the relative sense, and "Percentage of expected household income growth (reduction) in 2018 over 2017" measures future income growth expectation. Findings suggest that e-commerce participation significantly increased sample households' sense of economic gain relative to their fellow villagers and their future income growth expectation. Yet grouped comparisons offer different conclusions: E-commerce participation increased poor households' sense of economic gain compared with fellow villagers more than it did for non-poor households. E-commerce participation did little to increase poor households' future income growth expectation. Like many other poverty reduction programs, pro-poor e-commerce helps poor households with policy preferences but have yet to help them foster skills to prosper in the long run. The sustainability and quality of perceived relative economic gain for poor households are yet to be further observed and examined. All poverty reduction initiatives including pro-poor e-commerce must help poor households develop endogenous growth momentum to prosper beyond the effects of short-term pro-poor policies.*

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1. Introduction

With the increasing penetration of internet applications, there has been a growing interest in the

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social and economic effects of the internet among the public and academia. By breaking through market segmentation and broadening market access, e-commerce has emerged as a new channel for reducing poverty. Thriving e-commerce in China offers new experience for unraveling the effects of internet applications. Some studies suggest that e-commerce participation significantly boosts farmer households' incomes (Lu and Liao, 2016; Zeng, *et al*., 2018). Such income growth stems from the falling price of perishable farm produce thanks to effective information supply (Xu, *et al*., 2013). E-commerce allows professional farmer households to earn a significantly higher income by increasing profit margin and sales (Zeng, *et al*. 2018).

Yet most samples employed in existing studies are collected from "Taobao villages" where e-commerce merchants flourish on Taobao, China's largest e-commerce platform (Zeng, 2018), e-commerce hotspot regions (Lu and Liao, 2016) or specific agricultural sectors (Zeng, *et al*., 2018; Xu *et al*., 2013). As such, their research conclusions may not apply to average rural households, especially poor households, in ordinary rural regions. Despite the growing public interest in recent years, few empirical studies have been carried out to examine the poverty reduction effects of e-commerce. Existing discussions on this topic are focused on the basic concepts and models. The extent to which e-commerce delivers economic opportunities to participants is yet to be examined, and is of great relevance to China's "people-centered" development and the commitment to give people a "sense of gain." Hence, this paper aims to reveal rural households' sense of economic gain from e-commerce participation and whether such economic gains differ between poor and non-poor households.

With "sense of economic gain" as an outcome variable, this paper measures the inclusiveness of e-commerce participation by the following indicators, including "Self-evaluated income level relative to other households in the village," and "Percentage of expected household income increase/decrease in 2018 over 2017." Based on the nationwide village and household surveys conducted by the China Institute for Rural Studies (CIRS) at Tsinghua University in the summer of 2017, this paper identifies 6,242 rural households who have answered all questions in the surveys (together with their village conditions) to evaluate the effects of e-commerce participation on sense of economic gain. Compared with existing studies, this paper offers the following contributions: (i) It has extended the scope of research on the effects of e-commerce from specialized e-commerce villages to ordinary villagers and from professional farmer households to ordinary farmer households, including poor and non-poor households; (ii) it offers the first evaluation of the perceived economic benefits to e-commerce merchants in terms of relative income growth and future income expectation.

2. Literature Review and Research Hypotheses

2.1 Sense of Economic Gain and Determinants

Sense of economic gain is the primary outcome variable that this paper is concerned with. Research on the definition and indicators of the "sense of gain" among the populace remains limited, but may still offers some inspirations and support to this study. Existing studies define the "sense of gain" as an actual improvement in people's living standards and subjective satisfaction (Yang and Zhang, 2019; Wen and Liu, 2018). Some academics regard the "sense of gain" as a multidimensional concept encompassing the sense of economic gain, i.e. an individual's subjective level of satisfaction based on his/her real economic income (Yang and Zhang, 2019; Wen and Liu, 2018). Yang *et al*. (2019) classifies sense of economic gain into perceived income status relative to others, perceived income status compared with one's past economic status, and expected future income growth and its realization (Yang and Zhang, 2019). Obviously, existing studies all examine sense of economic gain with a multidimensional approach. Moreover, Liang (2018) examines the sense of economic gain of low-income households from overall and relative dimensions. Based on the multidimensionality and data availability of sense of economic gain, this paper measures sense of economic gain from two dimensions - self-evaluated level of household income relative to fellow villagers and future income growth expectation.

Sense of economic gain is subject to social environment, actual and perceived social status, and social policies. Ostensibly a subjective perception, the sense of gain is largely determined by certain objective factors (Zhang, 2018). Based on a national survey for low-income households conducted in 2016, a study finds that low-income households are less satisfied about the overall level of gain both in absolute and relative terms: External factors like region, community and the level of local economic development influence the sense of economic gain of low-income households both directly and indirectly through mediating effects (Liang, 2018). The focus of discussion in this paper is to unravel how e-commerce - a policy-supported industry with social and economic spillover effects - contributes to sense of economic gain among various groups of people in China.

2.2 Will E-Commerce Increase Sense of Economic Gain?

Via the internet as a new resource allocation mechanism (He, 2018), e-commerce allows farmers to earn a higher income by doing away with costly distribution links. In China, farm produce distribution is dominated by the wholesale market where price markups are applied at each level of distribution. Under this model, farmers wield no pricing power beyond their local market where farm produce is collected for distribution elsewhere, and cannot access the consumer market directly (Chen *et al*., 2019). Compared with the initial price quoted by farmers, farm produce ends up many times more expensive when they reach consumers after numerous distribution links, each with a price markup (Pan *et al*., 2018). Traditional resource allocation mechanism based on price signal may regulate the supply and demand of goods and services, but cannot rid the market of intermediaries the way resources are allocated over the internet (He, 2018). For farmers, these barriers will inevitably deprive them of economic gains that would otherwise come their way.

In contrast, internet applications optimize resource allocation by linking sellers with buyers across geographical barriers and allowing them to trade goods and services without resorting to an intermediary (He, 2018). With its information aggregation effects, the internet will create economic gains, efficiencies and social welfare beyond traditional economies of scale (Zhang, 2016). Empirical studies on Taobao villages and agricultural e-commerce platforms suggest that e-commerce is income enhancing for merchants (Lu and Liao, 2016; Zeng, *et al*., 2018).

Given the growing penetration of e-commerce and its potentials to upend the existing farm produce distribution market, the economic benefits of e-commerce participation should be universal for all farmer households at least in theory. Based on the above theoretical analysis, farmer households stand to gain from more efficient resource allocation through e-commerce participation. Hence, this paper puts forward the first hypotheses:

Hypothesis 1: E-commerce participation will increase farmer households' sense of economic gain.

Hypothesis 1a: E-commerce participation will increase farmer households' sense of economic gain compared with their fellow villagers who did not participate in e-commerce.

Hypothesis 1b: E-commerce participation will increase farmer households' income growth expectation.

2.3 Differences in Economic Gain from E-Commerce Participation among Farmer Households

According to existing theories, the lack of capital (Nurkse, 1953), especially human capital (Schultz, 1971), is the root cause of poverty. Poverty stems more from a dearth of capacity than from paltry incomes (Sen, 2001). Scant financial, human and social capital prevents the poor from economic and social participation. As proven in Chinese experience, human capital such as education is to blame as the chief culprit for yawning income gaps among rural households (Gao and Yao, 2006), and the case for capacity building among the poor is stronger than ever (Du, Park and Wang, 2005). As shown in provincial panel data, e-commerce is more efficient at reducing poverty in regions with higher levels of human capital (Tang, *et al*., 2018). When evaluating the income effects of e-commerce participation, it is vital to control for differences in the endowment of poor and non-poor households for e-commerce participation. Even if such endowment differences are controlled for, there may still be systematic differences in the economic gains for poor and non-poor households from e-commerce participation.

Existing empirical studies have revealed how poor and non-poor households benefit differently from certain pro-poor programs. Based on households and village-level panel data of 2001-2004 and the matching method, Park and Wang (2010) finds that poverty reduction programs implemented for whole villages led to significantly higher incomes and consumption of prosperous households without benefiting the poor. Similar to e-commerce, cooperatives have also been regarded as an ideal vehicle for lifting the poor out of poverty through self-assistance and mutual assistance. Yet as Hu's (2014) empirical study uncovers, high-income households benefited much more from Farmer Specialized cooperatives in poor regions than did poor households hamstrung by scant per capita assets to gain more from cooperatives.

Given the existence of capital constraints and empirical experience in similar sectors, there may be significant differences in economic gains from e-commerce between poor and non-poor households. Therefore, this paper puts forward the second group of hypotheses:

Hypothesis 2: Poor and non-poor households benefit differently from e-commerce participation;

Hypothesis 2a: Relative economic gains from e-commerce are smaller for poor households than for non-poor households;

Hypothesis 2b: Poor households expect a smaller future income growth from e-commerce compared with non-poor households.

3. Data Source and Methodology

3.1 Data Source

The China Institute for Rural Studies (CIRS) at Tsinghua University conducted summer surveys on agricultural and rural development (CIRS Survey) for seven years from 2012 to 2018. This paper employs CIRS2017 data with the theme of "Rural Entrepreneurship and New Rural Business Models" collected from questionnaires and interviews at village and household levels. In addition to basic village and household information, questionnaires about villages and households also include such information as family-operated bed and breakfasts, e-commerce economy, rural entrepreneurship, and targeted poverty reduction.

This survey employs non-probability sampling[1], including a combination of judgement sampling (a.k.a. expert choice or purposive sampling) and convenience sampling (a.k.a. accidental sampling): At the level of survey points (counties, townships and villages), the survey was carried out primarily with judgement sampling, and the CIRS expert team identified the topics and locations consistent with the theme of the survey;[2] at the level of household survey in selected villages, interviews were carried out

[1] Non-probability sampling is inferior to probability sampling in some respects, but is superior in others. As explained in *Designing Social Inquiry*, probability sampling may have serious deviations in determining the targets of observation, but when conducting research in one or two designated regions, expert selection can be superior to random sampling. Also, the deficiency of non-probability sampling data can be compensated for with a supplementary program. See: *Designing Social Inquiry* (2014), authored by Gary King, Robert O. Keohane, Sidney Verba, translated by Chen Shuo, Shanghai Truth & Wisdom Press, p.120-123; *Introduction to Survey Sampling* (2014), authored by Graham Kalton, translated by Wu Lingwei, Shanghai: Truth & Wisdom Press: Shanghai People's Publishing House, page 140-144.

[2] There are two types of survey teams: The first was led by CIRS expert teachers, and the other was organized by students themselves. Survey sites for the teachers were selected by the expert team based on their experience. Before departure, all teams had submitted the proposed topics consistent with the theme of the CIRS survey and survey sites, which were finalized by the CIRS expert team after some deletions.

with households relevant with the theme of the survey. In June 2017, the CIRS expert team delivered lectures and trainings to interviewers. In July and August 2017, survey teams were dispatched to various villages.

3.2 Methodology Selection

The main purpose of this paper is to evaluate the effects of e-commerce participation on rural households' sense of economic gain. For two reasons, the propensity score matching (PSM) appears to be the most appropriate method. First, the CIRS2017 data employed in this paper are not probability sampling data, and sample matching is an adjustment method for resolving the problem of statistical inference from non-probability sampling (Jin and Liu, 2016). The PSM is widely used in non-probability sampling inference with good effects (Liu, 2018). Based on the PSM, a statistical inference can be carried out with Efron's (1979) bootstrap repeated sampling technique using given observations without other assumptions or new observations. Second, there is a "selection bias" due to differences in households' initial resource endowment. Since households decide on their own whether or not to participate in e-commerce, it is necessary for such self-selection to be treated. Also known as the Rubin Causal Model (RCM) (Holland, 1986), Rubin's (1974) "counterfactual framework" evaluates the treatment effect with counterfactual characteristics as missing data. As a data balance method, the matching method identifies the members of a non-intervention group similar to those of the intervention group on the covariate, and uses the average result of the non-intervention group as a proxy to estimate the counterfactuals of the intervention group (Guo and Frazer, 2012). This paper employs Rosenbaum and Rubin's (1983) PSM with "propensity value" as the distance function, which balances the covariate with selection bias to obtain a uniform distribution.

Study on the sense of economic gain from e-commerce participation can be seen as an evaluation of the "treatment effect" . Rural households involved in e-commerce business constitute the "treatment group", and those not involved in e-commerce business are the "control group". Referencing the econometric application of the counterfactual framework (Chen, 2014), the average difference of outcome variable Y_i (income level or income expectation) is subject to whether a household is involved in e-commerce, expressed as:

$$Y_i = Y_{0i} + \left(Y_{1i} - Y_{0i}\right) D_i = \alpha + \beta X_i + \Delta D_i + \varepsilon_i \tag{1}$$

In equation (1), i is the number of individual household. Dummy variable $D_i = \{0,1\}$ denotes whether individual household i is involved in e-commerce business (1=Yes; 0=No). The outcome variable (sense of economic gain) Y is subject to a group of explanatory variables X, the average of which is influenced by e-commerce participation D. $(Y_{1i} - Y_{0i})$ or Δ is the average treatment effect (ATE) of e-commerce, and the average treatment effect on the treated (ATT) for rural households involved in e-commerce business is expressed as:

$$\mathrm{ATT} \equiv \mathrm{E}\left(Y_{1i} - Y_{0i} \middle| D_i = 1\right) \tag{2}$$

Since some of the samples may not participate in e-commerce at all, a simple comparison of the outcome variable between participants and non-participants may give rise to a selection bias. Thus, ATE consists of ATT and selection bias. For officials and policymakers, ATT matters more since it measures participants' gross return.

The reality is that households are either involved in e-commerce business or not involved at all. Namely, one of the choices made by households will always be observed. If a household is involved in e-commerce business, Y_{1i} will be observed, but the potential result of non-participation cannot be observed. If a household is not involved in e-commerce, Y_{0i} will be observed, but the potential outcome of participation cannot be observed. That is to say, the potential outcome of the counterfactual choice is a missing value. The evaluation of the treatment effect in the observation data comes down to the treatment of missing data. Propensity value analysis has been proven to be an effective statistical method for evaluating the treatment effect based on observation data. PSM identifies an individual j of the control group who corresponds to an individual i of the treatment group, whose measurable covariates are similar based on parametric or non-parametric regression (this paper employs logit model to estimate the propensity value), so that the outcome variable of individual j can be used as the counterfactual reference for individual i.

Based on the sample calculation treatment method after PSM, we proceed to estimate the ATT of rural households involved in e-commerce business with the following equation:

$$\text{ATT}=\frac{1}{N_1}\sum_{i:\,D_i=1}\left(Y_i-Y_{0i}\right) \tag{3}$$

3.3 Variable Explanation and Statistical Characteristics

In this paper, the explained variable reflects rural households' sense of economic gain from different dimensions. Existing empirical research recognizes the viability of measuring perceived gain among the Chinese public on both dimensions of time and reference group (Lyu and Huang, 2018). Similarly, this paper carries out an analysis on both dimensions of comparison with peers and future income expectation from the CIRS2017 questionnaire as variables of sense of economic gain. The outcome variable of perceived income gain compared with peers is "Self-evaluated income level compared with fellow villagers" at the time of survey (summer of 2017), which is divided into five grades from low, below average, average, above average to high. This question asks households about their perceived relative income level in the village. Future income expectation is measured by "Percentage of expected household income growth (reduction) in 2018 over 2017."

To ensure the use of the same samples for analysis on different dimensions, this paper retains questionnaires with answers to all questions, including 6,242 households. Among them, 13.8% (859) of all rural households are involved in e-commerce business; 33.5% of (2,093) rural households are registered poor households, and the rest (4,149) are non-poor households; 8.1% of poor households and 16.6% of non-poor households are involved in e-commerce.

Variables that may affect households' sense of gain include community environment, human capital, and material capital. These variables are based on 2016 information, which precedes perceived gain variable evaluated during the survey of 2017 and meets the above-mentioned criteria. The descriptive statistics of relevant variables are shown in Table 1. The t-test of mean difference suggests that apart from the household head's level of education, significant differences exist in the explained variable and covariates between households involved in e-commerce and those not involved. Based on the definitions of variables, households not involved in e-commerce are significantly disadvantageous to those that are involved in terms of endowment and external environment. To overcome the self-selection bias of households with respect to e-commerce participation, it is highly necessary to adopt an ATT evaluation model.

4. Analysis of Empirical Results

4.1 Measurement Results of the Sense of Economic Gain from E-Commerce Participation

Table 2 and 3 identify the treatment effects of sense of economic gain from e-commerce participation on the two dimensions. Given the existence of numerous comparable control group samples and the robustness of results, this paper simultaneously employs k-nearest neighbor matching and kernel matching methods, and calculates standard error with bootstrapping method in reporting estimation

Table 1: Descriptive Statistics of Variables and the t-Test of Group Mean Values

	Variable	Meaning	Value explanation	Mean value	Standard deviation	t-Test of mean value difference
Treatment variable	*WebSale*	Whether the household is engaged in online transactions, i.e. e-commerce participation variable	0=No; 1=Yes	0.14	0.35	N/A
Outcome variable	*IncLvl*	Self-evaluated income level of the household relative to fellow villagers	1=Low; 2=Below average; 3=Average; 4=Above average; 5=High	2.94	0.82	-0.55***
	IncExp	Percentage of expected household income growth (reduction) in 2018 over 2017	Measured in percentage. For instance, if household income is expected to grow by 20%, the value is "20"; if household income is expected to reduce by 30%, the value is "-30"	10.98	11.49	-2.77***
Grouping variable	*HHPvty*	Whether the household is a registered for household	0=No; 1=Yes	0.34	0.47	0.16***
Matching variable: Household status	*HeadGndr*	Gender of household head	0=Female; 1=Male	0.93	0.25	-0.02**
	HeadAge	Age of household head	Unit: Year	52.10	12.82	3.38***
	HeadEdu	Education level of household head	1=Uneducated; 2=Primary school; 3=Junior middle school; 4=High school; 5=College/junior college; 6=Postgraduate	2.58	0.91	-0.05
	HHLand	Household per capita arable land	Unit: *mu*	1.55	1.70	0.13**
	*HeadHlth*1	Type of household head's health status (Category 3 is reference group)	0=Other; 1=Rarely ill	0.80	0.40	-0.13***
	*HeadHlth*2		0=Other; 1=Frequent minor illnesses or chronic diseases	0.17	0.37	0.10***
	*HeadHlth*3		0=Other; 1=Severely ill or handicapped	0.11	0.31	0.08***
Matching variable: Community status	*Vlg_Water*1	Whether the village has access to tap water (Category 3 is reference group)	0=Other; 1=Full access	0.78	0.41	-0.16***
	*Vlg_Water*2		0=Other; 1=Partial access	0.16	0.37	0.11***
	*Vlg_Water*3		0=Other; 1=No access	0.06	0.23	0.05***
	*Vlg_Web*1	Whether the village has access to broadband connection/ digital TV (Category 3 is reference group)	0=Other; 1=Full access	0.68	0.47	-0.20***
	*Vlg_Web*2		0=Other; 1=Partial access	0.29	0.45	0.20***
	*Vlg_Web*3		0=Other; 1=No access	0.04	0.19	0.00
	*Vlg_Road*1	Whether the village has access to cement/asphalt road (Category 3 is reference group)	0=Other; 1=Full access	0.81	0.39	-0.12***
	*Vlg_Road*2		0=Other; 1=Partial access	0.17	0.37	0.10***
	*Vlg_Road*3		0=Other; 1=No access	0.02	0.14	0.02***
	Vlg_CntKM	Distance from village to county administration	Unit: Kilometer	20.13	14.38	-0.09

Notes: (1) Observations include 6,242 rural households;(2) t-test of mean value difference refers to the mean value difference of variables between households not involved in e-commerce business and those involved (the former minus the latter) and their significance; (3) ***, ** and *denote significance at 1%, 5% and 10% levels.

Source: Compiled by authors based on CIRS2017 data.

results. Under different matching methods, the average treatment effects on the treated (ATT) of e-commerce participation are similar on various dimensions, but differences exist between poor and non-poor households.

Rural households not involved in e-commerce business reported their relative income to be below average (2.869), and those who were involved in e-commerce business reported their relative income to be above average (nearest neighbor matching result is 3.304, and the kernel matching result is 3.360). E-commerce participation elevated the self-evaluated income level to above average, and the ATT is significant at 1%. Between poor and non-poor households, there are some differences in the level of ATT. Whatever the matching result, e-commerce participation increased poor households' sense of economic gain more significantly: The results are 0.391 relative to 0.376 in k-nearest neighbor matching, and 0.528 relative to 0.441 in kernel matching. To summarize, e-commerce participation increased the self-evaluated income level of rural households relative to their fellow villagers from below average to above average, and such an increase is more substantial among poor households.

Estimation results suggest that rural households engaged in e-commerce business expected their income to rise in 2018 at a rate higher by 1 to 2 percentage points compared with households not involved in e-commerce business. Specifically, the difference is 1.137 in the nearest neighbor matching, and 2.215 in the kernel matching. Judging by the results of grouped estimation, however, the effects of e-commerce on future (long-term) income growth expectation existed only for non-poor households. E-commerce participation increased the expected income growth of non-poor households by 2 to 3 percentage points (significant at 1% level); poor households, however, expected a miniscule income growth expectation from e-commerce participation in the long run. While the treatment effect in the k-nearest neighbor matching is insignificant, the treatment effect in the kernel matching is minuscule in terms of both economic significance (0.109 percentage points) and statistical significance (significant at 10% level). The effect of expected long-term economic gain for poor households is only 1/30 that of non-poor households.

In the results of evaluation based on the above two dimensions, both Hypothesis 1 "E-commerce participation will increase households' sense of economic gain" and Hypothesis 2 "There is a difference in the sense of economic gain from e-commerce participation between poor and non-poor households" have been verified. E-commerce participation will increase households' sense of economic gain no

Table 2: Effects of E-Commerce Participation among Households' Sense of Economic Gain Compared with Their Fellow Villagers

	K-nearest neighbor matching			Kernel matching		
	Control group	Treatment group	ATT	Control group	Treatment group	ATT
No grouping	2.869	3.304	0.435***	2.869	3.360	0.491***
Poor households	2.682	3.073	0.391***	2.682	3.210	0.528***
Non-poor households	2.973	3.349	0.376***	2.973	3.414	0.441***

Notes: (1) For the sense of economic gain relative to others, i.e. "Self-evaluated income level relative to fellow villagers," the score from 1 to 5 denotes five levels, i.e. "low, below average, average, above average and high." (2) ***, ** and * respectively denote significance at 1%, 5% and 10% levels. The standard error of ATT and the significance test results are obtained with bootstrap repeated sampling for 500 times; (3) K-kernel nearest neighbor matching employs 1-to-4 matching, and kernel matching employs secondary kernel matching with bandwidth of 0.06 by default.
Source: Results of analysis by the author based on CIRS2017 data.

Table 3: Expected Economic Gain from E-Commerce Participation

	K-nearest neighbor matching			Kernel matching		
	Control group	Treatment group	ATT	Control group	Treatment group	ATT
No grouping	10.603	11.740	1.137**	10.603	12.818	2.215***
Poor households	11.208	9.856	-1.352	11.208	11.317	0.109*
Non-poor households	10.267	12.163	1.896***	10.267	13.387	3.120***

Notes: (1) For the sense of economic gain relative to others, i.e. "Self-evaluated income level relative to fellow villagers," the score from 1 to 5 denotes five levels, i.e. "low, below average, average, above average and high." (2) ***, ** and * respectively denote significance at 1%, 5% and 10% levels. The standard error of ATT and the significance test results are obtained with bootstrap repeated sampling for 500 times; (3) K-kernel nearest neighbor matching employs 1-to-4 matching, and kernel matching employs secondary kernel matching with bandwidth of 0.06 by default.
Source: Results of analysis by authors based on CIRS2017 data.

matter compared with their fellow villagers or in terms of future income expectation. Yet there is a difference in the sense of economic gain from e-commerce participation between poor and non-poor households on both dimensions. While poor households reported a more significant improvement in their relative income status than did non-poor households, their future income growth expectation is eclipsed by that of non-poor households.

4.2 Common Support Domain and the Balance Test

First, overlap assumption is the premise for matching, i.e. the range of propensity score between treatment group and control group contains an overlap, i.e. "common support domain." To improve the quality of matching, a common practice is to retain samples whose scores fall into the "common support domain." Hence, differences in the "common support domain" under various matching methods will also incur sample losses. Losses of samples under the 1-to-4 k-nearest neighbor matching and kernel matching are the same. Among the three categories of ungrouped samples, poor households and non-poor households, sample losses are 0.7%, 1.6% and 1.7%, respectively. That is to say, only a small quantity of samples are lost under the PSM, and most observations are within the range of common values. Therefore, there is reason to believe that deviations from sample losses are relatively small in this case.

Second, given the significant differences in the initial conditions between households who had participated in e-commerce and those who had not (as shown in the mean t-test of Table 1), the impact of such "selection bias" should be removed wherever possible in evaluating the impact of e-commerce participation. The proper balancing of explanatory variables after the PSM is a necessary condition for estimating e-commerce participation to yield credible results. The balance test indicates that the specific matching methods employed to obtain the above results have all properly balanced the data. No matter which matching method is employed, the standardization deviations of all covariates are within 10% - even 3% for most covariates. Table 4 lists the balance test results of explanatory variables under different grouping conditions. Take ungrouped samples for instance, pseudo-R^2 drops from 0.073 before matching to 0.002-0.003 after matching. LR statistic is down from 364.540 before matching to 4.650-8.130 after matching, and the joint significance test of explanatory variables significantly changes from less than 1% before matching to high-probability rejection; the mean deviation and median deviation have decreased from above 25% and above 30% before matching to less than 3% after matching, respectively. For poor

Table 4: Balance Test Results of Explanatory Variables before and after Matching

Group/Matching method		Pseudo R^2	LR statistic	p value	Mean deviation	Median deviation
Ungrouped	Before matching	0.073	364.540	0.000	25.500	30.800
	After matching*	0.003	8.130	0.882	2.300	1.900
	After matching#	0.002	4.650	0.990	1.700	1.300
Poor households	Before matching	0.070	82.480	0.000	20.800	15.200
	After matching*	0.006	2.630	1.000	4.100	2.700
	After matching#	0.002	0.840	1.000	3.000	2.600
Non-poor households	Before matching	0.083	311.040	0.000	26.500	31.600
	After matching*	0.005	9.530	0.796	2.500	1.600
	After matching#	0.002	4.480	0.992	1.800	1.500

Note: * means 1-to-4 k-nearest neighbor matching; # is quadratic kernel matching with bandwidth of 0.06.
Source: Results of analysis by authors based on CIRS 2017 data.

and non-poor households, the balance test results all suggest that the explanatory variables are well-balanced after matching.

4.3 Sensitivity Analysis

There may be an omission of key variables in the selection of unobservable factors, which will result in a hidden bias. In this case, the estimation of the intervention effect with the empirical results will be biased. Therefore, a sensitivity analysis should be further carried out to estimate the level of the hidden bias.[3] Rosenbaum (2002) has developed a multitude of sensitivity analysis methods. Stata users have created a program *rbounds* to examine the sensitivity of research conclusions based on matching with Wilcoxon's signed-rank test, Hodges-Lehmann's point estimation, and interval estimation to investigate the sensitivity based on the research conclusions of matching (Guo and Frazer, 2012). Table 5 and 6 respectively report the sensitivity levels of the ATT of the sense of economic gain on the two dimensions with respect to the matching method. If Gamma is large (close to 2) and unilateral significance level starts to exceed 0.1, the research results will have relatively good robustness with respect to the hidden bias.

In Table 5, when Gamma=2, the ATT of the sense of economic gain for ungrouped, poor and non-poor households with respect to their fellow villagers is significant at 1%, 5% and 1% levels, which suggests that the ATT of sense of economic gain is relatively good robustness with respect to hidden bias under the matching method.

As shown in Table 6, when Gamma=2, the ATT of future income growth expectation remains significant at 1%. Yet the ATTs of future income growth expectation for ungrouped samples and non-poor households become sensitive when Gamma=1.17 and Gamma=1.34, respectively. Since 1.17 and

[3] For the approach and method of treatment for the hidden bias in Rosenbaum sensitivity analysis, please refer to: Shenyang Guo, Mark W. Fraser: *Propensity Score Analysis Statistical Methods and Applications*, translated by Guo Zhigang, Wu Xiwei, et al. Chongqing: Chongqing University Press, 2012, page 198-214.

Table 5: Sensitivity Level of the ATTs of Sense of economic gain Relative to Fellow Villagers

Group	Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
Ungrouped	1	0.000	0.000	0.500	0.500	0.375	0.500
	2	0.000	0.000	0.250	0.625	0.125	0.750
Poor	1	0.000	0.000	0.500	0.500	0.250	0.625
	2	0.014	0.000	0.125	0.667	0.000	0.875
Non-poor	1	0.000	0.000	0.375	0.375	0.375	0.500
	2	0.000	0.000	0.200	0.625	0.125	0.625

Notes: Gamma denotes log odds of differential assignment due to unobserved factors; sig+ and sig- denote the upper and lower bound significance levels, respectively; t-hat+ and t-hat- denote the upper and lower bound Hodges-Lehmann point estimates, respectively; CI+ and CI- denote the upper (0.95) and lower (0.95) bound confidence intervals, respectively.
Source: Results of analysis conducted by authors based on CIRS2017 data.

Table 6: Sensitivity Level of the ATTs of Future Income Growth Expectation

Group	Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
Ungrouped	1	0.001	0.001	1.250	1.250	0.500	1.875
	1.16	0.086	0.000	0.500	1.875	-0.250	2.625
	1.17	0.104	0.000	0.500	1.958	-0.250	2.625
Poor	1	0.083	0.083	-1.125	-1.125	-2.875	0.500
	2	0.000	0.993	-4.375	2.000	-6.250	3.750
Non-poor	1	0.000	0.000	1.875	1.875	1.000	2.625
	1.33	0.087	0.000	0.500	3.125	-0.250	3.875
	1.34	0.101	0.000	0.500	3.125	-0.250	4.000

Notes: Gamma denotes log odds of differential assignment due to unobserved factors; sig+ and sig- denote the upper and lower bound significance levels, respectively; t-hat+ and t-hat- denote the upper and lower bound Hodges-Lehmann point estimates, respectively; CI+ and CI- denote the upper (0.95) and lower (0.95) bound confidence intervals, respectively.
Source: Results of analysis conducted by authors based on CIRS2017 data.

1.34 are relatively small values, the ATTs of future income growth expectation are sensitive to the hidden bias to some extent for non-poor households (and ungrouped rural households that include non-poor households). Due to the limitations of data availability and observable factors, it is difficult for this study to conduct further treatment of the hidden bias, but we must be more cautious in explaining the ATTs of future income growth for non-poor and ungrouped rural households. Of course, the core conclusions of this paper are free from interference of the hidden bias, which will be discussed in the following paragraphs.

4.4 Explanatory Analysis of Estimation Results

Judging by the estimation result, e-commerce participation significantly increases sample households' sense of economic gain, both compared with their fellow villagers and in terms of future income growth expectation (corresponding to Hypothesis 1, Hypothesis 1a and Hypothesis 1b). While sense of economic gain indeed varies between different groups (corresponding to Hypothesis 2), e-commerce participation increases poor households' sense of economic gain compared with their fellow villagers more significantly (country to Hypothesis 2a). In terms of future income growth expectation, the effects of e-commerce participation are stronger for non-poor households (but this conclusion has a certain sensitivity to hidden bias), and such effects, however, are negligible for poor households (Hypothesis 2b is verified).

In the above results, there is a contradiction that becomes the core question that warrants attention in the conclusions, i.e. While e-commerce increases poor households' sense of economic gain compared with their fellow villagers much more than for their non-poor counterparts, it does little to increase poor households' future income growth expectation (robust). Due to data limitations, it is hard to find direct evidence to shed more light on this contradictory result. What we can do is to offer some possible explanations from an empirical perspective. A possible explanation on this result is that China's poverty reduction campaign over-relies on external policy support without creating sufficient endogenous momentum. Moreover, it takes time for the empowerment effects of e-commerce participation to materialize among poor populations who are deprived of resource endowment and competence.

First, a strong poverty reduction policy will divert resources to poor households in a short policy period. For poor households who have opted to participate in e-commerce, they have also received special policy support to escape poverty through e-commerce. Based on the surveys in Longnan Prefecture of Gansu Province, Wuyi County of Hebei Province, Suqian Prefecture and Qingchuan County of Sichuan Province, we have found that like other poverty reduction programs, the e-commerce platforms or online shops involved in the pro-poor e-commerce programs all granted special preferences specifically to poor households. For instance, priority was given to the purchase and sales of agricultural produce from poor households, who received guaranteed minimum dividend distribution. As a result, e-commerce participation will naturally increase poor households' self-evaluated relative income status in their villages. The policy preferences were granted specifically to poor households, making it more likely for them to gain more compared with their non-poor peers. Nevertheless, such pro-poor e-commerce programs may also create shocks to rural society and new inequalities by targeting at a specific group. We should be cautious about the "cliff effect" that may arise from shoveling resources excessively towards the poor at the risk of new inequalities.

Second, the lack of competence among poor households and scant endogenous momentum have restricted the policy effects of e-commerce. As an IT infrastructural channel, e-commerce is also a complete industrial chain with more demanding requirements on rural households' human capital. Yet the lack of human capital among poor households is hard to remedy in the short run, making it hard for the poor to unlock their full potentials. Moreover, it takes time for e-commerce to empower poor populations. For poor households, their income growth would not have been possible without policy support. For this reason, poor households cannot expect their income growth to sustain in the future since pro-poor policies may not stay with the completion of the poverty reduction program, and even their negative income growth expectation looms large. On the contrary, most non-poor households benefit from e-commerce with their skills rather than policy support, and expect their income to grow substantially through e-commerce participation. Despite the short-term benefits of policy support, average poor households cannot expect their income to keep rising once policy preferences are phased out. The lack of endogenous momentum among poor households remains an intractable problem.

Perceived gain is people's personal experience about how much they have benefited from economic development. By evaluating sense of economic gain from e-commerce participation and interpreting the results, this paper arrives at conclusions that help revisit the poverty reduction effects of pro-poor e-commerce and other forms of poverty reduction. According to the analysis, numerous pro-poor e-commerce programs carried out in China face the same dilemma as ordinary poverty reduction programs, i.e. how to foster endogenous momentum for poor households to prosper sustainably. This question is vital for policy makers to consider.

5. Conclusions and Policy Implications

Based on the data of 6,242 rural households and their villages in the non-probability sampling surveys conducted by Tsinghua University in 2017, this paper employs the propensity score matching (PSM) method to evaluate rural households' sense of economic gain from e-commerce participation relative to their fellow villagers and in terms of their future income growth expectation under a counterfactual framework. Findings indicate that e-commerce participation has increased sample households' sense of economic gain both relative to their fellow villagers and in terms of their future income growth expectation. However, the results differ between poor and non-poor households. While poor households reported a more substantial income growth relative to their fellow villagers, they had little expectation for income growth over a longer time horizon. Only the non-poor households expected e-commerce participation to generate a long-lasting effect on their future income growth.

This evaluation result is consistent with the effect of external support targeted at poor households in the course of China's fight against poverty. It is also consistent with the actual picture of the lack of endogenous momentum for poor populations. As a new internet business model, e-commerce is widely expected to contribute to poverty reduction in China. Yet policy makers must assess whether e-commerce participation will help poor households develop competence essential for earning a livelihood in the long run. The results of this research indicate that the effects of sense of economic gain from e-commerce participation are different between poor and non-poor households on various dimensions. Discussions on pro-poor e-commerce cannot be generalized or one-sided. Pro-poor e-commerce must address the root cause of poverty beyond short-term benefits to poor households. The sustainability and quality of e-commerce's pro-poor effects are yet to be further observed and examined. For poor households, the lack of skills presents a more prominent challenge to their long-term income growth expectation. For policymakers and private sectors, pro-poor e-commerce must focus on building capacity for poor households to benefit from e-commerce in the long run as an inclusive technology. This paper's conclusions are worth referencing for various poverty reduction initiatives, including e-commerce programs for the poor.

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