Internet Appendix to

"Financial Inclusion via FinTech: From Digital Payments to Platform Investments"

This appendix provides supplemental materials for the paper titled "Financial Inclusion via FinTech: From Digital Payments to Platform Investments." Section IA1 includes definitions of the variables used in the paper. Section IA2 outlines the development timeline of QRPay in the Shenzhen Transit Network. Section IA3 examines the relationship between consumption volatility and individual risk preference. Section IA4 includes other discussions and robustness tests on the impact of FinTech on risk-taking. Section 5 describes the survey design and summarizes basic facts from the survey.

Contents

IA1 Variable Definitions

FinTech Variables	
Log(QRPay)_t^i	The natural logarithm of the number of Alipay QR-Scan payments made by individual i in month t
Log(QRPay)_t^c	Equal-weighted average Log(QRPay)_t^i for all individuals residing in county c
County Log(QRPay)_t^i	Equal-weighted average Log(QRPay) of all individuals living in the same county as individual i, excluding the focal individual i herself
Peer Log(QRPay)_t^i	The predicted component of individual i's Log(QRPay) that can be explained by her county Log(QRPay)_t^i, estimated for each individual using the regression specification: Log(QRPay)_t^i=a+b*County Log(QRPay)_t^i $+\epsilon_t^i$. Peer Log(QRPay)_t^i is calculated as $\hat{b}^i$*County Log(QRPay)_t^i.
Idio Log(QRPay)_t^i	The part of individual i's Log(QRPay) that cannot be explained by Peer Log(QRPay)_t^i, calculated as Log(QRPay)_t^i - Peer Log(QRPay)_t^i
QRFrac_t^i	The fraction of consumption paid via Alipay QR-Scan out of total consumption paid via the entire Ant ecosystem for individual i in month t
QRFrac_t^c	QRFrac of county c is the equal-weighted average QRFrac for all individuals residing in the county.
Investment Variables	
Risky Purchase_t^i	Dummy variable that equals one if individual i purchases any risky mutual funds in month t, and zero otherwise
Risky Fraction_t^i	Fraction of risky fund purchase out of total fund purchase for individual i in month t. Risky Fraction equals zero if there is not any purchase.
Risky Redemption_t^i	Dummy variable that equals one if individual i redeems any risky mutual funds in month t, and zero otherwise
Risky Share_i	Fraction of risky fund purchase out of total fund purchase for individual i during our entire sample period
σ_{W}^i	Standard deviation of individual i's monthly portfolio return
$\text{Log(\#Funds)}_i$	Natural logarithm of the number of unique funds invested in by individual i
$\text{Log(\#Assets)}_i$	Natural logarithm of the number of unique asset classes invested in by individual i
Individual and County Characteristics Variables	
σ_{C}^i	Consumption growth volatility, calculated as the standard deviation of quarterly total consumption growth for individual i during our sample period. Total consumption includes all the consumption, both online and offline, paid via the entire Ant ecosystem.
Log(Age)_i	Natural logarithm of individual i's age in 2019 in years
Female_i	Dummy variable that equals one for female individuals
Log(C)_i	Natural logarithm of average monthly consumption via Ant e-commerce platform
Log(GDP)_c	Natural logarithm of county GDP in year 2016
Log(Income)_c	Natural logarithm of county average income per person in year 2016
Log(Population)_c	Natural logarithm of county population in year 2016
LowBank_c	Dummy variable that equals one if county c belongs to prefectures with below median bank coverage. Bank coverage is defined as number of bank branches in a prefecture.
$\text{LowParticipation}_c$	Dummy variable equal to one for counties with below-median participation rate in risky financial assets, estimated using 2017 CHFS data.
LowFraction_c	Dummy variable equal to one for counties where the average fraction of risky assets out of total financial assets is below the median, estimated using 2017 CHFS data.

IA2 QRPay Implementation in the Shenzhen Transit Network

The following outlines the timeline for the introduction of QRPay within Shenzhen's public transportation system.

Timeline:	Event
November 2016	The Shenzhen Municipal Government and Ant Financial Group signed a strategic cooperation agreement to develop Shenzhen into a role model for China's modern cities over a period of five years(https://www.sohu.com/a/118823283_119778).
March 2017	Shenzhen Tong began testing QR code payments on bus route B683, via Alipay. During the trial period, over 20,000 users activated the service, with nearly a hundred uses per day(https://www.mpaypass.com.cn/news/201703/28085727.html).
July 2017	Shenzhen joins the nationwide transportation card inter-connectivity network, and expanded QR code payments to bus routes 12, 17, and 213(https://m.bendibao.com/show795177.html).
July 2017	Passengers can access Shenzhen Tong via Wechat mini-programs(https://finance.china.com.cn/roll/20170720/4316730.shtml).
January 2018	All bus routes in Shenzhen allowed passengers to use the Shenzhen Tong QR code for payment(https://sz.chinadaily.com.cn/2018-01/19/content_35540550.htm).

IA3 Consumption Volatility and Individual Risk Preference

In this section, as motivated by financial theory, we examine the relation between consumption growth volatility and individual risk tolerance. For a mean-variance investor, as discussed in Markowitz (1952), Tobin (1958), or Merton's portfolio problem (Merton (1969, 1971)), the optimal portfolio weight w^* on risky asset is inversely proportional to the investor's risk-aversion coefficient γ:

$$w^* = \frac{\mu - r}{\gamma\, \sigma_R^2}\,, \tag{1}$$

where $\mu - r$ represents the risk premium of the risky asset, and σ_R represents its volatility. As solved by Merton (1971), the optimal portfolio weight w^* is linear in risk tolerance $1/\gamma$. Moreover, with the optimal consumption-to-wealth ratio being constant, consumption volatility σ_{C} equals portfolio volatility σ_{w}, and both are proportional to individual risk tolerance $(1/\gamma)$.[35]

With the micro-account level consumption and investment data from Ant, we are able to test whether the cross-sectional variation in σ_{C} indeed captures the cross-sectional variation in risk tolerance. We find empirical support for the effectiveness of σ_{C} as a reliable risk tolerance proxy. Firstly, in line with previous research (e.g., Ameriks et al. (2020), Calvet et al. (2021)), Table 5 shows that investors with higher consumption growth volatility exhibit higher risk preference, as indicated by their answers to the China Securities Regulatory Commission Survey. Secondly, our data reveals a positive relationship between consumption volatility and investors' realized risk-taking. To illustrate, we categorize individuals into 50 groups based on their consumption volatility and plot the average portfolio volatility for each group against the consumption volatility percentile in the upper panel of Internet Appendix Figure IA3. As indicated by the fitted lines, regressing portfolio volatility on the consumption volatility percentile across the 50 groups, the coefficient stands at 0.72 (t-stat=7.43) and the R-squared is 53%. In accordance with Mankiw and Zeldes (1991), our micro-level evidence suggests that consumption growth volatility effectively captures variations in risk tolerance

[35] While σ_{C} as a function of risk tolerance is exactly specified in the complete market setting of Merton, in a more general setting σ_{C} should still be an increasing function of risk tolerance. Specifically, consumption volatility serves as a measure of the sensitivity of state dependence of consumption, where the states could be outcomes of investments, endowments, labor and other factors. As long as the state dependence of consumption results from an individual's consumption choice (to maximize utility with available albeit incomplete financial instruments), then, even when markets are incomplete, more volatile consumption should correspond to higher risk tolerance.

across individuals.[36]

IA4 Other Discussions

In this section, we discuss the sample selection issues associated with the Ant data, the substitution of the Ant platform with traditional banking channels, the implications for the extensive margin of investment, and other robustness checks related to our baseline findings.

IA4.1 Sample Selection

Our main analyses are based on the Ant sample, which may not fully represent the entire Chinese population. To address this, we conduct additional analyses: (1) we weight the Ant sample to better match the demographic characteristics of the broader Chinese population, and (2) we examine the effect of digital payment adoption on risky asset investment using data from the China Household Finance Survey (CHFS).

The Ant sample tends to overrepresent younger individuals and females, with an average age of 30 and 61% female. To align the sample with the overall Chinese population, for whom risky asset investment is relevant, we apply a weighting scheme based on 2016 census data for individuals aged 20 to 60 in mainland China. We create weights for the Ant sample to match the population by age group, gender, and residential province, following the approach in Baker (2018). Panel A of Table IA1 compares the original and weighted Ant samples. After weighting, the average age is 37.99, and 49% of the sample is female—closer to the demographic profile of the broader population, where the average age is around 39 and the female fraction is 49%. This suggests the weighting is effective. Other characteristics, such as consumption level, QR-pay fraction, QR-pay frequency, are similar to the original sample. Panel B of Table IA1 reports the regression results using the weights. The economic magnitude and t-statistics remain consistent with the results in Table 2, supporting the robustness of our findings.

As an alternative test, we examine the effect of digital payment adoption on risky asset investment using the 2017 and 2019 waves of the China Household Finance Survey (CHFS), aligning the sample period with the Ant data. The sample is restricted to households present in both waves. Digital payment (DP) is a dummy variable indicating whether the household

[36] Our baseline measure of σ_C is based on total consumption (online and offline) via the Ant ecosystem. As a robustness check, we construct an alternative using only online consumption, which was already saturated during the sample period and excludes offline QRPay. Results remain qualitatively unchanged.

used digital payments in 2017. We analyze their risky asset investment in 2019, using two measures: *Risky Participation*, a dummy equal to 1 if the household invested in any risky asset in 2019, and *Risky Fraction*, the proportion of risky assets in the household's total investment portfolio. Risky assets include wealth management products, stocks, bonds, mutual funds, derivatives, gold, and foreign assets.

Table IA2 presents the relationship between digital payment adoption (DP) and household risky asset investment. We control for household-level characteristics such as total assets, consumption, liabilities, age, marital status, gender, education level, financial literacy, attention to economic and financial information, and risk preferences (for either the entire household or the household head). We also include county fixed effects in all specifications. Column (1) reports estimates of the effect of DP on households' decision to hold risky assets (Risky Participation), while Column (7) focuses on the proportion of total financial wealth allocated to risky assets (Risky Fraction). Across both specifications, the coefficient on the DP variable is positive and statistically significant, indicating that households adopting digital payment methods are more likely to participate in risky asset markets and allocate a greater share of their portfolios to these assets.

We further explore the heterogeneity of this result across households' education, financial literacy and risk preferences. In particular, we include interactions between DP and four measures: education (in years), financial literacy (the percentage of correct answers to financial knowledge questions in the survey), attention to economic and financial information (self-reported on a scale 1 to 5), and risk tolerance (0 for risk-averse, 1 for risk-neutral, and 2 for risk-seeking). In columns (2)-(5) and (8)-(11), we include the interaction between DP and each measure. We find a positive and significant interaction term for each specification. When we include all interactions in columns (6) and (12), we find that DP has a stronger impact for households with higher education and those who pay more attention to economic and financial information.

Taken together, the CHFS data broadly supports the Ant sample findings, showing that digital payment adoption promotes risky asset investment. Heterogeneity results also align with the financial inclusion interpretation, indicating that DP adoption enables risky investments for households with higher education and greater attentiveness to financial and economic information.

IA4.2 Substitution from Banks and Extensive Margin

Given that our data originates solely from the Ant Group, a legitimate concern is whether some investors might have transferred their existing mutual fund investments from banks to Alipay. This raises the question: does FinTech penetration genuinely lead to an increase in the extensive margin of risk-taking? While challenging to answer definitively, we address this issue from four perspectives:

First, our discussion in Section 4.2 suggests that the relationship between FinTech and risk-taking is unlikely to be primarily driven by the transfer of investments from banks. Mutual fund investments through banks typically depend on promotions by financial advisors at local bank branches. Therefore, residents of counties with fewer banks are less likely to have pre-existing investments in risky mutual funds through traditional financial institutions. Notably, we find a stronger effect of FinTech on individual risk-taking among those living in areas with fewer banks, indicating that FinTech is reaching individuals who are less likely to have prior banking relationships.

Second, we conduct a subsample analysis to examine how FinTech influences individuals based on whether their annual transfer-in amounts exceed or fall below the county's average per capita income. Individuals whose annual transfer-in amounts exceed the average income are less likely to have significant investment accounts elsewhere. Thus, their platform risk-taking is likely representative of their total risk-taking. We find that the effect of FinTech on risk-taking is present in both subsamples, as reported in Panel A of Table IA3. Specifically, a one standard deviation increase in Log(QRPay) during month t is associated with a roughly 2.6% increase in risky purchases in month $t+1$ for those with transfer amounts above the average income (t-stat=7.47), and a 2.2% increase for those below the average income (t-stat=7.46). This evidence suggests that the effect of FinTech penetration on risk-taking is not merely due to individuals switching their investments from banks to platforms, as even individuals without bank assets show an increase in their risk-taking.

Furthermore, our survey findings indicate that a significant portion of respondents initiated their mutual fund investments using Alipay.[37] Specifically, we asked in our survey: "Through which channel did you first purchase risky mutual fund products?" The responses revealed that 26% of participants made their initial purchases through Alipay. This indicates that one in four investors had no prior exposure to risky asset investments before using

[37]Please refer to the survey details in the Internet Appendix IA5.

Alipay, marking their first venture into risky fund investments through this platform.

Finally, at the aggregate level, we observe a concurrent increase in the value of mutual fund holdings and the number of mutual fund investors alongside the growth of FinTech penetration. The total net assets of non-money-market mutual funds rose from 4.6 billion RMB at the end of 2016 to 7.2 billion RMB at the end of 2019. The total number of effective mutual fund accounts increased from 265 million at the end of 2016 to 793 million at the end of 2019.[38] This trend aligns with our hypothesis that the integration of FinTech facilitates a widespread increase in participation in risky asset investments across the nation. When examining total mutual fund sales across different distribution channels, including banks, brokers, and third-party platforms, we find that, over our sample period, mutual fund purchases increased across all channels.[39] We further examine the monthly active users (MAU) growth of three categories: traditional channels, pure-play investment apps, and WeChat's BigTech super app. The MAU for the five largest banks in China shows a general increase, while Tiantian and Howbuy, pure-play investment apps, also saw positive but moderate growth. WeChat's wealth management platform showed limited activity in risky mutual fund investments. Overall, the growth in MAU for traditional banks and pure-play apps suggests that the expansion of risky mutual fund investments on Ant's platform was likely incremental, not at the expense of other channels.

In summary, the evidence from these four perspectives suggests an increase in risky asset participation at the extensive margin, driven by the frequent use of digital payments.

IA4.3 Access to Credit Provision

Ouyang (2021) and Bian, Cong, and Ji (2023) demonstrate that digital payments can potentially ease users' credit constraints by facilitating credit access for individuals in need. Would the frequent use of payment services encourage households to borrow from platforms and utilize the credit provided for investment purposes? This is unlikely to be the case. Firstly, Ant's credit service, Huabei, cannot be directly utilized for mutual fund investments. Additionally, mutual fund investments typically entail long-term commitments and possess a lower speculative nature compared to stocks. Furthermore, Huabei imposes an annual interest rate of approximately 14% (equivalent to a daily rate of 0.05%), while the average

[38]These numbers include both money market fund and risky mutual fund investors.

[39]One limitation of the total sales across different distribution channels is that the data includes both money market funds and non-money market funds.

annual returns for bond, equity, and mixed funds between 2010 and 2020 stand at 4.5%, 7.6%, and 9.3%, respectively. These factors make it improbable for users to leverage Huabei's credit for investment in mutual funds.

To further rule out the possibility that our findings are influenced by Huabei's credit provision, we examine the cross-sectional heterogeneity based on whether individuals have access to traditional bank credit. Individuals with access to credit cards through traditional banking channels are expected to be less influenced by the supplementary credit access provided by Alipay. Panel B of Internet Appendix Table IA3 reports the subsample results for individuals with and without credit cards. We find that the positive impact of digital payment on investment is statistically and economically significant for both groups. A one-standard-deviation increase in Log(QRPay) leads to a 1.66% increase in risky asset purchases for users with credit cards. Consequently, the enhancement of credit accessibility through FinTech is unlikely to be the primary driver of the effect of FinTech adoption.

IA4.4 Alternative Measure of FinTech Penetration

Our primary measure of FinTech adoption is the natural logarithm of the number of Alipay QR-Scan payments made by each individual each month. A potential concern is that high-income individuals, who generally consume more, might also use mobile payments more frequently. To address this issue, we also calculate QRFrac, which represents the fraction of Alipay QR-Scan consumption relative to total Alipay and Taobao consumption for each user. This serves as an alternative measure of FinTech adoption. We replicate our analyses using this alternative measure, maintaining the same regression settings as detailed in Section 3.

Panel B of Internet Appendix Table IA4 presents the baseline results based on the specification in Panel A of Table 2. Consistently, we find that a higher level of FinTech adoption in month t is linked to increased risk-taking in month $t+1$ across all model specifications. Specifically, a one standard deviation increase in month-t QRFrac predicts a 1.63% (t-stat = 8.69) increase in the probability of making a risky purchase and a 1.53% (t-stat=8.65) increase in the risky fraction in month $t+1$. In summary, the effect of FinTech penetration and adoption on investors' risk-taking behavior remains robust when using this alternative measure.

IA4.5 Other Robustness Tests

In our research, we conduct additional analyses to assess the robustness of our baseline findings regarding the relationship between FinTech penetration and individual risk-taking behaviors.

Firstly, our main analysis focuses on the behavior of individuals purchasing risky mutual funds. However, there's a possibility that investors are actively redeeming existing funds to acquire new ones, which could inflate our measure of risky purchases without actually increasing their holdings of risky assets. To address this, Internet Appendix Table IA5 presents the baseline results using redemption and net purchase as dependent variables. In the specification that includes time and user fixed effects, a one standard deviation increase in Log(QRPay) results in only a 0.35% rise in redemptions. Conversely, the effect on risky purchases is 2.72% in the same specification. As a result, a one-standard-deviation increase in FinTech adoption leads to a 1.22% increase in the probability of a net purchase of risky mutual funds in the following month.

Secondly, there might be concerns that our results are influenced by the economic conditions of the cities where individuals reside. In all our county-level analyses, we control for county-level Log(GDP), Log(Income), Log(Population), and their squared terms. Furthermore, we allow local economic conditions to have a time-varying impact on individual risk-taking by incorporating province×time and city×time fixed effects into our baseline specification. Panel A of Internet Appendix Table IA4 demonstrates that our results remain consistent both quantitatively and qualitatively. Specifically, a one standard deviation increase in Log(QRPay) leads to a 1.41% increase in risky purchases when province×time fixed effects are included, and a 1.42% increase when city×time fixed effects are included.

Finally, we explore whether QRPay technology also promotes the adoption of other financial services by examining the uptake of the Dingtou service. The Dingtou service, available through the Ant Platform, is an automated investment tool that enables users to make regular investments in mutual funds using a dollar-cost averaging strategy, thus facilitating wealth accumulation with ease and convenience. Internet Appendix Table IA6 indicates that QRPay penetration encourages the use of the Dingtou service. In our analysis, we create a dummy variable, Dingtou, which equals one if an individual uses the Dingtou function to purchase any risky funds in month $t + 1$, and zero otherwise. Similarly, Dingtou Fraction represents the proportion of risky fund purchases made via Dingtou relative to total purchases in month $t+1$. We apply the same baseline specification as in Table 2 to examine the contagion effect from QRPay to Dingtou.

Our findings reveal that a one standard deviation increase in month-t Log(QRPay) predicts a 1.38% increase in the probability of using the Dingtou service. When we further decompose Log(QRPay) into peer-driven (Peer Log(QRPay)) and idiosyncratic (Idio Log(QRPay)) FinTech adoption, we find consistent evidence that peer-driven FinTech penetration significantly influences individuals' adoption of the Dingtou service. Specifically, a one standard deviation increase in Peer Log(QRPay) and Idio Log(QRPay) results in 1.77% (t-stat=7.73) and 0.40% (t-stat=4.39) increases in the probability of Dingtou usage, respectively. Overall, the evidence suggests that the synergistic bundling effect of the super app extends beyond risky mutual fund purchases and facilitates the adoption of other financial services as well.

IA5 Survey of Mutual Fund Investment

In this section, we first discuss the survey design, the procedure for survey distribution and data collection. Then, we summarize some basic facts from the survey.

IA5.1 Survey Design and Data Collection

We administer the survey through a professional survey company. The survey took place in July 2022, with participants recruited via their online portal on a voluntary basis. Respondents had the option to complete the questionnaire on either a computer or a mobile device. The survey consists of three main sections. The first section focuses on participants' basic information, such as gender, age, education, income level, and their attitude towards investment risk. The second section delves into investment details, including types of financial investments and the total amount invested in mutual funds. The third section explores participants' requirements and preferences regarding mutual fund platform choices.

We collect an initial sample of 1,226 respondents. We exclude a few clusters of suspicious respondents who completed the survey almost simultaneously and provided identical answers to all questions. Since our objective is to understand investors' need for investment services, we focus on respondents who have a positive amount of total investment, and remove the responses in which the total investment amount is zero. To confirm the seriousness of their participation, we require participants to list one stock or mutual fund they currently hold.

Responses like "I don't know," "none," or blanks are eliminated from the sample. Consequently, these responses were removed in our subsequent analysis, resulting in a final sample size of 926.

IA5.2 Survey Results

Internet Appendix Table IA8 reports a detailed summary of the sample's demographic characteristics. The sample is highly educated and has high financial literacy: more than 75% of the respondents have a college or higher degree, and about 39% of the respondents have a major in economics, finance, management or international trade. Respondents are primarily middle-aged: over 70% of the sample are between ages 26 and 40. The median annual income is around between 60,000 and 120,000 RMB, and the median household net financial investment amount worth is between 50,000 and 100,000 RMB. In terms of risk tolerance level, about 67% of the respondents are willing to take a moderate level of risk and expect a stable return, and 44% of them will exhibit anxiety after a loss of 10–30%. In general, our sample comprises well-educated, financially literate individuals with moderate to high incomes, capable of tolerating moderate levels of risk. It does not reflect the typical average individual or household in China. Instead, the sample better represents the growing middle class in China, who are the ideal customer base for investment services.

To understand how these individuals initiated mutual fund purchases, we explicitly pose the following question: "Through which channel did you first purchase risky mutual fund products". Alipay accounts for 26% of the respondents. In other words, one in four of these investors had no previous experience with risky asset investments before using Alipay and started their first risky fund investment through this platform.

Our survey respondents tend to include more males, individuals with higher levels of education, and those with greater mutual fund investments. To evaluate the impact of this potential sampling bias, we analyze how the proportion of first-time mutual fund investors through Alipay varies across different demographic groups. Interestingly, we find that this proportion is significantly higher among participants with *lower education*, *lower income*, and *smaller investment amounts*: (a) Among those with a junior college education or below, 31% make their first mutual fund investment through Alipay, compared to only 18% among those with a doctoral degree. (b) Among respondents with less than 50,000 RMB in mutual fund investments, 39% start through Alipay, while this figure drops to 14% for those with over 1 million RMB. (c) Among participants earning less than 3,000 RMB per month, 47%

start through Alipay, whereas none of the respondents earning over 50,000 RMB per month do. Furthermore, while female respondents exhibit a slightly lower Alipay usage rate (21.9%) compared to the full sample average (25.6%), the difference is small.

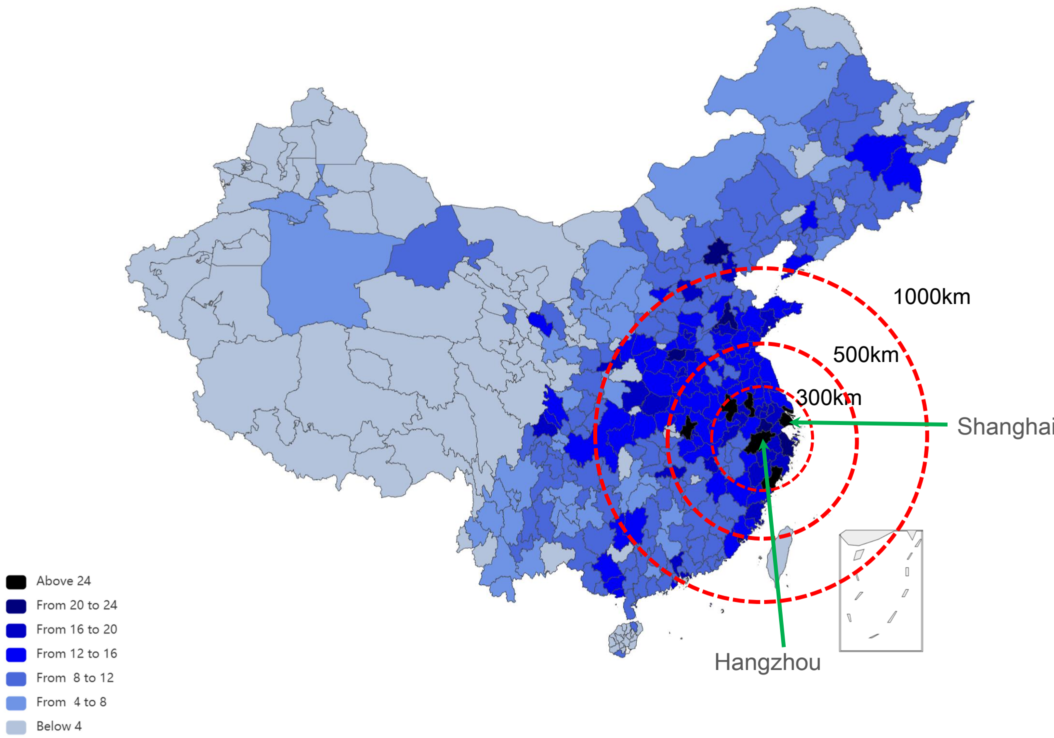
To enhance the representativeness of these findings, we apply similar weighting adjustments as described in Appendix Section IA4.1. The weighted estimates are 24.9% for the general population and 26.4% for the Ant sample, respectively, closely aligning with the unweighted figure. Overall, the survey evidence suggests that Alipay plays a significant role in onboarding new investors, particularly those with lower income, wealth, and education levels.

We further ask two questions related to the necessity and preference for a mutual investment platform. The first question is: "Which of the following characteristics is the primary reason for your choice of purchasing mutual funds through different platforms?" Among the 926 valid respondents who had invested a positive amount in mutual funds, the most popular responses were: "Availability of additional platform functions, such as payment, etc." (37.7%), "User-friendliness of the platform" (21.1%), and "Ease of accessing fund-related information" (16.7%). Other choices, including "Fund security," "Fees," "Fund variety," and "other factors," each constitutes a proportion of less than 10%.

The second question is: "If you have ever purchased mutual funds through the Alipay platform, what are the top three reasons for choosing this channel?" Among the 902 respondents who had used Alipay for mutual fund investment, the most cited reasons are: "Ease of managing investments, payments, and consumption all in one app" (52.4%), "Convenient access to information" (41.8%), "User-friendly platform interface" (49.0%), and "Trust in Alipay's safety and the safety of investment funds" (38.0%). In comparison, other factors such as "A wide range of mutual fund choices" and "Discounted fees" accounted for only 18.9% and 24.7%, respectively.

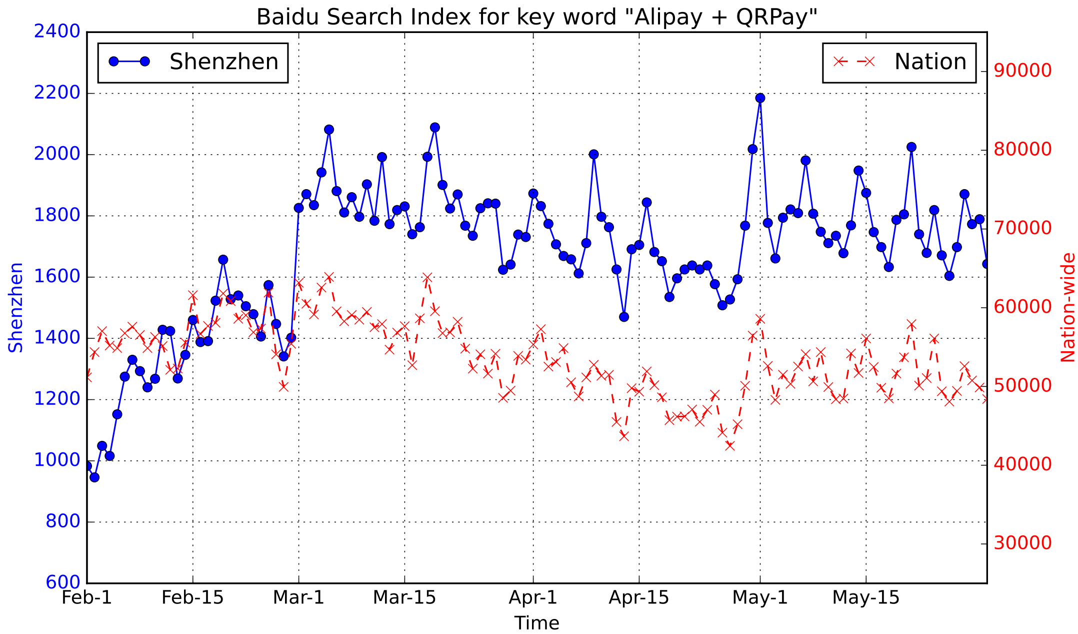
Taken together, the results from both questions suggest that non-monetary transaction costs have a greater influence than monetary costs when investors choose investment platforms.

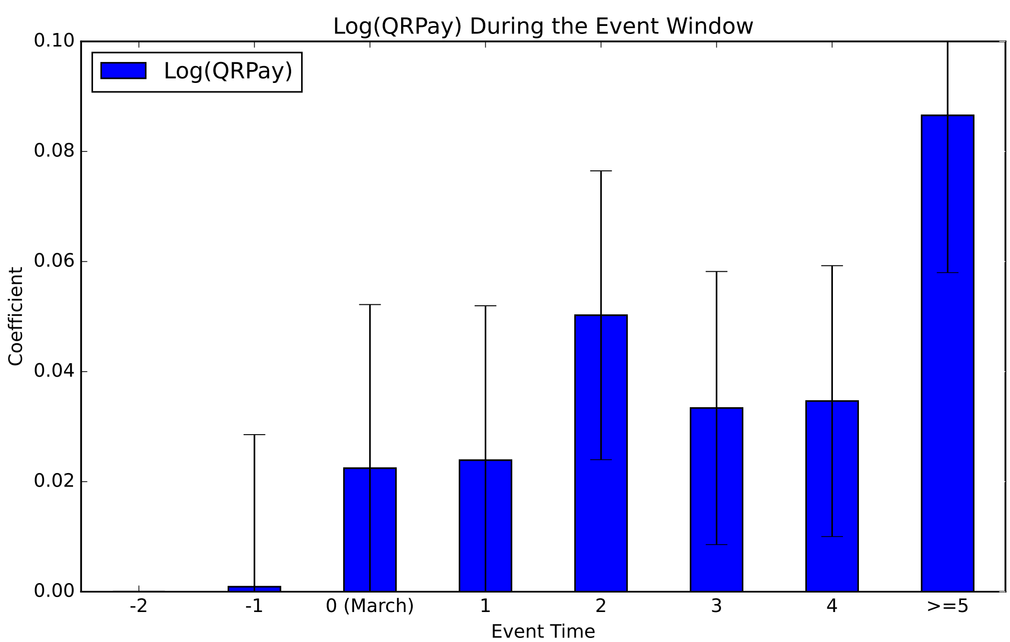
Figure IA1: **FinTech Penetration: Distance from Ant Headquarters**



This figure shows the geographic distribution of prefecture-level average FinTech penetration for the sample period from 2017Q1 to 2019Q1. Prefecture FinTech penetration is calculated as the average QRPay for individuals in a given prefecture during our sample. Centering around the headquarters of Ant in Hangzhou, regions within the 300, 500, 1000 kilometer radius from Ant are indicated using red dotted circles. The locations of Hangzhou and Shanghai are indicated by arrows.

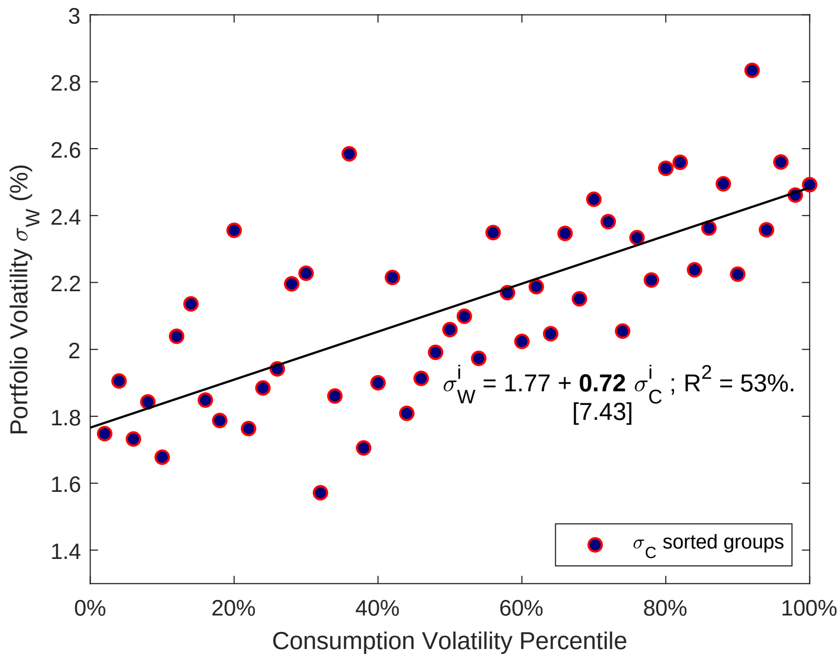
Figure IA2: **FinTech Penetration via Shenzhen Transit Network**



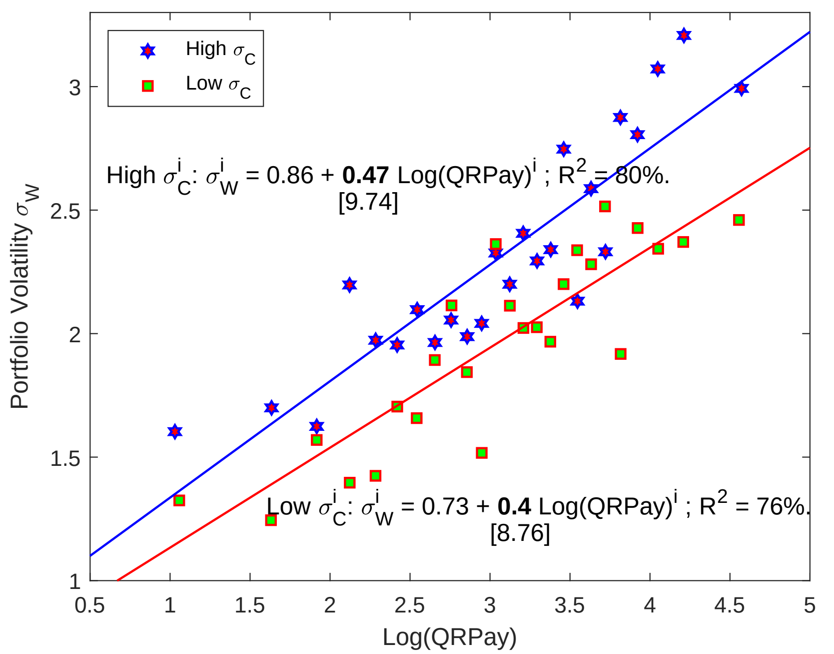


The upper graph illustrates the Baidu search index for the keywords "Alipay + QRPay." The blue solid line represents the search index for individuals in Shenzhen, while the red dotted line depicts the nationwide search index. The lower graph shows the change in Log(QRPay) relative to its value in month $t = -2$. This change is estimated using a specification similar to that in column (2) of Table 4, with the dependent variable replaced by Log(QRPay). Specifically, we regress Log(QRPay) on the *SZ* dummy and its interactions with event time dummies ($D(t = x)$), while controlling for individual characteristics and time fixed effects. The graph displays the coefficients of these interaction terms.

Figure IA3: **FinTech Adoption and Risk-Taking by σ_{C} Groups**



A: **Portfolio Volatility vs. Consumption Volatility**



B: **Portfolio Volatility vs. QRPay: By σ_{C} Groups**

In Panel A, we classify all individuals into 50 equal groups based on their consumption growth volatility (σ_{C}). We then plot the equal-weighted average of individual portfolio volatility against the percentile of σ_{C}. In Panel B, we sort all individuals into 2*25 groups based on their σ_{C} and Log(QRPay) independently. We then report the relation between the average portfolio volatility and average Log(QRPay) for the high and low σ_{C} groups, respectively.

Table IA1: **Individual FinTech Adoption and Risky Asset Investment with Population Weights**

Panel A compares the descriptive statistics of the original Ant sample with those of the Ant sample reweighted to population weights. We follow a method similar to Baker (2018) to weight the sample and conduct corresponding analyses. In particular, users in the Ant sample are weighted on three characteristics (age category, gender, and residential province) in order to match the observed distribution of individuals in China. We restrict the overall distribution to the individuals aged 20 to 60 in mainland China and obtain the corresponding population counts for each category in 2016 in the census data from the Chinese National Bureau of Statistic. Panel B reports the panel regression estimates of individual FinTech adoption on an individual's next-month risky fund investment, using weighted regression. The regressions are weighted by the individual's frequency in the population. Risky Purchase is a dummy variable that equals one if the individual purchases any risky fund in month $t+1$, and zero otherwise. Risky Fraction is the fraction of risky fund purchases out of total purchases in month $t+1$. See Appendix IA1 for variable definitions.

Panel A. Descriptive Statistics

	Unweighted					Weighted				
Variable	Mean	Median	Q1	Q3	STD	Mean	Median	Q1	Q3	STD
Age	30.35	29.00	24.00	35.00	7.82	37.99	38.00	29.00	46.00	10.26
Female	0.61	1.00	0.00	1.00	0.49	0.49	0.00	0.00	1.00	0.50
Consumption	2,155	1,259	743	2,235	17,064	2,284	1,256	733	2,254	27,518
QRPay	21.40	15.70	7.88	29.11	19.22	22.54	16.70	8.67	30.26	21.19
QRFrac	0.54	0.56	0.38	0.71	0.22	0.50	0.52	0.32	0.69	0.24

Panel B. Individual FinTech Adoption and Risky Fund Purchase (Weighted)

	Y=Risky Purchase$_{t+1}$				Y=Risky Fraction$_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(QRPay)	2.766***	2.256***	2.671***	1.432***	2.624***	2.146***	2.536***	1.374***
	(7.65)	(7.86)	(6.36)	(6.10)	(7.66)	(8.00)	(6.24)	(6.16)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
User FE	N	N	Y	Y	N	N	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y
Observations	1,224,470	1,224,470	1,224,470	1,224,470	1,224,470	1,224,470	1,224,470	1,224,470
R-squared	0.013	0.021	0.327	0.336	0.012	0.021	0.321	0.33
Within Group R2	0.0127	0.0086	0.00679	0.00138	0.0122	0.00835	0.00637	0.00132

Table IA2: **Digital Payment Adoption and Risky Asset Investment: Evidence from CHFS Data**

This table presents the effect of online payment adoption on household's risky asset investment, using data from the Chinese Household Finance Survey (CHFS). The household sample is restricted to the household in both the 2017 and 2019 wave of the survey. Risky participation is a dummy variable equal to 1 if the household invested in any risky asset in 2019 and 0 otherwise. Risky fraction represents the proportion of risky assets in the household's total investment portfolio in 2019. Here, risky assets includes wealth management product, stock, bond, mutual fund, derivatives, gold and foreign asset. The key independent variable, digital payment (DP), is a dummy variable indicating whether the household used digital payments in 2017. Control variables include household characteristics such as total assets, consumption, liabilities, age, marital status, gender, education level (in years), financial literacy, attention to economic and financial information, and risk preferences (for either the entire household or household head). In columns (2) to (6) and (8) to (12), we incorporate interaction terms involving the household head's education level, financial literacy, attention to economic and financial information, and risk preferences as indicated. The regression includes county fixed effects, and standard errors are clustered at the county level.

	Risky Participation						Risky Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Digital Payment (DP)	0.056***	0.027***	0.048***	-0.058***	0.038***	-0.063***	0.014***	0.005	0.011***	-0.026***	0.008*	-0.027***
	(7.52)	(4.03)	(6.41)	(-3.84)	(4.42)	(-4.18)	(3.49)	(1.41)	(2.95)	(-4.18)	(1.76)	(-4.49)
DP*Education		0.068***				0.054***		0.020***				0.015***
		(8.13)				(6.32)		(5.60)				(4.32)
DP*Financial Literacy			0.026***			0.009			0.008**			0.003
			(3.74)			(1.33)			(2.34)			(0.87)
DP*Attention				0.051***		0.038***				0.018***		0.014***
				(8.13)		(5.77)				(6.02)		(4.64)
DP*Risk Preference					0.038***	0.014					0.012**	0.004
					(4.26)	(1.50)					(2.53)	(0.77)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	14,312	14,312	14,312	14,312	14,312	14,312	14,312	14,312	14,312	14,312	14,312	14,312
R-squared	0.257	0.264	0.258	0.263	0.258	0.267	0.199	0.202	0.199	0.202	0.199	0.204
Within-group R2	0.089	0.098	0.091	0.097	0.091	0.102	0.055	0.058	0.056	0.059	0.056	0.061

Table IA3: **FinTech Adoption and Risky Investment, Subsample Analysis**

Panel A conducts a subsample analysis based on whether an individual's annual transfer amounts into Alipay are above or below the county-level average income per capita. Panel B examines the impact of FinTech adoption, conditional on investors' access to credit cards. The sample is divided into two groups: individuals with credit card access linked to their Alipay accounts and those without. We follow the same specification as in Table 2. Log(QRPay) is the natural logarithm of the number of Alipay QR-Scan payments in month t. The dependent variable is Risky Fraction, which is the proportion of risky fund purchases relative to total purchases. The control variables include Log(Age), Female, Log(C), and σ_C, along with time and user fixed effects as specified. The sample period spans from January 2017 to March 2019. The standard errors are double-clustered at both the time and user levels. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. See Appendix IA1 for variable definitions.

Panel A. Conditional on Inflow and Income

	Inflow>Income				Inflow<=Income			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(QRPay)	2.621***	2.125***	2.551***	1.373***	2.215***	1.736***	2.403***	1.302***
	(7.47)	(7.98)	(5.91)	(6.25)	(7.46)	(7.48)	(5.85)	(6.17)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
User FE	N	N	Y	Y	N	N	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y
Observations	944,970	944,970	944,970	944,970	355,030	355,030	355,030	355,030
R-squared	1.10%	2.10%	28.80%	29.80%	0.90%	2.00%	24.20%	25.30%
Within-group R2	1.11%	0.80%	0.50%	0.11%	0.93%	0.60%	0.56%	0.13%

Panel B. Conditional on Credit Card Access

	With Credit Card				Without Credit Card			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(QRPay)	2.865***	2.429***	2.797***	1.660***	2.281***	1.746***	2.379***	1.207***
	(7.51)	(7.98)	(5.73)	(6.38)	(7.25)	(7.38)	(5.99)	(6.08)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
User FE	N	N	Y	Y	N	N	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y
Observations	470,314	470,314	470,314	470,314	829,686	829,686	829,686	829,686
R-squared	1.0%	1.9%	33.8%	34.7%	1.0%	2.0%	23.2%	24.3%
Within-group R2	1.03%	0.76%	0.51%	0.14%	0.98%	0.64%	0.52%	0.10%

Table IA4: **Alternative Specifications and Alternative Measures**

Panel A presents the robustness test for the baseline specification reported in Table 2. In columns (1) and (2), we incorporate province-by-time fixed effects. Columns (3) and (4) include city-by-time fixed effects. Additionally, columns (5) and (6) provide a subsample analysis for individuals residing within a 300 km radius of the Ant headquarters. Panel B examines the effect of FinTech on individual risk-taking using an alternative measure of FinTech penetration. FinTech penetration is measured by QRFrac, which is calculated for each individual on a monthly basis as the proportion of consumption paid via Alipay relative to the total consumption paid through both Alipay and Taobao. Refer to Appendix IA1 for detailed variable definitions. Statistical significance is indicated by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

Panel A. Alternative Specifications

	Province*Time FE		City*Time FE		Distance to Ant<=300 KM	
	Risky Purchase	Risky Fraction	Risky Purchase	Risky Fraction	Risky Purchase	Risky Fraction
	(1)	(2)	(3)	(4)	(5)	(6)
Log(QRPay)	1.406***	1.350***	1.419***	1.361***	1.331***	1.269***
	(6.31)	(6.39)	(6.32)	(6.40)	(5.46)	(5.41)
Controls	Y	Y	Y	Y	Y	Y
User FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	1,300,000	1,300,000	1,299,844	1,299,844	344,344	344,344
R-squared	29.50%	28.90%	29.90%	29.30%	31.80%	31.20%
Within-group R2	0.11%	0.11%	0.12%	0.11%	0.08%	0.07%

Panel B. QRPay Fraction as an Alternative Measure

	Y=Risky Purchase$_{t+1}$				Y=Risky Fraction$_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
QRFrac	1.625***	1.244***	0.943***	0.289***	1.531***	1.176***	0.885***	0.275
	(8.69)	(9.54)	(4.84)	(4.00)	(8.65)	(9.63)	(4.75)	(3.95)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
User FE	N	N	Y	Y	N	N	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y
Observations	1,300,000	1,300,000	1,300,000	1,300,000	1,300,000	1,300,000	1,300,000	1,300,000
R-squared	0.7%	1.9%	28.1%	29.4%	0.6%	1.8%	27.5%	28.7%
Within-group R2	0.7%	0.5%	0.1%	0.0%	0.6%	0.5%	0.1%	0.0%

Table IA5: **Redemption and Net Purchase**

The table reports the panel regression estimates of individual FinTech adoption on an individual's next-month risky fund redemption and net purchase of risky fund. Risky Redemption is a dummy variable that equals one if the individual redeems any risky fund in month $t+1$, and zero otherwise. Net purchase is a dummy variable that equals one if the purchase amount is higher than the redemption amount in month $t+1$, and zero otherwise. We follow the same specification as in Table 2. Log(QRPay) is the natural logarithm of the number of Alipay QR-Scan payments in month t. We control for individual characteristics, including Log(Age), Female, Log(C), and σ_C. All independent variables are standardized with a mean of zero and a standard deviation of one. We include time fixed effect and user fixed effect as indicated. The sample period is from January 2017 to March 2019. Standard errors are double clustered at the user and time levels. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. See Appendix IA1 for variable definitions.

Panel A. Individual FinTech Adoption

	Risky Redemption$_{t+1}$				Net Purchase$_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(QRPay)	0.479***	0.528***	0.370***	0.352***	2.444***	1.969***	2.459***	1.219***
	(8.90)	(8.13)	(5.92)	(7.31)	(7.49)	(7.43)	(6.05)	(6.06)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
User FE	N	N	Y	Y	N	N	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y
Observations	1,300,000	1,299,844	1,300,000	1,299,844	1,300,000	1,299,844	1,300,000	1,299,844
R-squared	0.3%	1.1%	13.3%	14.0%	1.1%	2.8%	26.4%	27.9%
Within-group R2	0.30%	0.29%	0.04%	0.03%	1.07%	0.68%	0.50%	0.09%

Panel B. Peer-driven vs. Idiosyncratic FinTech Adoption

	Risky Redemption$_{t+1}$				Net Purchase$_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Log(QRPay)	0.569***	0.687***	0.523***	0.692***	3.061***	2.634***	4.535***	2.505***
	(9.25)	(8.66)	(4.17)	(8.12)	(7.86)	(7.78)	(5.78)	(5.79)
Idio Log(QRPay)	0.255***	0.259***	0.256***	0.259***	0.900***	0.847***	0.913***	0.866***
	(5.29)	(5.21)	(5.83)	(5.79)	(4.77)	(4.84)	(4.78)	(5.05)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
User FE	N	N	Y	Y	N	N	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y
Observations	1,299,844	1,299,844	1,299,844	1,299,844	1,299,844	1,299,844	1,299,844	1,299,844
R-squared	0.3%	1.1%	13.3%	14.0%	1.2%	2.8%	26.6%	28.0%
Within-group R2	0.3%	0.3%	0.0%	0.0%	1.2%	0.8%	0.8%	0.1%

Table IA6: **Individual FinTech Adoption and Engagement with Dingtou Function**

The table reports the panel regression estimates of individual FinTech adoption on an individual's next-month usage of Dingtou Service. Dingtou is a dummy variable that equals one if the individual uses Dingtou function to purchase any risky funds in month $t+1$, and zero otherwise. Dingtou Fraction is the fraction of risky fund purchases via Dingtou out of total purchases in month $t+1$. In Panel A, Log(QRPay) is the natural logarithm of the number of Alipay QR-Scan payments in month t. In Panel B, we decompose Log(QRPay) into peer-driven and idiosyncratic-driven components by estimating the following regression for each individual i: $\text{Log(QRPay)}_t^i = a^i + b^i * \textit{Peer Log(QRPay)}_t^i + \epsilon_t^i$. *Peer Log(QRPay)* is the predicted component of individual i's Log(QRPay) that can be explained by her County Log(QRPay) ($= \hat{b}^i *\text{County Log(QRPay)}_t^i$). *Idio Log(QRPay)* is calculated as Log(QRPay) minus *Peer Log(QRPay)*. We control for individual characteristics, including Log(Age), Female, Log(C), and σ_C. All independent variables are standardized with a mean of zero and a standard deviation of one. We include time fixed effect and user fixed effect as indicated. The sample period is from January 2017 to March 2019. Standard errors are double clustered at the user and time levels. We report both whole-sample and within-group R-squared. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. See Appendix IA1 for variable definitions.

Panel A. Individual FinTech Adoption and Dingtou Purchase

	Y=Dingtou$_{t+1}$				Y=Dingtou Fraction$_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(QRPay)	1.381***	1.275***	0.968***	0.563***	1.114***	1.033***	0.778***	0.465***
	(7.60)	(10.08)	(4.43)	(6.64)	(6.91)	(9.52)	(3.84)	(6.16)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
User FE	N	N	Y	Y	N	N	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y
Observations	1,300,000	1,300,000	1,300,000	1,300,000	1,300,000	1,300,000	1,300,000	1,300,000
R-squared	1.1%	1.5%	46.6%	47.0%	1.0%	1.3%	44.7%	45.1%
Within-group R2	1.1%	1.0%	0.2%	0.0%	1.0%	0.9%	0.2%	0.0%

Panel B. Peer-driven vs. Idiosyncratic FinTech Adoption

	Y=Dingtou$_{t+1}$				Y=Dingtou Fraction$_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Log(QRPay)	1.771***	1.694***	1.695***	1.071***	1.432***	1.379***	1.375***	0.938***
	(7.73)	(10.69)	(3.74)	(5.92)	(6.95)	(9.96)	(3.19)	(5.69)
Idio Log(QRPay)	0.404***	0.394***	0.426***	0.409***	0.315***	0.308***	0.334***	0.321***
	(4.39)	(4.51)	(4.89)	(4.91)	(4.04)	(4.13)	(4.40)	(4.43)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
User FE	N	N	Y	Y	N	N	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y
Observations	1,299,844	1,299,844	1,299,844	1,299,844	1,299,844	1,299,844	1,299,844	1,299,844
R-squared	1.2%	1.5%	46.7%	47.0%	1.0%	1.4%	44.7%	45.1%
Within-group R2	1.2%	1.1%	0.3%	0.1%	1.0%	0.9%	0.2%	0.1%

Table IA7: **Distance from Ant as Instruments – Individual Evidence**

This table replicates the 2SLS estimation results of Table 3 using individual-level data. The sample consists of individuals residing within a 300km radius of Ant headquarters. Columns (1) to (3) report the first-stage estimates of Log(QRPay), while columns (4) to (9) report the second stage estimates for predicting Risky Purchase and Risky Fraction. Time fixed effects are included in all the specifications. In columns (3), (6), and (9), we also include city-by-time fixed effects. The sample period is from January 2017 to March 2019. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively. See Appendix IA1 for variable definitions.

	First Stage			Second Stage					
	Y=Log(QRPay)			Y=Risky Purchase$_{t+1}$			Y=Risky Fraction$_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log($\hat{\text{QRPay}}$)				6.245**	5.771***	8.843**	5.875**	5.459***	8.087**
				(2.75)	(2.96)	(2.60)	(2.67)	(2.88)	(2.47)
Log(Dist from Ant)	-0.073***	-0.101***	-0.122***						
	(-4.34)	(-5.41)	(-3.37)						
Log(Dist from Ant)×Time		0.030***	0.038***						
		(8.41)	(4.81)						
County Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
City*Time FE	N	N	Y	N	N	Y	N	N	Y
Observations	357,588	357,588	357,588	344,344	344,344	344,344	344,344	344,344	344,344
R-squared	23.9%	23.9%	21.2%	1.8%	1.8%	2.0%	1.7%	1.7%	1.9%

Table IA8: **Summary Statistics for Survey Respondents**

This table shows the summary statistics for the valid survey respondents. The total number of valid survey participants comprises 926 individuals who (1) completed the survey, (2) had a positive investment in mutual funds, and (3) provided a valid response to the question "Please list the name of a fund or stock that you currently own." We present the percentage of responses in each category within this sample of 926 respondents. For the final question, "What are the top three reasons for choosing Alipay?", we report the percentage of each response among the 902 respondents who have invested in mutual funds through the Alipay platform.

	% of Respondents		% of Respondents
Gender		**Income (RMB) per month**	
Male	64.04	Below 3000	5.94
Female	35.96	3001-5000	15.55
		5001-10000	43.63
Age		10001-15000	24.95
Below 18	0.97	15001-20000	6.70
18-25	21.38	20001-50000	3.02
26-30	39.09	Above 50000	0.22
31-40	34.13		
21-50	4.32	**Total amount of financial investment, including bank deposit, stocks,**	
Above 50	0.11	**mutual fund, wealth management products, future, options, etc.**	
		Below 50,000	13.28
Education		50,000-100,000	31.21
Junior college	21.68	100,000-500,000	44.06
College	63.24	0.5-1 million	9.50
Master	13.85	Above 1 million	1.94
PhD	1.23		
		What is the total scale of your mutual fund investment	
Have you received an education related to finance?		**(excluding money market funds)**	
My major is related to economics (such as economics, finance,		Below 50,000	34.67
management, international trade, etc.).	38.77	50,000-100,000	40.71
I have learnt some finance by myself from textbooks and books	28.73	100,000-500,000	21.17
I have obtained some financial knowledge through the Internet.	28.08	0.5-1 million	2.70
No, I have not received any education related to finance at all.	4.10	Above 1 million	0.76
Others	0.32		
		Through which channel did you first purchase risky mutual fund products	
Occupation		Banks	18.14
Ordinary employees	32.94	Brokers	25.81
Government officials/civil servants	11.77	Fund Companies	25.70
Enterprise managers (including junior and senior managers)	23.22	Alipay (Ant Fortune)	25.59
Financial practitioner	13.82	Other third-party distribution channels (including Tiantian, Tencent)	4.75
Freelancer	11.23		
Student	6.80	**What is the main reason influencing your decision to purchase mutual funds**	
Retired	0.11	**through various platforms?**	
Other	0.11	Availability of additional platform functions, such as payment, etc.	37.69
		User-friendliness of the platform	21.06
Willingness to take risk		Ease of accessing fund-related information	16.74
Not willing to take any risk	2.16	Fund security	9.50
Low risk, low return	20.63	Fund variety	7.24
Moderate risk, stable return	67.17	Fees	7.24
High risk high return	10.04	Other factors	0.54
At what point of investment loss do you experience significant anxiety?		**What are the top three reasons for choosing Alipay? (Alipay investment users only)**	
Below 10%	7.34	Ease of managing investments, payments, and consumption all in one app	52.38
10%-30%	43.63	Convenient access to information	41.79
30%-50%	39.96	User-friendly platform interface	49.03
50%-70%	5.94	Discounted fees	24.73
Above 70%	1.08	Trust in Alipay's safety and the safety of investment funds	38.01
Will not experience anxiety	2.05	A wide range of mutual fund choices	18.90