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Does Mobile Payment Adoption Really Increase Online Shopping Expenditure in China?[1]

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LINK TO ABSTRACT

Wei Yang, Puneet Vatsa, Wanglin Ma, and Hongyun Zheng (2023) examine whether Chinese consumers do more online shopping expenditure if they have adopted mobile payment instruments. Yang et al. do so with data from the 2017 Chinese General Social Survey (CGSS). They find that there is effectively a significant spending effect for women but not for men.

We show that Yang et al.'s research has multiple flaws. First, they make a number of econometric mistakes. Second, from a conceptual point of view, Yang et al.'s research has critical validity issues. If one wants to examine whether mobile payments lead consumers to spend more when shopping online, one should ideally consider only individuals who actually engage in e-commerce *and* have a mobile payment means in their portfolio. Respondents who do not fulfil both conditions cannot be tempted by the assumed higher convenience of mobile payments—or m-payments—to spend more freely (compared with other payment instruments). Unfortunately, Yang et al.'s sample includes a substantial share of respondents who do not even have access to the Internet and/or do not own a mobile phone.

Below, we replicate Yang et al.'s analysis, first, with the appropriate econometric approach and, subsequently, with a corrected sample; that is, a sample from which we removed respondents with an online expenditure of 0, as well as respondents who did not have a mobile phone for their own use. After these corrections, the gender difference seemingly goes in the opposite direction, and the

1. We initially submitted our note to *Economic Analysis and Policy*, but it was not sent out for review for the following reason: "In the past, we may have published comments under an old category 'Policy debates and controversies', however, this category is not being used currently" (email from the editor).

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spending coefficient is dramatically smaller.

After summarising Yang et al.'s method and results, we point out the econometric and conceptual flaws in Yang et al.'s approach, and then examine whether there is a spending effect if one uses the correct approach and sample.

Yang et al.'s research

Yang et al. exploit data for the year 2017 taken from the open-access, nationally representative CGSS database. For its 2017 edition, the CGSS used a multi-stage stratified sampling approach to select 12,582 respondents from 28 provinces of mainland China. However, whereas all survey participants completed the section of the questionnaire that dealt with mobile payments, only 4,132 were asked to also complete the special module on household shopping expenditure. Missing observations further reduced Yang et al.'s sample size to 3,644, with 1,681 male and 1,963 female respondents (Yang et al. 2023, 103).

With these data, Yang et al. estimate an instrumental-variable Tobit model. The justification for this choice lies in potential endogeneity combined with a censored dependent variable. The dependent variable is censored because there is a lower bound of zero on online expenditure. The endogeneity issue stems from the possibility that unobserved factors simultaneously affect individuals' decision to adopt mobile payments (MP_i) as well as their online shopping expenditure (OSE_i); think, for example, of individuals' openness to innovations.

Concretely, Yang et al. jointly estimate the below two equations (2023, 102). They do so separately for men and women, as they also want to investigate gender differences.

$$\boldsymbol{OSE}_i^{*J} = \boldsymbol{MP}_i a + X_i \beta + \varepsilon_i,\ \boldsymbol{SE}_i^J = \max(0,\ \boldsymbol{OSE}_i^{*J}) \tag{1}$$

$$\boldsymbol{MP}_i^{*J} = X_i \delta + IV_i \gamma + \eta_i \tag{2}$$

In equation (1), $\boldsymbol{OSE}_i^{*J}$ ($\boldsymbol{SE}_i^{*J}$ in Yang et al.'s notation) is a continuous latent variable representing the online shopping expenditure of individual i, with J = 1 for men and J = 2 for women. $\boldsymbol{OSE}_i^J$ is the observed expenditure obtained by censoring the latent expenditure at 0. MP_i is a dummy that denotes individual i's mobile payment adoption status, and X_i is a vector of control variables. In equation (2), $\boldsymbol{MP}_i^{*J}$ represents the probability that a man (J = 1) or a woman (J = 2) adopts mobile payments. X_i is again a vector of control variables and IV_i is the instrumental variable. Specifically, IV_i is the ratio of mobile payment adopters to the number of other respondents within the same province. The underlying assumption is that this ratio is positively correlated with m-payment adoption—because of a learning effect—but uncorrelated with online expenditure.

TABLE 1. Impacts of mobile payment adoption on online shopping expenditure: IV-Tobit estimation

	Men		Women	
	MP	OSE	MP	OSE
Variables	(1)	(2)	(3)	(4)
MP		13.149 (8.857)		21.716*** (7.329)
Age	−0.017*** (0.001)	0.058 (0.152)	−0.015*** (0.001)	0.182* (0.111)
Primary school	−0.068** (0.030)	1.051 (1.170)	−0.046** (0.018)	1.437* (0.822)
Middle school	0.011 (0.032)	1.465* (0.807)	0.061** (0.024)	−0.665 (0.850)
High school	0.075* (0.039)	2.016* (1.116)	0.238*** (0.032)	−2.748 (1.963)
Technical school	0.182*** (0.039)	1.952 (1.909)	0.301*** (0.033)	−3.676 (2.420)
College	0.192*** (0.040)	3.488* (2.023)	0.290*** (0.033)	−1.711 (2.359)
Marital status	−0.009 (0.019)	1.641*** (0.569)	−0.027* (0.015)	−0.602 (0.594)
Family size	0.003 (0.006)	−0.273* (0.165)	0.003 (0.005)	−0.095 (0.158)
Socioeconomic status	−0.013 (0.010)	−0.720** (0.309)	−0.013 (0.009)	−0.507* (0.293)
Life satisfaction	−0.004 (0.010)	−0.333 (0.235)	0.019** (0.009)	−0.126 (0.281)
Medical insurance	0.033 (0.028)	−1.633 (1.125)	0.048* (0.026)	0.146 (0.801)
Car ownership	0.092*** (0.021)	1.261 (0.969)	0.065*** (0.019)	1.107 (0.707)
Urban	0.098*** (0.021)	0.425 (1.066)	0.121*** (0.019)	−0.633 (1.061)
East	0.052** (0.023)	1.168 (0.791)	0.029 (0.022)	1.728** (0.683)
Central	0.024 (0.021)	−0.300 (0.512)	0.066*** (0.019)	−0.529 (0.694)
IV	0.162** (0.071)		0.235*** (0.064)	
Constant	1.076*** (0.084)	9.669 (10.305)	0.798*** (0.078)	−18.218*** (7.022)
Sample size	1,681	1,681	1,963	1,963

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. Online shopping expenditure is measured in 1,000 Yuan. For education, the reference group is Illiterate; for region, it is Western. Source: Yang et al. (2023, Table 3).

Table 1 reports Yang et al.'s key results (and is a reproduction of their Table 3). For our purposes, the most important observations are that mobile payment adoption positively affects women's online shopping expenditure—in regression (4)—and that there is no such effect for men—in regression (2). Yang et al. say that this gender difference "is somewhat surprising given that women express lower confidence than men in online payment methods and online shopping" (2023, 107).

In what follows, we show that the gender difference would seem to go in the other direction once the spending effect is examined with the correct econometric approach and for the appropriate samples.

Yang et al.'s econometrics

Unfortunately, in spite of the data availability statement in Yang et al.'s article, we were not provided with their dataset. We eventually managed to reassemble their sample on our own—but for three observations, the cause of which is unclear to us. In particular, we have two additional male respondents and one additional female respondent in our sample. However, all our descriptive statistics are identical, or close to identical, to those in Yang et al.'s Table 1 (2023, 104); see Section A.1 in our Appendix.

Yet, to our surprise, we were unable to replicate Yang et al.'s results in their Table 3, even though we mimicked the approach described in their paper. After much trial and error, we discovered that Yang et al. make two econometric mistakes. For one, they do not use sampling weights, whereas—as mentioned in Section 2—the CGSS relied on multi-stage stratified sampling. In such as setting, it is crucial to apply correct sample-to-population ratios; otherwise estimates will be biased. Second, unlike reported, the first stage of Yang et al.'s model is *not* estimated using probit. It was only when we used OLS in the first stage that we were able to replicate their results for the *MP* regressions (see Section A.2 in our Appendix).

In Table 2, we have therefore re-estimated Yang et al.'s regressions with the correct econometric approach. As can be seen, there are several differences compared to the results in Table 1. For our purposes, the most important are (1) the dramatic drop in the coefficients on *MP*, and (2) the fact that there would now appear to be a spending effect for men too.[4] Other, less important differences relate to the impact, in the second stage, of the variables *Car ownership* and *Urban*.

4. A Wald test indicates that the coefficients on *MP* are not significantly different between men and women (z = -0.742, p = 0.458).

TABLE 2. Impacts of mobile payment adoption on online shopping expenditure: IV-Tobit estimation, with sampling weights, same sample as in Yang et al. (2023)

	Men		Women	
	MP	OSE	MP	OSE
Variables	(1)	(2)	(3)	(4)
MP		4.918*** (0.816)		5.777*** (0.821)
Age	−0.087*** (0.006)	−0.032 (0.020)	−0.085*** (0.005)	0.008 (0.016)
Primary school	−0.391 (0.272)	−0.193 (0.927)	0.394 (0.275)	0.548 (0.653)
Middle school	0.194 (0.248)	0.843 (0.765)	0.851*** (0.270)	0.009 (0.656)
High school	0.307 (0.269)	1.606* (0.830)	1.497*** (0.290)	0.662 (0.718)
Technical school	0.857*** (0.264)	2.142*** (0.820)	1.878*** (0.299)	1.015 (0.765)
College	1.069*** (0.308)	3.603*** (0.916)	1.981*** (0.388)	2.544*** (0.847)
Marital status	0.205 (0.187)	1.297*** (0.480)	−0.154 (0.157)	−0.622 (0.443)
Family size	−0.019 (0.045)	−0.300** (0.127)	0.003 (0.035)	−0.267*** (0.100)
Socioeconomic status	−0.045 (0.067)	−0.694*** (0.246)	−0.102 (0.067)	−0.753*** (0.197)
Life satisfaction	−0.007 (0.067)	−0.189 (0.215)	0.082 (0.073)	0.179 (0.199)
Medical insurance	0.138 (0.186)	−1.003 (0.851)	0.296 (0.213)	0.859* (0.489)
Car ownership	0.320** (0.128)	1.436*** (0.380)	0.209* (0.114)	1.599*** (0.339)
Urban	0.535*** (0.132)	0.987*** (0.360)	0.707*** (0.128)	1.194*** (0.298)
East	0.167 (0.147)	1.521*** (0.369)	0.120 (0.153)	2.196*** (0.336)
Central	−0.065 (0.154)	0.196 (0.381)	0.427*** (0.150)	0.197 (0.318)
IV	1.628*** (0.435)		2.444*** (0.452)	
Constant	2.559*** (0.595)	−1.631 (1.835)	1.087 (0.667)	−5.195*** (1.972)
Sample size	1,683	1,683	1,964	1,964

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. Online shopping expenditure is measured in 1,000 Yuan. For education, the reference group is Illiterate; for region, it is Western. Source: Authors' estimates based on CGSS.

Validity issues

Next to the econometric mistakes, Yang et al.'s analysis also suffers from several other flaws. The most important concern the sample selection, but there are also problems that are intrinsic to the data. Below, we first discuss the problems of the latter type.

But a preliminary remark is that even though Yang et al. predominantly use the term "adoption" of mobile payments, this should, in fact, be read as use (rather than mere ownership). Indeed, questions A30g and A30h of the 2017 CGSS read, respectively, "In the past 12 months, have you ever used WeChat Pay?" and "In the past 12 months, have you ever used Alipay's mobile payment function? That is, to pay with Alipay on your mobile phone?" (our translation). The focus on use is fortunate because, for there to be an impact on expenditure, it is usage that matters; ownership is not sufficient.

Yet, there are several problems with the measurement of *MP*. For one, as Yang et al. (2023, 103) themselves point out, "mobile payments are not restricted to online shopping; they are also used at traditional brick-and-mortar retailers and public transit systems." This implies that there may well be respondents who use their m-payment instrument only offline—and never online. For these respondents, one should not expect to see an online spending effect. [5]

Note also that the authors do not know which other (online) payment instruments, apart from cash, the respondents have—whereas these instruments are substitutes. The authors would seem to implicitly assume that m-payment adopters use this instrument for, if not all, then the bulk of their online expenditure. This does not need to be the case. Clearly, from the two survey questions above, Yang et al. cannot identify which adopters regularly use m-payments for their online purchases.

MP is also mismeasured in another respect. Yang et al. mention that "the 2017 CGSS only focused on respondents' use of WeChat Pay and Alipay" (2023, 103); see the questions above. Yang et al. argue that WeChat Pay and Alipay are the dominant mobile payment services in China, and that this "justifies the appropriateness of employing 2017 CGSS data for th[eir] study" (ibid.). While

5. In Yang et al.'s sample, some 42 percent of the respondents make mobile payments, either online, offline or both. The CNNIC report for December 2016 puts the number of users of *online* mobile payment services at 496.2 million, equivalent to 64.2 percent of Internet users and 34.1 percent of the total population (2017, 71 Figure 60). This suggests that 7.9 percent (42% − 34.1%) of Yang et al.'s sample—and 18.7 percent of their adopters—use m-payments offline but not online. At first sight, this would seem to make Yang et al.'s results stronger, as they find a spending effect (for females) even when one should not expect such an effect for a non-negligible share of their adopters. However, it does imply that the results of their first-stage regression, for *MP,* are not 'clean.'

the former is correct, the latter is not (or not entirely): respondents who do not use WeChat Pay and Alipay but do use another mobile payment service will be misclassified as non-adopters.[6]

Next, if *MP* is mismeasured (as just explained), then the authors' instrumental variable—"the ratio of mobile payment adopters to the number of other respondents within the same province" (Yang et al. 2023, 103)—is also mismeasured.

Yet another data problem is that Yang et al. have only a very rough proxy of the dependent variable of their second-stage equation (1), OSE_i^{*J}, "the online shopping expenditure of *individual i*" (2023, 102; our emphasis). Indeed, the CGSS collects consumption expenditure not on the individual but on the household level and is divided into ten categories (of which online shopping is one). To guesstimate the online shopping expenditure of the individual respondent, Yang et al. divide household online expenditure by the number of household members. This is not without its assumptions as to who does what part of the e-commerce shopping. We come back to this in our concluding remarks.

Apart from the above problems, which are intrinsic to the CGSS data (and which we cannot solve either), there are also problems with Yang et al.'s sample selection. These problems are perhaps the biggest problems. When explaining why they use a Tobit model rather than an OLS regression, the authors state: "Some individuals in our sample, including both mobile payment adopters and non-adopters, did not purchase online—this results in a number of zero values for the dependent variable (i.e., household online shopping expenditure)" (2023, 102). In fact, the authors would have done better to remove these observations that have a zero value for the dependent variable from their sample. Intuitively, someone who does not shop online does not need to make a decision as to which payment instrument to use. They can thus not be tempted to spend more by the higher convenience of m-payments nor by the discounts offered—the two channels in Yang et al.'s theoretical framework (2023, 101 Figure 1). Many non-shoppers are probably not even aware of the discounts.[7]

Note that whereas Yang et al. talk about "*some* individuals" (2023, 101;

6. According to Analysys' China's "Third-party Mobile Payment Market Quarterly Monitoring Report" (**link**), in the first quarter of 2017 Alipay had a market share, in value, of 53.7 percent and WeChat Pay 39.51 percent—leaving (only) 6.79 percent for other mobile payment services. Obviously, these numbers do not translate one-on-one into user numbers, as they are influenced by the number and value of transactions. According to data provider Merchant Machine, in 2017 mobile wallet users accounted for 47 percent of the population in China (**link**). Assuming that this number is comparable with the 42 percent in Yang et al.'s sample, 5 percent of their respondents would (also) use a mobile payment service other than Alipay and WeChat Pay, so that 8.6 percent (5% ÷ 58%) of the non-adopters are potentially misclassified.

7. One of the referees suggested an alternative solution to removing the non-shoppers from the sample (see below).

emphasis added), the non-shoppers in their sample account for 57.5 percent! Let us also point out that several of the non-spenders do not even have Internet access. Overall, in Yang et al.'s sample, 41 percent of the men and 43 percent of the women did not use the Internet (including mobile Internet) in the past year. This is consistent with the overall 55.8 percent internet penetration rate in China in 2017 (CNNIC 2018).

Still concerning sample selection, respondents who do not own a mobile payment instrument should, in principle, have been excluded—even if they do shop online. Indeed, when having to pay for an online purchase and being sent to the checkout, these respondents are unlikely to contemplate installing WeChat Pay or Alipay on the spot if they have never used it before, either online or offline. Put differently, the added convenience of mobile payments is unlikely to come into play.

Note in this respect that extant models of payment behaviour assume that, when having to pay for a transaction, consumers choose between the instruments they already have. As Sergei Koulayev et al. write (2016, 294): "In our two-stage model, consumers first adopt a portfolio of payment instruments, such as debit, credit, cash, and check. Then, consumers choose how much to use each instrument in different contexts, such as online, essential retail, and nonessential retail" (see also Klee 2006, 2).

Put differently, testing for a spending effect of m-payments should not involve, as Yang et al. do, comparing the online expenditure of users and non-users. Rather the test should ideally consist in identifying respondents who own an m-payment instrument (and are thus in a position to immediately use it for online purchases), and then testing whether the (relative) *frequency* of use—which, to be clear, may be zero—affects their online expenditure.[8]

In practice, such a test is impossible with the CGSS data. For one, the survey does not inquire about the frequency of use of the m-payment instruments that are covered (nor, for that matter, of other instruments). Second, the data do not allow to separate respondents who do not possess a mobile payment instrument from those who do but have not used it in the past 12 months.

There is, however, room to improve upon Yang et al.'s test. In the next section, we will exploit question A30d of the CGSS—"Do you have a mobile phone for your own use?"—to at least eliminate respondents who do not own a mobile phone. These number 10.6 percent.

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8. It can be argued that one should, as Zhao et al. (2022) do, examine *total* expenditure (that is, online plus offline), so as to check that an increase in online expenditure, if any, is not just a shift from offline to online. Given that we think even our final results are not fully reliable (as explained in the Conclusion), we saw no need to perform tests with total expenditure.

There are overlays between the statistics mentioned so far. Only 7.5 percent of the respondents who do not personally own a mobile phone engage in e-commerce. More interestingly, the bulk of the non-spenders—86.2 percent—are respondents who do not use either WeChat Pay or Alipay; see also Figure 2 in Yang et al. (2023, 104). The implication is that no less than 49.5 percent of Yang et al.'s sample have a 0 for both *MP* and *OSE*. As will become clear below, these observations to a large extent drive Yang et al.'s results and cause an overestimation of the spending effect.

A spending effect?

Here we present the results of our replication—with corrected samples—of Yang et al.'s regressions; that is to say, of the regressions presented in Table 2 above. We eliminated respondents who do not own a mobile phone and/or who do not shop online. Oddly enough, some of the online shoppers reported not having used the Internet (including mobile Internet) in the past year. This is probably related to the way Yang et al. construct their *OSE* variable, namely as household online expenditure divided by the number of household members (see previous section). If all online shopping in a household was done by one or more *other* members of the household, then it is clearly not the respondent who decided on the payment instrument to use, and it does not matter whether he or she has a mobile payment instrument or not. In other words, any spending effect would be spurious. We therefore also removed the (so-called) online shoppers who reported not having used the Internet.[9]

The expungings are considerable: 9 percent of the men and 12 percent of the women proved to have no mobile phone, 57.8 percent of the men and 57.2 percent of the women did not shop online, and 4 percent and 4.5 percent supposedly

9. As mentioned in footnote 7, one of the referees suggested an alternative solution, which would allow to keep certain non-spenders in the sample. The alternative would consist in estimating a Heckman two-stage model. The first stage would explain the extensive margin (whether a respondent shops online) and the second stage the intensive margin (the amount of money spent on online shopping, contingent on shopping online at all).

The suggestion is a valid one. Our approach has the drawback that it conflates two issues: respondents not having the technical means to shop online and/or pay for it with a mobile payment instrument vs. not being an online shopper. In neither case does testing for a spending effect makes sense, but the cause is different. The suggested approach would allow one to separate the two issues, provided that one first removes from the sample respondents without a mobile phone and/or access to the Internet.

Still, we did not apply it, mainly because Yang et al.'s approach is already two-stage, in view of the possible endogeneity between the adoption of mobile payments and online shopping; see eqs. (1)–(2). If we were to opt for the alternative approach, we would no longer control for this and, more importantly for our purposes, lose comparability with Yang et al.'s results.

shopped online but did not access the Internet. These three corrections reduce the male sample from 1,683 to 640 respondents, and the female sample from 1,964 to 750.

TABLE 3. Impacts of mobile payment adoption on online shopping expenditure: IV-Tobit estimation, with sampling weights, reduced samples

	Men		Women	
	MP	OSE	MP	OSE
Variables	(1)	(2)	(3)	(4)
MP		1.665^{**} (0.832)		3.362^{***} (0.896)
Age	-0.074^{***} (0.009)	−0.018 (0.021)	-0.067^{***} (0.008)	0.050^{**} (0.023)
Primary school	−0.984 (0.667)	1.878^{**} (0.755)	−0.484 (0.352)	1.089 (0.770)
Middle school	−0.769 (0.579)	1.041^{**} (0.486)	0.032 (0.320)	0.325 (0.657)
High school	−0.214 (0.602)	1.312^{**} (0.575)	0.240 (0.332)	0.512 (0.672)
Technical school	0.129 (0.594)	1.583^{**} (0.458)	1.030^{***} (0.357)	1.058 (0.702)
College	0.111 (0.636)	3.023^{***} (0.613)	1.087^{**} (0.505)	2.332^{***} (0.784)
Marital status	−0.344 (0.344)	1.332^{**} (0.543)	-0.477^{*} (0.255)	−0.325 (0.532)
Family size	-0.033 (0.084)	-0.739^{***} (0.124)	0.040 (0.054)	-0.707^{***} (0.111)
Socioeconomic status	0.046 (0.113)	−0.353 (0.287)	−0.044 (0.111)	-0.847^{***} (0.229)
Life satisfaction	0.254^{**} (0.111)	−0.222 (0.251)	0.094 (0.130)	0.257 (0.241)
Medical insurance	0.252 (0.332)	−1.194 (0.945)	−0.512 (0.430)	1.099^{**} (0.559)
Car ownership	0.082 (0.179)	0.989^{***} (0.375)	0.077 (0.158)	0.628^{*} (0.360)
Urban	0.439^{*} (0.247)	0.384 (0.379)	0.355^{*} (0.208)	0.251 (0.302)
East	0.150 (0.259)	2.162^{***} (0.367)	0.366 (0.240)	2.042^{**} (0.317)
Central	0.178 (0.310)	0.684^{*} (0.371)	0.505^{**} (0.244)	−0.059 (0.280)
IV	1.600^{**} (0.789)		0.766 (0.702)	
Constant	2.517^{**} (1.059)	2.951 (1.906)	3.294^{***} (1.161)	−0.935 (2.132)
Sample size	640	640	750	750

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. Online shopping expenditure is measured in 1,000 Yuan. For education, the reference group is Illiterate; for region, it is Western. Source: Authors' estimates based on CGSS.

TABLE 4. Impacts of mobile payment adoption on online shopping expenditure: IV-Tobit estimation, with sampling weights, reduced samples, dependent variable in log form

	Men		Women	
	MP	OSE	MP	OSE
Variables	(1)	(2)	(3)	(4)
MP		1.233** (0.533)		0.371 (0.609)
Age	−0.072*** (0.009)	0.008 (0.008)	−0.066*** (0.009)	0.006 (0.008)
Primary school	−0.939 (0.640)	0.993*** (0.383)	−0.479 (0.364)	0.076 (0.318)
Middle school	−0.690 (0.538)	0.758*** (0.204)	0.047 (0.336)	0.006 (0.283)
High school	−0.136 (0.566)	0.856*** (0.219)	0.260 (0.343)	0.341 (0.285)
Technical school	0.182 (0.556)	1.096** (0.184)	1.021*** (0.364)	0.637** (0.289)
College	0.111 (0.581)	1.385*** (0.193)	0.947** (0.416)	0.701** (0.293)
Marital status	−0.330 (0.325)	0.195 (0.156)	−0.402 (0.304)	−0.005 (0.131)
Family size	−0.003 (0.080)	−0.262*** (0.038)	0.032 (0.068)	−0.293*** (0.041)
Socioeconomic status	−0.055 (0.080)	−0.055 (0.080)	−0.059 (0.110)	−0.275*** (0.058)
Life satisfaction	0.211* (0.109)	0.054 (0.073)	0.088 (0.131)	0.060 (0.062)
Medical insurance	0.296 (0.295)	−0.355* (0.183)	-0.528 (0.513)	0.186 (0.170)
Car ownership	0.082 (0.175)	0.397*** (0.120)	0.064 (0.156)	0.422*** (0.100)
Urban	0.457** (0.232)	0.277* (0.163)	0.336 (0.224)	0.520*** (0.145)
East	−0.119 (0.300)	0.623*** (0.153)	0.370 (0.270)	0.856** (0.317)
Central	0.080 (0.302)	0.156 (0.170)	0.503** (0.245)	0.216 (0.154)
IV	2.271*** (0.811)		0.708 (0.893)	
Constant	2.296** (1.019)	−1.999** (0.828)	3.346*** (1.167)	−0.458 (0.866)
Sample size	640	640	750	750

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. For education, the reference group is Illiterate; for region, it is Western. Source: Authors' estimates based on CGSS.

Tables 3 and 4 present our regression results. To be clear, apart from reducing the sample to one that is more appropriate, in Table 3 we followed the same approach as in Table 2. In Table 4, in line with C. Zhao et al. (2022), we additionally expressed the dependent variable in log form. We did so because, on closer scrutiny, *OSE* has a substantial share of observations with extreme values. Such outliers are likely to create a heteroscedasticity problem, even with robust standard errors. The log transformation of *OSE* proved to make the distribution more symmetrical (see Section A.3 in our Appendix).

As can be seen, the most important differences between our results in our Tables 3 and 4 and Yang et al.'s original results (for the full samples) are (1) the dramatic drop in the coefficients on *MP* between Table 1 and Table 3, and (2) the fact that in our results there would appear to be a spending effect for men too. In Table 4, the spending effect for women even disappears.

The intuition behind the first difference is straightforward. By eliminating the respondents who do not own a mobile phone and/or who do not shop online, we eliminated all respondents with a 0 for both *MP* and *OSE* in regressions (2) and (4) (49.3 percent of the men and 49.7 percent of the women). Clearly, these observations artificially pushed up the coefficient of *MP* in Yang et al.'s samples. In our samples in Tables 3 and 4, the existence of a spending effect depends on whether respondents who engage in e-commerce *and* use a mobile payment instrument (either online or offline) spend significantly more online than respondents who engage in e-commerce but do not use m-payments.

Let us also point out that the spending effect implied in Yang et al.'s original results is implausibly high. Given that their outcome variable is measured in thousand yuan per capita per year, the coefficient on *MP* in regression (4) in Table 1 would imply that women who use m-payment spent an *additional* 21,716 yuan online. Using the same exchange rate as Yang et al. (2023, 104), namely 1 USD = 6.64 yuan, this is equivalent to 3,270 USD—at a time, in 2017, when Chinese GDP per capita was 8,817 USD (**link**). Clearly, the coefficients in Table 3 are more realistic: they point to an increase in online spending of 1,665 yuan (251 USD) for men and 3,362 yuan (506 USD) for women.

As for the dissimilar gender effect, let us stress that Yang et al. do not provide a convincing explanation for the gender difference that they find. They refer to Francisco Liébana-Cabanillas et al. (2014) as proof that "mobile payment adoption affects men's and women's online shopping behaviors differently" (Yang et al. 2023, 102), but Liébana-Cabanillas et al.'s research is about how gender moderates the effect of constructs such as perceived usefulness and perceived ease of use on the intention to adopt a mobile payment instrument; it is not about the impact on online spending. It is thus not clear where the gender effect, if any, would come from.[10] It should also be stressed that, given the way Yang et al. construct *OSE*,

10. A Wald test again shows that the coefficient on MP is not significantly different between men and women ($z = 1.065, p = 0.299$).

one cannot be sure that the online shopping that is attributed to a respondent has actually been performed by that person.

Discussion and conclusions

Yang et al.'s (2023) analysis of whether the use of mobile payments leads consumers to spend more online suffers from econometric mistakes and conceptual flaws. A key conceptual oversight is the inclusion in their sample of respondents who do not own a mobile phone and/or do not use the Internet. Yang et al. should also have taken into account, in one way or another, that, among the remaining respondents, there are some who do not shop online. Once the data is treated (more) appropriately and the econometrics are corrected, the positive spending effect becomes dramatically smaller and even disappears completely for women.

While an improvement over Yang et al., our tests are not perfect either. For one, they inherit the four problems intrinsic to the CGSS data. In particular, using household online expenditure per capita to proxy *individual* online expenditure would seem problematic. In dual-adult households, this will result in a valid test of the spending effect only in symmetric situations; that is, when both partners shop online (or not) and when they both use a mobile payment instrument (or not).[11] Asymmetric situations entail biases. For example, when the respondent does not shop online but their partner does, then part of the online shopping of the partner is incorrectly attributed to the respondent. When they both shop online and the respondent uses WeChat Pay or Alipay but their partner does not, there is a potential spending effect for the respondent but not for the partner. Hence, equally splitting the online spending risks diluting the spending effect.

Together with the absence, in the CGSS survey, of information about respondents' frequency of use of m-payments and their ownership of other online payment instruments, these problems preclude further improvements of our tests.[12] We would therefore advise against using 2017 CGSS data for the research question at hand.

To wrap up, Yang et al.'s answer to the question in the title of their article cannot be relied upon. And, unfortunately, our improved tests are not worth much either.

11. When they both shop online, an additional condition is that they do so to (more or less) the same extent. Otherwise the online expenditure of the respondent is over- or underestimated.
12. In an attempt to overcome the problems with the measurement of *OSE*, we isolated single-person and single-adult households. Unfortunately, the resulting samples proved too small.

Appendix

Data and code for this research are available via the journal's website (**link**).

Also, the original dataset in Chinese, do file to translate it, and do file to generate the dataset (as contained in the previous link) are provided by the authors (**link**).

In this Appendix, we first introduce Yang et al.'s dataset in more detail and explain how we reassembled their sample. We then demonstrate that we were able to replicate Yang et al.'s results only by making econometric mistakes. Lastly, we justify the log transformation of the dependent variable that we apply in the final step in our paper (see Table 4).

Yang et al.'s dataset

Yang et al. (2023) use the 2017 wave of the Chinese General Social Survey (CGSS), administered by Chinese academic institutions. The survey contains responses of 12,582 individuals who were selected by means of multi-stage stratified random sampling. The respondents are based in rural and urban areas across 28 provinces of mainland China. The survey is nationally representative. As reported by Ma et al. (2022), one respondent in each household was selected for the face-to-face interview. Individual-level questions include socio-demographic and economic status, objective and perceived measures of quality of life, etc.

The CGSS database also contains household-level variables. In particular, in a special module of the 2017 wave, 4,132 individuals reported at least one of the following types of expenses for their household: (1) household food expenses, (2) non-food items, (3) clothing, (4) housing, (5) purchases of durables, (6) transportation and communication spending, (7) leisure and travel, (8) education spending, (9) medical expenses, and finally (10) household online expenses—which is the expenditure that Yang et al. concentrate upon.

Of the 4,132 respondents mentioned above, we dropped all individuals who had a missing value for, or refused to answer, the question on online expenses. We also dropped six respondents who are 90 years and older. Finally, we dropped all households with a missing value for any of the variables listed in Yang et al.'s Table 1 (2023, 103); that is, the variables they use in their regressions. As a result, our sample contains responses of 3,647 individuals, of which 1,683 are male and 1,964 are female. This is very close to the 1,681 male and 1,963 female respondents in Yang et al.'s sample. (Where the difference of three observations comes from is unclear to us.) Note that the descriptive statistics on all variables presented in Table A1, and all statistics presented in Table A2, are exactly the same as in Yang et al.'s Tables 1 and 2. In other words, the small discrepancy in the number of observations has no impact worth mentioning.

TABLE A1. Replication of Yang et al.'s sample: descriptive statistics

	Male	Female	Mean difference	p-value
Online shopping expenditure	1.38	1.35	0.03	0.854
Mobile payment	0.42	0.41	0.01	0.658
Age	51.21	50.45	0.76	0.166
Illiterate	0.06	0.15	−0.09	0.000
Primary school	0.22	0.23	−0.01	0.608
Middle school	0.31	0.27	0.04	0.004
High school	0.14	0.13	0.01	0.434
Technical school	0.16	0.11	0.04	0.000
College	0.11	0.11	0.01	0.575
Married	0.78	0.77	0.01	0.383
Family size	2.72	2.83	−0.10	0.026
Socioeconomic status	3.84	3.77	0.07	0.010
Life satisfaction	3.71	3.81	−0.11	0.000
Medical insurance	0.93	0.93	−0.00	0.859
Car ownership	0.28	0.28	0.00	0.892
Urban	0.63	0.63	0.00	0.808
East	0.44	0.43	0.00	0.776
Central	0.33	0.32	0.01	0.574
West	0.23	0.25	−0.01	0.344
IV	0.42	0.41	0.01	0.036
Did not use internet	0.41	0.43	−0.01	0.415
Has no mobile phone	0.09	0.12	−0.04	0.000
Observations	1683	1964		
Source: Authors' estimates based on GCSS survey.				

TABLE A2. Replication of Yang et al.'s sample: mean differences of selected variables between mobile payment adopters and non-adopters

	Male				Female			
	Adopters	Non-adopters	Mean difference	p-value	Adopters	Non-adopters	Mean difference	p-value
Online shopping expenditure	2.88	0.30	2.58	0.000	2.97	0.23	2.74	0.000
Age	37.77	60.83	−23.06	0.000	37.22	59.64	−22.42	0.000
Illiterate	0.01	0.09	−0.08	0.000	0.01	0.25	−0.24	0.000
Primary school	0.04	0.35	−0.31	0.000	0.07	0.34	−0.27	0.000
Middle school	0.27	0.34	−0.07	0.003	0.25	0.28	−0.03	0.089
High school	0.17	0.11	0.06	0.000	0.20	0.08	0.12	0.000
Technical school	0.26	0.08	0.18	0.000	0.22	0.04	0.19	0.000
College	0.24	0.02	0.21	0.000	0.24	0.01	0.23	0.000
Married	0.71	0.83	−0.11	0.000	0.75	0.78	−0.03	0.098
Family size	2.94	2.56	0.38	0.000	3.08	2.65	0.43	0.000
Socioeconomic status	3.69	3.95	−0.26	0.000	3.57	3.91	−0.34	0.000
Life satisfaction	3.65	3.75	−0.1	0.020	3.88	3.76	0.12	0.002
Medical insurance	0.92	0.93	−0.01	0.404	0.92	0.93	−0.01	0.484
Car ownership	0.46	0.15	0.31	0.000	0.45	0.16	0.28	0.000
Urban	0.81	0.50	0.31	0.000	0.81	0.50	0.31	0.000
East	0.56	0.35	0.21	0.000	0.54	0.36	0.18	0.000
Central	0.26	0.38	−0.11	0.000	0.27	0.36	−0.09	0.000
West	0.18	0.27	−0.1	0.000	0.19	0.29	−0.10	0.000
IV	0.48	0.38	0.1	0.000	0.46	0.37	0.09	0.000
Did not use internet	0.02	0.69	−0.67	0.000	0.01	0.71	−0.71	0.000
Has no mobile phone	0.00	0.15	−0.15	0.000	0.00	0.21	−0.21	0.000
Observations	702	981			805	1159		
Source: Authors' estimates based on GCSS survey.								

Yang et al.'s econometric problems

As explained in the main text, we could not replicate Yang et al.'s results with the sample presented in Table A1. Eventually we discovered that the authors must have made two technical mistakes: (1) while the data they use were obtained by means of stratified random sampling, they failed to use sampling weights; and (2) unlike reported in their article, the first stage of their model is apparently not estimated using probit.

Indeed, it was only when we omitted sampling weights *and* used OLS in the first stage that we obtained the results in Table A3. As can be seen, these results are almost exactly the same as those that Yang et al. report in their article, in Table 3 on p. 106 (reproduced as Table 1 in our paper). This implies that, although Yang et al. (2023) claim that they have used probit in their first-stage model, their results are, in fact, based on OLS. In particular, Yang et al.'s first-stage is based on the Linear Probability Model (LPM), where coefficients correspond to changes in probabilities in response to changes in the respective variables. This means that Yang et al.'s interpretation of their first-stage results is wrong. Also, LPM has several problems, such as probabilities beyond the 0 to 1 interval. One should therefore really use probit to estimate the first-stage model.

In Table A4, which appears as Table 2 in our paper, we therefore first had to re-estimate Yang et al.'s regressions with the correct econometric approach. The results suggest that mobile payment use has a statistically significant impact on household online expenses, and this for both men and women. In isolation, these corrections to Yang et al. suggest that their original results overestimate the economic significance of the impact of mobile payment adoption for female respondents and underestimate it for male respondents. However, in our paper we administer yet other corrections.

TABLE A3. Replication of Yang et al.'s results, no sampling weights, OLS in first stage

	Male		Female	
	Mobile payment	Online shopping expenditure	Mobile payment	Online shopping expenditure
Model	OLS	Tobit	OLS	Tobit
Mobile payment		11.479^{*} (6.259)		18.269^{***} (5.311)
Age	-0.017^{***} (0.001)	0.030 (0.108)	-0.015^{***} (0.001)	0.129 (0.080)
Primary school	-0.067^{**} (0.030)	0.926 (1.065)	-0.046^{**} (0.018)	1.274^{*} (0.756)
Middle school	0.013 (0.032)	1.449^{*} (0.800)	0.061^{***} (0.024)	−0.489 (0.761)
High school	0.074^{*} (0.039)	2.136^{**} (1.001)	0.234^{***} (0.032)	−1.899 (1.496)
Technical school	0.181^{***} (0.039)	2.253 (1.496)	0.297^{***} (0.033)	−2.590 (1.811)
College	0.189^{***} (0.040)	3.810^{**} (1.588)	0.285^{***} (0.033)	−0.650 (1.788)
Married	−0.010 (0.019)	1.648^{***} (0.553)	-0.028^{*} (0.015)	−0.647 (0.557)
Family size	0.003 (0.006)	-0.270^{*} (0.160)	0.003 (0.005)	−0.082 (0.147)
Socioeconomic status	−0.014 (0.010)	-0.736^{**} (0.293)	−0.013 (0.009)	-0.544^{**} (0.267)
Life satisfaction	−0.004 (0.010)	−0.328 (0.226)	0.019^{**} (0.009)	−0.062 (0.252)
Medical insurance	0.034 (0.028)	−1.590 (1.100)	0.048^{*} (0.026)	0.305 (0.731)
Car ownership	0.090^{***} (0.021)	1.422^{*} (0.753)	0.067^{***} (0.019)	1.296^{**} (0.596)
Urban	0.095^{***} (0.021)	0.592 (0.814)	0.117^{***} (0.019)	−0.170 (0.798)
East	0.040^{*} (0.024)	1.333^{**} (0.618)	0.016 (0.022)	1.967^{***} (0.570)
Central	0.021 (0.021)	−0.216 (0.471)	0.063^{***} (0.019)	−0.267 (0.566)
IV	0.222^{***} (0.071)		0.303^{***} (0.065)	
Constant	1.059^{***} (0.084)	−7.850 (7.428)	0.778^{***} (0.078)	-15.27^{***} (5.356)
Observations	1683	1683	1964	1964

Source: Authors' estimates based on GCSS survey. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A4. Impact of mobile payment adoption on online shopping expenditure: IV-Tobit estimation, with sampling weights

	Male		Female	
	Mobile payment	Online shopping expenditure	Mobile payment	Online shopping expenditure
Model	Probit	Tobit	Probit	Tobit
Mobile payment		4.918*** (0.816)		5.777*** (0.821)
Age	−0.087*** (0.006)	−0.032 (0.020)	−0.085*** (0.005)	0.008 (0.016)
Primary school	−0.391 (0.272)	−0.193 (0.927)	0.394 (0.275)	0.548 (0.653)
Middle school	0.194 (0.248)	0.843 (0.765)	0.851*** (0.270)	0.009 (0.656)
High school	0.307 (0.269)	1.606* (0.830)	1.497*** (0.290)	0.662 (0.718)
Technical school	0.857*** (0.264)	2.142*** (0.820)	1.878*** (0.299)	1.015 (0.765)
College	1.069*** (0.308)	3.603*** (0.916)	1.981*** (0.388)	2.544*** (0.847)
Married	0.205 (0.187)	1.297*** (0.480)	−0.154 (0.157)	−0.622 (0.443)
Family size	−0.019 (0.045)	−0.300** (0.127)	0.003 (0.035)	−0.267*** (0.100)
Socioeconomic status	−0.045 (0.067)	−0.694*** (0.246)	−0.102 (0.067)	−0.753*** (0.197)
Life satisfaction	−0.007 (0.067)	−0.189 (0.215)	0.082 (0.073)	0.179 (0.199)
Medical insurance	0.138 (0.186)	−1.003 (0.851)	0.296 (0.213)	0.859* (0.489)
Car ownership	0.320** (0.128)	1.436*** (0.380)	0.209* (0.114)	1.599*** (0.339)
Urban	0.535*** (0.132)	0.987*** (0.360)	0.707*** (0.128)	1.194*** (0.298)
East	0.167 (0.147)	1.521*** (0.369)	0.120 (0.153)	2.196*** (0.336)
Central	−0.065 (0.154)	0.196 (0.381)	0.427*** (0.150)	0.197 (0.318)
IV	1.628*** (0.435)		2.444*** (0.452)	
Constant	2.559*** (0.595)	−1.631 (1.835)	1.087 (0.667)	−5.195*** (1.972)
Observations	1683	1683	1964	1964

Source: Authors' estimates based on GCSS survey. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Justification of the log transformation of the dependent variable

As their main dependent variable, Yang et al. use annual household online expenditure per household member. To obtain values for this variable, they divide past year's household online expenditure at the household level by the number of household members. The mean household online expenditure per household member used by Yang et al. is reported in Table A1 and, separately for men and women, in Table A2. Importantly, 2,096 households of the 3,647 (or 57.47 percent!) reported that they had spent zero yuan online. In other words, as we stress in the paper, Yang et al. included in their analysis households/individuals who did not even engage in e-commerce.

Figure A1 plots the distribution of annual household online expenses for respondents who reported non-zero online expenses. As can be seen, more than 90 percent of respondents spent, per household member in one year, around 10,000 yuan or lower. As the figure shows, the distribution is skewed with some large observations on the tail. These outliers are likely to create a heteroscedasticity problem even if one specifies robust standard errors options in one's regressions.

Figure A1. Distribution of household online expenses

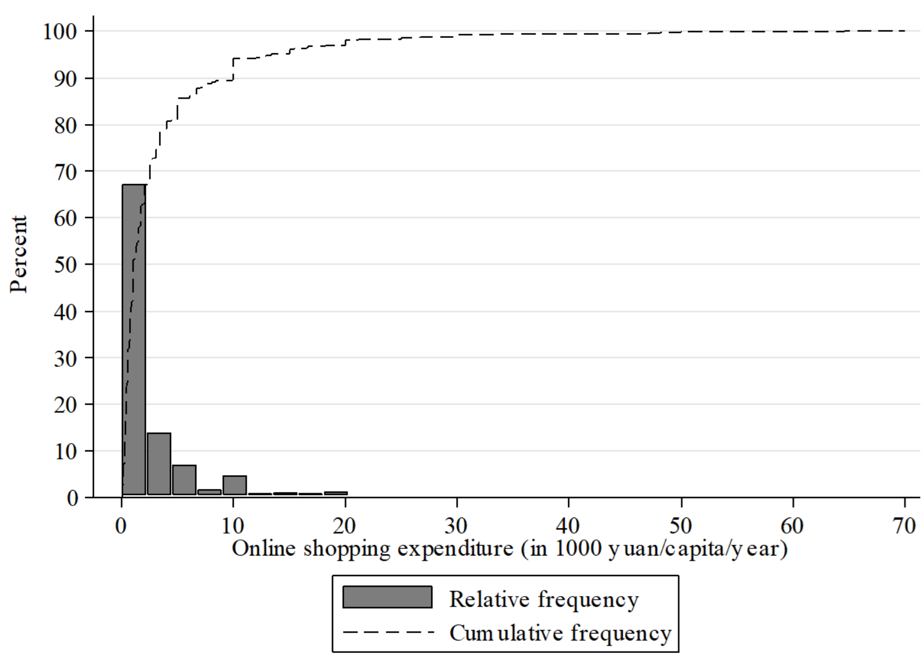
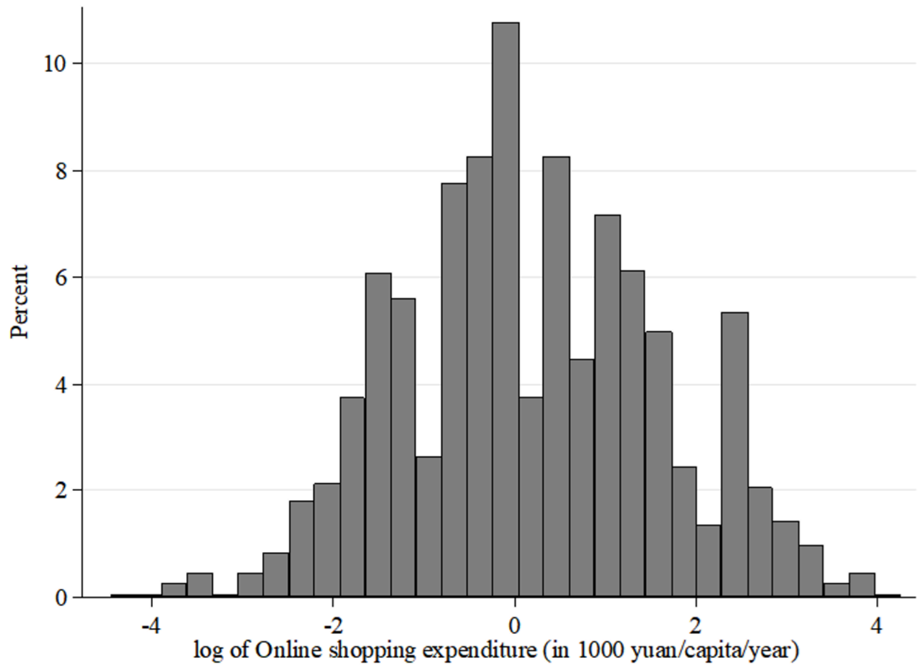


Figure A2 shows that a log transformation of household online expenses results in a symmetrical distribution of the variable. We are therefore convinced that household online expenses must be used in the log form if one wants to limit the impact of possible influential cases that can bias the results.

Figure A2. Log of household online expenses



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