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Online or not online: the impact of business owner's risk preference on the adoption of e-business

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Abstract
The significant growth of internet users has driven businesses to develop their capacity in e-commerce and meet the increasing demand for e-consumption, e-services, and e-business. To gain the benefits of e-business, firms may choose to extend or transit their offline-operated businesses to online or hybrid modes. Opportunities are accompanied by risks in this process. Therefore, it is important to understand how business owners' financial risk preferences affect their choice of business operation models, namely, online and offline operations. Using data from the China Household Finance Survey (CHFS) in 2017 and 2019, this study examined the impacts of business owners' risk preferences on e-business adoption, considering social insurance as a moderator on the relationship between risk effect and online business operation. In addition, we used heterogeneity examination to test for regional differences between rural and urban areas. Our results show that, compared to high-risk takers, low-risk takers are less likely to choose online or hybrid businesses; and having social insurance reduces the effect of risk preference on adopting e-business. This finding indicates social insurance may provide financial security to business owners with low-risk preferences and makes them more likely to adopt online business, whilst it may distort adoption incentives for high- and medium-risk groups. Results of the heterogeneity examination suggest a discrepancy in the risk preference effect on the adoption of e-business between the rural and urban areas: the impact of risk preference is found to be significantly higher on businesses in the rural area than those in the urban area.

Keywords Financial risk preference · e-business · Multi-valued treatment model · Social insurance · China

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1 Introduction

China has the largest population on the internet and is expected to remain in the leading position in the future. According to the Ministry of Industry and Information Technology in China, about 53% of China's total population were internet users, and in particular, the percentage of mobile device users has rapidly increased and overpassed those using personal computers (PCs) in 2014 [1]. Currently, people use both PCs and mobile devices to obtain and share information as well as to conduct economic activities, such as online shopping and online payment [2]. This trend is supported by fast-growing telecommunication technologies, such as telecommunication bandwidth, as China has overtaken the leading position of the U.S. regarding the installed telecommunication bandwidth; and a large proportion of these are high-speed internet connections, covering both urban and rural areas [3]. Hence, firms in China tend to seek opportunities and obtain the benefits of electronic business (e-business) by extending or shifting offline operations to online operations. However, the transition can be perceived to be risky given there has no ready-to-use templates, and the attempt of applying the e-commerce experience of the developed countries has been disappointing [4], [5]. Hence, firms may not obtain the required recourses, facilities, and services to support e-business, leading to high implementation costs and risk of failure, in particular for small and medium enterprises (SMEs) [6]. As for the hybrid model (i.e., having both online and offline operations), critics come from the high operation cost and boundary management concerning the allocation of resources to the online and offline unit [7]. Note that, compared to developed countries, businesses in developing countries are less tolerant of failure [8]. Therefore, whilst the increasing demand for online services and consumption, the majority of firms are reluctant to extend or transit their offline businesses to online businesses in China.

The literature on e-business adoption has mainly focused on e-commerce technologies, for example, B2B e-commerce technologies [9–12], e-commerce tools [13], mobile marketing [14], or at a high level of industry 4.0 in the manufacturing industry [15]. However, results of the existing studies are mainly based on empirical analyses of small samples (between 100 and 300 observations). Besides the weakness in small samples, those studies usually consider firm characteristics and contextual factors (e.g., external environment and regional and country-level characteristics) whilst ignoring the "human" factors, such as the preference of owners or managers and cognitive issues. The literature on technology adoption analysis has provided an extensive discussion about the importance of "human" factors and how the characteristics of decision-makers influence innovation or technology adoption across different contexts (e.g., Internet-of-Things, digitalisation, and Internet 4.0 technologies) for entrepreneurs and business owners [16–18]. Notably, some researchers believe "human" factors become the most important determinants when compared to other main factors regarding technology adoption [16], [19], [20]. Hence, in the context of e-commerce adoption for firms, "human" factors need to be considered because business owners and managers are the decision-makers who ultimately choose adoption or non-adoption of e-commerce. The existing studies on e-commerce adoption tend to either look into the consumer side [21–23], such as understanding consumers' intentions toward e-commerce adoption [24], or analyse firms' adoption of e-commerce using conceptual models [25], [26], or focusing on contextual issues (e.g., technological, organisational and environmental (TOE) factors) [11–13], [18], [23]. However, as for "human" factors in e-commerce adoption, there are only a handful of studies, for example, Rahayu and Day [6], Bollweg et al. [27], and Scupola [28] that explored business owners' or managers' attitudes toward digitalization and their readiness and perceptions of e-commerce technologies.

Given the high uncertainty of new technology, in particular internet- and communication-related technologies, risk-related factors may result in potential loss attributed to technology adoption [29]. Hence, users' perceived risk of e-technologies and e-services may negatively affect adoption intentions [24], [30], [31]. Whilst bringing in benefits, e-commerce may also come with risks and uncertainties for business owners. Thus, risk factors should be considered in the adoption decisions. However, at the firm level, none of those studies shown above consider risk issues when analysing "human" factor effects on e-commerce adoption. Users of e-commerce are mainly consumers and households: existing studies consider risk factors, such as perceived risk, in the adoption of e-commerce (e.g., internet banking and mobile payment) and e-services from the perspective of consumers [24], [29], [31–33]. Note that most of the studies consider the impact of perceived risks on users' adoption intentions rather than on the "real" adoption in practice (e.g., [24], [31], [33]). The above facts indicate a clear research gap in the study of e-commerce adoption such that the risk-related "human" factors, have been ignored in the decision-making of e-commerce or e-business adoption.

Therefore, this study aims to empirically investigate the impact of risk preference of business owners on their choices of business operation models, namely traditional offline operation, online operation, and hybrid operation. Notably, although the impact of risk concerns has been addressed in e-commerce adoption from the consumer side (e.g., online shopping or online banking) [24], [32] and in studies on technology adoption [34] and investment decisions [35], risk factors have not been discussed from the perspective of business owners. Empirically, although most existing studies have targeted consumers' adoption of e-commerce [2], [21], [22], the studies provide evidence that risk factors must not be ignored in understanding adopters' choices of e-commerce adoption. Hence, we use a multi-valued treatment model to control for selection bias in the relationship between risk preference and e-business adoption. Our results show that business owners' risk preferences lead to different choices of e-business adoption: medium- and high-risk takers are more likely to adopt e-business than low-risk takers and these differences are widened in the rural area; social security may help moderate the effect of risk preference on the adoption of e-business possibly due to the financial security perceived by the business owners when having social insurance. Being the first attempt, the study contributes to the literature on e-commerce adoption by addressing the important role of financial risk preference on business owners' adoption of e-business using a sample of 5,301 observations. In addition, our finding on the moderating role of social insurance provides insights into the development of supporting instruments to encourage the adoption of e-business. The finding of rural and urban differences is also of great importance to policymakers in allocating recourses and support to businesses in rural China.

The remaining paper will be structured as follows. Section 3 specifies the empirical analysis models and presents the sample data and descriptive statistics of the variables used in the study. Section 4 provides results and discussions, followed by the last section to conclude.

2 Theoretical background and conceptual analysis framework

E-commerce adoption has been driven by structural shifts at the industry or policy level (e.g., via marketing and technology development) and related to individual activities of business owners (e.g., the extension of retail channels) [36]. Amongst all the factors that influence the adopters' decisions, perceived risks are regarded as one of the most important barriers to adopting e-commerce, given the uncertainty and costs associated with it [32]. Different from the past technology adoption research that has mainly focused on the positive utility gains from technology adoption [36], the perceived risk theory factors out the barriers, such as perceived risk, technology type, and individual characteristics (e.g., age and gender) to e-commerce adoption [29], [37]. Being widely applied in marketing and behavior studies, the perceived risk theory helps explain the relationship between risk-related factors and individuals' decision-making on consumption and technology adoption [24], [38–40]. In the context of e-commerce adoption, Featherman and Pavlou [29] define perceived risk as "the potential for loss in the pursuit of a desired outcome of using an e-service". According to the perceived risk theory, whilst risk preferences are relatively stable based on individual characteristics (e.g., demographic factors), they may change with contextual factors, such as regional development of digital technology, and sources of information and learning options provided to business owners [41]. That is to say, business owners are not randomly exposed to information and/or learning opportunities that are perceived to be more risky (e.g., for risk aversion) or less risky (e.g., for risk seeking) [42], and hence they may make different judgments about the profile of e-commerce investment regarding risks and returns [32]. Figure 1 illustrates a conceptual framework showing how business owners' risk preferences affect e-commerce adoption. Here, to correct the selection bias in the relationship between risk preferences and e-commerce adoption, the multi-valued treatments are formed by including individual characteristics of business owners that form the "stability" of risk preferences and contextual factors that may change business owners' risk preferences over time.

In addition, an important household asset class that has received less attention is social insurance products that would significantly reduce risks faced by business owners. The role of social insurance has been largely discussed in the literature on households' investment decisions in finance and asset investment studies [43]. When viewed through the lens of risk sharing, social insurance is believed to deal with market failures (e.g., inequity and information asymmetry) and improve individuals' wellbeing [44]. In the context of China, the social insurance scheme has been expanded from a single system focusing on the state sector to various plans covering the private sectors for both urban and rural areas: the participation rate of individual firms is now among the highest in the world [45], and the government has heav-

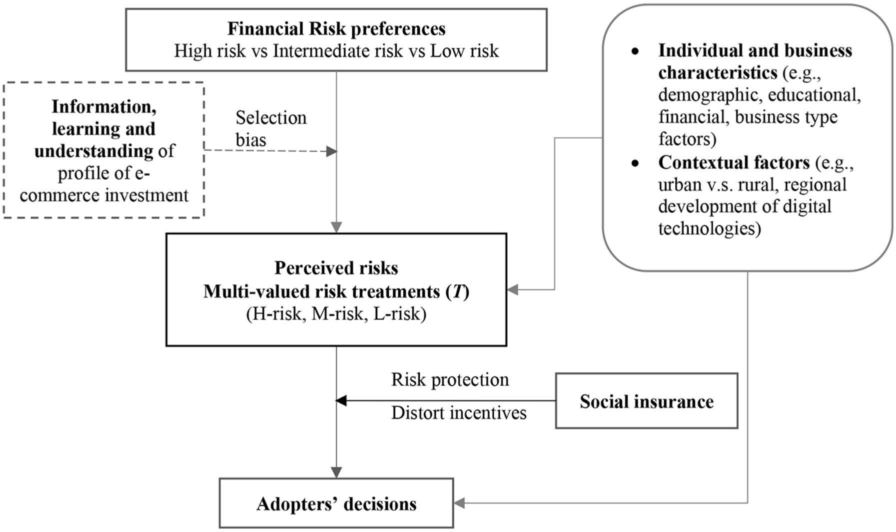

Fig. 1 Conceptual analysis framework
*The figure is created using Microsoft word

ily subsidised the rural residents toward contributions [46]. Thus, social insurance helps business owners hedge income risk and adoption risk: having social insurance may help increase the business owner's financial certainty, reduce one's financial risk concerns [47], and hence increase the adoption of e-business [32]. The existing studies show that the negative effect of risk concerns on e-technology adoption could be reduced if the feeling of insecurity and uncertainty is alleviated via, for example, trust, saving, and knowledge [24], [31], [33], [48]. In that way, having social insurance (functioning like saving) may provide economic incentives for business owners (who may be forward-looking) [49] to reduce their insecurity and help mediate the negative effect of perceived financial risks on e-commerce adoption [48]. Alternatively, although social insurance is regarded to protect investors, the risk protection benefits come at a cost known as the moral hazard issue [49], [50]. It distorts the incentives of households and may lead to early retirement, low investments, and excessive consumption of medical care [44]. In our case, for example, we assume that risk lovers are more likely to adopt e-commerce but having social insurance may twist one's risky choice (i.e., e-commerce adoption) via its impact on an individual's perceived risk. Therefore, adding social insurance to empirical analysis is like evaluating a system that combines social insurance with individual investment-based accounts - it is unclear how social insurance changes the incentives of insured business owners that might affect their investment decisions on e-commerce.

3 Methods

3.1 Empirical specifications

Selection bias often exists in people's decision-making process regarding technology or practice adoption. For example, it may occur in the decision process of information acquisition and technology adoption: people who tend to adopt the technology could be those who are more likely to reach out and acquire the relevant information about the technology [51], [52]. As stated in the conceptual analysis framework, self-selection bias may also exist in the relationship between financial risk preference and the adoption of e-business: business owners' decision on e-commerce adoption is a function of the perceived risk associated with the investment of e-commerce, such as financial risk, time risk, and performance risk. That is, perceived risks emerge when individuals are uncertain about the potential outcomes of a behaviour, in our case e-commerce adoption, in particular when the outcome is associated with possible losses in a risky choice [53]. Notably, perceived risks of e-commerce adoption are varied due to the inherent risk preferences of business owners [42], [54], i.e., low-, medium-, and high-risk preferences. The multi-valued treatment analysis framework works well to capture (though not the unobserved) the observed factors that may influence decision-makers' risk preferences. However, the existing literature on e-commerce adoption has either ignored the role of risk factors [9], [10], [14] or simply include them as exogenous variables [27]. Therefore, we employ a multi-valued treatment model to deal with the selection bias in the relationship between financial risk preference and the adoption of e-business. The model has the advantage of modelling more than two treatments, in our case, high-risk preference, medium-risk preference, and low-risk preference of financial investment. The selection of covariates in the multi-valued treatment process is based on the existing literature on factors affecting individuals' risk preferences and/or perceived risks: individual characteristics (age, marital status, education, and income level), business characteristics (e.g., business type), and contextual factors (e.g., regional economic and technological development) [24], [29], [37]. We follow Boonstra et al. and Burgette et al. [55], [56] to use a "doubly robust" approach (IPTW) to estimate the pairwise average treatment effects through a weighted linear regression model (a binary logit model in our case) with the weights drawn from the multi-valued treatment process, i.e., the generalized boosted model (GBM).

Here, the decision on e-commerce adoption is empirically modelled following the utility maximization theory [57], which has been widely used in the literature on adoption analysis. Based on the model, a business owner only adopts a technology, in our case e-commerce, if and only if it provides superior expected utility than the utility of non-adoption [57], [58]. That is, the adoption of e-commerce maximizes a business owner's utility subject to the perceived risks associated with the adoption, in particular when returns to adoption are uncertain and associated with certain risks, such as production risk, operation risk, and marketing risk [51], [52]. We assume the i^{th} business owner's adoption of e-business Y_i is determined by a sample selection model $(i = 1, 2, ..., n)$:

$$T_i[j] = \begin{cases} 1, & if\, T_i = j \\ 0, & otherwise \end{cases}, \tag{1}$$

where T_i is the observed treatment status. When $T_i = j$, $T_i[j]$ denotes the receiving of j^{th} risk treatment for the i^{th} business owner. $Y_i = Y_i[j]$ for $j = L, M, H$, where $j = L$ denotes the household's financial investment decision had it received a low-risk treatment (i.e., low-risk preference); $j = M$ denotes medium-risk treatment (i.e., medium-risk preference); and $j = H$ denotes high-risk treatment (i.e., high-risk preference). We then fit three GBMs and estimate the probability of getting into each risk treatment group ($T_i[j]$), i.e., $\hat{p}_j(X_i)$ denoting the probability that each individual received risk preference treatment *j* given the observed pre-treatment covariates (e.g., individual and firm characteristics). X_i is the set of *K* observed covariates to be included in both the data matching process and the post-matching regression based on Eq. (2). Hence, the estimated probabilities can then be used to calculate weights of the average treatment effect (ATE), $w_i[j] = {}^{1}\!/_{\hat{p}_j(X_i)}$, which are then employed in a binary logit model to estimate the ATEs of financial risk preference on e-business adoption[1]:

$$\log\left(\frac{\text{Prob}(Y_i = 1)}{\text{Prob}(Y_i = 0)}\right) = \alpha_i + \lambda_1 T_i[H] + \lambda_2 T_i[M] + X_i\beta + \varepsilon_i, \tag{2}$$

where $T_i[M]$ and $T_i[H]$ represents the medium- and high-risk treatment, with $T_i[L]$ set as the base group. Thus, λ_1 and λ_2 denote the IPTW estimators used to estimate the ATE between the high- and low-risk group and between the medium- and low-risk group, respectively. β are the unknown regression coefficients associated with the covariates X_i to be estimated; α_i is the constant and ε_i is the error term.

Although an individual's financial risk preference does not change in a short term, it may change with one's financial risk tolerance which can be improved by the individual's achievement in financial success or increased certainty of one's financial situation [47], [59]. As stated in the conceptual framework, we tend to explore if social insurance could moderate the risk preference effect on business owners' adoption of e-business. Hence, we add a variable, social insurance, and its interactions with risk treatments $T_i[H]$ and $T_i[M]$ to Eq. (2) to test for the moderation role of social insurance on risk preference effect on the adoption of e-business.

3.2 Data and variables

Data used in this study was mainly sourced from the 2017 and 2019 China Household Finance Survey (CHSF) conducted by the Southwestern University of Finance and Economics. The CHFS is a nationwide finance survey and was firstly conducted in 2011. After that, the survey is performed every two years. The sample size increases from 8,438 households in 2011 to 34,643 households in 2019. Besides reporting

[1] In this study, we estimate treatment effects through comparing the relative effectiveness of all possible pairs of risk treatments based on a most commonly used summary statistics, i.e., average treatment effect (ATE).

individual households' financial activities, the 2017 and 2019 CHFS surveys include information about households that own and run businesses, namely business owners or entrepreneurial households. Notably, the same questions regarding households' e-business adoption were asked in the 2017 and 2019 surveys whereas the previous surveys could not provide the same information. Also, the 2017 and 2019 CHFS surveys cover 1,360 communities and villages in 29 provinces in China, consistently. Besides using the CHFS surveys, to control for the external impact of digital development, we used the digital inclusive finance index at the province level in 2016 and 2018 and merged it with the CHSF dataset. The index is built by Beijing University, based on the data on digital inclusive finance from Ant Financial Services [60], [61]. By merging and filtering the dataset, we drew a sample to only include households that own and run businesses, making the final sample of 5,301 observations[2] (1,422 and 3,879 in 2017 and 2019, respectively).

We collected information about business owners' adoption of e-business (outcome variable), their financial risk preferences (treatment variables), as well as individual and firm-level characteristics and contextual factors (covariates). The detailed descriptions of all variables are included in Table 1 and the descriptive statistics are presented in Table 2. Here, the outcome variable is a dummy variable, taking the value of one, if the business owner adopted an online business or hybrid business (with some part of the business conducted online), zero otherwise. The selection of the covariates in the study is based on the existing literature on the factors affecting the adoption of e-technologies and e-services, where the key factors include characteristics of business owners (e.g., age, gender, and education level) and businesses (e.g., firm type) and the contextual factors, such as regional development (e.g., rural versus city, city level, and regional digital development) [5], [10], [28], [29], [62]. As shown in Table 2, the adoption rate of e-business is low, with only 17.3% of the observations adopting e-business[3]. The multi-valued treatments include three treatment dummies, representing business owners' financial risk preferences, including low-risk preference, medium-risk preference, and high-risk preference. The majority of the observations fall into the low-risk treatment group (72.7%), followed by 19.1% in the medium-risk treatment, and only 8.2% in the high-risk treatment group. The average total household income was 87,370 RMB (13,730.73 USD) and half of the business owners are small and normal taxpayers. Geographically, about 25% of respondents lived in rural areas, and most of them belong to second and third-tier cities[4]. As for the social-economic situation of the business owners, they aged around 49.63 years old, and 52.6% were male; they fell on the score of 3.57 school education (i.e., between junior high and high school) and 93% of them were married; 70.6% business owners had social insurance, and the average score of health status for the business owners was 2.419, with a scale from 1 indicating "very good" to 5 "very

[2] We excluded 76 observations due to incomplete information.

[3] Due to the low adoption of e-business, we combined the online business and hybrid business into one group, representing the adoption of e-business.

[4]. Not that there is no official definition of Chinese city classification. However, city-levels are often referred to "Chinese city tier system" by various media publications for purposes including commerce, transportation, tourism, education etc. (Chinese city tier system. (n.d)). For example, Beijing, Shanghai, Guangzhou, and Shenzhen are positioned in the first-tier cities.

Table 1 Variable definition

Variable	Variable type	Description
adoption of e-business	Dummy variable	E-business adoption, = 1 if the business owner adopted an online business or hybrid business model, =0 otherwise.
risk preference	Categorical variable	Households are divided into three categories according to their risk attitudes. The treatment is the risk attitude of the household head, based on the survey question: If you have a choice, what kind of investment will you make? Respondents are considered high-risk takers when they chose high-risk and high-returns projects or projects with slightly high-risk and slightly high returns. Respondents are considered medium-risk takers when they chose projects with average risk and returns. Those selecting the option 'not willing to take any risks' were the low-risk preference group.
total_income	Continuous variable	Amount of annual household income. It consists of income from wages and salary, net profit from agricultural and business activities, income from all forms of property, and transfer income.
taxpayer	Categorical variable	This is a categorical variable: small taxpayer (=1), general taxpayer (=2), and others (=3).
rural	Dummy variable	This is a dummy variable equal to 1 when the household is in a rural area, zero otherwise.
city-level	Categorical variable	This is a categorical variable: first-tier city (=1), second-tier city (=2), and third-tier city (=3).
age	Continuous variable	Age of the respondent in years.
gender	Dummy variable	Gender of the respondent, equalling one if male and zero otherwise.
education	Scale variable	Education level of the respondent: no schooling at all (=1), primary school (=2), junior high (=3), high school (=4), technical secondary school (=5), junior college (=6), bachelor's degree (=7), master's degree (=8), doctorate (=9).
married	Dummy variable	Marital status of the respondent, equalling one if married and zero otherwise.
social insurance	Dummy variable	This is a dummy variable, equal to 1 if the household has any of the following social pension insurances: pension from government or public institution; basic pension insurance for urban employees; new social pension insurance for rural residents; social pension insurance for urban residents; social pension insurance for urban and rural residents, and zero otherwise.
health	Scale variable	Compared with peers, the condition of the head of household: very good (=1), good (=2), ordinary (=3), bad (=4), and very bad (=5).
digital payment	Dummy variable	This is a dummy variable, equalling one if the respondent's family had digital payment accounts and zero otherwise.
finance digital development	Continuous variable	The digital inclusive finance index at the province level in 2018.
Year	Dummy variable	Year of the survey, equalling one if the observation is taken from the 2019 survey and zero if taken from 2017.

bad"; most of their families had digital payment accounts, such as WeChat pay and Alipay. Last, the average score of the finance digital development index was 304.8.

To further show the differences in the adoption of e-business and other characteristics of business owners across different risk preferences, we split the sample into three risk treatment groups. Figure 2 shows the distribution of e-business adoption across

Table 2 Descriptive statistics of the variables used in the study

Variables	Mean	SD	Min	Max	Observations
Outcome *Y*					
Adoption of e-business	0.173	0.376	0.000	1.000	5301
Treatment *T*					5301
high-risk treatment	0.082	0.273	0.000	1.000	431
medium-risk treatment	0.191	0.392	0.000	1.000	1004
low-risk treatment (base)	0.727	0.444	0.000	1.000	3866
Covariate *X*					
total income (1,000 RMB)	135.669	422.664	0.365	12122.418	5301
taxpayer:					5301
small taxpayer (base)	0.192	0.394	0.000	1.000	1015
general taxpayer	0.312	0.316	0.000	1.000	595
Others	0.496	0.460	0.000	1.000	3691
rural	0.247	0.431	0.000	1.000	5301
city-level					5301
first-tier city (base)	0.269	0.369	0.000	1.000	1428
s-tier city	0.146	0.279	0.000	1.000	772
third-tier city	0.585	0.612	0.000	1.000	3101
age	49.63	12.948	19.000	90.000	5301
gender	0.526	0.499	0.000	1.000	5301
education	3.708	1.592	1.000	8.000	5301
married	0.930	0.255	0.000	1.000	5301
social insurance	0.706	0.452	0.000	1.000	5301
health status	2.419	0.918	1.000	5.000	5301
digital payment	0.864	0.343	0.000	1.000	5301
finance digital development	304.8	27.065	263.100	377.700	5301
year	0.732	0.786	0.000	1.000	5301

Note: for the categorical variables, those marked as base denoting the base category are excluded from the empirical analysis; the mean of dummy and categorical variables represents proportion. For example, the mean of 0.173 for the adoption of e-commerce represents 17.3% of business owners who adopted e-commerce

the three risk preference groups, where the high-risk group has the highest percentage of e-business adoption and the low-risk group has the lowest. Also, Fig. 2 illustrates significant differences between the groups of high-risk preference and low-risk preference (8%) and between the medium-risk and low-risk group (8.3%). Note that, the mean differences between the high- and low-risk group and between the medium- and low-risk group are found to be statistically significant, based on the *t*-test results shown in columns 6 and 7, Table 3. The difference in e-business adoption between the high- and medium-risk group seems to be relatively small (0.3%) and statistically insignificant (column 5 Table 3). A similar trend can be observed when comparing group means of the covariates across three treatment groups. That is, for most covariates, mean differences are found to be statistically significant between the groups of high- and low-risk and between the medium- and low-risk.

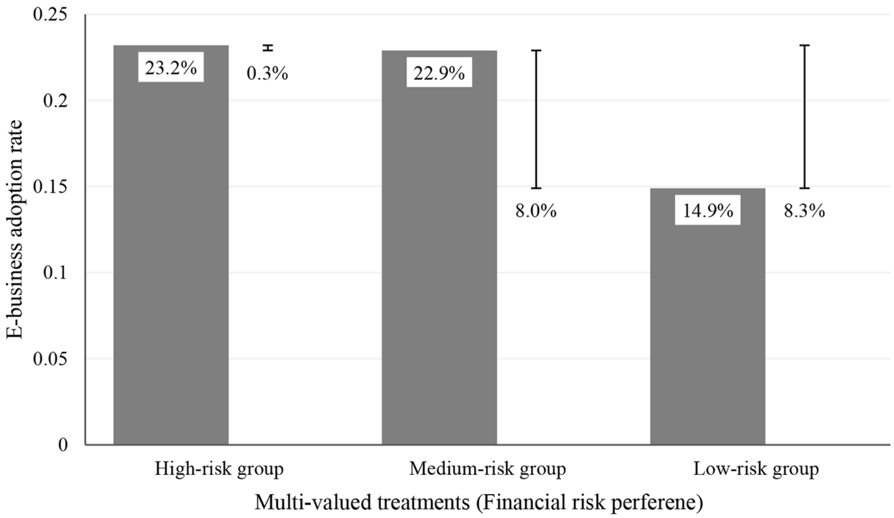

Fig. 2 Comparison of e-business adoption across three risk treatment groups
*The figure is created using Microsoft excel

4 Results and discussion

4.1 Results on the risk preference and social insurance on business owners' adoption of e-business

Table 4 reports the regression results based on Eq. (2) of the risk preference effect on business owners' adoption of e-business, with M1 representing the base model and M2 representing the model with social insurance and the interactions between the social insurance and treatment variables, and M0 is the simple model without covariates. For all three models (M0, M1, and M2), the estimated ATEs show that high and medium-risk individuals are more likely to adopt e-business than low-risk preferred ones. This finding is consistent with the existing studies on the exploration of the relationship between risk preference and technology adoption [34], [63] that risk-averse individuals are less willing to invest in new technologies [35]. Note that, the ATEs are estimated to be the highest for M0, compared to those of M1 and M2, indicating that the estimations may be inaccurate with no covariates included in the model. When having social insurance (column 6 Table 4), the low-risk preferred individuals are 1.11 times more likely to adopt e-business than those not having one; high- and medium-risk preferred individuals are less likely to adopt e-business when having social insurance with a factor of 0.887 and 0.872, respectively. These findings indicate that having social insurance reduces the differences between the high- and low-risk preferred business owners as well as the medium- and low-risk preferred owners regarding the likelihood of e-business adoption. In addition, the social insurance and social insurance*high risk treatment and social insurance*medium risk treatment interactions are found to be jointly significant at a 5% level, respectively. That is to say, having social insurance also influences e-business adoption for high-

Table 3 Comparison of the means of variables across risk treatment groups

Variable	Mean			Mean difference		
	High-risk group	Medium-risk group	Low-risk group	High vs. Medium	High vs. Low	Medium vs. Low
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome *Y*						
Adoption of e-business	0.232	0.229	0.149	0.003	0.083***	0.080***
Covariate *X*						
total income (1,000 RMB)	237.369	187.959	110.760	49.41	126.609***	77.199***
rural	0.168	0.170	0.275	-0.002	-0.107***	-0.105***
age	43.610	42.450	52.17	1.16	-8.560***	-9.720***
gender	0.613	0.522	0.517	0.091***	0.096***	0.005
education	4.689	4.472	3.400	0.217*	1.289***	1.072***
married	0.844	0.848	0.961	-0.004	-0.117***	-0.113***
social insurance	0.651	0.650	0.736	0.001	-0.085***	-0.086***
taxpayer						
small taxpayer 0.244	0.237	0.174	0.007	0.070***	0.063***	
general taxpayer 0.152	0.159	0.095	-0.007	0.057***	0.064***	
Others 0.603	0.604	0.731	-0.001	-0.128***	-0.127***	
health status	2.260	2.282	2.472	-0.022	-0.212***	-0.190***
city-level						
first-tier city (base)	0.087	0.236	0.677	-0.149	-0.590*	-0.441**
second-tier city	0.096	0.163	0.741	-0.067	-0.645**	-0.578***
third-tier city	0.075	0.163	0.762	-0.088	-0.687**	-0.599**
digital payment	0.968	0.948	0.831	0.020	0.137***	0.117***
finance digital development	306.4	304.5	304.000	2.400	1.900	0.500
year	0.079	0.221	0.700	-0.142	-0.621***	-0.479***

Note: ***p<0.01, **p<0.05, *p<0.1 for Welch two sample *t*-test of mean differences in two treatment groups

and medium-risk preferred business owners, albeit to a lesser extent than for low-risk preferred ones. A detailed calculation of the odds ratios for each of the two interacted groups (i.e., risk preferences and social insurance) can be found in the Appendix (Appendix Table 1). The above findings are consistent with the existing studies on individuals' risk tolerance in the adoption of digital technology, such as online banking and online shopping [59] – risk concerns about digital technology may prevent consumers from adopting e-commerce [21], [22]. However, social insurance has a negative moderation role in the relationship between risk preference and e-business adoption such that: (1) for low-risk preferred business owners, having social insurance increases their risk tolerance of investing in e-business [47], [59]; (2) social insurance is perceived to provide more certainty for low-risk preferred business owners than medium- and high-risk preferred ones, and hence increases the low-risk group's willingness to adopt e-business more than the other two groups; (3) social insurance may distort business owners' incentives in e-business investment for high- and medium-risk groups.

Except for household income, marital status, and health status, most of the covariates are found to impact business owners' adoption of e-business (note that the inter-

Table 4 Estimated results of the multi-valued treatment models of risk effect and impact of other factors on e-business adoption

	M0 (simple-model)		M1 (Base-model)		M2 (Social insurance interaction)	
	Odds Ratio	Standard error	Odds Ratio	Standard error	Odds Ratio	Standard error
(1)	(2)	(3)	(4)	(5)	(6)	(7)
ATE ($\hat{\lambda}_1$)	1.519***	0.052	1.390***	0.061	1.266***	0.017
ATE ($\hat{\lambda}_2$)	1.143*	0.029	1.128*	0.052	1.212*	0.051
social insurance	-	-	-	-	1.110**	0.003
$\hat{\lambda}_1$*social insurance	-	-	-	-	0.872*	0.103
$\hat{\lambda}_2$*social insurance	-	-	-	-	0.887*	0.136
total income (1,000 RMB)	-	-	1.000	0.0000002	1.000	0.0000001
general taxpayer	-	-	0.820**	0.096	0.812**	0.096
others	-	-	0.866	0.166	0.871	0.266
rural	-	-	0.427***	0.067	0.422***	0.067
s-tier city	-	-	0.966	0.036	0.989	0.044
third-tier city	-	-	0.886*	0.032	0.812**	0.096
age	-	-	0.990***	0.003	0.719***	0.108
gender	-	-	1.116**	0.056	1.119**	0.056
education	-	-	1.149***	0.019	1.143***	0.020
married	-	-	0.940	0.107	0.919	0.108
health status	-	-	1.009	0.032	1.007	0.032
digital payment	-	-	0.959	0.1	1.017***	0.001
finance digital development	-	-	1.006***	0.001	1.007***	0.001
year	-	-	1.012***	0.002	1.014***	0.003
intercept	-	-	0.031***	0.435	0.033***	0.441
Observations	5301		5301		5301	
Log Likelihood	-5976.238		-3978.021		-3856.916	
Akaike Inf. Crit.	9631.8		7729.6		7701.5	

Note: for ease of interpretation, we exponentiated the coefficient estimates of the binary logit models to derive the odds ratio, and standard errors are with the coefficient estimates; $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

pretations are based on M2). In particular, compared to small taxpayers, business owners who are general taxpayers are 0.812 times less likely to adopt e-business. This is consistent with studies on the comparison of small and large firms' adoption of e-commerce that small businesses show a more positive attitude toward e-commerce services than larger businesses - larger businesses only express willingness to adopt e-commerce in the area of improved operational efficiency [64]. Business owners living in rural areas are 0.422 times less likely to adopt e-business than those living in urban areas; individuals who belong to third-tier cities are 0.812 times less likely to adopt e-business than those living in first-tier cities. These findings echo the results of existing studies on the rural-urban digital divide in e-commerce adoption [65] and the uneven development of digital technologies across different regions in China [66]. In addition, business owners who are young, male, and have higher education levels tend to adopt e-business. Digital-related factors, such as individuals' use of digital payment and regional digital development, are found to affect business owners' e-business adoption. In particular, if the business owner has digital payment accounts, he/she is 1.017 times more likely to adopt online e-business; a higher level of regional digital development, in our case digital finance development at the province level, is found to be associated with a higher likelihood of e-business adoption. When looking at the year variable, business owners are more likely to adopt as time goes by.

4.2 Heterogeneity examination: rural versus urban

Given the significant difference in e-business adoption between the rural and urban business owners, we further split the data into a rural and urban sample to examine the heterogeneous effect of financial risk preference on business owners' adoption of e-business. The estimation results are shown in Table 5, with M3 and M4 representing the rural and urban model, respectively.

Table 5 Estimated results of the multi-valued treatment models of risk effect and impact of other factors on e-business adoption for the rural and urban sample

	M3 (Rural)		M4 (Urban)	
	Odds Ratio	Standard error	Odds Ratio	Standard error
(1)	(2)	(3)	(4)	(5)
ATE ($\hat{\lambda}_1$)	1.671**	0.192	1.362**	0.127
ATE ($\hat{\lambda}_2$)	1.346***	0.356	1.278*	0.113
social insurance	1.305**	0.114	1.129**	0.031
$\hat{\lambda}_1$*social insurance	0.635***	0.137	0.786**	0.105
$\hat{\lambda}_2$*social insurance	0.763***	0.042	0.892	0.153
total income (1,000 RMB)	1.000	0.000001	1.000	0.00002
general taxpayer	0.598**	0.244	0.772**	0.1303
others	0.917	0.108	0.983	0.080
s-tier city	1.103	0.193	0.998	0.152
third-tier city	0.733**	0.103	0.899***	0.040
age	0.999	0.006	0.988***	0.004
gender	0.734**	0.123	1.279***	0.064
education	1.688**	0.054	1.215***	0.022
married	0.445	0.616	0.860	0.116
health status	0.978	0.066	0.988	0.038
digital payment	1.694**	0.135	1.316*	0.148
finance digital development	1.010***	0.002	1.006***	0.001
year	1.023***	0.003	1.013***	0.002
intercept	0.021***	1.038	0.0247***	0.516
Observations	1310		3991	
Log Likelihood	-1256.521		-4032.675	
Akaike Inf. Crit.	3044.8		6971.52	

Note: for ease of interpretation, we exponentiated the coefficient estimates of the binary logit models to derive the odds ratio, and standard errors are with the coefficient estimates; $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

When social insurance is not in place, comparing the estimated ATEs ($\hat{\lambda}_1$ and $\hat{\lambda}_2$) between the two models, financial risk preference is found to have a higher impact on the adoption of e-business for business owners in rural areas than on those in urban areas. Specifically, business owners having medium- and high-risk preferences are 1.346 and 1.671 times more likely to adopt e-business than those with low-risk preferences in the rural area; whilst for those living in urban areas, the probability of adopting e-business is 1.278 and 1.362 times higher for medium- and high-risk preferred individuals than that of the low-risk group. These findings align with the results of Shi and Yan [67] that urban residents are more likely to participate in economic activities under uncertainty (e.g., investment in risky financial assets) than their rural peers. Besides a larger impact of risk preference on e-business adoption, the moderation effect of social insurance is found to be significantly larger on individuals in rural areas than on those in urban areas. Notably, low-risk preferred individuals having social insurance are 1.305 and 1.129 times more likely to adopt e-business than those not having one in rural and urban areas, respectively. In addition, having social insurance reduces the differences in the odds of adopting e-business between the high- and low-risk group for both the rural and urban respondents, but a greater impact of social insurance is found in the rural area than that in the urban area (with a factor of 0.635 versus 0.786). A similar trend can be observed between the medium- and low-risk groups, but the interaction term between social insurance and medium-risk treatment is not significant in the urban sample. A detailed calculation of the odds ratios for each of the two interacted groups (i.e., risk preferences and social insurance) can be found in the Appendix (Appendix Tables 2 and 3). As for other covariates, the values and significance levels of the estimated odds ratios show a similar trend as the estimation results shown in Table 4. One exception is gender, where female business owners are more likely to adopt e-business in rural areas. It is noted that digital development, such as the use of digital payment and provincial finance digital development, seems to have a greater impact on e-business adoption for business owners living in rural areas than for those in urban areas. This finding, again, echoes the unequal distribution of digital development between rural and urban China, where rural internet users only take up about 38% of the total internet users [68]. Thus, the development of digital transformation in rural areas may have a greater impact on rural residents' willingness to adopt e-business. The differences in the results of M3 and M4 confirm the heterogeneous effects of financial risk preference, social insurance, and digital development on the adoption of e-business in rural and urban China. These findings indicate that, due to the digital- and knowledge divide, low-risk preferred people in rural areas tend to be more conservative and have lower risk tolerance for new technologies, in our case e-business. Therefore, the existence of social insurance can provide more financial certainty and affordability for them to invest in e-business, compared to those living in cities [69].

5 Conclusion

This study provides evidence of how business owners' risk preferences affect their adoption of e-business using the data drawn from the 2017 and 2019 CHSF surveys. A multi-valued treatment model is used to capture selection bias in the decision-making process of business owners concerning the endogeneity of their financial risk preferences. Our results show that, compared to the low-risk preferred group, medium- and high-risk preferred business owners are more likely to adopt e-business, regardless of having or not having social insurance. In addition, social insurance is found to moderate the risk preference effect on e-business adoption: having social insurance may reduce the difference in the likelihood of e-business adoption between high- and low-risk groups and medium and low-risk groups. The heterogenous examination further reveals significant differences in the risk effect on e-business adoption between rural and urban entrepreneurial households; social insurance tends to affect rural business owners more than their urban peers. Results and findings of the study contribute to the literature on e-commerce adoption by filling the gap in understanding the impact of risk preference on e-business adoption from the perspective of business owners, given the existing studies mainly focus on "stories" from the consumer side. In addition, the moderation effect of social insurance on the relationship between risk preference and e-business adoption provides a potential mechanism for encouraging business owners, in particular those with low-risk preferences, to adopt e-business. Our results of the rural and urban differences in e-business adoption provide evidence of the rural-urban divide in digital development.

The study also provides several policy implications to promote the adoption of e-business. First, the "human" factors, in our case individuals' risk preferences, should be considered in understanding business owners' choice of e-business adoption. Hence, to encourage e-business adoption, policymakers may consider using supporting policies to alleviate business owners' risk concerns about e-business adoption. Second, given the role of social insurance in promoting the adoption of e-business, policymakers should design or utilise similar incentive channels to improve business owners' confidence in e-business adoption, especially for those with low-risk tolerance. Third, the clear rural-urban divide in e-business adoption requires the attention of policymakers. It is of great importance for policymakers to provide more support to businesses in rural areas by, for example, allocating recourses and offering training on e-commerce and e-business.

Note that, although the study tends to highlight the importance of risk factors in e-commerce adoption, there are other "human" factors, such as attitudes and awareness that are regarded to influence business owners' adoption of e-commerce. However, due to the availability of information about those "human" factors, we could not include those factors in the empirical analysis. We suggest future studies gather relevant information to test for both the risk preference effect and impacts of other cognitive factors in e-business adoption.

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