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The effect of internet usage on perceptions of social fairness: Evidence from rural China

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ABSTRACT

Using Chinese Social Survey data for 6205 geographically distributed rural households, this paper assesses the impact of Internet usage on social fairness perceptions (SFPs) among Chinese farmers. To address the potential selection bias associated with voluntary Internet usage, the analysis employs an endogenous ordered probit model whose results suggest that, in general, Internet usage has a statistically significant and negative impact on farmer SFPs. Nonetheless, an additional disaggregated analysis reveals that this impact is heterogeneous among different age groups and geographic regions, as well as between male and female household heads.

1. Introduction

Because perceived social fairness matters for individual thinking, feeling, decision-making, and behavior, positive social fairness perceptions (SFPs) serve as a foundation for social stability (Fehr, 2001; Konow, 2003; Tao, 2015). These perceptions, however, may be negatively influenced by social problems such as income inequality, political corruption, and unemployment, thereby challenging the balance between social development and social stability. Creating a harmonious society and promoting sustainable economic development thus requires a solid understanding of the incentives and constraints that affect individual SFPs. Among the several studies on the factors that influence these perceptions (Carman, 2010; Harrison & Sayogo, 2013; Sun & Xiao, 2012; Tao, 2015), one Scottish survey identifies democratic participation and institutional trust as primary contributors (Carman, 2010), while a study for China pinpoints social security and income distribution policies (Sun & Xiao, 2012). Governmental budget transparency is also positively associated with SFPs (Harrison & Sayogo, 2013), as are earnings comparison, degree of corruption, unemployment, and upward comparison being the primary generators of perceived unfairness (Tao, 2015).

In this study, we contribute to the literature by investigating how Internet usage impacts people' perceptions of social fairness. As a further contribution, we perform a disaggregation analysis to assess the heterogeneity of the Internet usage effects on SFPs. This issue has been overlooked in the literature, despite empirical evidence that age (Tirado-Morueta, Aguaded-Gómez, & Hernando-

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Gómez, 2018), gender (Penard, Poussing, Mukoko, & Tamokwe Piaptie, 2015), and geographic location (Alderete, 2019; Martínez-Domínguez & Mora-Rivera, 2020) determine individual Internet behaviors. We focus on farmers' SFPs and utilize open-access data from the Chinese Academy of Social Sciences' Chinese Social Survey. Compared with urban residents, farmers are a subpopulation that tends to be more socially and financially vulnerable than its urban counterpart. In particular, these farmers are less likely to be exposed to information because whereas Internet penetration increased dramatically in urban China from 10.5% in 2006 to 59.6% in 2018, in rural areas, it rose from a low 3.1% to only 38.4% (see Fig. A1 in Appendix) (CNNIC, 2018).

Because farmers' Internet usage decisions tend to be influenced by both observable demographics (e.g., age, gender, education, and political identity) and unobservable factors like innate ability and motivation, our primary analytic tool is an ordered probit model with an endogenous regressor (i.e. endogenous ordered probit (EOP) model). The EOP model can address the selection bias inherent in these choices. Previous studies have applied nonparametric methods such as propensity score matching (PSM) model (Yao, Liu, & Cui, 2020; Zhang, Sun, Ma, & Valentinov, 2019) and inverse probability-weighted with a regression adjustment (IPWRA) estimator (Danso-Abbeam & Baiyegunhi, 2018; Liu, Ma, Renwick, & Fu, 2019). However, neither of them can address the selection bias from unobservables.

The general effects of Internet usage on users' daily lives are well documented, including positive benefits like the provision of online entertainment (e.g., music, video, and games) (Chen, 2012), online communication (e.g., email, Wechat, and Facebook) (Martínez-Domínguez & Mora-Rivera, 2020; Sum, Mathews, Hughes, & Campbell, 2008), and easy access to diverse information and online shopping (Ford, 2014; Pénard, Poussing, & Suire, 2013), which may help to reduce depression, maintain social relations, and save time and money, respectively. For example, while one Australian study finds Internet usage to be helpful in relieving social loneliness (Sum et al., 2008), research for the US shows it to increase subjective mental well-being and reduce depression in older adults (Ford, 2014). Similarly, an analysis of household data from Luxembourg demonstrates its significant positive relation with life satisfaction (Pénard et al., 2013).

On the other hand, some authors stress Internet usage's negative effects, such as reducing the time available for face-to-face interaction (Lee, Leung, Lo, Xiong, & Wu, 2011) and creating addictive behaviors (e.g., gambling, online gaming, and pornography), which are not only detrimental to mental health but strengthen social isolation (Dutta & Chye, 2017; Longstreet, Brooks, & Gonzalez, 2019; Mesch, 2001). For instance, not only are frequent Internet users in Israel more socially isolated than infrequent users (Mesch, 2001), but problematic (e.g., addictive) Internet usage may increase depression (Dutta & Chye, 2017) and other negative emotional states (Longstreet et al., 2019).

Nonetheless, although the extant research separately identifies the socioeconomic and demographic characteristics that affect SFPs and the impact of Internet usage on everyday life, no previous studies combine the two elements by examining how Internet usage specifically affects individual perceptions of social fairness. Yet in the digital era, rapid information diffusion via the Internet frequently motivates individuals to compare themselves with peers − both in their immediate environment and online – giving the Internet a significant role in perceptions of fairness. In fact, research in behavioral economics documents not only that personal behavior is often closely related to fairness preferences but that individuals would rather sacrifice their interests to punish those who violate fairness norms (Gintis, Boyd, & Fehr, 2007). As a result, perceptions of social unfairness may frustrate individuals' work efficiency, weaken their confidence in the system, and even reduce their sense of national identity (Stiglitz, 2012). Given the importance of Internet usage in peoples' lives and works, understanding the association between Internet usage and individual SFPs can provide invaluable guidance for policymakers in designing programs and policy instruments to improve subjective well-being and facilitate social development and stability through the use of modern technologies like the Internet.

The remainder of this paper is structured as follows: Section 2 outlines the conceptual framework, Section 3 introduces the econometric approach, and Section 4 describes the data set and reports the descriptive statistics. Section 5 then discusses the empirical results, and Section 6 concludes the paper.

2. Conceptual framework

Perceptions of social fairness are subjective emotional experiences based on comparison of one's social conditions with those of others (Fehr, 2001), a judgment affected not only by absolute but also relative remuneration (Festinger, 1954). The wide body of literature that supports SFPs' pivotal role in individual behavior and social stability generally agrees that perceptions of social unfairness can generate indignation, which may negatively affect not only individual health (physical and mental) but also work efficiency, thereby hindering the effectiveness of economic growth.

Against this backdrop, we argue that as rapidly growing information technologies broaden access to social information, increase social transparency, and feed the public tendency for comparison with others, Internet usage greatly influences individual perceptions of fairness (van Praag, 2011) − either positively or negatively − via a variety of pathways (see Fig. 1). In the first pathway, access to myriad innovative goods and the diverse lives of strangers may raise Internet users' material aspirations and widen the scope of their social comparisons, possibly generating a sense of relative deprivation and frustration that negatively affects their SFPs (Schussler & Axhausen, 2009). This dynamic is explained by social comparison theory, which posits that individuals compare themselves with others to correctly evaluate their own living conditions and social status (Festinger, 1954). For example, Internet communication platforms allow users to display positive images of themselves, which can reduce the SFPs of others by generating envy and bitterness (Cohen-Charash & Mueller, 2007; van Praag, 2011). The Internet also facilitates the dissemination of negative news and information − including the unequal distribution of educational resources, excessive income, large urban-rural gaps, and political corruption − which may change citizen perceptions of the society in which they live, including its level of social fairness.

The second pathway is an assumed positive association between Internet usage and SFPs that stems not only from extensive

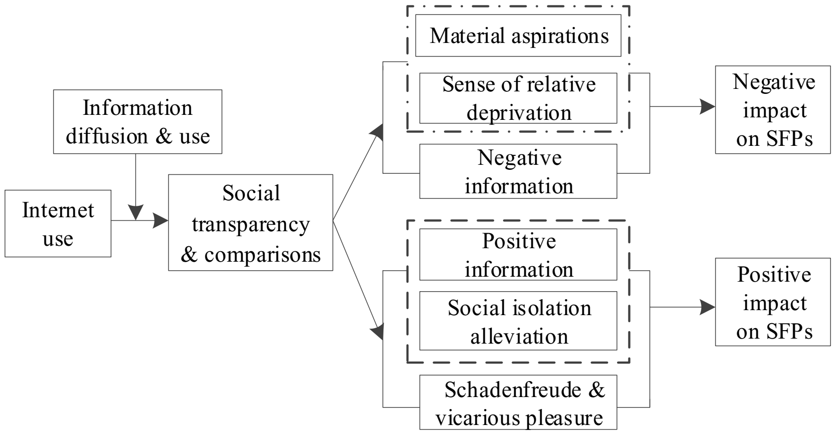

Fig. 1. Relation between Internet usage and SFPs.

information access but also from broad social networking. For our population of farmers, for example, the Internet provides abundant information on such relevant topics as agricultural production, marketing, and finances while also increasing their social interactions with friends and relatives. This latter tends not only to raise the farmers' sense of social identity and sense of belonging but also to relieve their social isolation. Internet usage can thus improve SFPs by satisfying the higher demands in Maslow's hierarchy of needs; namely, belongingness, self-esteem, and self-actualization (Stoyanov, 2017). The information exposure it provides may also strengthen feelings of *schadenfreude* at others' misfortunes or elicit vicarious pleasure at surpassing their achievements. Yet, even though these pathways are well recognized, the research to date fails to explain exactly how and to what extent Internet usage affects farmer SFPs, whether positively or negatively. This current study addresses this shortcoming by using a rigorous econometric model to measure this effect.

3. Empirical strategy

3.1. Modelling the Internet usage effect on farmers' social fairness perceptions

Because Internet usage may have either a positive or negative impact on farmer SFPs, we assume these latter to be a function of an Internet usage dummy (N_i) and a vector of explanatory variables (S_i):

$$F_i^* = \varphi N_i + \delta S_i + \mu_i \text{ with } F_i = \begin{cases} 1 \text{ } if \text{ } F_i^* \le C_1 \\ 2 \text{ } if \text{ } C_1 < F_i^* \le C_2 \\ \cdots \\ K \text{ } if \text{ } C_{K-1} \le F_i^* \end{cases} \tag{1}$$

where F_i^* is an unobserved latent variable representing farmer *i*'s social fairness perceptions, represented by an observed categorical variable F_i. This latter is determined by the unknown cutoffs C_1, C_2, …, C_{K-1}, which satisfy the condition that $C_1 < C_2 < \cdots < C_{K-1}$. In addition to the Internet usage dummy N_i, S_i is a vector of explanatory variables, φ and δ are the parameters to be estimated, φ captures the effect of Internet usage on SFPs, and μ_i is a random error term.

If N_i were exogenous, Eq. (1) could be estimated using an ordered probit model. However, in this study, such is not the case. First, farmers select themselves into Internet users or nonusers, depending on inherent traits, meaning that the two groups may differ systematically in observed characteristics. Second, unobserved factors such as innate ability may simultaneously affect both the farmers' Internet decisions and their SFPs. Therefore, failure to address the potential endogeneity of N_i implied by this duality would lead to a biased estimate of the Internet usage effect on farmer SFPs.

3.2. Model selection

The different approaches used in the literature to correct for selection bias associated with a binary treatment variable include propensity score matching (PSM) model and inverse probability-weighted with a regression adjustment (IPWRA) estimator (Baiyegunhi, Majokweni, & Ferrer, 2019; Danso-Abbeam & Baiyegunhi, 2018; Liu et al., 2019; Yao et al., 2020; Zhang et al., 2019). However, despite the use of IPWRA (PSM) to measure the impact of pesticide management practices (an outsourced agricultural extension program) on the welfare (net farm income) of smallholders in Ghana (Danso-Abbeam & Baiyegunhi, 2018) and South Africa (Baiyegunhi et al., 2019), these methods can account only for selection bias from observable factors, never from unobservables. An endogenous ordered probit (EOP) model, in contrast, can sufficiently address selection bias by taking into account both the observed and unobserved heterogeneities and then estimating the direct impact of Internet usage on SFPs. This study thus employs an EOP model for its primary analyses but adopts a conditional mixed process (CMP) approach for its robustness check. Like the EOP method, the CMP approach addresses the selection bias arising from both observed and unobserved heterogeneities, but they use different estimators in calculations (Kawakatsu & Largey, 2009; Roodman, 2011).

3.3. Endogenous ordered probit model

The EOP model jointly estimates two equations: Eq. (1), which models the farmers' Internet usage decisions and social fairness perceptions, and Eq. (2), a latent model whose observable components enable indirect expression of the utility difference. First, following the literature on Internet use and information access (Ma, Nie, Zhang, & Renwick, 2020; Ma, Zhou, & Liu, 2020; Nie, Sousa-Poza, & Nimrod, 2017), we model the Internet usage decision in a random utility maximization framework that assumes the farmers to be rational and risk neutral individuals who make this decision to achieve maximal utility. Hence, given utility difference N_i^* between using the Internet (N_{iU}) and not using the Internet (N_{iN}), individual i will choose to use the Internet if $N_i^* = N_{iU} - N_{iN} > 0$. Next, to observe N_i^* directly, we express it as a function of the observable components in the latent model:

$$N_i^* = \beta Z_i + \varepsilon_i \text{ with } N_i = \begin{cases} 1 \; if \; N_i^* > 0 \\ 0 \; otherwise \end{cases} \tag{2}$$

where the Internet usage dummy N_i is equal to 1 for users and 0 for nonusers; β is a vector of the parameters to be estimated; Z_i is a vector of explanatory variables (including age, gender, education, political identity, and marital status); and ε_i is a random error term, which is assumed to be normally distributed with zero mean.

The EOP model estimates Eqs. (1) and (2) simultaneously using a limited information maximum likelihood (LIML) estimator (Kawakatsu & Largey, 2009) and under the assumption that the random errors (μ_i, ε_i) in Eqs. (1) and (2) have a correlation, i.e. $\rho_{\mu\varepsilon} = \text{corr}(\mu_i, \varepsilon_i)$.

The significance of $\rho_{\mu\varepsilon}$ has an important econometric interpretation. That is, a statistically significant $\rho_{\mu\varepsilon}$ would suggest the presence of selection bias from unobserved factors, meaning that the use of either a PSM model or an IPWRA estimator is producing biased estimates of the Internet usage effect on farmer SFPs.

As in Kawakatsu and Largey (2009), we obtain the consistent EOP estimators by implementing the following log-likelihood for the entire sample:

$$lnL = \sum_{i=1}^{n} \log\Pr\left(C_{F_i-1} \le F_i^* < C_{F_i}, \underset{-}{b}_i \le N_i^* < \bar{b}_i\right) \tag{3}$$

where $\left(\underset{-}{b}_i, \bar{b}_i\right)$ are $r * 1$ vectors with j-th element. In particular, $\left(\underset{-}{b}_{ij}, \bar{b}_{ij}\right) = (-\infty, 0)$ if $N_{ij} = 0$, and $\left(\underset{-}{b}_{ij}, \bar{b}_{ij}\right) = (0, +\infty)$ if $N_{ij} = 1$, with $j = 1, \ldots, r$. To test whether Internet usage and farmer SFPs are independent, we conduct a test under the null hypothesis that $\rho_{\mu\varepsilon}$ is equal to zero.

Although the EOP model can be identified on the non-linearity of the system, for a better identification, the Internet usage equation should include at least one variable that is absent from the social fairness perceptions equation. In this study, we follow Oskorouchi & Sousa-Poza (2020) and construct two county-level instrumental variables (IVs) that are correlated with Internet usage but are not directly correlated with farmer SFPs. The first variable (IV1) represents the share of total internet users in the total samples in a county, while the second variable (IV2) represents the share of rural Internet users in the total rural samples in a county. These IVs can safely be considered exogenous because our dependent variables are not clustered within counties. The validity of the employed IVs are tested based on the Sargan test and Basmann test of overidentifying restrictions (Wooldridge, 2010). The results (lower part of Table 3) show that Sargan test and Basmann test can be rejected (P-values are not statistically significant), indicating that the two IVs are valid as they satisfy the exogeneity requirement.

4. Data and descriptive statistics

4.1. Data

To collect the open-access data for its nationally representative Chinese Social Survey (CSS), in 2013 the Chinese Academy of Social Sciences used a multistage, stratified, probability-to-size proportional cluster sampling method to select and interview households from both urban and rural areas. Data collection employed a structured questionnaire administered in face-to-face interviews by highly experienced enumerators specifically trained for the CSS project. The wide range of topics covered included socio-demographics (e.g., age, gender, education, political identity, marital status, endowment insurance, and social status), Internet usage and life satisfaction, and most relevant for this study, social fairness. The resulting data set, which covers 31 provinces distributed among China's Eastern, Central, and Western regions, comprises 2908 urban and 7298 rural observations ($n = 10{,}206$), the former of which we exclude because the study focuses on rural households. After data cleaning by dropping observations with missing information, this rural sample consists of 6205 rural households, containing 1310 Internet users and 4895 nonusers. In each household, one person was selected and interviewed.

The main treatment variable, Internet usage, takes the value of one if a farmer uses the Internet through telephone lines, local area networks, or wireless networks, and zero otherwise.

Table 1
Variable definitions and descriptive statistics.

Variables	Definitions	Mean (SD)[a]
Internet usage	1 if respondent uses the Internet, 0 otherwise	0.21 (0.41)
Social fairness perceptions	Self-reported Social fairness perceptions by individual farmers (from 1 = strongly unfair to 4 = strongly fair)	2.68 (0.60)
Age_young	1 if respondent's age is less than 44 years, 0 otherwise	0.45 (0.50)
Age_middle	1 if respondent's age is between 45 and 59 years, 0 otherwise	0.35 (0.48)
Age_old	1 if respondent's age is higher than 60 years, 0 otherwise	0.20 (0.40)
Gender	1 if respondent is male, 0 otherwise	0.44 (0.50)
Illiterate	1 if respondent is illiterate, 0 otherwise	0.15 (0.36)
Primary school	1 if respondent attended/completed primary school, 0 otherwise	0.33 (0.47)
Middle school;	1 if respondent attended/completed middle school, 0 otherwise	0.36 (0.48)
High school	1 if respondent attended/completed high school, 0 otherwise	0.09 (0.29)
Technical school	1 if respondent attended/completed technical school, 0 otherwise	0.03 (0.18)
College	1 if respondent attended/completed college, 0 otherwise	0.03 (0.17)
Political identity	1 if respondent is a member of the CPC[b], 0 otherwise	0.09 (0.29)
Unmarried	1 if respondent is unmarried, 0 otherwise	0.09 (0.28)
Married or cohabiting	1 if respondent is married or cohabiting, 0 otherwise	0.86 (0.35)
Divorced or widowed	1 if respondent is divorced or widowed , 0 otherwise	0.07 (0.25)
Endowment insurance	1 if respondent has an endowment insurance, 0 otherwise	0.58 (0.49)
Social status	Self-reported social status by an individual farmer (from 1 = low to 5 = high)	2.31 (0.91)
Life satisfaction	Self-reported life satisfaction by an individual farmer (from 1 = strongly unsatisfied to 6 = strongly satisfied)	3.77 (1.16)
IV1	The share of total Internet users in the total samples in a county	0.28 (0.13)
IV2	The share of rural Internet users in the total rural samples in a county	0.22 (0.12)
Observations	6205	

[a] Standard deviation.
[b] Communist Party of China.

The dependent variable, farmer SFPs, is measured by a category variable. During the survey, the respondents were asked to answer the question "What is your overall perception of social fairness?". The answer is measured by survey respondent ratings of social fairness on one of four levels: 1 = strongly unfair, 2 = relatively unfair, 3 = relatively fair, and 4 = strongly fair. For our age and geographic location variables in the aggregate analyses, we adopt the National People's Congress of China's age categories of young (≤44 years), middle-aged (45–59), and old (≥60 years) and their regional breakdown of Eastern, Central, and Western regions.

4.2. Descriptive statistics

Our explanatory variables, drawn from the extant literature on Internet use and subjective well-being (e.g., Asadullah, Xiao, & Yeoh, 2018; Cai & Wang, 2018; Hacker & Steiner, 2002; Leng, Ma, Tang, & Zhu, 2020; Lohmann, 2015; Ma, Nie, et al., 2020; Mills & Whitacre, 2003; Rice & Katz, 2003; Tirado-Morueta et al., 2018), are listed in Table 1 with their descriptive statistics.

In our sample, approximately 21% of the respondents were Internet users. The mean score of the self-reported SFPs was 2.68 (out of 4). The samples of the respondents who were less than 44 years, between 45 and 59 years and higher than 60 years accounted for 45%, 35% and 20%, respectively. About 44% of respondents were male. Regarding education, our descriptive results showed that 15% of the respondents were illiterate, 33% of them attended/completed primary school, and 9% of them attended/completed high school. Only around 9% of respondents belonged to the Communist Party of China (the CPC). The majority (86%) were married or cohabiting with a partner, with only 9% unmarried and 9% divorced or widowed. Just over half (58%) carried endowment insurance. Whereas the mean score of self-reported social status was only 2.31 (out of 5), the average life satisfaction score was 3.77 (out of 6), suggesting that the majority enjoyed a relatively high level of life satisfaction.

As regards the systematic differences in demographic and socioeconomic characteristics between Internet users and nonusers (see Table 2), the former is generally younger, more highly educated, and more likely to be male, unmarried, and members of the CPC. They are, however, less likely to carry endowment insurance. Although Internet users also tend to have higher social status than nonusers, their ratings of life satisfaction are lower. Most important, they perceive social fairness to be lower, with a mean difference from nonusers that is significant at the 1% level (see the lower part of Table 2).

As Fig. 2 illustrates, the levels of social fairness perceived by Internet users are generally lower than the assessments of nonusers, although the results vary among different categories. For example, whereas 68.46% of nonusers rated social fairness at 3 (relatively fair), only 54.66% of Internet users did so, just as 3.84% of nonusers rated it at 4 (strongly fair) compared to a mere 1.30% of users. When we break out the SFP assessments by age, gender, and region (Fig. 3A, B, and C, respectively), we find that the SFP means also differ notably between Internet users and nonusers. For example, those for older farmers (≥60) are the highest among the three age groups, with Internet users generally reporting lower SFPs than their nonuser counterparts within the same group. The SFP means for both male and female Internet users are also lower than those for nonusers (Fig. 3B). Geographically, however, the lowest social fairness ratings appear among both Internet users and nonusers in China's Eastern region, albeit still lower for the former than the latter (Fig. 3C).

Table 2
Mean differences in characteristics between Internet users and nonusers.

Variables	Internet users (N = 1310)	Nonusers (N = 4895)	Differences in means	t-Value
Age_young	0.88 (0.01)	0.33 (0.01)	0.55***	44.84
Age_middle	0.10 (0.01)	0.41 (0.01)	−0.32***	−24.31
Age_old	0.02 (0.00)	0.26 (0.02)	−0.24***	−22.00
Gender	0.51 (0.01)	0.42 (0.01)	0.10***	6.57
Illiterate	0.01 (0.00)	0.20 (0.01)	−0.19***	−17.27
Primary school	0.08 (0.01)	0.40 (0.01)	−0.32***	−24.08
Middle school	0.47 (0.01)	0.32 (0.01)	0.15***	10.38
High school	0.21 (0.01)	0.06 (0.00)	0.14***	18.00
Technical school	0.11 (0.01)	0.01 (0.00)	0.09***	18.60
College	0.12 (0.01)	0.00 (0.00)	0.12***	23.00
Political identity	0.27 (0.01)	0.05 (0.00)	0.22***	25.72
Unmarried	0.29 (0.02)	0.02 (0.00)	0.26***	28.67
Married or cohabiting	0.68 (0.01)	0.90 (0.00)	−0.22***	−15.68
Divorced or widowed	0.03 (0.00)	0.08 (0.00)	−0.05***	−5.98
Endowment insurance	0.45 (0.01)	0.61 (0.01)	−0.16***	−11.38
Social status	2.47 (0.02)	2.24 (0.01)	0.23***	8.28
Life satisfaction	3.66 (0.03)	3.78 (0.02)	−0.12***	−3.86
IV1	0.35 (0.00)	0.26 (0.00)	0.09***	25.91
IV2	0.29 (0.00)	0.20 (0.00)	0.09***	26.09
Social fairness perceptions	2.51 (0.02)	2.72 (0.01)	−0.21***	−12.12

Notes: Standard errors are in parentheses.
*** $p < .01$.

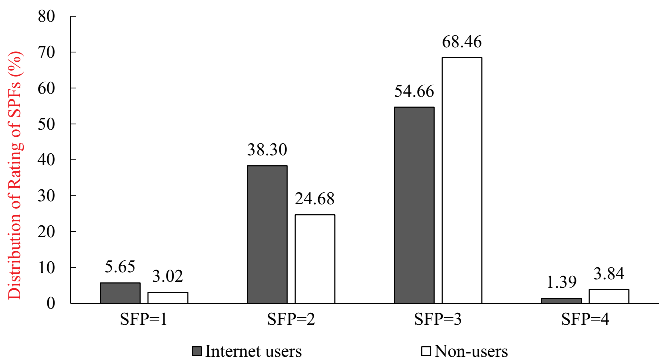

Fig. 2. Internet usage/SFPs relation for Internet users versus nonusers.

In general, the results outlined in Table 2 and Figs. 2 and 3 indicate that Internet usage does indeed reduce farmer perceptions of social fairness, with the Fig. 3 results additionally suggesting the existence of heterogeneity in this effect. Hence, because a simple mean difference comparison cannot control for confounding factors that may jointly affect the farmers' Internet usage decision and their SFPs, our main analysis employs a rigorous EOP econometric method capable of estimating an unbiased and consistent effect of the former on the latter.

5. Empirical results and discussion

As previously indicated, to measure the Internet usage effect on farmer SFPs, we use a LIML estimator to estimate Eqs. (1) and (2) jointly. As Table 3 shows, the correlation coefficient of $\rho_{\mu\varepsilon}$ is statistically significant, suggesting the presence of a selection bias originating from unobserved factors (Kawakatsu & Largey, 2009). The finding justifies the validity of using the EOP model as an estimation strategy.

5.1. Determinants of Internet usage

As regards the determinants of Internet usage, the statistically significant and negative coefficients of age_middle and age_old variables suggest that relative to younger farmers, middle-aged and old farmers are less likely to use the Internet. Compared with younger farmers, the older ones are less skilled in Internet usage, and they are less aware of the benefits associated with Internet usage. This finding of a negative relationship between age and Internet usage mirrors the negative correlation observed for Spain, where individuals over 64 years are also the least likely to use the Internet (Lera-López, Billon, & Gil, 2011). The coefficient of gender,

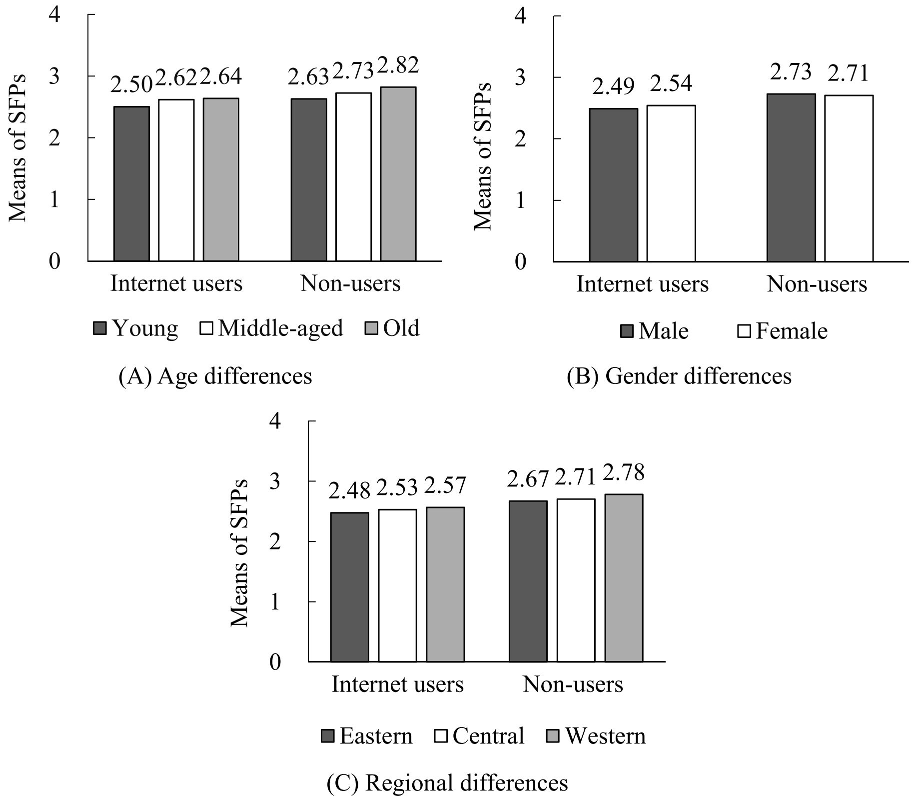

Fig. 3. Internet usage/SFPs relation by age, gender, and region.

in contrast, is significantly positive, suggesting that male farmers are more likely than female farmers to use the Internet. Given that, in rural areas, men are more likely than women to migrate to urban regions for better work opportunities, the Internet becomes a vital tool for communicating with family members at home. This finding echoes that for the US, where the probability of Internet usage is lower for females than for males (Bimber & Barbara, 2003).

The coefficients of the education-related variables are all positive and statistically significant. The findings suggest that relative to those who are illiterate, better-educated farmers are more likely to use the Internet, which is in line with evidence that individuals with more years of schooling are more inclined to adopt such technological innovations (Ma, Zhou, & Liu, 2020; Martínez-Domínguez & Mora-Rivera, 2020). Better education not only raises farmer awareness of the Internet's positive benefits but improves their skill in its use. Internet usage is also significantly positively affected by political identity, with farmers who are CPC members having a higher probability of Internet use, which mirrors the converse that those with no political identity tend to lack Internet skills and opportunities for use (Hacker & Steiner, 2002). Another important influence on the farmers' Internet usage decisions is marital status, with those who are married or cohabiting being less likely than their unmarried counterparts to be Internet users (see Table 3). One possible explanation is that married or cohabiting farmers have more household affairs to deal with and thus spend less time on the Internet.

Social status also appears to exert a statistically significant and positive effect, with those self-reporting a higher social status more likely to use the Internet, confirming the already identified positive association between economic status and Internet use (Mills & Whitacre, 2003). It may be that higher status individuals are more aware of the benefits associated with modern technologies because they must use them to interact with others when expanding their social networks and accumulating wealth. Lastly, although the significant and positive coefficients of the IV1 and IV1 suggest that county-level Internet use rates matter with individual farmers' Internet use status, while these variables do not appear to affect their SFPs.

5.2. Determinants of social fairness perceptions

5.2.1. Results from Internet usage variable

According to our estimates of SFP determinants (see Table 3), Internet usage can exert a statistically significant and negative impact on farmer SFPs by creating new virtual reference groups for self-comparison. If these reference groups are performing better physically, financially, and psychologically, it may elicit feelings of frustration or a sense of relative deprivation (Gintis et al., 2007;

Table 3
Internet usage effect on farmer SFPs: EOP vs. OP estimates.

Variables	EOP		OP
	Internet usage (coefficients)	SFPs (coefficients)	SFPs (coefficients)
Internet usage		−0.840 (0.111)***	−0.182 (0.046)***
Age_middle	−1.059 (0.056)***	0.007 (0.045)	0.168 (0.038)***
Age_old	−1.514 (0.108)***	0.122 (0.054)**	0.311 (0.049)***
Gender	0.133 (0.047)***	0.031 (0.031)	0.020 (0.032)
Primary school	0.206 (0.119)*	−0.132 (0.047)***	−0.083 (0.049)*
Middle school;	0.863 (0.113)***	−0.057 (0.032)*	−0.064 (0.052)
High school	1.319 (0.125)***	−0.138 (0.074)*	−0.249 (0.070)***
Technical school	1.649 (0.148)***	0.002 (0.105)	−0.210 (0.098)**
College	2.153 (0.173)***	0.075 (0.119)	−0.189 (0.107)*
Political identity	0.240 (0.078)***	0.091 (0.058)	0.045 (0.058)
Married or cohabiting	−0.768 (0.085)***	−0.284 (0.070)***	−0.133 (0.065)**
Divorced or widowed	−0.734 (0.141)***	−0.300 (0.090)***	−0.169 (0.088)*
Endowment insurance	−0.075 (0.047)	0.107 (0.031)***	0.095 (0.033)***
Social status	0.129 (0.027)***	0.121 (0.017)***	0.100 (0.018)***
Life satisfaction	0.003 (0.021)	0.198 (0.014)***	0.202 (0.014)***
Province dummies	Yes	Yes	Yes
IV1	1.259 (0.348) ***		
IV2	1.258 (0.320)***		
Constant	−1.393 (0.169)***		
Cut points			
Cut1		−1.199 (0.105)***	−0.820 (0.194)***
Cut2		0.180 (0.108)*	0.610 (0.194)***
Cut3		2.621 (0.123)***	3.153 (0.198)***
$\rho_{\mu\varepsilon}$	0.387 (0.063)***		
Log-pseudo likelihood	−7166.232		−5151.052
Wald χ^2	698.01		703.15
Prob > χ^2	0.000		0.000
Tests of overidentifying restrictions			
Sagan test	Chi2(1) = 1.271, Prob. = 0.259		
Basmann test	Chi2(1) = 1.262, Prob. = 0.261		
Observations	6205		6205

Notes: Robust standard errors are in parentheses.
The reference age category is "age_young"; The reference education category is "illiterate"; The reference for marital status is "unmarried".
*** $p < .01$.
** $p < .05$.
* $p < .1$.

Tao, 2015), thereby lowering SFPs. Such reduction may also result from Internet dissemination of socially negative information – for example, political corruption, violence, and immorality. Even the Internet's ability to raise individuals' material aspirations may decrease subjective well-being when these aspirations are not satisfied (Lohmann, 2015). This risk of SFP reduction is particularly high in farming villages or small rural communities, whose traditionally narrow scope of comparison increases exponentially with Internet exposure to broad online reference groups.

To test our finding using an alternative specification, we re-estimate the Internet usage effect on SFPs using an ordered probit (OP) model, which yields a coefficient of Internet usage that is mathematically larger than the EOP coefficient: −0.840 versus −0.182 (see Table 3). This outcome is possible because a simple OP model treats all explanatory variables as exogenous, and thus, fails to control for any endogeneity in the Internet usage variable (thereby introducing a risk of biased estimates (Kawakatsu & Largey, 2009). It should be noted, however, that this finding of an overestimated Internet usage effect on SFP is consistent with the previously estimated positive correlation coefficient of $\rho_{\mu\varepsilon} = 0.387$.

To provide a deeper understanding, we empirically examine how different online activities, including browsing news, trading emails, searching for materials, chatting, using Weibo/Blog, playing online games, shopping online and conducting online investment and finance, affect farmer SFPs. The descriptive results (Table A1 in the Appendix) show that browsing news, chatting and searching for materials are the top three online activities, while conducting online investment and finance is the least common activity among them. The empirical results (Table A2 in the Appendix) reveal that farmer SFPs are mainly negatively affected by news browsing and online shopping. The findings are in line with the first pathway analysis in Fig. 1 and they indicate that a negative impact of Internet usage on farmer SFPs exists. News browsing may increase farmers' social comparison and facilitate their access to negative information such as political corruption and violence, while online shopping can raise farmers' material aspiration and widen the scope of their social comparison such as earning and purchasing power comparison (Cohen-Charash & Mueller, 2007; Lohmann, 2015; Schussler & Axhausen, 2009). Both generate a sense of relative deprivation and frustration, which consequently lower farmer SFPs.

5.2.2. Results for control variables

As regards the other factors that affect farmer SFPs in the EOP model, the coefficient of age_old variable is significantly positive, suggesting that relative to their younger counterparts, older farmers perceive higher SFPs. The negative and statistically significant coefficients of education variables suggest that relative to illiterate farmers, farmers who attend/completed primary school, middle school and high school perceive social fairness to be lower. Relative to their illiterate counterparts, the educated farmers may have an idealistic view of the world and a high expectation towards social justice, and thus, they are more likely to have lower perceptions of social fairness when the expectations cannot be fulfilled. The coefficients of married or cohabiting and divorced or widowed are significantly negative, raising the possibility that a higher susceptibility to family conflicts and disputes may lead these groups to perceive lower levels of social fairness than their unmarried counterparts. The remaining coefficients, however, are all significantly positive. The positive and significant coefficient of endowment insurance suggests that insured farmers rating social fairness more highly, perhaps because the insurance proxies a public good and service availability that mitigates their income gap (Baird, 2004). The significantly positive social status coefficient likewise indicates that farmers with higher self-reported social status perceive social fairness to be higher. This is probably because those positioned more favorably in society are more likely to accept existing social inequality and perceive their milieu as impartial (Wilkinson, Pickett, & De Vogli, 2010). This pattern of significantly positive coefficients implying higher SFPs also hold for life satisfaction.

5.3. Robustness check

To check the robustness of our finding of a negative Internet usage effect on farmer SFPs, we also analyse the impact of Internet usage on farmer SFPs, using a conditional mixed process (CMP) model. It should be noted that both the EOP model and CMP model can account for both observed and unobserved selection biases. The EOP estimation relies on a LIML estimator while the CMP model depends on a maximum likelihood estimator (namely, the Geweke-Hajivassiliou-Keane multivariate normal simulator) (Gates, 2006; Kawakatsu & Largey, 2009; Roodman, 2011). The CMP results (Table A3 in the Appendix) show that Internet usage is significantly negatively associated with farmer SFPs, which confirms the earlier EOP results.

5.4. Heterogeneous effects of Internet usage on social fairness perceptions

Because the results in Table 3 reveal only a homogenous effect of Internet usage on farmer SFPs, we test for the presence of heterogeneity by estimating the effect by age, gender, and survey region (with estimations for the other control variables available upon request). As Table 4 shows, even though both coefficients are statistically significant at the 1% level, the negative effect of Internet usage on SFPs is larger for middle-aged (45–59 years) than for younger farmers (≤ 44 years), presumably because the former are more critical about social issues and perceive social fairness as lower. We find no significant Internet usage effect, however, on the SFPs of older farmers (≥ 60 years).

The disaggregated analysis by gender then suggests that the negative effect of Internet usage on SFPs is larger for male than for female farmers, as reflected by the respective Internet usage coefficients of -0.976 and -0.729. This finding indicates the presence of a digital gender divide that not only matters for farmer SFPs but indicates different uses of the Internet during leisure time. For example, whereas female farmers tend to use the Internet for entertainment, online shopping, and social chatting, male farmers are more inclined to use it to search for political and economic information, making them more likely to be affected by evidence of inequality that reduces their SFPs (Moghaddam, 2010).

Because of prior documentation of significant regional differences in Internet usage stemming from differences in institutional arrangements, information and communication technology (ICT) infrastructure construction, and demographic and regional characteristics (Leng et al., 2020; Ma, Nie, et al., 2020; Martínez-Domínguez & Mora-Rivera, 2020; Tirado-Morueta et al., 2018), we also investigate the disaggregated effects of Internet usage on SFPs by region. As shown in the lower part of Table 4, Internet usage has the larger negative impact on SFPs of farmers in the Central and Eastern regions, with coefficients of -0.945 and -0.938, respectively. The impact of Internet usage on SFPs of farmers in China's Western region is the lowest, with a coefficient of -0.872. In China, the Western region is less economically developed, relative to the Central and Eastern regions. For example, in 2018, the disposable incomes were 18,286 yuan/capita for Eastern region, 13,954 yuan/capita for Central region and 11,831 yuan/capita, respectively (National Data, 2020).[1] Thus, the heterogenous Internet usage effects on farmer SFPs among different regions can be attributed to the regional gaps in income and living standards and the differences of people's spiritual and material pursuits.

5.5. Additional analysis

To derive a deeper understanding of the impact of Internet usage on SFPs, we also estimate this effect using the sample of households from urban areas, where the Internet penetration rate in 2018 was 74.6% compared to 38.4% in rural areas (see Fig. A1 in the Appendix). This rural-urban divide is also marked by significant inequalities in broadband services, awareness of the Internet's benefits, and information availability. According to the analytic results (see Table A4), Internet usage also has a statistically significant effect on urban individuals' SFPs.

[1] Yuan is the Chinese currency, with I USD = 7.07 yuan in April 2020.

Table 4
Disaggregated effects of Internet usage on farmer SFPs: EOP estimates.

	Sample size	Coefficients
Disaggregated analysis by age		
Age_young (≤44 years)	2797	−1.027 (0.124)***
Age_middle (45–59 years)	2152	−1.171 (0.270)***
Age_old (≥60 years)	1256	−0.783 (0.652)
Disaggregated analysis by gender		
Male	2749	−0.976 (0.070)***
Female	3456	−0.729 (0.192)***
Disaggregated analysis by region		
Eastern	2307	−0.938 (0.138)***
Central	1859	−0.945 (0.203)***
Western	2039	−0.872 (0.191)***

Notes: Robust standard errors are in parentheses.
*** $p < .01$.

6. Conclusions and policy implications

The most important finding of this EOP-based analysis is that Internet usage has a statistically significant and negative effect on the social fairness perceptions of the 6205 Chinese farmers in our CSS sample. Unlike the nonparametric approaches such as PSM model and IPWRA estimator, which address only observed selection bias, the EOP approach can sufficiently account for both observed and unobserved selection biases. Additional disaggregated CMP estimations not only confirm the presence of this negative relationship between Internet usage and farmer SFPs once the selection bias is controlled for but also show farmer SFPs to be affected by education, marital status, (non) enrolment in endowment insurance, social status and life satisfaction. As regards the farmers' decisions to actually use the Internet, the primary determinants are age, gender, education, political identify, marital status and social status.

The disaggregated analyses further reveal that the effects of Internet usage on the farmers' SFPs are heterogeneous among different age groups and different survey regions, as well as between male and female household heads. More specifically, Internet usage has the largest and most negative effect on the SFPs of middle-aged farmers (relative to younger and older farmers), male farmers (relative to female farmers), and those living in China's Central region (relative to those living in the Eastern and Western zones). This statistically significant and negative impact of Internet usage on SFPs also holds for urban households.

Our finding that Internet usage negatively affects farmer SFPs underscores the importance of the government's role in cultivating a positive network environment. Farmer SFPs are mainly negatively affected by their online activities such as news browsing and online shopping. Positive farmer SFPs are an important objective criterion for measuring the good governance of society, and thus, the government should guide the social media to report news in a fair, objective and authentic way. Also, the government needs to cultivate people's rational consumption concept and keep their expenditures within the limits of their income through Internet media. Because the effect of Internet usage is heterogeneous among farmers of different ages and geographic locations, as well as between male and female household heads, government efforts to improve farmer SFPs should not only target different age groups but also take into account gender and regional differences. At the same time, given the important link between endowment insurance and higher ratings of perceived social fairness, government policies aimed at facilitating access to such coverage could be useful in improving farmer assessments of societal fairness.

As regards additional scholarly input, even though this analysis of cross-sectional data for 6205 Chinese rural households has produced valuable insights, future studies could usefully expand understanding of the dynamic effects of Internet usage on SFPs by making use of panel and time-series data sets as they become available. Likewise, because farmer SFPs appear to be affected primarily by online activities (e.g., browsing for information, entertainment, expanding social networks, electronic commerce, and online purchasing), future research might focus on identifying the exact effects of different online activities and which incentives and mechanisms could improve SPFs in the interests of a harmonious and stable society.

This paper is subject to a limitation. Correctly recording farmers' perceptions of social fairness with face-to-face interviews is a big challenge. Farmers may be sensitive to express their true perceptions about social fairness. Some people tend to under-report their perceptions, especially their negative perceptions about society, for social desirability reasons. Thus, the dependent variable is subject to potential measurement error. If the measure error is correlated with internet usage, which is highly possible in this case, it will introduce a new source of bias. For example, older people are less likely to use the internet and they are also less likely to report their true negative perceptions of social fairness.

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Appendix A. Appendix

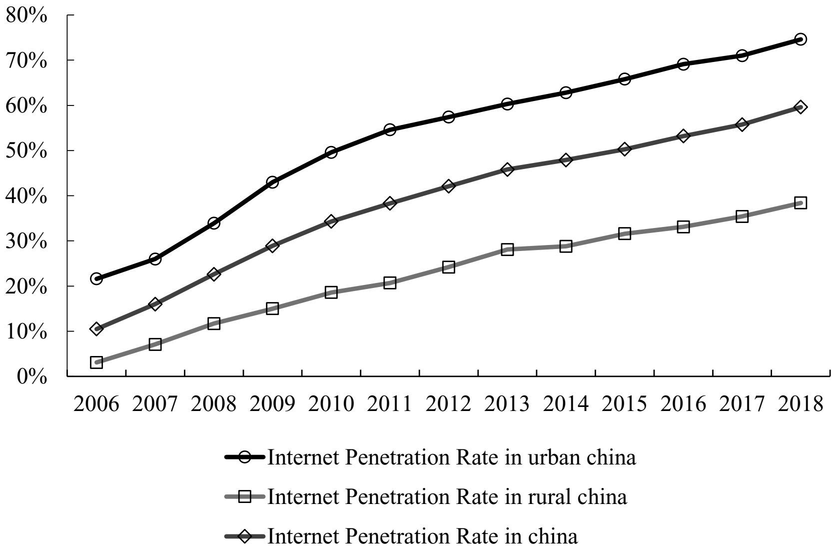

Fig. A1. Internet penetration rate in China (2006–2018).

Table A1
Descriptive statistics of the variables reflecting Internet users' online activities.

Variables[a]	Mean (S.D.)
Browsing news	3.61 (1.69)
Trading emails	1.09 (1.64)
Searching for materials	2.55 (1.80)
Chatting	3.12 (1.91)
Using Weibo/Blog	1.35 (1.88)
Playing online games	1.59 (1.89)
Shopping online	0.95 (1.24)
Conducting online investment and finance	0.16 (0.70)

[a] These variables show the frequencies of these online activities, with 0 = Never; 1 = a few times per year; 2 = at least one time per month; 3 = at least one time per week; 4 = several times per week; and 5 = almost every day.

Table A2
Impact of online activities on farmer SFPs: OP estimates.

Variables	SFPs (coefficients)
Online activities	
Browsing news	−0.059 (0.024)***
Trading emails	0.027 (0.024)
Searching for materials	0.001 (0.024)
Chatting	0.001 (0.022)
Using Weibo/Blog	0.027 (0.021)
Playing online games	−0.015 (0.018)
Shopping online	−0.090 (0.030)***
Conducting online investment and finance	−0.004 (0.055)
Control variables	
Age_middle	−0.004 (0.117)
Age_old	0.243 (0.254)
Gender	−0.060 (0.069)
Primary school	−0.746 (0.308)**
Middle school;	−0.735 (0.286)**
High school	−0.900 (0.294)***

(continued on next page)

Table A2 (*continued*)

Variables	SFPs (coefficients)
Technical school	−0.884 (0.302)***
College	−0.889 (0.305)***
Political identity	0.110 (0.092)
Married or cohabiting	−0.138 (0.090)
Divorced or widowed	−0.117 (0.222)
Endowment insurance	0.153 (0.071)**
Social status	0.123 (0.042)***
Life satisfaction	0.271 (0.033)***
Province dummies	Yes
Cut points	
Cut1	−1.019 (0.392)***
Cut2	0.553 (0.395)
Cut3	3.135 (0.413)***
Log-pseudo likelihood	−5140.907
Wald χ^2	171.738
Prob > χ^2	0.000
Observations (Internet users)	1310

Notes: Robust standard errors are in parentheses.
The reference age category is "age_young"; The reference education category is "illiterate"; The reference for marital status is "unmarried".
*** $p < .01$.
** $p < .05$.
* $p < .1$.

Table A3
Internet usage effect on farmer SFPs: CMP estimates.

Variables	Internet usage (coefficients)	SFPs (coefficients)
Internet usage		−0.831 (0.113)***
Age_middle	−1.075 (0.056)***	0.008 (0.046)
Age_old	−1.521 (0.107)***	0.124 (0.055)**
Gender	0.143 (0.046)***	0.032 (0.031)
Primary school	0.215 (0.121)*	−0.132 (0.031)***
Middle school;	0.892 (0.115)***	−0.057 (0.033)*
High school	1.330 (0.126)***	−0.143 (0.074)*
Technical school	1.686 (0.148)***	0.002 (0.098)
College	2.202 (0.169)***	0.074 (0.110)
Political identity	0.246 (0.077)***	0.091 (0.055)*
Married or cohabiting	−0.741 (0.079)***	−0.278 (0.070)***
Divorced or widowed	−0.684 (0.131)***	−0.291 (0.094)***
Endowment insurance	−0.082 (0.045)*	0.107 (0.032)***
Social status	0.131 (0.026)***	0.121 (0.018)***
Life satisfaction	0.005 (0.020)	0.199 (0.015)***
Province dummies	Yes	Yes
IV1	1.248 (0.304)***	
IV2	1.223 (0.335)***	
Constant	−1.432 (0.174)***	
Cut points		
Cut11		−1.190 (0.106)***
Cut12		0.190 (0.111)*
Cut13		2.633 (0.129)***
$\rho_{\mu\varepsilon}'$	0.402 (0.075)***	
Log-pseudolikelihood	−7255.609	
Wald χ^2	2442.33	
Prob > χ^2	0.000	
Observations	6205	

Notes: Robust standard errors are in parentheses.
The reference age category is "age_young"; The reference education category is "illiterate"; The reference for marital status is "unmarried".
*** $p < .01$.
** $p < .05$.
* $p < .1$.

Table A4
Internet usage effect on the SFPs of urban residents: EOP estimates.

Variables	EOP	
	Internet usage (coefficients)	SFPs (coefficients)
Internet usage		−0.984 (0.179)***
Age_middle	−0.831 (0.072)***	−0.245 (0.078)***
Age_old	−1.692 (0.106)***	−0.347 (0.115)***
Gender	0.100 (0.064)	0.011 (0.051)
Primary school	0.554 (0.309)*	0.278 (0.154)*
Middle school;	0.937 (0.287)***	0.268 (0.139)*
High school	1.286 (0.289)***	0.227 (0.150)
Technical school	1.590 (0.294)***	0.316 (0.162)*
College	1.940 (0.293)***	0.236 (0.172)
Political identity	0.141 (0.084)*	0.242 (0.066)***
Married or cohabiting	−0.622 (0.143)***	0.068 (0.103)
Divorced or widowed	−0.445 (0.184)**	0.262 (0.136)*
Endowment insurance	0.248 (0.074)***	0.074 (0.059)
Social status	0.066 (0.038)*	0.097 (0.030)***
Life satisfaction	0.061 (0.029)**	0.268 (0.023)***
Province dummies	Yes	Yes
IV1	1.523 (0.207)***	
Constant	−1.452 (0.343)***	
Cut points		
Cut1		−0.523 (0.193)
Cut2		0.864 (0.207)***
Cut3		3.445 (0.258)***
$\rho_{\mu\varepsilon}$″	0.441 (0.106)***	
Log-likelihood	−3017.286	
Wald χ^2	325.99	
Prob > χ^2	0.000	
Observations (urban samples)	2158	

Notes: Robust standard errors are in parentheses.
The reference age category is “age_young”; The reference education category is “illiterate”; The reference for marital status is “unmarried”.
*** $p < .01$.
** $p < .05$.
* $p < .1$.

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