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E-COMMERCE PARTICIPATION, FACTOR ALLOCATION EFFICIENCY, AND UPWARD CLASS MOBILITY OF RURAL HOUSEHOLDS: EMPIRICAL EVIDENCE FROM THE CHINA FAMILY PANEL STUDIES

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Abstract: Whether digital commerce can reshape, rather than merely supplement, the economic position of rural households is central to debates on inclusive growth in developing countries. Drawing on nationally representative panel data from six waves (2010-2020) of the China Family Panel Studies (CFPS), this paper examines whether e-commerce participation promotes the upward class mobility of rural households and whether the effect operates through improved factor allocation efficiency. A rural household is defined as participating in e-commerce if any member uses the internet for business or operates online sales. Upward mobility is measured by movements across within-wave household income quintiles and by occupational class upgrading of the household head. Two-way fixed-effects estimates indicate that e-commerce participation significantly raises the probability of upward mobility, and the results survive instrumental-variable estimation exploiting the interaction between village terrain ruggedness and national online retail growth, propensity score matching, and alternative mobility measures. Mechanism analysis shows that participation reallocates household labor toward nonfarm activities, encourages farmland transfer-out, and improves access to formal credit, with these factor-reallocation channels jointly accounting for roughly one-third of the total effect. Heterogeneity analysis reveals larger gains among households in the bottom income quintiles, indicating that e-commerce can serve as an inclusive ladder of mobility provided that entry barriers are lowered.
Keywords: E-commerce participation; Factor allocation efficiency; Upward social mobility; Rural households; China Family Panel Studies

1 INTRODUCTION

Over the past two decades, China has experienced the fastest expansion of electronic commerce in the developing world. The number of people buying and selling products online grew from practically zero in 2000 to more than 400 million by 2015, and rural areas have become the new frontier of this expansion [1]. The proliferation of "Taobao villages", in which a substantial share of households engage in online retailing, illustrates how digital platforms can penetrate peripheral rural markets and reconfigure local production systems [2-3]. Since 2014, the Chinese government has promoted the National Rural E-commerce Comprehensive Demonstration program, embedding e-commerce into the rural revitalization strategy and the poverty alleviation agenda [4].

What e-commerce does to rural households, however, remains contested. Village-level randomized evidence indicates that the arrival of e-commerce mainly reduces the rural cost of living through cheaper and more diverse consumption goods, while average production-side gains for the typical rural producer are limited [1]. Survey evidence from Taobao villages shows that households selling online earn substantially more than matched non-participants, yet participation is selective, favoring younger and better-educated households [5]. Quasi-experimental studies likewise document sizable income gains for adopters, whereas case studies caution that e-commerce booms may inflate local land and labor costs and foster informal production arrangements [6-8]. Almost all of this literature evaluates outcomes in levels: income, consumption, or employment at a point in time.

Conspicuously absent is the question of mobility. For rural households, welfare depends not only on the level of income but also on the capacity to move across economic positions: from smallholder farming into nonfarm employment, from wage work into self-employment, and from the lower rungs of the income distribution toward the middle. Such upward class mobility lies at the heart of stratification research and of policy debates about equality of opportunity [9-11]. In rural China, mobility has historically been constrained by fragmented landholding, thin credit markets, and institutional barriers that distort the allocation of labor, land, and capital [12]. Recent evidence based on the China Family Panel Studies shows that rural intergenerational occupational mobility, although higher than urban mobility, remains concentrated in low-prestige jobs [13].

This paper connects these two strands of literature. We ask whether e-commerce participation promotes the upward class mobility of rural households, and whether the effect operates through improved factor allocation efficiency. Conceptually, e-commerce relaxes three classic constraints on rural households. It lowers information and market-entry costs [14-15]; it mitigates the credit constraints that underpin occupational choice through platform-based digital credit and payment records [16-17]; and it raises the return to reallocating labor and land toward higher-value nonfarm uses. E-commerce may therefore function as a market-integration device that reduces factor misallocation and converts static

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income gains into dynamic mobility [18-19].

Using six waves of the CFPS (2010-2020), we construct an unbalanced panel of rural households and estimate two-way fixed-effects models of upward mobility. Because participation is not random, we address endogeneity through an instrumental-variables strategy that interacts village terrain ruggedness with national online retail growth, together with propensity score matching and alternative mobility definitions. The estimates indicate that e-commerce participation raises the probability of upward income mobility by about eight percentage points and of occupational class upgrading by about five percentage points. Roughly one-third of the total effect is mediated by factor reallocation, including shifts of household labor toward nonfarm activities, farmland transfer-out, and improved credit access. The gains are significantly larger among households in the bottom income quintiles, suggesting conditional inclusiveness.

This study makes three contributions. First, it shifts the evaluation of rural e-commerce from income levels to class mobility, linking the digital economics literature with the stratification literature. Second, it introduces factor allocation efficiency as the mechanism that bridges market integration and mobility, thereby connecting the misallocation literature with research on rural e-commerce [18]. Third, it provides nationally representative panel evidence, complementing existing studies based on regional surveys of Taobao villages.

2 LITERATURE REVIEW AND HYPOTHESES

2.1 E-Commerce and Rural Household Outcomes

A first body of work documents the welfare consequences of rural e-commerce along several margins. On the consumption side, e-commerce integration lowers local prices and expands product variety, generating purchasing-power gains that are largest for durable goods and remote villages [1]; at the national scale, e-commerce has reduced spatial consumption inequality [20]. On the production side, participation is associated with higher household income, mainly through sales income rather than wage or transfer income, and with shifts in cropping and input decisions [5-7]. At the regional level, e-commerce clusters stimulate entrepreneurship, county-level economic development, women's economic empowerment, and may narrow the urban-rural income gap [21-24]. At the same time, the diffusion of e-commerce is spatially concentrated and can induce informality and rising factor costs [2, 8]. What remains unknown is whether these gains translate into durable movements across economic positions rather than transitory improvements within a fixed position.

2.2 Class Mobility and Its Determinants

Theories of intergenerational and intragenerational mobility emphasize the role of family resources under credit constraints, and empirical research has developed both income-rank and class-structural approaches to measuring mobility [9, 25-26]. Cross-country evidence links higher inequality to lower mobility, a relationship known as the Great Gatsby Curve [10-11]. China combines high income inequality with a rural population whose mobility has long been shaped by the household registration system, collective land institutions, and segmentation between agricultural and non-agricultural labor markets [27]. Analyzing CFPS data from 2014 to 2022, Huang et al. find that intergenerational occupational mobility is higher in rural than in urban China but is concentrated in low-prestige occupations [13], and that migration substantially raises mobility. These findings imply that channels capable of opening access to higher-return occupations could have outsized mobility effects in rural areas. Digital technology is a plausible such channel, yet it has rarely been examined from the mobility perspective.

2.3 Factor Allocation Efficiency as a Mechanism

A third strand of literature attributes low agricultural productivity and sluggish structural transformation in developing countries to the misallocation of factors across producers and uses [18-19]. Cross-country evidence shows that differences in the allocation of land across farms account for a large share of international agricultural productivity gaps, and that agricultural labor productivity lags far behind non-agricultural productivity [12, 28]. In rural China, fragmented land rights, migration frictions, and credit rationing prevent labor, land, and capital from flowing to their most productive uses, trapping households in low-return farming.

E-commerce can be interpreted as a market-integration technology that relaxes precisely these frictions. By reducing information asymmetries, it raises the shadow return to nonfarm labor and to land consolidation [14]. By generating verifiable digital transaction records, it relaxes credit constraints and expands participation in digital financial markets [17]. By lowering entry costs, it enables households that were previously excluded from entrepreneurship to switch occupations [29]. Together, these channels predict that e-commerce participation improves the allocation of household factors and, through that channel, facilitates upward mobility. We therefore propose:

H1: E-commerce participation increases the probability of upward class mobility of rural households.

H2: The positive effect of e-commerce participation on upward mobility is partially mediated by improved factor allocation efficiency, reflected in nonfarm labor reallocation, farmland transfer-out, and access to formal credit.

H3: The mobility effect of e-commerce participation is stronger for households that are initially disadvantaged in the income distribution, provided they manage to participate.

3 DATA, VARIABLES, AND EMPIRICAL STRATEGY

3.1 Data

The data come from the China Family Panel Studies, a nationally representative biennial survey conducted by the Institute of Social Science Survey at Peking University [30]. The CFPS covers 25 provinces and collects detailed information on household demographics, income, occupation, land, internet use, and financial behavior. We use the six waves from 2010 to 2020 and retain households with rural hukou at baseline. After dropping observations with missing key variables, the final sample is an unbalanced panel of 28,436 household-year observations covering 9,682 rural households.

3.2 Variable Definitions

The dependent variable is upward class mobility, measured in two ways. First, income mobility is captured by an indicator equal to one if the household's per-capita income percentile, computed within each wave, crosses to a higher quintile relative to the previous wave. Second, occupational mobility is captured by an indicator equal to one if the household head's occupation upgrades along a class ordering from agricultural labor, to nonfarm manual work, to clerical or service work, and to self-employment or managerial-professional positions, following the class-analytic tradition [9].

The key explanatory variable, e-commerce participation, equals one if any household member reports using the internet for business purposes or operating online sales in a given wave, following the operationalization of CFPS-based e-commerce research [21]. Mechanism variables proxy factor allocation efficiency along three margins: the share of household labor engaged in nonfarm activities, an indicator for transferring contracted farmland out through the rental market, and an indicator of access to formal credit. Control variables include the household head's age and its square, gender, years of schooling, household size, the dependency ratio, and per-capita contracted land.

3.3 Model Specification

The baseline specification is a two-way fixed-effects linear probability model: the mobility indicator of household i in province p at wave t is regressed on e-commerce participation, time-varying controls, household fixed effects, and wave fixed effects, with standard errors clustered at the village level. Household fixed effects absorb all time-invariant determinants of both participation and mobility, such as innate entrepreneurial ability.

Two threats to identification remain: time-varying shocks that simultaneously induce participation and mobility, and reverse causality. We therefore instrument e-commerce participation with the interaction between village terrain ruggedness, which raises the cost of logistics rollout and is plausibly exogenous to household mobility conditional on fixed effects, and the logarithm of national online retail sales, which captures the aggregate expansion of e-commerce. Robustness is further assessed with propensity score matching combined with wave-by-wave comparisons, ordered logit models of the direction of quintile transitions, and the exclusion of the 2020 wave affected by the COVID-19 pandemic.

4 EMPIRICAL RESULTS

4.1 Descriptive Statistics

Table 1 reports descriptive statistics. In the full sample, 21.8 percent of household-wave observations record an upward income-quintile transition and 9.6 percent record occupational upgrading, while 7.4 percent of observations correspond to e-commerce participation. Participating households are younger, better educated, and more likely to engage in nonfarm activities, confirming that participation is selective and underscoring the need for the identification strategies described above.

Table 1 Descriptive Statistics of the Main Variables

Variable	Mean	S.D.	Definition
Upward income mobility	0.218	0.413	=1 if household income percentile moves to a higher quintile than previous wave
Upward occupational mobility	0.096	0.294	=1 if household head's occupation upgrades along the class ordering
E-commerce participation	0.074	0.262	=1 if any member uses the internet for business or online sales
Nonfarm labor share	0.412	0.356	Share of household labor in non-agricultural activities
Farmland transfer-out	0.168	0.374	=1 if household rents out contracted farmland
Formal credit access	0.213	0.409	=1 if household has outstanding formal or platform-based credit
Head age (years)	51.3	12.6	Age of the household head
Head schooling (years)	6.9	4.1	Years of schooling of the household head
Household size	3.9	1.8	Number of household members
Log per-capita income	8.72	1.05	Log of household per-capita annual income (yuan, 2010 prices)

Source: China Family Panel Studies (CFPS), waves 2010-2020; 28,436 household-year observations on 9,682 rural households.

4.2 Baseline Results

Table 2 presents the baseline estimates. Column (1), which includes only wave and province fixed effects, shows that e-commerce participation is associated with an 11.2 percentage point higher probability of upward income mobility. Adding household-level controls in column (2) reduces the coefficient to 0.091, and replacing province effects with household fixed effects in column (3) yields a coefficient of 0.083, significant at the one-percent level. Given that the baseline probability of upward mobility is about 22 percent, the estimate implies that participation raises the likelihood of moving up by more than one-third relative to the mean, supporting H1.

Table 2 Baseline Estimates: E-Commerce Participation and Upward Income Mobility

Variable	(1) Province & wave FE	(2) + Controls	(3) Household & wave FE
E-commerce participation	0.112*** (0.018)	0.091*** (0.015)	0.083*** (0.014)
Controls	No	Yes	Yes
Province FE	Yes	Yes	No
Household FE	No	No	Yes
Wave FE	Yes	Yes	Yes
Observations	28,436	28,436	28,436
R-squared	0.064	0.121	0.327

Note: Dependent variable is the upward income-quintile mobility indicator. Robust standard errors clustered at the village level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.3 Robustness Checks

Table 3 reports robustness checks. Column (1) presents the instrumental-variables estimates. The first stage is strong, with a Kleibergen-Paap F-statistic of 38.6, and the second-stage coefficient, 0.152, remains significant, suggesting that, if anything, measurement error and attenuation bias the baseline estimates downward. Column (2) restricts the comparison to propensity-score-matched participants and non-participants and yields a similar coefficient of 0.079. Column (3) replaces the dependent variable with occupational upgrading and obtains a significant coefficient of 0.046, while column (4) excludes the 2020 wave and leaves the results essentially unchanged. Ordered logit estimates of the direction of quintile transitions, not reported for brevity, deliver the same qualitative conclusion.

Table 3 Robustness Checks

Variable	(1) IV-2SLS	(2) PSM sample	(3) Occupational upgrading	(4) Excl. 2020 wave
E-commerce participation	0.152** (0.061)	0.079*** (0.021)	0.046*** (0.011)	0.085*** (0.016)
Controls	Yes	Yes	Yes	Yes
Household & wave FE	Yes	Yes	Yes	Yes
KP first-stage F	38.6	-	-	-
Observations	28,436	6,118	28,436	23,815

Note: Column (1) instruments e-commerce participation with village terrain ruggedness interacted with log national online retail sales. KP F denotes the Kleibergen-Paap first-stage F-statistic. *** p<0.01, ** p<0.05, * p<0.1.

4.4 Mechanism: Factor Allocation Efficiency

Table 4 examines the mechanism. Columns (1) to (3) show that e-commerce participation significantly increases the nonfarm labor share of the household by 11.8 percentage points, raises the probability of transferring farmland out by 5.7 percentage points, and improves access to formal credit by 9.2 percentage points. These patterns are consistent with participation relaxing labor-market, land-market, and credit-market frictions simultaneously. Column (4) adds the three factor-reallocation variables to the baseline mobility regression: the coefficient on e-commerce participation falls from 0.083 to 0.054 and remains significant, implying that improved factor allocation efficiency mediates roughly 35 percent of the total effect, in support of H2. The remaining direct effect likely reflects demand-side channels, such as higher product prices and reduced marketing margins, that raise income within a given occupation.

Table 4 Mechanism Analysis: Factor Reallocation Channels

Variable	(1) Nonfarm labor share	(2) Farmland transfer-out	(3) Formal credit	(4) Upward mobility
E-commerce participation	0.118*** (0.022)	0.057** (0.023)	0.092*** (0.019)	0.054*** (0.013)
Nonfarm labor share	-	-	-	0.141*** (0.018)
Farmland transfer-out	-	-	-	0.069*** (0.017)
Formal credit access	-	-	-	0.058*** (0.015)
Controls & FE	Yes	Yes	Yes	Yes
Observations	28,436	28,436	28,436	28,436

Note: Columns (1)-(3) report the effect of e-commerce participation on each factor-allocation margin; column (4) adds the three channels to the baseline mobility regression. *** p<0.01, ** p<0.05, * p<0.1.

4.5 Heterogeneity Analysis

Table 5 explores heterogeneity. The mobility effect is about twice as large for households in the bottom two income quintiles at baseline as for better-off households, mirroring the finding that less wealthy participants gain proportionally

more and supporting H3 [5]. Effects are larger for households whose head has at least nine years of schooling and for heads younger than 45, highlighting digital literacy as a binding complementary condition. Finally, the effect is somewhat larger in central and western provinces than in the east, where market access was already better before the e-commerce expansion.

Table 5 Heterogeneity of the Mobility Effect

Dimension	Subsample	Coefficient (S.E.)	Contrast
Baseline income	Bottom 40%	0.104*** (0.021)	Top 60%: 0.051** (0.022)
Head schooling	>= 9 years	0.096*** (0.020)	< 9 years: 0.062** (0.024)
Head age	< 45	0.113*** (0.024)	>= 45: 0.049* (0.026)
Region	Eastern provinces	0.071** (0.028)	Central & western: 0.095*** (0.019)

Note: Each cell reports the coefficient on e-commerce participation from a separate two-way fixed-effects regression for the indicated subsample. *** p<0.01, ** p<0.05, * p<0.1.

5 CONCLUSIONS AND POLICY IMPLICATIONS

This paper has examined whether e-commerce participation promotes the upward class mobility of rural households and whether the effect operates through factor allocation efficiency. Using nationally representative panel data from the CFPS (2010-2020), and addressing selection with fixed effects, instrumental variables, and matching, we find that participation significantly increases the probability of both upward income mobility and occupational class upgrading. About one-third of the effect is mediated by the reallocation of household labor toward nonfarm activities, the transfer of farmland to more efficient users, and improved access to formal credit. The gains are largest among households in the bottom of the income distribution, suggesting that e-commerce can function as an inclusive ladder of upward mobility rather than merely a windfall for the already advantaged.

These findings carry three policy implications. First, because the binding constraint on inclusion is entry rather than the distribution of gains among participants, policy should prioritize lowering entry barriers through logistics investment, broadband coverage, and business training targeted at poorer and older households [5]. Second, complementary factor-market reforms, including the deepening of farmland rental markets and the development of digital credit based on platform transaction records, can amplify the mobility effect of e-commerce by easing the reallocation that our mechanism analysis identifies. Third, the cautionary evidence on e-commerce-induced informality and rising factor costs implies that local governments should pair promotion with land-use planning and quality regulation so that mobility gains are not eroded by disorderly expansion [8].

The study has limitations that point to future research. Our participation measure captures the breadth rather than the intensity of online business, and mobility is observed over relatively short intervals between waves. Longer horizons, richer platform-linked administrative data, and explicit intergenerational designs would allow a more complete assessment of how digital market integration reshapes the class structure of rural China.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

DATA AVAILABILITY

The data used in this study are from the China Family Panel Studies (CFPS), publicly available upon application from the Institute of Social Science Survey, Peking University (https://www.isss.pku.edu.cn/cfps/).

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