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

Claire Yurong Hong   Xiaomeng Lu   Jun Pan

Abstract

We study household finance in the age of FinTech, where digital payments are integrated with various financial services through all-in-one super-apps. We hypothesize that increased FinTech adoption via digital payments can lower the non-monetary costs (e.g., psychological barriers) associated with financial market participation. We find that higher FinTech adoption leads to greater participation and increased risk-taking in mutual fund investments. Using distance from Ant as an instrument for FinTech penetration, as well as the exogenous penetration of QRPay in Shenzhen, we further provide causal evidence from digital payment to risky fund investment. Moreover, the effect of FinTech is stronger among individuals who are otherwise more constrained, those with higher risk tolerance, or those living in under-banked counties.

---

*Hong (yrhong@saif.sjtu.edu.cn) and Pan (junpan@saif.sjtu.edu.cn) are from Shanghai Advanced Institute of Finance, Shanghai Jiao Tong University. Lu (xiaomenglu@fudan.edu.cn, Corresponding author) is from International School of Finance, Fudan University. We thank Shashwat Alok, Sabine Bernard, Dion Bongaerts, Greg Buchak, John Campbell, Jennifer Carpenter, Darrell Duffie, Bing Han, Baixiao Liu, Jun Liu, Yu-Jane Liu, Wenlan Qian, Jinfei Sheng, Yang Sun, Huan Tang, Shangjin Wei, Luana Zaccaria, Haikun Zhu, Xin Zou, and conference and seminar participants at the EFA 2021, FIRS 2021, CICF 2021, NFA 2021, CFRC 2021, CIRF 2021, ABFER 2022, SIF 2022, CFRC 2022, CFAM 2022, Luiss Finance Workshop 2023, CEIBS Finance and Accounting Symposium 2023, Journal of Finance and Data Science Conference 2023, ABFER Capital Market Development, NYU Stern CGEB China Initiative Research Seminar, Luohan Academy Webinar, Asia-Pacific Corporate Finance Workshop, the Bank of Finland Institute for Emerging Economies, Central Banks of the SEACEN Centre, the Bank of Lithuania, CKGSB, Korean University, McGill University, Monash University, PBC at Tsinghua University, NSD at Peking University, FISF at Fudan University, SUFE, Shanghai Jiao Tong University, SAIF, Renmin University of China, IFS at Southwestern University of Finance and Economics, Stevens Institute of Technology, George Mason University, Melbourne University, Deakin University, and the Chinese Academy of Sciences for their helpful discussions and comments. We thank Xuan Li and Yijian Sun for excellent research assistance. Hong acknowledges financial support from the National Natural Science Foundation of China [Grant 72003125]. Lu acknowledges financial support from the National Natural Science Foundation of China [Grant 72473028]. The authors acknowledge and appreciate the support from the Digital Economy Open Research Platform (www.deor.org.cn). All data was sampled and desensitized and was remotely analyzed on the Ant Open Research Laboratory in an Ant Group Environment, which is only remotely accessible for empirical analysis.

1 Introduction

In the constantly evolving FinTech sector, BigTech companies such as Amazon and Apple in the US, Paytm in India, and Alipay in China have ventured into the realm of financial services. They integrate digital payments, a cornerstone of modern finance, with essential household financial functions like borrowing, lending, and investing within their digital ecosystems. This all-in-one approach, supported by their vast user bases, enables these tech giants to engage with a diverse spectrum of households and reshape financial practices.

We propose that FinTech, through its comprehensive all-in-one business model, can enhance household participation in risky asset markets. A significant challenge in household finance is the limited participation of individuals in financial markets. Despite the potential benefits, research indicates that both monetary costs (such as transaction fees) and non-monetary costs (such as information acquisition, familiarity, and trust) substantially deter individuals from optimally investing in risky assets.[1] While the technological efficiency of FinTech platforms can significantly reduce or even eliminate the transaction costs associated with market participation, the more profound impact may stem from the reduction of non-monetary costs. By adopting FinTech, individuals can build familiarity through the repeated use of digital payments. This continuous engagement can gradually help overcome psychological barriers, ultimately facilitating investment through the all-in-one platform.

Measuring FinTech Adoption – Our empirical study utilizes an account-level dataset obtained from Ant Group, which tracks individual digital payments via Alipay, mutual fund investments through Ant Group's investment platform, and online consumption on the Taobao e-commerce platform.[2] Notably, all three activities can be initiated from Alipay, China's pioneering super app. The dataset also includes basic individual information, such as age, gender, and residential location. The data spans from January 2017 to March 2019, a period marked by a rapid increase in offline digital payments through Alipay across China.

[1] Haliassos and Bertaut (1995), Campbell (2006), and Vissing-Jørgensen and Attanasio (2003) show that many households do not invest in risky assets, even though financial theory suggests that all households, regardless of their risk aversion, should allocate a portion of their wealth to risky assets when the risk premium is positive. Additionally, Hong, Kubik, and Stein (2004) and Guiso, Sapienza, and Zingales (2008) highlight the importance of familiarity and trust in addressing the low-participation puzzle.

[2] Similar platforms include Toss in South Korea, Paytm in India, Nubank in Brazil, and M-Pesa in Kenya, among others. This model is particularly popular in emerging markets where existing infrastructure is still developing.

Between 2017 and 2018, offline digital payments in the form of QR code scans surged tenfold in China, reaching a total of 7.2 trillion RMB by the end of 2018. This rapid expansion is central to our empirical design, capturing the process of FinTech adoption from zero to one. We measure individual-level FinTech adoption based on how much and how quickly an individual embraces this new technology. Specifically, our measure, QRPay_t^i, represents the number of Alipay digital payments made by individual i in month t. While the level of QRPay may stabilize in the long run as digital payments become the dominant payment method, within our sample period, it contains valuable information about an individual's FinTech adoption due to the varying speeds and intensities of digital payment adoption across different regions and individuals.

The FinTech penetration map of China (Figure 1), observed over time, vividly illustrates the gradual expansion of QRPay from its origins in Hangzhou, where Ant Group's headquarters are located, to encompass the entire nation. In 2016, QR code payments were a rare sight, mainly seen near Hangzhou. However, by 2020, they had become an integral part of daily life for most Chinese citizens. While individual-level differences might be influenced by personal traits and experiences, this county-level variation is likely more exogenous, attributed to the gradual penetration of the new technology across different regions in China. By analyzing variations in risk-taking behavior across different levels of FinTech adoption, both at the individual level and across geographical regions in China, we aim to provide evidence on how FinTech affects individual participation in risky investments and promotes financial inclusion.

From FinTech Adoption to Platform Investments – To assess individuals' participation in risky investments, we use the mutual fund investment data from Ant's investment platform. In China, FinTech platforms were given permission to distribute mutual funds in 2012, with Ant emerging as the leading player, accounting for over half of the FinTech distribution market share.[3] Individuals on this platform can choose from risk-free money market funds and six types of risky mutual funds (bond, mixed, equity, index, QDII, and gold). To gauge individuals' participation in risky mutual funds, we employ two metrics: "risky purchase," a dummy variable indicating whether an individual purchases any risky fund in

[3] See Hong, Lu, and Pan (2025) for details on the development of FinTech platforms. Notably, Ant's major competitor, WeChat, did not begin offering mutual fund distribution services until 2018.

a specific month, and "risky fraction," representing the proportion of the total purchase amount allocated to risky funds in a specific month.

Tracking individuals' participation in risky investments on the platform along the dimension of their FinTech adoption, we find strong evidence that repeated usage of QRPay increases the probability of individuals investing through the FinTech platform. Specifically, a one-standard-deviation increase in month-t FinTech adoption predicts 2.72% (t-stat=7.78) increase in the probability of risky fund purchase in month $t+1$. Given that the average probability of an individual purchasing any risky fund in a given month is 9.16%, this improvement is substantial. The estimates remain qualitatively similar when user and time fixed effects are included, indicating that the results are robust to time-invariant individual characteristics and aggregate market effects.[4]

Additionally, we decompose FinTech penetration into peer-effect-driven penetration (Peer Log(QRPay)) and idiosyncratic-driven adoption (Idio Log(QRPay)). Peer Log(QRPay) captures more exogenous variations in an individual's QRPay usage, explained by the usage of others within the same county. Using peer adoption as an instrument helps mitigate self-selection bias and reverse causality, as it is unlikely for an individual with a risk-taking incentive to influence others to use QRPay a month earlier. We find that peer-level FinTech penetration significantly predicts individual risky fund investments, with a magnitude of 3.39% (t-stat=8.15). This effect is much greater than that of idiosyncratic QRPay usage, which has a magnitude of only 1.05% (t-stat=5.0).

To further establish the causal link between FinTech adoption and platform investment, we employ a county's distance from Hangzhou as an instrumental variable (IV) to capture the exogenous variation in FinTech penetration. According to our discussions with Ant, the initial promotion of QRPay relied heavily on physical, ground-level efforts. Unlike other web-based technologies that can be easily promoted online or through advertisements, QRPay required persuading local merchants to adopt the payment system, starting in areas close to Hangzhou and gradually expanding to more distant regions.[5] Therefore, a county's physical

[4]The results remain robust when using net purchase as the dependent variable, as well as when including province×time or city×time fixed effects. Additionally, we demonstrate the robustness of the findings through nationwide population-weighted regression and analyses based on data from the China Household Finance Survey (CHFS). These robustness checks are discussed in detail in Internet Appendix Section IA4.

[5]In the book "Ant Financial: The Rise of a Tech Financial Unicorn" by You Xi, the author also highlights

distance from Hangzhou provides unique insights into FinTech penetration and is arguably independent of individuals' mutual fund investment incentives.

To ensure that the distance to Ant is not confounded by proximity to Shanghai, which might reflect local economic conditions, we limit our IV analysis to a smaller radius around Ant's headquarters. This strategy balances the broader variations in QRPay penetration observed nationwide with the geographical and economic proximity of cities within this confined area. By using distance to Ant as an instrument and controlling for the natural logarithm of county-level GDP, income, and population, along with their squared terms to account for non-linear effects, we find that a one-standard-deviation increase in the instrumented county-level QRPay predicts a 2.51% (t-stat=2.24) increase in risky purchase. Further allowing distance to have a time-varying effect on FinTech penetration and including city×time fixed effects in our IV estimation, we obtain qualitatively similar evidence.

Finally, to further establish the causal impact of FinTech penetration on individual risk-taking, we employ a difference-in-differences approach to examine the introduction of QRPay in the Shenzhen Transit Network. In November 2016, the Shenzhen Municipal Government and Ant Financial Group signed a strategic cooperation agreement to transform Shenzhen into a model modern city over five years. Beginning in March 2017, Shenzhen Tong started testing QR code payments on bus route B683 via Alipay, expanded to additional routes in July 2017, and eventually implemented the system city-wide in January 2018. By comparing Shenzhen residents to a nationwide sample and a propensity score-matched sample of individuals with similar characteristics, we find that risky purchases for Shenzhen individuals increase by 1.49% (t-stat=3.87) following the introduction of QRPay in the public transit system. Moreover, the dynamic timing analysis indicates that the effect is primarily driven by the period during and after the introduction of QRPay. Overall, both the distance-to-Ant IV test and the Shenzhen Transit Network test strengthen the evidence for a causal interpretation between FinTech penetration and individual risky fund purchases.

Who Benefits More from FinTech Inclusion – To examine the influence of FinTech inclusion on individual welfare and its heterogeneous effects across different demographic groups, we analyze whether FinTech has a more pronounced impact on investors who faced

this ground promotion strategy. Unlike QRPay, the investment platform's promotion strategy was primarily web-based, taking place online through the Alipay app since 2014.

greater constraints prior to its introduction, specifically those with higher risk preferences and those residing in regions with limited access to financial products. Consistent with Ameriks et al. (2020), Calvet et al. (2021), and Cohen and Einav (2007), we observe that males, younger individuals, and those with higher consumption levels and higher consumption growth volatility exhibit greater risk preferences, as measured by their responses to the China Securities Regulatory Commission survey. Notably, consistent with the classical consumption-based portfolio choice theory by Merton (1971), we observe a positive relation between consumption growth volatility and individual risk preference, echoing the aggregate finding of Mankiw and Zeldes (1991). Using individual characteristics as well as the fitted risk tolerance proxy, we find a significantly stronger effect of FinTech on risk-taking for individuals who are male, have high consumption growth volatility, and exhibit higher risk preferences. This suggest that high risk-tolerant investors, with the advent of FinTech, become less constrained and can actively take more risk through the platform.

From a geographical standpoint, FinTech has the potential to bridge the gap left by traditional banks, particularly in regions that are under-banked and have limited access to financial products. Our analysis, conducted in counties with above- and below-median bank coverage (or financial product coverage), reveals that the benefits of FinTech inclusion predominantly originate from counties with below-median financial coverage. When focusing on under-banked individuals, we compare their response to FinTech adoption with a matched sample of individuals in well-banked areas. We find that financially mature, wealthy, and risk-tolerant individuals in low-bank-coverage regions increase their risk-taking significantly more with FinTech adoption compared to their counterparts in well-banked areas. While well-banked individuals have access to traditional investment infrastructure, FinTech offers under-banked individuals an alternative. Overall, the evidence suggests that FinTech enhances financial inclusion by expanding access to investment services, particularly for those who previously had limited opportunities to invest in risky assets.

Finally, to further evaluate the welfare implications, we study the performance and portfolio allocation of households' FinTech investments. We find that the mutual funds held by Ant investors tend to have slightly higher alphas compared to all funds in the broader market. Given that retail investors, on average, underperform compared to institutions and that mutual funds in China typically outperform their passive benchmarks (e.g., Chi (2013) and Jones et al. (2023)), investing with delegated portfolio management has the potential to improve welfare for individuals willing to take such financial risks.[6] Additionally, regarding asset allocation, FinTech adoption results in more diversified portfolios across multiple funds and asset classes, as well as higher Sharpe ratios, underscoring the potential diversification benefits from platform investments.

Mechanism – The spillover effect from digital payment usage to risky mutual fund investments can arise through both monetary and non-monetary channels. However, we contend that reductions in monetary costs, such as transaction fees, are unlikely to be the primary driver. Such reductions would typically predict a general increase in participation, independent of individual QRPay usage. Instead, we argue that non-monetary factors – such as information acquisition, enhanced financial literacy through learning and education on platform, and the familiarity and trust developed via repeated interaction – play a more significant role.

To provide evidence on the presence of these non-monetary mechanisms, we obtain additional data from Ant Group on Alipay's monthly login frequency and visits to the "Fortune" tab. This tab serves as the gateway to the investment section, where users can access detailed mutual fund information and the latest market updates. We observe a significant increase in login frequency and "Fortune" tab visits during the month of, and slightly before, the first purchase of risky funds on the platform. These logins and visits remain elevated in subsequent months, indicating that investors continue to seek information from the platform.

Furthermore, we find that, compared to initial purchases, FinTech adoption has a greater impact on subsequent purchases of high-risk and unfamiliar fund styles. Individuals tend to initially purchase bond and gold funds for their first risky fund investment, then gradually expand to higher-risk funds, such as equity, mixed, index, and QDII funds, for subsequent purchases. While this pattern does not directly test the familiarity channel, it supports the hypothesis that individuals use FinTech platforms to gradually engage in risky investments, starting with products they are most familiar with and progressively venturing into riskier options.

[6] One caveat is that although investing in financial markets has a positive risk premium, the ultimate profit from investments depends on realized returns. Individuals must carefully navigate the inherent trade-off between risk and return.

Finally, we conduct a survey to understand why mutual fund investors choose different platforms. Among the 926 respondents, non-monetary transaction costs are the main factors influencing their platform choice. The most common reasons are: "Availability of additional platform functions, such as payment" (38%), "User-friendliness of the platform" (21%), and "Ease of accessing fund-related information" (17%). Other factors, such as "Fees," "Fund variety," each accounted for less than 10%. Among those who have invested through Alipay, the top three reasons for choosing this platform are: "Ease of managing investments, payments, and consumption all in one app" (52%), "Convenient access to information" (42%), and "User-friendly platform interface" (49%).

Related Literature – Our study contributes to the existing literature that explores how technological advancements can address the puzzle of low participation rates in financial markets.[7] Barber and Odean (2002), Choi, Laibson, and Metrick (2002), Bogan (2008), and Reher and Sokolinski (2021) document that web-based trading platforms, and robo-advisory services encourage active engagement in financial markets. Additionally, D'Acunto, Prabhala, and Rossi (2019) show that robo-advisors help mitigate investors' behavioral biases. Our contribution lies in investigating the influence of digital payments on individuals' willingness to invest in risky mutual funds. Unlike the technologies examined in previous studies, digital payments do not directly enhance households' access to investment services. Instead, the positive impact of digital payments on investments arises from the trust and familiarity built up when households frequently use FinTech platforms for payments. This psychological channel is consistent with the existing literature that emphasize the significance of familiarity and trust in addressing the low-participation puzzle (e.g., Hong, Kubik, and Stein (2004), Guiso, Sapienza, and Zingales (2008), Gennaioli et al. (2015), and Okat, Paaso, and Pursiainen (2023)).

Our paper also adds to the emerging literature focusing on the evolving landscape of BigTech platforms, particularly emphasizing the bundling feature of digital payments. This integration of digital payments within comprehensive super apps has significant implications for households' access to various financial services. While concerns persist about the monop-

[7]Studies by Christiansen, Joensen, and Rangvid (2008), Calvet, Campbell, and Sodini (2009), and Calvet et al. (2023) indicate that lower participation costs, higher income, better education, increased financial sophistication, and securities with non-linear payoff designs are associated with higher participation rates.

olistic power and data privacy issues associated with BigTech platforms (e.g., Frost et al. (2019), Boissay et al. (2021), Bian, Ma, and Tang (2021)), recent research has also shed light on the positive aspects of the BigTech ecosystem. Specifically, Buchak, Hu, and Wei (2022), Chen and Jiang (2022) find that digital payment facilitates the usage and enhances the liquidity premium of connected money market products. Ouyang (2021), Bian, Cong, and Ji (2023), Chen, Huang, Lin, and Sheng (2022), Gambacorta, Huang, Li, Qiu, and Chen (2023), and Liu, Lu, and Xiong (2022) document that BigTech lending contributes to financial inclusion by expanding credit access for individuals, small businesses and firms. Our research aligns with this prevailing trend, but with a unique focus on individuals' investment choice.[8]

The rest of our paper is organized as follows. Section 2 describes our data and the institutional background. Section 3 documents the impact of FinTech penetration and adoption on risky investment participation. Section 4 focuses on the welfare implications. Section 5 discusses potential economic mechanisms. Section 6 concludes.

2 Data and Institutional Background

2.1 An All-in-One Ecosystem

Ant Group launched its all-in-one ecosystem, Alipay, as early as 2004. This ecosystem integrates a wide range of sectors, including payments, investments, e-commerce, and everyday life services such as food delivery and hotel bookings. By consolidating these services into a single, comprehensive "super app," Alipay provides users with a convenient and efficient experience, eliminating the need to switch between multiple applications for different tasks. Central to Alipay's ecosystem is the digital payment function, which serve as the foundation for bundling a variety of services. As illustrated in Panel A of Figure 2, the QR-Scan payment feature is prominently displayed at the top of the Alipay app's homepage, acting as a gateway to the extensive financial and non-financial services offered within the

[8]In a broader context, our research is also related to the growing literature on the adoption of digital payments in emerging markets and its impact on underserved individuals, merchants, and entrepreneurs (Jack and Suri (2011), Higgins (2020), Suri, Bharadwaj, and Jack (2021), Agarwal et al. (2019), and Agarwal et al. (2020), among others).

ecosystem. Alipay has been a pioneer in leveraging the synergy between digital payments and other services. However, other major tech companies with large user bases are also adopting similar bundling strategies, such as Apple and Google. The growing prevalence of bundling is further evidenced by partnerships and acquisitions in the FinTech space, such as Stripe's collaboration with Klarna, SumUp's acquisition of Tiller, and Rapyd's acquisition of Valitor.

Our study examines the impact of household digital payment usage on their investments in platform-based mutual funds. Beyond demographic data, we are able to track the monthly investment activity, digital payment usage, and spending patterns of a randomly selected sample of 50,000 individuals from January 2017 to March 2019. The sample is drawn from the entire Ant community and includes individuals who conducted at least one transaction involving a money market fund, a risky mutual fund, or a short-term wealth management product on the Ant platform prior to the study period. Given Alipay's vast user base of 1.3 billion individuals and the observation that a significant majority of users engage in risk-free money market fund (MMF) investments via Yu'ebao (Buchak, Hu, and Wei (2022)), our sample is reasonably representative of both Alipay's user community and the broader Chinese population.

Table 1 provides descriptive statistics for the sample. Among the 50,000 individuals, 60% are female, with an average age of 30.4 years and an average monthly e-commerce expenditure (via Taobao) of 2,155 RMB. Approximately half of the sample has made substantial investments (defined as risk-free and risky fund investments totaling at least 100 RMB), and 17,406 individuals have participated in risky mutual fund investments.

Compared to the national sample, the Ant sample is slightly skewed toward a younger and more female population. To alleviate potential concerns about sample selection bias, we provide a detailed comparison between the Ant sample and the overall Chinese population. Additionally, we perform further analyses, including reweighting the Ant sample to better align with the demographic characteristics of the broader population and conducting robustness checks using external datasets, as detailed in Internet Appendix Section IA4.

2.2 Measuring FinTech Adoption Using QR-Scan Payment

The development of digital payments in China can be traced back to 2004, initially designed to foster trust between online buyers and sellers during the early days of e-commerce. The widespread adoption of QR-Scan mobile payments is a more recent development, propelling China toward a cashless society. Over 852 million people now use mobile digital payments for their daily transactions, with street vendors across China ready to accept QR-Scan payments through Alipay.[9] We observe a rapid increase in the use of QR-Scan payments, shown by both economy-wide statistics and our Ant sample data, during our sample period. In just two years, the volume of QR-Scan payments jumped from 0.6 trillion yuan in 2017 to 7.2 trillion yuan by the end of 2018. As shown in Panel B of Figure 2, the economy-wide ratio of QR-Scan payments to total offline spending (indicated by the red line) increased from about 8.0% in 2017 to 85.3% by the end of 2018. This trend is also reflected in our data by the sharp rise in how often people used QR-Pay: the average number of monthly QR-Pay transactions per person (shown by the blue line) went up from 12.6 times per month in January 2017 to 39.0 times per month in December 2018. The similar movement of these two lines suggests that our Alipay payment data accurately captures the spread of QR-Scan mobile payments during the sample period.

Inspired by the rapid growth of QR-Scan payments in our sample, we measure each person's adoption of FinTech by looking at how often they use Alipay each month.

$$\text{FinTech Adoption}_t^i = \text{Log}(\text{QRPay}_t^i),$$

where QRPay_t^i is the total number of Alipay payments made by individual i in month t.[10] Over the long run, as mobile payments become the dominant payment method, the level of QRPay may stabilize. However, during our sample, which covers a time of dramatic expansion in offline mobile payment, the level of QRPay contains valuable information about

[9] As the leader in mobile payment during our sample period, Alipay accounted for 55% of the market share in 2017, followed by WeChat Pay at 38%. However, WeChat did not start to develop the mutual fund distribution service until late 2018.

[10] As an alternative, we also compute: $\text{QRFrac}_t^i = \text{QRpay Amount}_t^i / \text{Total Consumption Amount}_t^i$, where QRpay Amount_t^i is the total amount of Alipay consumption, and $\text{Total Consumption Amount}_t^i$ includes both Alipay consumption and Taobao consumption (consumption on the e-commerce platform of Alibaba). Internet Appendix IA4.4 provides the details.

the speed and intensity with which individuals adopt the new technology.

Panel A of Table 1 highlights significant cross-sectional variation in FinTech adoption among individuals in our sample. On average, users make 21.4 Alipay mobile payments per month, with a standard deviation of 19.2 payments. Additionally, 54% of total consumption within the Ant ecosystem is paid via Alipay mobile payments, with a standard deviation of 22%. This substantial variation in QRPay usage likely reflects both individual willingness to adopt new technology and the exogenous penetration of FinTech across different regions in China. From an individual perspective, Panel B of Table 1 shows that younger and male users tend to have higher levels of Log(QRPay). From a geographical perspective, the speed at which local governments and vendors adopt QR-Scan technology appears to play a critical role in driving local residents' adoption of the technology.

Figure 1 illustrates the geographical distribution of FinTech penetration across China, measured as the monthly average QRPay for each prefecture from 2017Q2 to 2018Q4, based on our sample of Alipay users.[11] As shown in the four maps, QRPay usage varies significantly across regions and over time. In early 2017, Hangzhou, the headquarters of Ant Group, emerged as the epicenter of FinTech penetration, with the average individual in Hangzhou using Alipay 24.9 times per month for consumption. In contrast, other prefectures reported an average QRPay usage of just 5.87 during the same period. Over time, FinTech adoption gradually spread from Hangzhou to the more inland regions of China. By 2018Q4, while Hangzhou maintained its leadership in FinTech penetration, other prefectures experienced substantial growth, with their average QRPay usage increasing to 18.85 – more than three times the 2017Q2 level. A comparison of Panel A and Panel D in Figure 1 reveals an interesting pattern: prefectures near Hangzhou, which already had high QRPay usage in early 2017, experienced relatively smaller increases in FinTech penetration during 2018. In contrast, prefectures located further inland saw much larger increases over the same period. This staggered diffusion of Alipay during our sample period underscores the role of relatively exogenous geographical factors in driving variation in QRPay usage.

[11] China's administrative divisions are organized hierarchically, with provinces at the top, followed by prefectures, and then counties. For clarity in graphical illustrations, we use prefecture-level observations. In our regression analyses, however, we rely on the more granular county-level data.

2.3 Platform Investments of Mutual Funds

The development of the investment function dates back to 2013 with the launch of Yu'ebao by Alipay, which stands as the largest risk-free money market fund globally. This platform enables customers to invest their pocket money within the ecosystem. Subsequently, in 2014, Ant expanded its offerings to include mutual fund distribution services, granting investors access to a wide range of risk-free and risky mutual funds.

We are able to obtain the detailed monthly purchase and redemption transactions made by each investor on the Ant investment platform. For a sub-sample period from August 2017 to December 2018, we also obtain information on their detailed fund holdings and portfolio monthly returns. In terms of fund style, Ant's investment platform carries a wide variety of fund asset classes. Besides risk-free money market funds (MMF), there are six types of risky mutual funds available on the Ant platform: bond, mixed, equity, index, QDII, and gold funds. To capture each individual's participation in risky mutual fund investment, we construct two measures. "Risky purchase" is a dummy variable that equals one if the individual purchases any risky mutual funds in a given month, and zero otherwise; "Risky fraction" is the fraction of risky fund purchase amount out of the total fund purchase in a given month. As shown in Table 1, the probability for an average individual to purchase any risky mutual fund in a given month is 9.16%, and the average risky fraction is 8.75%.

We also construct measures to capture the outcome of risk-taking for individuals in our sample. We include only users with meaningful investment amounts, by requiring a user to have at least 100 RMB total purchase amount (including both risk-free and risky funds) throughout our sample period, which leaves us with 28,393 users. These 28,393 users have an average total purchase amount of 41,080 RMB, equivalent to around 6,000 US dollars.[12] The median value of total purchases is 3,011 RMB, which is also a non-trivial magnitude, given that the median value of online consumption per month is 1,259 RMB. "Risky share" is the average fraction of investment in risky mutual funds (=1-MMF/Total). "Portfolio volatility" (σ_{W}) is the standard deviation of an individual's portfolio's monthly returns. For the 28,393 users with non-trivial investment, they on average allocate 50.76% of their capital

[12]In terms of portfolio holdings amounts, an average individual has an average holding amount of 7,650 RMB in our sample, with a standard deviation of 36,661 RMB.

into risky mutual funds, with a portfolio volatility of 2.13%. In terms of portfolio allocations, an average individual invests in 3.71 funds across 1.93 asset classes.[13]

Panel B of Table 1 further reports the correlation among the key variables. Consistent with our intuition, "risky share" and "portfolio volatility" are positively correlated, with a pair-wise correlation of 0.48. In addition, individuals with higher risky shares and higher portfolio volatility on average also exhibit a higher level of portfolio diversification, as captured by the number of funds and number of asset classes. Finally, turning to the correlation between risk-taking and individual personal characteristics, we find the relationship is consistent with the prior literature that males and younger users tend to have higher risky shares and portfolio volatility.[14]

This study was remotely conducted on the Ant Open Research Laboratory in an Ant Group Environment. All data was sampled, desensitized, and analyzed on the Ant Open Research Laboratory. The laboratory is a sandbox environment where the authors can only remotely conduct empirical analysis, and individual observations are invisible. The main regression variables include basic variables, investment variables, and consumption variables.

3 FinTech Penetration and Risky Fund Investment

In this section, we investigate the contagion effect of FinTech penetration, particularly through QRPay, on individuals' investments in risky mutual funds. To further establish the causal relationship between FinTech penetration and individual risk-taking, we use an instrumental variable (IV) approach and a Difference-in-Differences event study.

3.1 Individual FinTech Adoption and Risk Taking

To explore the impact of FinTech adoption on individual's participation in risky mutual fund investment, we estimate the following regression specification:

[13] Contrary to the excessive stock trading documented in Odean (1999), individuals in our sample, on average, conduct approximately 8.9 transactions and trade during only three out of the 27 months observed. This behavior is likely due to investors exhibiting reduced levels of speculative activity within the context of delegated portfolio management.

[14] See Sunden and Surette (1998), Jianakoplos and Bernasek (1998), Barber and Odean (2002), etc.

$$\text{Risky Purchase}_{t+1}^{i} = \alpha + \beta_1 \cdot \text{Log}(\text{QRPay}_t^i) + \sum_j \gamma_j \cdot \text{Control}_{j,t}^i + \epsilon_t^i,$$

where an individual's risky investment behavior in month $t+1$ is regressed on the logarithm of their QRPay activity in month t. While it is plausible that individuals adopt digital payments to facilitate risky investments, focusing on this lead-lag relationship helps mitigate concerns about reverse causality. The model includes controls for individual characteristics such as age, gender, monthly online consumption levels, and quarterly consumption growth volatility (σ_C).[15] Individual and time fixed effects are included as indicated.

Panel A of Table 2 reports that a one-standard-deviation increase in individual-level Log(QRPay) predicts a 2.72% (t-stat = 7.78) increase in the probability of purchasing a risky mutual fund in the following month. When time fixed effects are included, the coefficient slightly decreases to 2.21 (t-stat = 8.13), suggesting that the results are not merely driven by unobserved aggregate changes or time trends in risky investment participation. With the inclusion of individual fixed effects, the coefficient remains robust at 2.66 (t-stat = 6.07). This indicates that, for a given individual, time-series variation in Log(QRPay) is a significant predictor of risky investment participation. Finally, when both time and individual fixed effects are included, the coefficient on Log(QRPay) remains significant at 1.41 (t-stat = 6.32).

To address concerns that the relationship between QRPay usage and risky fund investment may be driven by endogenous selection – where individuals use Alipay specifically for investment purposes – we decompose Log(QRPay) into two components: peer-effect-driven usage and idiosyncratic-driven usage. Peer-effect-driven QRPay adoption reflects passive usage influenced by changes in an individual's local environment, such as adoption by merchants, friends, and neighbors in the same county. Conversely, the idiosyncratic component captures individual-specific factors, such as a person's tech-savviness, risk appetite, or other personal characteristics unrelated to peer effects.

In particular, for each individual, we estimate the following regression specification:

$$\text{Log(QRPay)}_t^i = a^i + b^i * \text{County Log(QRPay)}_t^i + \epsilon_t^i,$$

[15] We use online consumption to control for each individual's consumption (wealth) level, because the offline consumption would capture the effect of QRPay.

where County Log(QRPay)$_t^i$ is the equal-weighted average Log(QRPay) of all individuals in the same county as individual i, excluding the focal individual i herself. Peer Log(QRPay)$_t^i$ is calculated as $\hat{b}^i$*County Log(QRPay)$_t^i$, and Idio Log(QRPay)$_t^i$ is calculated as Log(QRPay)$_t^i$ - Peer Log(QRPay)$_t^i$. The peer-effect component represents the portion of an individual's Log(QRPay) explained by the FinTech adoption of their peers, while the idiosyncratic component reflects the portion not explained by peer adoption, capturing individual-specific or self-selection factors.

Panel B of Table 2 examines the impact of peer-effect-driven and idiosyncratic FinTech adoption on risky fund investment using a regression framework similar to Panel A. In column (1), the coefficient on Peer Log(QRPay) is 3.39 (t-stat =8.15), while the coefficient on Idio Log(QRPay) is 1.05 (t-stat = 5.00). Both variables are standardized to have a mean of zero and a standard deviation of one. The relative magnitudes of these coefficients indicate that variation in Peer Log(QRPay) has a substantially larger impact on risky fund purchases than variation in Idio Log(QRPay). This suggests that risky investment decisions are more strongly influenced by peer-effect-driven QRPay usage, which is relatively exogenous to individual choices. Even when controlling for individual fixed effects, time fixed effects, or both, the coefficients for Peer Log(QRPay) consistently remain larger than those for Idio Log(QRPay).

Finally, we conduct a series of robustness tests to validate our findings. These tests include redefining risky investment using net purchases (Internet Appendix Table IA5), adding province-by-time or city-by-time fixed effects, and subsample analysis (Internet Appendix Table IA4 and Table IA3). Details on these robustness checks are provided in Internet Appendix Section IA4.5. Overall, the results reinforce the significant influence of FinTech adoption—particularly peer-effect-driven adoption—on individuals' decisions to invest in risky mutual funds.

3.2 Distance-from-Ant as an Instrument

To determine the causal impact of FinTech penetration on participation in risky investments, we use the distance from Ant Group's headquarters as an instrument to capture plausibly exogenous variation in FinTech penetration. As outlined in Section 2.2, the rollout of Alipay's QR-Scan technology began at Ant's headquarters and progressively extended to more remote areas. This expansion required a costly ground-level promotional effort, with Ant's marketing team engaging directly with local merchants to persuade them to adopt QRPay as a payment method. In contrast, the promotion of the mutual fund investment feature was not geographically constrained.[16]

We first validate the use of a county's distance from Ant's headquarters as an instrument for FinTech penetration. A potential complication arises due to the proximity of Ant's headquarters in Hangzhou to Shanghai, China's economic hub. Consequently, a county's distance from Ant often correlates with its distance from Shanghai. If proximity to major metropolitan areas like Shanghai influences individuals' participation in risky investments, our IV analysis might mistakenly attribute the effects of Shanghai to Ant. To mitigate this issue, we adjust the county subsamples based on their distance from Ant. Additionally, we conduct a first-stage IV regression using the distance from Shanghai as a placebo test.

The rationale for this placebo test is illustrated in Internet Appendix Figure IA1, which shows the locations of Ant's headquarters and Shanghai on a map of China, along with 1000 km, 500 km, and 300 km radii around Ant's headquarters. To differentiate the effects of Ant's headquarters from those of Shanghai, we compare the first-stage estimation results for counties located within various radii around Ant. The underlying assumption is that for counties far from Ant, the distances from Ant and Shanghai are highly correlated. Conversely, for counties closer to Ant, these distances can differ significantly. Panel A of Table 3 presents the first-stage IV regression results using Log(Distance from Ant) and Log(Distance from Shanghai) as instrumental variables. To account for county-level economic conditions, we control for Log(GDP), Log(Population), and Log(Income), as well as their squared terms.

Table 3 shows a significantly negative relation between Log(QRPay) in a county and its distance from Ant headquarters. The coefficient on Log(Dist from Ant) is -0.24 (t-stat = -13.20) for the whole sample. When focusing on counties within a smaller radius around Ant, the effect remains qualitatively similar, though with a slightly reduced magnitude. For example, within 300 km of Ant, the coefficient on Log(Dist from Ant) is -0.17 (t-stat $=-4.16$). This is partly because counties near Ant already exhibit relatively high FinTech

[16] Ant's staff have confirmed that there were no on-site promotions or offline advertisements for the investment function during our sample period.

penetration during our sample period, whereas more distant counties have greater potential for FinTech development. Moreover, the F-statistics for Log(Distance from Ant) are 174.26 for the whole sample and 17.34 for the subsample within 300km of Ant, thus passing the weak instrument test in Stock and Yogo (2002).

In contrast, when examining counties within a smaller radius around Ant, the coefficients on Log(Distance from Shanghai) become insignificant and even turn positive. Specifically, for counties within 300 km, the coefficient on Log(Distance from Shanghai) in column (8) is 0.103 (t-stat= 1.47). This difference between the effects of Shanghai and Ant's headquarters aligns with our intuition: for counties far from Ant, the distances from Ant and Shanghai largely overlap, causing Log(Distance from Shanghai) to capture some of the effects of Log(Distance from Ant). However, within smaller radii, only the distance from Ant correlates with FinTech penetration, while the distance from Shanghai has no explanatory power.[17] Therefore, to accurately identify the effect of distance on FinTech penetration, we concentrate our IV analysis on the subset of counties within a 300 km radius of Ant's headquarters.[18]

Panel B of Table 3 presents the first and second stage IV estimates, using the distance to Ant's headquarters as the instrument. Columns (1) through (3) display the first-stage estimates. Beyond the static relationship between distance and Log(QRPay) shown in column (1), we also account for the possibility that distance has a time-varying effect on FinTech penetration in column (2). As illustrated in Figure 1, at the start of our sample period, counties closer to Ant exhibited significantly higher FinTech penetration compared to those further away. However, as QR-Scan payments became more widespread throughout China, the impact of distance diminished. Supporting this hypothesis, the coefficient on the interaction term, Log(Dist from Ant)$\times$Time, is significantly positive, indicating a decreasing influence of distance on FinTech adoption over time. Column (3) further incorporates City$\times$Time fixed effects into the estimation, which helps account for any influences driven by time-varying city-level economic conditions. This specification essentially leverages within-city distance variations to identify the effect of FinTech on risk-taking.

[17] In unreported analyses, we also conduct placebo tests using distances from other tier-one cities (Beijing, Shenzhen, and Guangzhou) as instruments in the first-stage regression. The coefficients on these placebo distance measures are found to be insignificant.

[18] Internet Appendix Table IA4 shows that our baseline results remain robust for the subsample within a 300 km radius of Ant headquarters.

Columns (4) through (6) report the second stage estimates for risky purchases, using the instrumented Log(QRPay) from columns (1) to (3), respectively. Similarly, columns (7) through (9) present the results for the risky fraction. Across various specifications, we consistently find that the instrumented Log(QRPay) significantly predicts risky purchases within a 300 km radius of Ant's headquarters. For instance, a one-standard-deviation increase in $\text{Log}(\widehat{\text{QRPay}})$ estimated from column (1) results in a 2.51% increase in risky purchases (t-stat=2.24) and a 2.37% (t-stat=2.20) increase in the risky fraction. The magnitude of these effects is similar or even larger when accounting for the dynamic effect of distance and when including city×time fixed effects.[19] Overall, the IV analysis supports a causal interpretation of digital payment penetration on participation in risky funds.

3.3 A Quasi-Natural Experiment of ShenZhen Transit Network

Next, we conduct an additional test utilizing the quasi-exogenous introduction of QRPay in the Shenzhen public transit system to evaluate its impact on risky fund purchases. In November 2016, the Shenzhen Municipal Government and Ant Financial Group entered into a strategic cooperation agreement aimed at transforming Shenzhen into a model modern city over five years. Beginning in March 2017, Shenzhen Tong initiated a pilot program for QR code payments on bus route B683 via Alipay, expanding to additional routes by July 2017, and eventually implementing the system city-wide by January 2018[20].

Consistent with this rollout of QRPay in Shenzhen, we observe a significant increase in the Baidu search index for "QRPay + Alipay" among Shenzhen residents compared to a nationwide sample, as illustrated in the upper graph of Internet Appendix Figure IA2. The lower graph of Internet Appendix Figure IA2 further shows the change in Log(QRPay) relative to its value in month $t = -2$, where $t = 0$ corresponds to March 2017, for Shenzhen residents benchmarked against residents nationwide. Consistently, we observe a significant increase in Log(QRPay) starting in March 2017, with the effect gradually building up as QRPay was progressively adopted across the transit network. This quasi-natural experiment allows us to examine the impact of the exogenous penetration of QRPay on individuals'

[19] Internet Appendix Table IA7 demonstrates that the IV estimates are similar, or even stronger, when using individual-monthly observations.

[20] Internet Appendix Section IA2 provides more detail regarding the timeline.

investments in risky mutual funds, as the introduction of QRPay into the transit network is unlikely to be driven by Shenzhen residents' risk-taking incentives.

We evaluate the effect of QRPay penetration using a difference-in-differences approach, by comparing the risky fund purchasing behavior of Shenzhen residents with that of a control group, both before and after the introduction of QRPay in Shenzhen. The regression specification is as follows:

$$\text{Risky Purchase}_t^i = \alpha + \beta \times SZ^i + \theta \times SZ^i \times Post_t + \sum Controls_t^i + \gamma_t + \epsilon_t^i,$$

where SZ is a dummy variable set to one for individuals in Shenzhen, while $Post$ is a dummy variable set to one for observations after March 2017. The control variables include Log(Age), Female, Log(C), and σ_{C}, along with time fixed effects denoted by γ_t. The sample period is from January 2017 to December 2017.

Columns (1), (3), (5), and (7) of Table 4 demonstrate a significant increase in risky fund purchases among Shenzhen residents compared to both the nationwide sample and propensity score-matched individuals. For example, the probability of a risky purchase for Shenzhen residents, when benchmarked against the propensity score matched control group, increases by 1.27% (t-stat=2.51) in the post-March 2017 sample compared to the pre-March 2017 sample. We observe a similar magnitude of increase when using the nation-wide control group and when using the risky fraction as the dependent variable.

To further explore the dynamic timing effects of QRPay penetration, we include time dummies $D(t = x)$ around the event and their interactions with SZ, where $t = 0$ corresponds to March 2017, and $t \geq 5$ corresponds to months on and after August 2017. Consistently, we find that the effect of QRPay primarily manifests in the months on and after March 2017, indicating that the coefficients on the interaction terms are not influenced by any pre-existing trends. Overall, this event study surrounding the introduction of QRPay into Shenzhen's transit network supports the contagion effect from fintech to risky mutual fund investment.

4 FinTech Inclusion and Welfare Implications

This section explores individual heterogeneity within our sample to understand who benefits most from FinTech inclusion. Here, financial inclusion refers to providing individuals with financial products and services that meet their needs, with a particular focus on access to investment services. This includes the availability, usability, and effectiveness of FinTech platforms in facilitating investments. Specifically, we refer to expanding investment opportunities for individuals who previously had limited access to risky assets due to various frictions. Section 4.1 focuses on individual risk preferences, while Section 4.2 explores the impact contingent on local financial product coverage. Furthermore, Section 4.3 assesses the portfolio outcomes of investments.

4.1 Individual Characteristics and Risk Preference

The challenge in studying the effect of risk preference on risk-taking behavior lies in accurately capturing individuals' risk preferences, which are not directly observable. A common approach is to use survey-based risk tolerance responses to capture individual risk tolerance. However, survey responses can be subject to attenuation biases and measurement errors (Ameriks et al. (2020)). In our sample, the distribution of risk preferences based on surveys from the China Securities Regulatory Commission is highly skewed. To mitigate the measurement errors inherent in survey responses, we map the survey-based risk preferences to individual characteristics. This approach allows us to develop a comprehensive measure of risk preference that is predicted by individual characteristics.

Panel A of Table 5 presents the determinants of survey-based risk tolerance. Consistent with Ameriks et al. (2020) and Calvet et al. (2021), we find that males, younger individuals, and those with higher consumption levels exhibit greater risk preferences.[21] Importantly, we also observe a positive relationship between consumption growth volatility and individual risk tolerance, providing empirical support for the classical consumption-investment problem as posited by Merton (1971). Under the classical Merton framework, with the optimal consumption-to-wealth ratio being constant, we have consumption volatility σ_C equaling

[21]The effect of age on risk aversion and on risk-taking is a bit mixed, consistent with Cohen and Einav (2007) who document a U-shape between age and risk aversion.

portfolio volatility σ_{W}, and both are inversely proportional to individual risk aversion.[22]

Panel B of Table 5 further investigates the effect of FinTech on portfolio risk-taking, conditional on individual risk preferences. We limit our analysis to individuals with meaningful investment amounts, defined as users with at least 100 RMB in total purchases (including both risk-free and risky funds) on the Ant platform. Investment outcomes are measured by the portfolio's risky share and portfolio volatility. The risky share is defined as the average fraction of investment in risky funds, while portfolio volatility is the standard deviation of realized monthly portfolio returns for each individual.[23] We find a significant positive relationship between risky share and Log(QRPay), consistent with findings in Section 3. The interaction term between Log(QRPay) and individual characteristics indicates that the impact of QRPay on risky fund investment is stronger among individuals with higher risk preferences, particularly male investors and those with higher consumption growth volatility. In columns (5) and (10), when using predicted risk preferences based on age, gender, consumption level, and consumption volatility (Column (5) of Panel A), we find that individuals with higher risk preferences have a higher risky share. A one standard deviation increase in risk appetite results in an additional 0.34% increase in risky share, on top of the 2.25% increase from a one standard deviation effect of Log(QRPay).

Finally, columns (6) to (10) present results for portfolio volatility, σ_{W}. The heterogeneous effect of risk tolerance, captured by the coefficient on Log(QRPay) $\times$ Risk appetite, mirrors the findings for risky share. Overall, these results support our hypothesis that investors with higher risk tolerance, who might otherwise be more constrained without FinTech, benefit more from FinTech inclusion.

4.2 Individuals in Under-Banked Area

In this section, we explore the impact of FinTech on risk-taking across counties with varying degrees of financial coverage. Suri (2017) show that mobile money in developing economies can facilitate digital transactions for unbanked individuals. Accordingly, we aim

[22] As the main focus of this paper is the relationship between FinTech penetration and individual mutual fund investment, we leave it to Internet Appendix Section IA3 to discuss the role of consumption growth volatility as a proxy for individual risk tolerance.

[23] Our focus is on individuals' final portfolio allocation and riskiness, rather than their monthly participation decisions, as risk tolerance is not directly related to the portfolio-building process.

to test whether the emergence of QRPay will similarly benefit individuals who previously lacked access to financial products in the pre-FinTech era.

4.2.1 Conditional on County-Level Financial Product Coverage

We start by analyzing the impact of FinTech penetration on risky purchase fraction, conditioning on county-level bank coverage and financial product coverage. We measure bank coverage by counting the total number of bank branches within the county's prefecture. To identify under-banked regions, we introduce a dummy variable, LowBank, which equals one for counties located in prefectures with bank branches below the median, and zero otherwise. As an alternative, we also use the 2017 China Household Finance Survey (CHFS) data to measure county-level financial product coverage.[24] We consider two financial coverage ratios: one is the risky participation rate for individuals in a county, and the other is the average fraction of risky asset investment out of total financial assets.[25] We calculate each individual's risky participation measures and then average them across individuals to derive the county-level measures. "Low Participation" and "Low Fraction" are dummy variables that equal one for counties with below-median participation in risky financial assets and below-median average fraction of risky assets, respectively.

Table 6 reports the estimates, conditional on local financial product coverage. Across all specifications, we consistently find significantly positive coefficients for the interaction term. For instance, in column (2), a one-standard-deviation increase in Log(QRPay) raises the average local individual risky purchase fraction by 2.0% (t-stat=4.98) the following month. In counties with below-median bank coverage, the same increase boosts risky purchases by an extra 0.40% (t-stat=2.38), leading to a combined effect of 2.4%. When we control for the interaction of Log(QRPay) with county-level economic conditions (Log(GDP), Log(Income), Log(Population)), the interactions remain significant with similar economic magnitude, indicating that the results are not driven by county characteristic.

As a graphical illustration, Figure 3 confirms that FinTech predominantly benefits areas

[24] Though the CHFS allows us to directly measure households' investment activity, it could also capture the demand-side activities rather than the supply-side.

[25] Total financial assets include cash, deposits, WMPs, mutual funds, stocks, bonds, golds, and money in social security accounts.

with limited traditional bank services. Prefectures are categorized based on their bank coverage levels. In the top panel, risky share is plotted against Log(QRPay) for both low- and high-bank coverage groups. A 10% increase in Log(QRPay) raises risky share by 5.9% (t-stat=2.52) in low-bank-coverage prefectures, whereas the impact in high bank coverage areas is minimal. This distinction is also evident in the bottom panel, where changes in risky share are plotted against changes in Log(QRPay), emphasizing the strong contrast between low- and high-bank coverage regions. Overall, the evidence is consistent with the hypothesis that the effect of FinTech on risk-taking is stronger among counties that are under-covered by traditional banks and have limited access to financial products.

4.2.2 Matched Sample of High- and Low-Bank Areas

To ensure that our results are not driven by population distribution differences between areas with high and low bank coverage, we further explore the individual-level effects of FinTech adoption using a matched sample approach. Out of the 28,393 investors with non-trivial investments, 4,053 are located in counties with below-median bank coverage. We match each individual from a low-bank area with a corresponding individual from a high-bank area based on gender, birth year, consumption levels, and consumption volatility. As demonstrated in Panel A of Table 7, the matched individuals from low-bank and high-bank areas exhibit very similar characteristics.

Panel B of Table 7 presents the impact of Log(QRPay) on portfolio volatility (σ_{W}) for both the low- and high-bank groups, estimated while controlling for individual characteristics as in column (1) of Table 5. Consistently, the effect of Log(QRPay) is notably more substantial for the low-bank group, with a coefficient estimate of 0.51 (t-stat=5.26), compared to 0.25 (t-stat=2.82) for the high-bank group. This difference is 0.26 with a t-statistic of 2.01.

We next investigate the impact of FinTech on individuals with varying characteristics and risk tolerance. To this end, within both high- and low-bank groups, we classify individuals into two subgroups based on median consumption, gender, age, consumption volatility, and the predicted risk appetite from Table 5. We find that the effect of FinTech penetration is stronger among low-bank individuals who are mature, financially well-off, and have a higher risk appetite. These individuals tend to have greater investment capabilities and investment needs. While they can typically rely on traditional banking services in high-bank areas, FinTech serves as a viable alternative for those residing in low-bank regions.

Specifically, for mature individuals (aged between 30 and 55), the effect of Log(QRPay) on risk-taking, as measured by σ_{W}, is 0.49 (t-stat=4.37) in low-bank areas, which is 0.41 (t-stat=2.66) higher than in high-bank regions. Similarly, high-wealth individuals (indicated by higher consumption levels) exhibit a coefficient of 0.65 (t-stat=4.69) in low-bank areas, which is 0.48 (t-stat=2.57) higher than in high-bank regions. Additionally, females and individuals with high consumption growth volatility in low-bank areas also demonstrate strong risk-taking behavior due to FinTech penetration. Finally, by separating individuals based on their predicted risk appetite, we find that the effect of FinTech is especially pronounced for high-risk-tolerant investors in low-bank areas. The difference in high-low bank coefficient estimates for high-risk appetite individuals is 0.35 (t-stat=1.74), while the difference is insignificant for low-risk appetite individuals. Overall, the evidence suggests that the effect of FinTech is more pronounced for individuals, particularly those with investment needs, living in low-bank areas.

4.3 Implications on Portfolio Outcome

Finally, we explore whether investors can truly benefit from FinTech inclusion to enhance their investment outcomes. Academic research often suggests that engaging with risky assets can allow investors to capture the positive equity risk premium. However, individual investors frequently exhibit behavioral biases that could negate the benefits of such engagement.[26] Moreover, the ultimate profit from investments depends on realized returns, and individuals must navigate the inherent trade-off between risk and return. While assessing the welfare implications of platform investments can be challenging, this section aims to provide insight by analyzing the portfolio performance and asset allocation decisions of Ant investors.

[26] For instance, Calvet, Campbell, and Sodini (2007) show that the costs associated with non-participation diminish considerably when accounting for the inefficiencies of non-participating investors.

4.3.1 Performance of Platform Funds vs. All Funds

To evaluate portfolio performance, we start by comparing the performance of three sets of mutual funds: all funds in the market, Ant platform funds, and funds chosen by Ant investors based on their allocations. We focus on the realized fund performance for the period from April 2019 to December 2021, starting immediately after the end of our Ant sample to avoid any in-sample bias. Fund performance is evaluated based on a two-factor model with equity and bond factors.[27]

Panel A of Table 8 presents the findings. For all funds in the market, the value-weighted average monthly alphas are 0.46% (t-stat=1.01) for equity funds, 1.00% (t-stat=1.72) for mixed funds, and 0.02% (t-stat=0.88) for bond funds, consistent with existing literature on the presence of positive alphas in Chinese actively-managed mutual funds (Chi (2013), Jiang (2019)). The performance of Ant platform funds in each fund category closely mirrors that of the overall market funds.[28] Finally, examining Ant investors' portfolio holdings as of March 2019, we find their chosen funds tend to outperform those of an average fund in the market. Monthly alphas for equity, mixed, and bond funds held by Ant investors are 1.00%, 1.18%, and 0.05%, respectively, exceeding the corresponding market averages of 0.46%, 1.00% and 0.02% for these fund categories slightly. Hence, the evidence suggests that Ant investors tend to select funds with slightly higher performance, indicating their investment decisions are sound on average. Moreover, Tan et al. (2023) and Jones et al. (2023) show that retail investors in China, on average, lose to institutional investors in the stock market. Some retail investors have low financial literacy, exhibit behavioral biases, and, not surprisingly, their order flow negatively predicts future returns. Hence, compared with direct investment in the stock market, it seems that investing through delegated portfolios can potentially yield higher returns for investors who are willing to take such risk.

[27] The equity factor is computed as value-weighted China A-share stock returns minus the risk-free rate. The bond factor is computed as China aggregate comprehensive bond index returns minus the risk-free rate.

[28] This is to some extent expected, as Hong, Lu, and Pan (2025) shows that around 80% of the entire universe of mutual funds is available for sale via the Ant platform.

4.3.2 Portfolio Diversification and Sharpe Ratios

Next, we explore another potential benefit of investing: diversification. By spreading investments across various fund styles, investors can potentially achieve equivalent expected returns while minimizing portfolio volatility, provided the returns of these assets are not perfectly correlated.[29] To assess diversification benefits, we use three metrics: the number of funds, the number of asset classes, and the Sharpe ratio. Specifically, the Sharpe ratio is calculated as the expected portfolio return divided by the expected portfolio volatility.[30]

Our cross-sectional regression analysis shows that individuals with higher levels of FinTech adoption tend to construct more diversified portfolios, spreading their investments across a larger number of funds and asset classes. As shown in Panel B of Table 8, a one-standard-deviation increase in Log(QRPay) is associated with a 10.6% increase in the number of funds and a 6.7% increase in the number of asset classes held by an individual. These effects are even more pronounced when county fixed effects are included in the analysis. Furthermore, we find that this increased diversification translates into improved portfolio performance, as measured by the Sharpe ratio. A one-standard-deviation increase in FinTech penetration corresponds to a 1.33% rise in the monthly Sharpe ratio when county fixed effects are accounted for. In summary, our findings suggest that FinTech adoption enhances portfolio diversification, enabling investors to allocate their wealth across a broader range of assets and, in turn, improve their risk-adjusted returns as reflected in the Sharpe ratio.

5 Economic Mechanism

In this section, we explore the economic mechanisms underlying our findings, which can be broadly categorized into monetary and non-monetary costs. Monetary costs include fund fees and minimum purchase requirements, while non-monetary costs involve factors such as information acquisition, enhanced financial literacy, and the familiarity and trust developed

[29] For instance, the stock-bond correlation is of -0.21 during our sample period.

[30] We use historical data spanning from 2005 to 2019 to estimate expected returns and the variance-covariance matrix. Sharpe ratios are set to zero for investors who have not invested in risky assets, as they do not earn a risk premium. Another method for calculating the Sharpe ratio involves applying a CAPM framework, similar to Calvet, Campbell, and Sodini (2007). However, given our analysis is already at the factor level, we directly estimate expected returns from historical mutual fund performance.

through repeated use of digital payments. Both types of costs likely play a role in individual investors' investment decision. However, reductions in monetary costs, such as transaction fees, are unlikely to be the primary driver, as these would typically lead to a universal increase in participation, irrespective of an individual's use of QRPay. We provide evidence in support of the non-monetary costs channel by documenting investor login activity around initial purchases (Subsection 5.1), analyzing subsequent purchasing dynamics (Subsection 5.2), and using survey data to identify main investment drivers (Subsection 5.3).

5.1 Event Study of First Purchase

Super apps may facilitate learning and information acquisition, leading to improved financial literacy.[31] To proxy for the time and effort investors spend learning about financial products, we acquire additional data from Ant Group regarding Alipay's monthly login frequency and Fortune tab visit frequency. The Fortune tab acts as the gateway to the investment section, providing users with access to detailed mutual fund information and the latest market updates. Due to data availability constraints, our sample period spans from September 2020 to December 2023, which is slightly later than the period used in the main analysis.[32]

We first verify that initiating purchases of risky assets typically correlates with increased login and visit activities. To investigate this, we conduct an event study centered around a user's first risky mutual fund purchase. We define the treatment group as users whose first purchase of risky assets exceeds 100 RMB in a given month between September 2020 and December 2023. For each treated event, we construct a control group using propensity score matching, by pairing each treated user with a control user that shares similar personal characteristics, consumption patterns, and digital payment information. We then compare the Alipay monthly login frequency and Fortune tab visit frequency between the treated and control groups for the six months surrounding the first purchasing event ($t = 0$), as reported in Figure 4.

Our findings indicate that prior to the event month, there is no significant difference in

[31] We thank the AE and two anonymous referees for suggesting this channel.

[32] We also obtain corresponding mutual fund investment and digital payment usage data for this new period, and verify that our main analysis between QRPay and risky investment still holds.

login and visit activity between the treated and control groups, suggesting that the matching is effective. In contrast, during the month of the first risky purchase, the treatment group experiences a significant increase in both overall Alipay logins and Fortune tab visits compared to the control group. This difference further widens in event month $t+1$ before slightly declining in the subsequent months. The persistent, significant difference in Fortune tab visits after the initial purchase suggests that investors continue to seek information from the platform. In terms of economic magnitude, during the month of their first risky fund purchase, treated users log into the Fortune tab 30 times more than the control group.

We then validate that digital payment usage leads to an increase in subsequent login activity, using a panel regression framework. Table 9 presents the relationship between digital payment usage in month t and the frequency of Alipay logins and Fortune tab visits in the following month. In the full model, which includes time and user fixed effects (column 4 of both panels), we find that a 1% increase in digital payment activity is associated with a 0.13% increase in Alipay logins and a 0.14% increase in Fortune tab visits.

Taken together, these results suggest that higher digital payment usage leads to more frequent engagement with the Alipay app, especially its Fortune section. This finding is consistent with the hypothesis that the link between digital payment usage and risky investments is driven by improved financial literacy, as users invest time and effort in learning about financial products when considering their first risky fund purchase.

5.2 First and Subsequent Purchases

Next, we propose that frequent engagement with digital payment systems fosters familiarity and trust, which can help individuals overcome the psychological barriers to investing. To explore this mechanism, we analyze the likelihood of individuals purchasing unfamiliar and high-risk funds both during their initial investment and in subsequent transactions. If investors initially shy away from risky assets due to a lack of trust or familiarity but gradually build trust and familiarity through regular use of digital payments, we should observe a shift from low-risk to higher-risk funds and from familiar to unfamiliar assets as their adoption of FinTech increases.

To test this hypothesis, we investigate the initial and subsequent purchase of risky assets by individuals. To account for subsequent purchases, we use After1stPurc, which is a dummy variable equal to one in month t if an individual has made any purchases of risky assets as of month $t-1$, and zero otherwise. We incorporate both After1stPurc and After1stPurc×Log(QRPay) into the regression model in Table 2. The coefficient on the interaction term, After1stPurc×Log(QRPay), captures the additional impact of Log(QRPay) on subsequent purchases.

Comparing the results across different styles of funds, as shown in Table 10, two patterns emerge. Firstly, in the case of riskier funds, Log(QRPay) demonstrates a larger impact on subsequent purchases compared to its impact on initial purchases. For instance, a one-standard-deviation increase in Log(QRPay) increases the probability of an initial purchase of bond funds by 0.172% with no significant additional impact on subsequent purchases. For mixed funds, which carry higher risk compared to bond funds, a one-standard-deviation increase in Log(QRPay) is associated with a 0.667% increase in initial purchases. However, the effect on subsequent purchases amounts to 1.505% (=0.667%+0.838%), representing a 2.26-fold increase relative to the impact on initial purchases. Likewise, for equity, index, and QDII funds, the impact of Log(QRPay) on subsequent purchases is magnified by factors of 5.89, 4.95, and 7.94, respectively. This consistency aligns with the observation that these fund categories are even riskier than mixed funds.

Secondly, the impact of Log(QRPay) is more pronounced for subsequent purchases of unfamiliar fund styles compared to familiar ones. Consistent with the observation in Badarinza et al. (2019) that investors in emerging markets are well-acquainted with gold as a tangible asset, we find that the effect of Log(QRPay) on the subsequent purchase of gold funds is less than half of its impact on initial purchases. However, for unfamiliar assets, like QDII funds, which allocate capital to foreign assets, the influence of Log(QRPay) on subsequent purchases is 7.94 times its effect on initial purchases. This significant shift in magnitude is in line with the tendency of investors to exhibit a preference for familiar options, displaying hesitancy towards investing in foreign and unfamiliar assets. This bias tends to diminish as familiarity and trust accumulate through repeated payment usage, underscoring the critical role of familiarity and trust as key drivers in the impact of FinTech adoption.[33]

[33] In untabulated results, we show that the above pattern is not driven by performance or volatility chasing. When controlling for the interaction of Log(QRPay) with both the contemporaneous and past performance of

5.3 Survey Evidence

Finally, we conduct an online survey to explore the factors influencing mutual fund investors' choice of platforms. A detailed description of the survey can be found in Internet Appendix Section IA5. The results suggest that non-monetary transaction costs have a greater influence than monetary costs when investors choose investment platforms.

Two survey questions directly address this issue. The first question asks: "Which of the following characteristics is the primary reason for your choice of purchasing mutual funds through different platforms?" Among the 926 valid respondents, the most popular responses are: "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 factors, including "Fund security," "Fees," "Fund variety," and "other factors," each accounted for less than 10%.

The second question is: "If you have purchased mutual funds through Alipay, what are your top three reasons for using this platform?"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.

6 Conclusions

The entry of tech firms into the financial sector has the potential to dismantle physical barriers and unshackle the mental constraints for individuals, allowing them to participate more freely in financial markets. FinTech platforms, offering diverse financial services and challenging conventional institutions, raise a critical need for rigorous research and policy-making efforts to protect early adopters and comprehend the long-term impact on household

funds within each asset category (Ret_t and $\text{Ret}_{(t-12,t]}$), as well as the volatility of fund returns ($\text{STD}_{(t-12,t]}$), we find that the coefficients on Log(QRPay)×After1stPurc remain similar both economically and statistically. These results are available upon request.

finances.

Our research highlights the advantages of tech firms providing comprehensive financial services through all-in-one ecosystems. Unlike traditional financial institutions, FinTech's evolution involves bundling payment functions with various financial and non-financial services via "super apps" like Alipay. Despite concerns about BigTech platforms' monopolistic power (e.g. Frost et al. (2019)), integrating risky asset investment is desirable, especially in emerging markets where rapid income growth demands urgent financial services. Technology-based solutions, which are both cost-effective and scalable, offer promising answers, filling the void left by traditional financial institutions in regions lacking sufficient infrastructure.

However, FinTech development also poses challenges. Like any innovation, FinTech has its downsides. Rapid growth, such as in China's mutual-fund distribution, can also amplify investors' performance chasing, which further encourages excessive risk-taking by fund managers, as documented in Hong, Lu, and Pan (2025). This complexity emphasizes the intricate nature of FinTech regulation. No universal solution exists; policymakers must grasp FinTech's multifaceted development, understanding the biases and frictions it may amplify or mitigate. Therefore, it is imperative to develop a more profound understanding of how FinTech influences various aspects of household financial decisions, emphasizing the necessity for further academic research in this domain.

References

Agarwal, S., Ghosh, P., Li, J., and Ruan, T. (2019). Digital payments induce over-spending: Evidence from the 2016 demonetization in India. Working Paper.

Agarwal, S., Qian, W., Ren, Y., Tsai, H.T., and Yeung, B.Y. (2020). The real impact of FinTech: Evidence from mobile payment technology. Working Paper.

Ameriks, J., Kézdi, G., Lee, M., and Shapiro, M.D. (2020). Heterogeneity in expectations, risk tolerance, and household stock shares: The attenuation puzzle. Journal of Business & Economic Statistics 38(3), 633–646.

Badarinza, C., Balasubramaniam, V., and Ramadorai, T. (2019). The household finance landscape in emerging economies. Annual Review of Financial Economics *11*, 109–129.

Baker, S.R. (2018). Debt and the response to household income shocks: Validation and application of linked financial account data. Journal of Political Economy 126(4), 1504–1557.

Barber, B.M. and Odean, T. (2002). Online investors: Do the slow die first? The Review of Financial Studies 15(2), 455–488.

Bian, B., Ma, X., and Tang, H. (2021). The supply and demand for data privacy: Evidence from mobile apps. Working Paper.

Bian, W., Cong, L.W., and Ji, Y. (2023). The Rise of E-Wallets and Buy-Now-Pay-Later: Payment Competition, Credit Expansion, and Consumer Behavior. Working Paper.

Bogan, V. (2008). Stock market participation and the Internet. Journal of Financial and Quantitative Analysis 43(1), 191–211.

Boissay, F., Ehlers, T., Gambacorta, L., and Shin, H.S. (2021). *Big Techs in Finance: On the New Nexus Between Data Privacy and Competition*, pp. 855–875. Cham: Springer International Publishing.

Buchak, G., Hu, J., and Wei, S.J. (2022). FinTech as a financial liberator. Working Paper.

Calvet, L.E., Campbell, J.Y., Gomes, F., and Sodini, P. (2021). The cross-section of household preferences. Working Paper.

Calvet, L.E., Campbell, J.Y., and Sodini, P. (2007). Down or out: Assessing the welfare costs of household investment mistakes. Journal of Political Economy 115(5), 707–747.

Calvet, L.E., Campbell, J.Y., and Sodini, P. (2009). Measuring the financial sophistication of households. American Economic Review 99(2), 393–98.

Calvet, L.E., Celerier, C., Sodini, P., and Vallee, B. (2023). Can security design foster household risk-taking? The Journal of Finance 78(4), 1917–1966.

Campbell, J.Y. (2006). Household finance. The Journal of Finance 61(4), 1553–1604.

Cen, X. (2024). Smartphone trading technology, investor behavior, and mutual fund performance. Management Science 70(10), 6897–6916.

Chen, T., Huang, Y., Lin, C., and Sheng, Z. (2022). Finance and firm volatility: Evidence from small business lending in China. Management Science 68(3), 2226–2249.

Chen, Z. and Jiang, Z. (2022). The liquidity premium of digital payment vehicle. Working Paper.

Chi, Y. (2013). Performance evaluation of Chinese actively managed stock mutual funds. Working Paper.

Choi, J.J., Laibson, D., and Metrick, A. (2002). How does the Internet affect trading? Evidence from investor behavior in 401(k) plans. Journal of Financial Economics 64(3), 397–421.

Christiansen, C., Joensen, J.S., and Rangvid, J. (2008). Are economists more likely to hold stocks? Review of Finance 12(3), 465–496.

Cohen, A. and Einav, L. (2007). Estimating risk preferences from deductible choice. American economic review 97(3), 745–788.

D'Acunto, F., Prabhala, N., and Rossi, A.G. (2019). The promises and pitfalls of robo-advising. The Review of Financial Studies 32(5), 1983–2020.

Frost, J., Gambacorta, L., Huang, Y., Shin, H.S., and Zbinden, P. (2019). BigTech and the changing structure of financial intermediation. Economic Policy 34(100), 761–799.

Gambacorta, L., Huang, Y., Li, Z., Qiu, H., and Chen, S. (2023). Data versus collateral. Review of Finance 27(2), 369–398.

Gennaioli, N., Shleifer, A., and Vishny, R. (2015). Money doctors. The Journal of Finance 70(1), 91–114.

Guiso, L., Sapienza, P., and Zingales, L. (2008). Trusting the stock market. The Journal of Finance *63*, 2557–2600.

Haliassos, M. and Bertaut, C.C. (1995). Why do so few hold stocks? The Economic Journal 105(432), 1110–1129.

Higgins, S. (2020). Financial technology adoption: Network externalities of cashless payments in Mexico. American Economic Review forthcoming.

Hong, C.Y., Lu, X., and Pan, J. (2025). FinTech platforms and mutual fund distribution. Management Science 71(1), 488–517.

Hong, H., Kubik, J.D., and Stein, J.C. (2004). Social interaction and stock-market participation. The Journal of Finance 59(1), 137–163.

Jack, W. and Suri, T. (2011). Mobile money: The economics of M-PESA. Working Paper, National Bureau of Economic Research.

Jianakoplos, N.A. and Bernasek, A. (1998). Are women more risk averse? Economic inquiry 36(4), 620–630.

Jiang, W. (2019). Investment Funds in China. The handbook of China's financial system (Chapter 15).

Jones, C.M., Shi, D., Zhang, X., and Zhang, X. (2023). Retail trading and return predictability in China. Journal of Financial and Quantitative Analysis, 1–37.

Liu, L., Lu, G., and Xiong, W. (2022). The Big Tech Lending Model. Working Paper.

Mankiw, N.G. and Zeldes, S.P. (1991). The consumption of stockholders and nonstockholders. Journal of Financial Economics 29(1), 97–112.

Markowitz, H. (1952). Portfolio selection. The Journal of Finance 7(1), 77–91.

Merton, R.C. (1969). Lifetime portfolio selection under uncertainty: The continuous-time case. The Review of Economics and Statistics, 247–257.

Merton, R.C. (1971). Optimal portfolio and consumption rules in a continuous-time model. Journal of Economic Theory 3(4), 373–413.

Odean, T. (1999). Do investors trade too much? American Economic Review 89(5), 1279–1298.

Okat, D., Paaso, M., and Pursiainen, V. (2023). Trust in finance and consumer FinTech adoption. Working Paper.

Ouyang, S. (2021). Cashless payment and financial inclusion. Working Paper.

Reher, M. and Sokolinski, S. (2021). Automation and inequality in wealth management. Working Paper.

Stock, J.H. and Yogo, M. (2002). Testing for weak instruments in linear IV regression. Working Paper.

Sunden, A.E. and Surette, B.J. (1998). Gender differences in the allocation of assets in retirement savings plans. The American Economic Review 88(2), 207–211.

Suri, T. (2017). Mobile money. Annual Review of Economics *9*, 497–520.

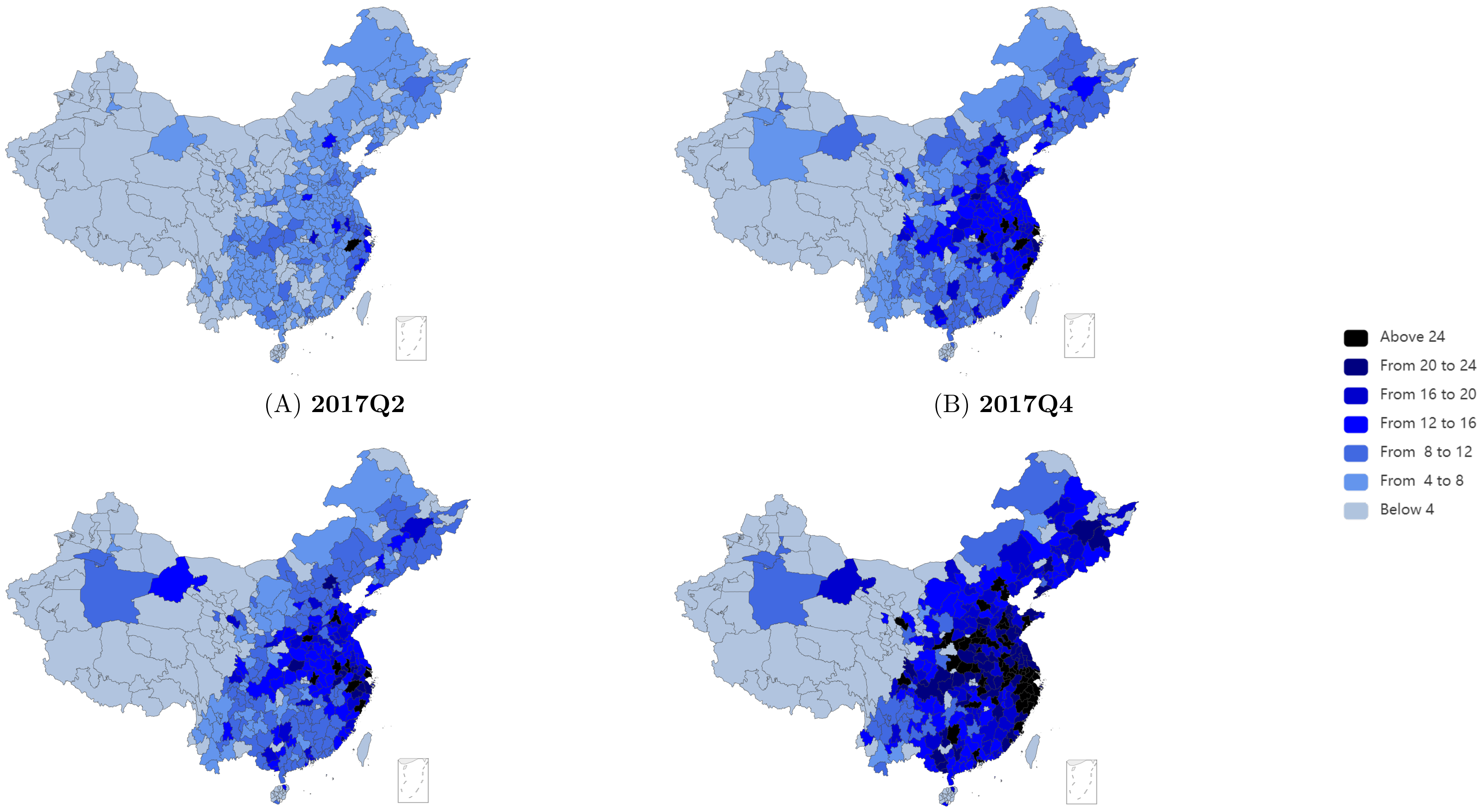
Suri, T., Bharadwaj, P., and Jack, W. (2021). Fintech and household resilience to shocks: Evidence from digital loans in Kenya. Journal of Development Economics *153*, 102697.

Tan, L., Zhang, X., and Zhang, X. (2023). Retail and institutional investor trading behaviors: evidence from China. Annual Review of Financial Economics *16*.

Tobin, J. (1958). Liquidity preference as behavior towards risk. The Review of Economic Studies 25(2), 65–86.

Vissing-Jørgensen, A. and Attanasio, O.P. (2003). Stock-market participation, intertemporal substitution, and risk-aversion. American Economic Review 93(2), 383–391.

Figure 1: **Geographic Distribution of FinTech Penetration**



(A) **2017Q2**

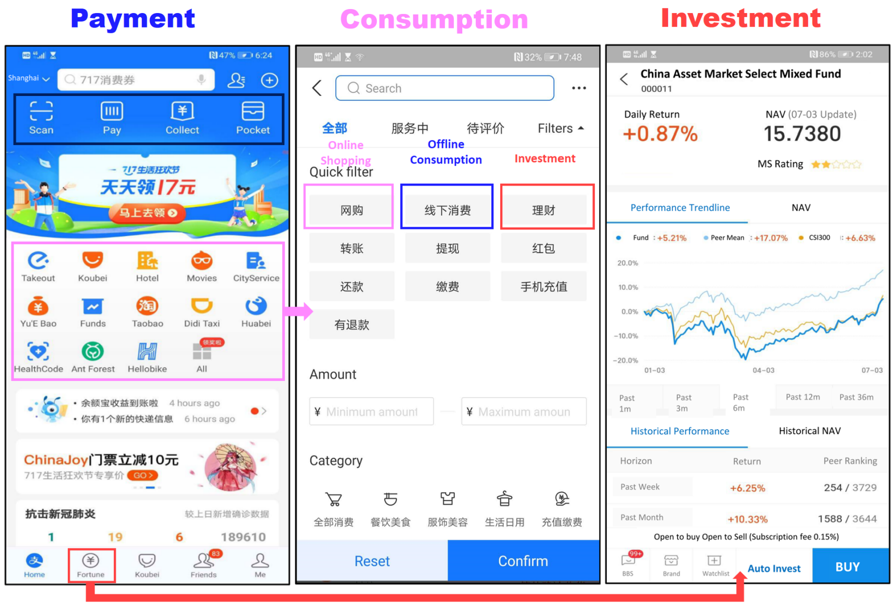
(B) **2017Q4**

(C) **2018Q2**

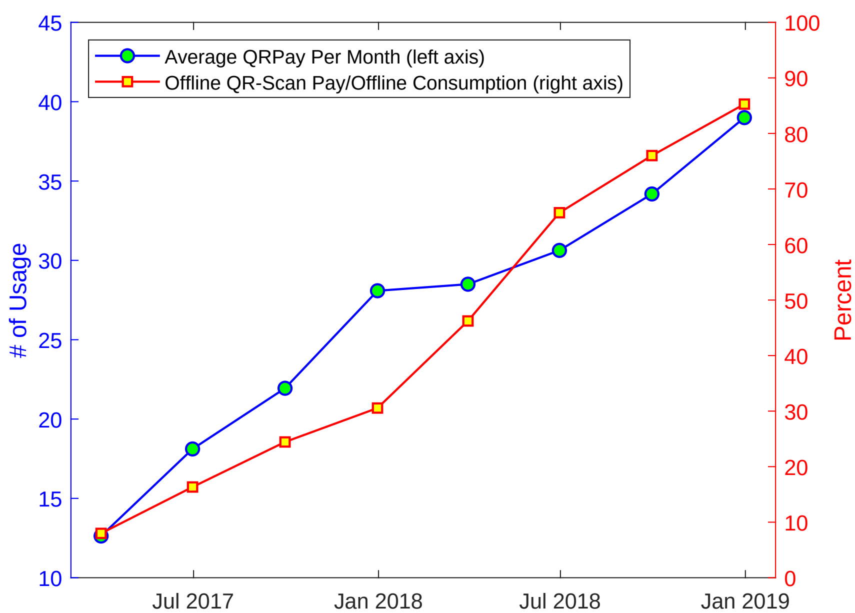
(D) **2018Q4**

Panels A to D display the geographic distribution of prefecture-level FinTech penetration from 2017Q2 to 2018Q4. Prefecture-level FinTech penetration is calculated as the average *QRPay* for individuals within a given prefecture. The darker the color, the higher the FinTech penetration.

Figure 2: **FinTech in China — Payment, Consumption, and Investment**



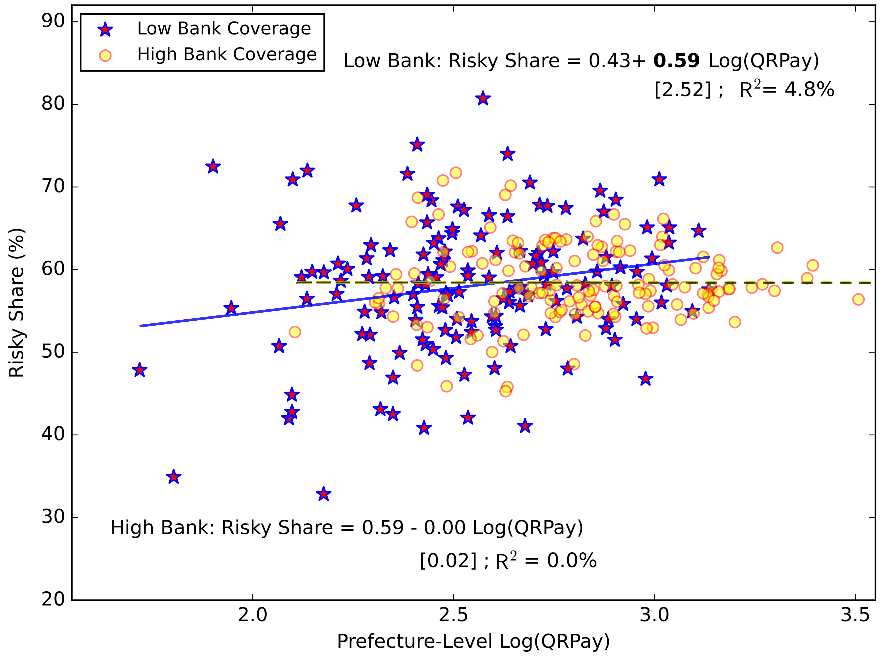
A: **Alipay User Interface**



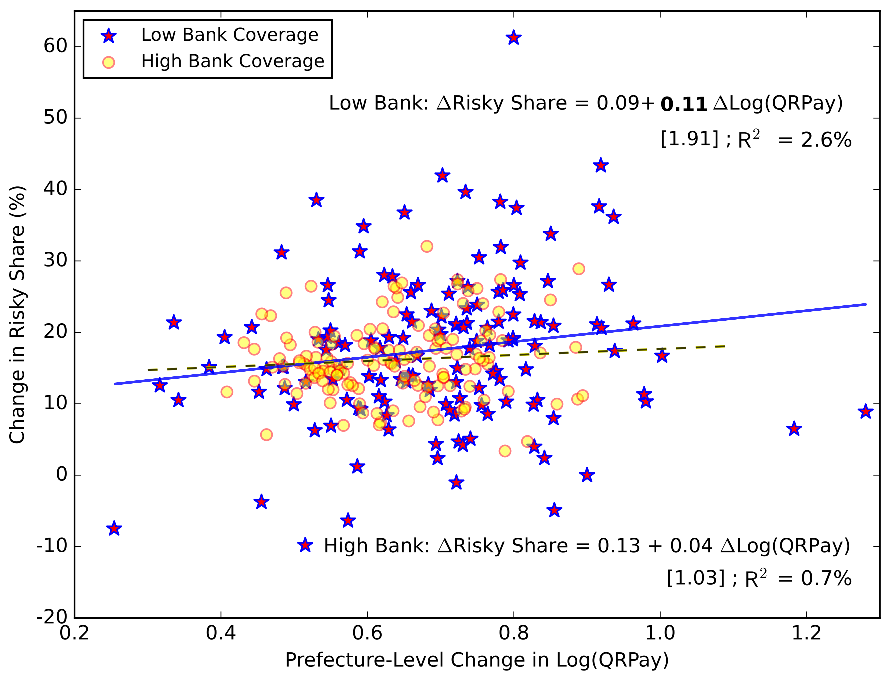
B: **Offline QR-Scan Payment and Alipay Payments**

Panel A presents sample pages from the Alipay user interface. The left screenshot displays the app's main page, while the middle screenshot showcases various functions offered through the Ant platform, including online shopping, offline consumption, and investment. The right screenshot illustrates a mutual fund page within the investment function. In Panel B, two time series are plotted: the average number of Alipay payment transactions per individual per month in our Ant sample and the nationwide total offline QR-Scan payments as a percentage of total offline consumption in China.

Figure 3: **FinTech Penetration and Traditional Banking Coverage**



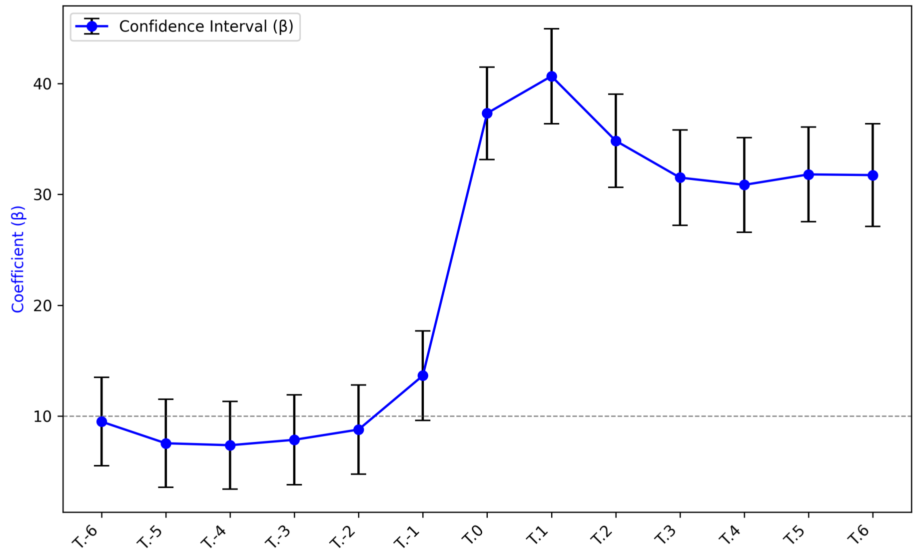
A: **Prefecture-Level Log(QRPay)**



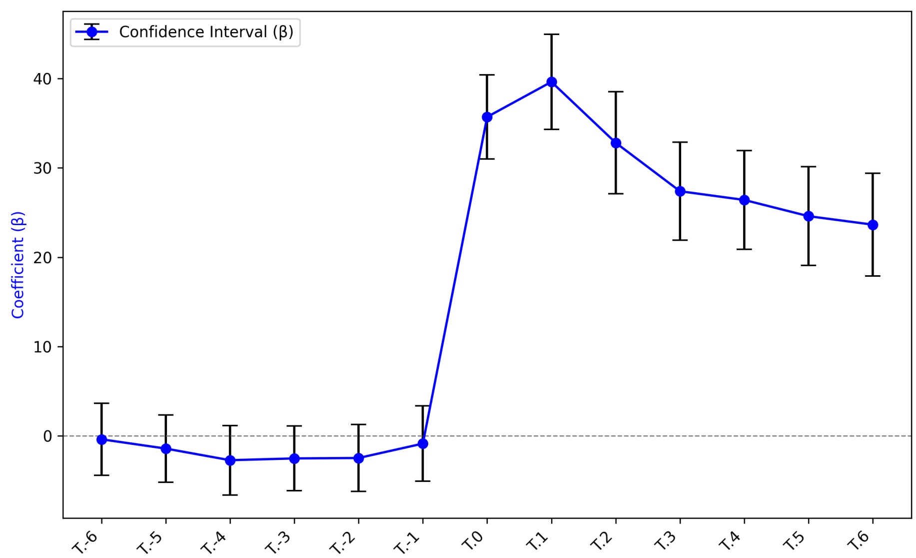
B: **Prefecture-Level ΔLog(QRPay)**

We classify all prefectures into two groups based on the median cut-off of the number of local bank branches. Panel A plots risky share of each prefecture against the prefecture-level Log(QRPay) for prefectures with high and low bank coverage, respectively. Panel B plots the change in risky share from 2017 to 2018 against the change in prefecture-level Log(QRPay) from 2017 to 2018 for prefectures with high and low bank coverage, respectively.

Figure 4: **Login and Page Visits around First Risky Fund Purchase**



A: **Alipay Login**



B: **Fortune Tab Visit**

In this figure, we identify the month when a user makes first significant investment in risky assets, and plot the Alipay login frequency and Fortune tab visit frequency around that event month. A user-month enters the treatment group if the user's first purchase of risky assets exceeds 100 RMB in a given month. Each treated user is matched one-to-one with a control user based on average consumption, QRpay, gender, and age. Panel A plots the difference in Alipay login between treated and control groups around the event month. Panel B shows the difference in Fortune tab visits. Month $t = 0$ marks the first risky fund investment for the treated group.

Table 1: **Summary Statistics**

Panel A and Panel B report the summary statistics and correlation matrix for the main variables in our sample. Age is defined at 2019 in years. Female is a dummy that equals one for female investors, and zero otherwise. Consumption (C) is the average monthly online (Taobao) consumption in RMB. σ_{C} is consumption growth volatility, calculated as the standard deviation of quarterly total consumption growth. QRPay is the number of Alipay QR-Scan payments made in an average month. QRFrac is the fraction of consumption paid via Alipay QR-Scan out of total consumption. To capture individual investment behavior, Risky Purchase is a dummy variable that equals one if the individual purchases any risky mutual funds in a given month, and zero otherwise. Risky Fraction is the fraction of risky fund purchase out of total fund purchase in a given month. Risky Redemption is a dummy variable that equals one if the individual redeems any risky mutual funds in a given month, and zero otherwise. For individuals who have ever made at least 100 RMB purchase of funds (including both risk-free and risky funds), we also construct variables to measure their portfolio allocation outcomes, including the fraction of risky funds investment (Risky Share), portfolio monthly return volatility (σ_{W}), number of funds invested (#Funds), and number of asset classes invested (#Assets), total amount of wealth invested (InvtWealth). See Internet Appendix IA1 for detailed variable definitions.

Panel A. Summary Statistics

Variable	N	Mean	Median	Q1	Q3	STD
Age	50,000	30.4	29.0	24.0	35.0	7.8
Female	50,000	0.6	1.0	0.0	1.0	0.5
Consumption (C)	50,000	2,155	1,259	743	2,235	17,064
σ_{C}	50,000	1.01	0.73	0.51	1.12	0.92
QRPay	50,000	21.40	15.70	7.88	29.11	19.22
QRFrac	50,000	0.54	0.56	0.38	0.71	0.22
Risky Purchase (%)	1,350,000	9.16	0.00	0.00	0.00	28.85
Risky Fraction (%)	1,350,000	8.75	0.00	0.00	0.00	28.11
Risky Redemption (%)	1,350,000	1.79	0.00	0.00	0.00	13.26
Risky Share (%)	28,393	50.76	51.09	0.00	99.80	46.15
σ_{W} (%)	28,393	2.13	0.18	0.00	2.71	4.66
#Funds	28,393	3.71	2.00	1.00	4.00	5.85
#Assets	28,393	1.93	1.00	1.00	3.00	1.30
InvtWealth	28,393	41,080	3,011	461	20,001	415,037

Panel B. Correlation Matrix

	Log(Age)	Female	Log(C)	σ_C(%)	Log(QRPay)	QRFrac	Risky Share	σ_W(%)	Log(#Funds)	Log(#Assets)	Log(InvtWealth)
Log(Age)	1.00	0.00	0.13	0.04	-0.24	-0.08	-0.09	-0.07	-0.10	-0.13	0.18
Female	0.00	1.00	0.04	-0.10	-0.08	-0.14	-0.12	-0.09	-0.11	-0.13	-0.03
Log(C)	0.13	0.04	1.00	0.08	0.15	-0.41	0.01	0.00	0.02	0.00	0.17
σ_C(%)	0.04	-0.10	0.08	1.00	-0.09	0.18	0.01	0.02	0.02	0.01	0.05
Log(QRPay)	-0.24	-0.08	0.15	-0.09	1.00	0.53	0.13	0.08	0.19	0.18	0.05
QRFrac	-0.08	-0.14	-0.41	0.18	0.53	1.00	0.06	0.03	0.07	0.08	0.03
Risky Share	-0.09	-0.12	0.01	0.01	0.13	0.06	1.00	0.48	0.26	0.32	-0.18
σ_W(%)	-0.07	-0.09	0.00	0.02	0.08	0.03	0.48	1.00	0.26	0.27	0.01
Log(#Funds)	-0.10	-0.11	0.02	0.02	0.19	0.07	0.26	0.26	1.00	0.82	0.42
Log(#Assets)	-0.13	-0.13	0.00	0.01	0.18	0.08	0.32	0.27	0.82	1.00	0.22
Log(InvtWealth)	0.18	-0.03	0.17	0.05	0.05	0.03	-0.18	0.01	0.42	0.22	1.00

Table 2: **Individual FinTech Adoption and Risky Fund Investment**

The table reports the panel regression estimates of individual FinTech adoption on an individual's next-month risky fund investment. 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 $t+1$. 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: $\text{Log(QRPay)}_t^i = a^i + b^i * \text{County Log(QRPay)}_t^i + \epsilon_t^i$. 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 Internet Appendix IA1 for variable definitions.

Panel A. Individual FinTech Adoption and Risky Fund Purchase

	Y=Risky Purchase$_{t+1}$				Y=Risky Fraction$_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(QRPay)	2.719***	2.206***	2.660***	1.413***	2.549***	2.073***	2.509***	1.356***
	(7.78)	(8.13)	(6.07)	(6.32)	(7.76)	(8.27)	(5.97)	(6.40)
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	1.2%	2.2%	28.4%	29.4%	1.1%	2.1%	27.8%	28.8%
Within R-sq.	1.2%	0.9%	0.5%	0.1%	1.1%	0.8%	0.5%	0.1%

Panel B. Peer-driven vs. Idiosyncratic FinTech Adoption

	Y=Risky Purchase$_{t+1}$				Y=Risky Fraction$_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Log(QRPay)	3.387***	3.043***	4.811***	2.896***	3.168***	2.861***	4.520***	2.784***
	(8.15)	(8.27)	(5.74)	(6.24)	(8.12)	(8.43)	(5.52)	(6.29)
Idio Log(QRPay)	1.047***	0.997***	1.058***	1.013***	0.999***	0.953***	1.011***	0.970***
	(5.00)	(5.06)	(5.04)	(5.26)	(5.03)	(5.10)	(5.07)	(5.30)
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	1.3%	2.3%	28.6%	29.5%	1.3%	2.2%	28.0%	28.8%
Within R-sq.	1.3%	0.9%	0.8%	0.1%	1.3%	0.9%	0.8%	0.1%

Table 3: **Distance from Ant as Instruments for FinTech Penetration**

This table presents the 2SLS estimation results, using the physical distance from Ant headquarters as an instrument for FinTech penetration. Panel A illustrates the impact of distance on FinTech penetrations for subsamples of counties within 1000km, 500km, and 300km of Ant headquarters. In columns (1) to (4), Log(Dist from X) represents the natural logarithm of the distance from Ant headquarters, while in columns (5) to (8), it represents the distance from Shanghai. We control for the natural logarithm of county-level GDP (Log(GDP)), population (Log(Population)), and income per person (Log(Income)), as well as the square terms of these county controls (i.e., Log(GDP)^2, Log(Population)^2, and Log(Income)^2). Additionally, we control for bank coverage using, LowBank, a dummy variable that equals one if the county belongs to prefectures with below-median bank coverage, and zero otherwise. Panel B provides the first and second stage IV estimates for regions within a 300km radius of Ant headquarters. To capture the time-varying effects of distance on FinTech penetration, we further include the interaction term of distance from Ant and time as an instrument for Log(QRPay). Time is the number of years since January 2017. 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 Internet Appendix IA1 for variable definitions.

Panel A. Effect of Distance on FinTech Penetration, Y=Log(QRPay)

	Ant Headquarters				Shanghai			
	All	<1000 km	<500 km	<300 km	All	<1000 km	<500 km	<300 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Dist from X) (a)	-0.241***	-0.160***	-0.122***	-0.166***	-0.213***	-0.095**	0.109*	0.103
	(-13.20)	(-5.83)	(-3.08)	(-4.16)	(-10.60)	(-2.75)	(1.74)	(1.47)
County Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	20,202	12,376	5,902	4,212	20,202	12,376	5,902	4,212
R-squared	74.5%	73.8%	74.1%	73.3%	73.3%	72.6%	73.5%	71.4%
F-stat (a)	174.26	33.94	9.49	17.34	112.3	7.57	3.04	2.15

Panel B. IV Regression for Counties within 300 km from Ant

	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($\widehat{\text{QRPay}}$)				2.512**	2.310**	3.630**	2.368**	2.189**	3.406**
				(2.24)	(2.22)	(2.56)	(2.20)	(2.17)	(2.46)
Log(Dist from Ant)	-0.166***	-0.230***	-0.363***						
	(-4.16)	(-5.06)	(-4.23)						
Log(Dist from Ant)×Time		0.071***	0.124***						
		(6.33)	(3.14)						
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	4,212	4,212	4,108	4,212	4,212	4,108	4,212	4,212	4,108
R-squared	73%	73%	84%	40%	40%	52%	39%	38%	51%

Table 4: **FinTech Penetration via Public Transportation**

This table presents the difference-in-differences regression estimates examining the adoption of QRPay in Shenzhen's public transportation system. In March 2017, Ant Financial collaborated with Shenzhen Tong to introduce QRPay on public bus routes. The variable *SZ* is a dummy that equals one for individuals in Shenzhen, while Post equals one for observations post-March 2017. To assess the dynamic timing effects, we include time dummies $D(t = x)$ around the event and their interactions with *SZ*, where *t=0* corresponds to March 2017. Columns (1), (2), (5), and (6) report results estimated using the full sample of individuals. In columns (3), (4), (7), and (8), we apply propensity score matching to pair individuals in Shenzhen with counterparts of similar Log(Age), Female, Log(C), Log(QRPay), and σ_{C}, using data from January 2017. The sample period spans from January 2017 to December 2017. All regressions control for individual characteristics and include time fixed effects. Standard errors are double-clustered by time and individual. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

	Y=Risky Purchase				Y=Risky Fraction			
	Whole Sample		Matched Sample		Whole Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SZ	0.022	0.25	0.435	0.093	0.049	0.245	0.453	0.093
	(0.06)	(1.00)	(0.76)	(0.24)	(0.12)	(0.99)	(0.78)	(0.25)
$SZ \times Post$	1.493***		1.272**		1.468***		1.248**	
	(3.87)		(2.51)		(4.09)		(2.60)	
$SZ \times D(t=-1)$		-0.507		0.12		-0.507		0.12
		(-1.48)		(0.31)		(-1.47)		(0.30)
$SZ \times D(t=0)$		-0.177		0.904**		-0.082		0.961**
		(-0.64)		(2.75)		(-0.30)		(2.93)
$SZ \times D(t=1)$		0.436		1.265***		0.501*		1.324***
		(1.56)		(4.58)		(1.80)		(4.88)
$SZ \times D(t=2)$		0.785***		0.964***		0.848***		0.964***
		(3.77)		(4.23)		(4.08)		(4.23)
$SZ \times D(t=3)$		1.072***		1.325***		1.153***		1.276***
		(5.10)		(6.30)		(6.13)		(6.46)
$SZ \times D(t=4)$		0.696***		1.446***		0.750***		1.550***
		(3.23)		(6.41)		(3.64)		(7.17)
$SZ \times D(t \geq 5)$		1.679***		1.904***		1.639***		1.873***
		(3.61)		(3.25)		(3.95)		(3.69)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	600,000	600,000	39,840	39,840	600,000	600,000	39,840	39,840
R-squared	0.7%	0.7%	0.8%	0.8%	0.6%	0.6%	0.8%	0.8%

Table 5: **FinTech Adoption and Portfolio Risk Taking, Conditional on Individual Risk Appetite**

The table presents cross-sectional regression estimates examining the impact of FinTech adoption on portfolio risk taking, conditional on individuals' risk appetite. Panel A reports the relation between survey-reported individual risk appetite, Log(Risk Level), and individual characteristics, including Log(Age), Female, Log(C), and σ_C. Panel B reports the relation between individual portfolio risk taking and individual risk appetite. Risky Share is the average fraction of risky funds investment in the entire sample period, while σ_W is the standard deviation of individual portfolio monthly return in percent. The independent variables include individual characteristics and the predicted risk appetite derived from these characteristics, as specified in column (5) of Panel A. All continuous independent variables, as well as risk appetite, are standardized to have a mean of zero and a standard deviation of one. The sample excludes individuals with fund purchases totaling less than 100 RMB, encompassing both risk-free and risky mutual funds. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. See Internet Appendix IA1 for variable definitions.

Panel A. Determinants of Risk Appetite

	(1)	(2)	(3)	(4)	(5)
Female	-0.143***				-0.146***
	(-15.36)				(-15.52)
Log(Age)		-0.001			-0.012**
		(-0.30)			(-2.58)
Log(C)			0.047***		0.051***
			(10.34)		(10.84)
σ_C				0.021***	0.010**
				(4.65)	(2.19)
County FE	Y	Y	Y	Y	Y
Observations	49,355	49,355	49,355	49,355	49,355
R-squared	2.2%	1.7%	1.9%	1.7%	2.4%

Panel B. Portfolio Risk Taking and Individual Risk Appetite

	Risky Share					σ_W				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log(QRPay)	2.674***	2.158***	2.259***	2.271***	2.245***	0.474***	0.405***	0.380***	0.379***	0.371***
	(8.17)	(8.87)	(9.32)	(9.34)	(9.25)	(9.88)	(11.69)	(11.54)	(11.61)	(11.42)
Log(QRPay)×Female	-0.719*					-0.165***				
	(-1.87)					(-2.94)				
Log(QRPay)×Log(Age)		0.800***					-0.095***			
		(3.80)					(-3.72)			
Log(QRPay)×Log(C)			0.224					-0.008		
			(1.12)					(-0.30)		
Log(QRPay)× σ_C				0.372*					0.076***	
				(1.95)					(2.62)	
Log(QRPay)× Risk $\hat{\text{Appetite}}$					0.337*					0.080***
					(1.80)					(2.89)
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	49,994	49,994	49,994	49,994	49,994	28,383	28,383	28,383	28,383	28,383
R-squared	4.3%	4.3%	4.3%	4.3%	4.3%	4.8%	4.9%	4.8%	4.8%	4.9%

Table 6: **FinTech Adoption and Portfolio Risk Taking, Conditional on Local Financial Coverage**

The table reports the effect of county-level FinTech penetration on risky fund participation, conditional on local financial coverage. The dependent variable is the average fraction of risky fund purchase in month $t+1$. In columns (2) to (3), local financial coverage is captured by LowBank, a dummy variable that equals one for counties with a below-median number of bank branches, and zero otherwise. In columns (4) to (7), we capture local financial product coverage using data from 2017 CHFS (China Household Finance Survey Data). We first calculate each individual's risky participation rate and then average these rates across individuals to derive county-level measures of risky asset participation. Low Participation is a dummy variable equal to one for counties with below-median participation in risky financial assets and zero otherwise, while Low Fraction equals one for counties where the average fraction of risky assets out of total financial assets is below the median, and zero otherwise. Log(QRPay) is the natural logarithm of the number of Alipay QR-Scan payments in month t, averaged across individuals in the county. The coefficients of interest are the interaction between financial coverage proxies and Log(QRPay). We also control for the natural logarithm of county-level GDP, population, income per person, and their squared terms. All continuous independent variables are standardized with a mean of zero and a standard deviation of one. The sample period is from January 2017 to March 2019. Standard errors are double-clustered at the county and month level. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. See Internet Appendix IA1 for variable definitions.

	Y=Risky Fraction						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(QRPay)	2.083***	2.000***	1.995***	2.048***	2.055***	2.047***	2.053***
	(5.39)	(4.98)	(4.89)	(5.30)	(5.31)	(5.30)	(5.31)
Log(QRPay)×LowBank		0.396**	0.403**				
		(2.38)	(2.35)				
Log(QRPay)×Low Participation				0.352*	0.308*		
				(2.06)	(1.87)		
Log(QRPay)×Low Fraction						0.385**	0.345**
						(2.23)	(2.10)
Log(QRPay)×Log(GDP)			-0.025		-0.092		-0.092
			(-0.29)		(-1.00)		(-1.01)
Log(QRPay)×Log(Income)			0.027		0.029		0.033
			(0.30)		(0.33)		(0.36)
Log(QRPay)×Log(Population)			0.072		0.063		0.062
			(1.06)		(0.93)		(0.92)
County Controls	Y	Y	Y	Y	Y	Y	Y
Observations	20,202	20,202	20,202	20,202	20,202	20,202	20,202
R-squared	12.3%	12.5%	12.6%	12.4%	12.4%	12.4%	12.4%

Table 7: **FinTech Adoption and Risk Taking for Matched Sample**

This table examines the effect of FinTech adoption on risk-taking for individuals in high- and low-bank coverage counties, based on a matched sample of individuals. We match each individual in a low bank coverage county with an individual in a high bank coverage county, by requiring the two to share the same gender, same year of birth, and have the closest value of consumption level (Log(C)) and consumption growth volatility (σ_C). Panel A reports the summary statistics for individuals from both low- and high-bank coverage counties within the matched sample, along with the differences between these groups. Panel B reports the regression estimates for the effect of FinTech on portfolio risk taking (σ_W). We regress individual σ_W on Log(QRPay), while controlling for individual characteristics, including Log(Age), Female, Log(C), and σ_C. The coefficients for Log(QRPay) are estimated separately for individuals in high- and low-bank coverage areas, with the final column displaying the difference in coefficient estimates between these two groups. The results are reported for the entire matched sample and for subsamples defined by median cutoffs based on gender, mature individuals (ages 30 to 55), consumption level, and σ_C. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Panel A. Summary Statistics for Matched Sample

	Low Bank			High Bank		Low-High	
Variable	N	Mean	STD	Mean	STD	Mean	t-stat
Female	4,053	0.59	0.49	0.59	0.49	0.00	
Log(Age)	4,053	3.43	0.24	3.43	0.24	0.00	(0.03)
Log(C)	4,053	7.25	0.82	7.25	0.81	0.00	(0.12)
σ_C	4,053	1.10	1.01	1.09	1.01	0.01	(0.33)
Log(QRPay)	4,053	2.25	0.86	2.77	0.88	-0.52	(-26.91)
σ_W (%)	4,053	2.12	4.62	2.28	5.01	-0.16	(1.45)

Panel B. Effect of FinTech on σ_W (Coefficients on Log(QRPay)

	Low Bank	High Bank	Difference		Low Bank	High Bank	Difference
All	0.505***	0.245***	0.260**				
	(5.26)	(2.82)	(2.01)				
Male	0.610***	0.322**	0.288	Female	0.416***	0.158	0.258*
	(3.46)	(2.20)	(1.26)		(3.96)	(1.49)	(1.73)
Age [30,55]	0.486***	0.077	0.409***	Age<30 or Age>55	0.529***	0.467***	0.062
	(4.37)	(0.73)	(2.66)		(3.22)	(3.26)	(0.28)
High Consumption (C)	0.651***	0.176	0.475**	Low Consumption (C)	0.356***	0.305**	0.050
	(4.69)	(1.43)	(2.57)		(2.68)	(2.48)	(0.28)
High σ_C	0.701***	0.359***	0.342*	Low σ_C	0.339***	0.122	0.217
	(4.60)	(3.02)	(1.78)		(2.86)	(0.96)	(1.25)
High Risk Appetite	0.583***	0.233*	0.350*	Low Risk Appetite	0.416***	0.240**	0.176
	(3.81)	(1.78)	(1.74)		(3.64)	(2.11)	(1.09)

Table 8: **Fund Performance and Diversification Benefit**

Panel A reports the monthly alpha for the mutual fund industry as a whole (All Funds), funds available for sale on Ant Platform (Ant Funds), and funds invested by Ant investors (Ant Investor Held), respectively. Fund alpha is estimated using a two-factor model for the period from April 2019 to December 2021. In the left two columns, we form value-weighted portfolios using each fund's last quarter's total net assets as the portfolio weights for all funds and Ant funds, respectively. In the third column, we form a value-weighted portfolio using Ant investors' holdings amounts as the portfolio weights. The right three columns report the corresponding estimates for equal-weighted fund portfolios. Panel B reports the effect of FinTech adoption on individuals' portfolio allocation outcomes. Log(#Funds) and Log(#Assets) are the natural logarithms of the number of unique funds and number of unique asset classes invested in by the investor, respectively. Sharpe ratio (in percent) is computed as expected portfolio excess return ($w_i^{'}E(ret-rf)$) scaled by expected portfolio volatility (σ_i), where expected return and variance-covariance matrix are both estimated using historical data from 2005 to 2019 and one-year deposit rate is used as the risk-free rate. We include county fixed effects as indicated. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Panel A. Monthly Fund Alpha, 2019.4-2021.12

		VW			EW		
		All Funds	Ant Funds	Ant Investor Held	All Funds	Ant Funds	Ant Investor Held
Bond	Mean	0.02%	0.04%	0.05%	0.01%	0.02%	0.02%
	t-stat	(0.88)	(1.05)	(0.74)	(0.20)	(0.27)	(0.36)
Mixed	Mean	1.00%*	1.04%	1.18%*	0.97%**	1.03%	1.23%*
	t-stat	(1.72)	(1.72)	(1.91)	(2.08)	(2.05)	(2.02)
Equity	Mean	0.46%	0.80%	1.00%*	0.60%	0.72%	0.78%
	t-stat	(1.01)	(1.41)	(1.83)	(1.35)	(1.50)	(1.58)

Panel B. Portfolio Diversification

	Log(#Funds)		Log(#Assets)		Sharpe ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(QRPay)	0.106***	0.128***	0.067***	0.086***	0.955***	1.326***
	(22.28)	(22.88)	(21.34)	(23.29)	(15.02)	(18.34)
Log(Age)	-0.068***	-0.060***	-0.052***	-0.046***	-0.640***	-0.527***
	(-14.60)	(-12.06)	(-17.99)	(-14.84)	(-11.01)	(-8.76)
Female	-0.155***	-0.148***	-0.109***	-0.106***	-1.393***	-1.247***
	(-15.83)	(-14.75)	(-18.17)	(-16.95)	(-12.07)	(-10.52)
Log(C)	0.001	0.001	-0.006**	-0.006**	0.068	0.088
	(0.30)	(0.24)	(-2.14)	(-2.21)	(1.27)	(1.64)
σ_C	0.019***	0.018***	0.010***	0.009***	0.082	0.083
	(4.22)	(3.89)	(3.51)	(3.36)	(1.40)	(1.39)
County FE	N	Y	N	Y	N	Y
Observations	20,033	20,023	20,033	20,023	20,033	20,023
R-squared	6.2%	10.2%	7.1%	11.5%	3.4%	8.2%

Table 9: **FinTech Adoption and Page Visit Activities**

The table reports the panel regression estimates of individual FinTech adoption on an individual's next-month login and fortune tab visit activities. In Panel A, the dependent variable is the natural logarithm of the number of Alipay login frequency in month $t+1$. In Panel B, the dependent variable is the natural logarithm of the number of Fortune tab visits in month $t+1$. Log(QRPay) is the natural logarithm of the number of digital payment usage in month t. We control for individual characteristics, including Log(Age) and Female. We include time fixed effect and user fixed effect as indicated. Login data is acquired for the same sample of users as in our main analyses. The sample period spans from September 2020 to December 2023 due to data availability. Standard errors are double-clustered at the user and time levels. We report the within-group R-squared. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively.

Panel A. Y = Log(Alipay Login)				
	(1)	(2)	(3)	(4)
Log(QRPay)	0.305	0.293	0.166	0.129
	(75.75)	(79.37)	(21.16)	(29.79)
Controls	Y	Y	Y	Y
Time FE	N	Y	N	Y
User FE	N	N	Y	Y
Observation	1,920,898	1,920,898	1,920,898	1,920,898
Within R-squared	9.63%	9.02%	4.20%	2.73%
Panel B. Y = Log(Fortune Tab Visit)				
	(1)	(2)	(3)	(4)
Log(QRPay)	0.329	0.318	0.177	0.141
	(40.72)	(41.91)	(17.85)	(23.77)
Controls	Y	Y	Y	Y
Time FE	N	Y	N	Y
User FE	N	N	Y	Y
Observation	1,920,898	1,920,898	1,920,898	1,920,898
Within R-squared	9.49%	9.04%	3.07%	1.99%

Table 10: **Initial and Subsequent Purchase of Each Asset Class**

This table presents the impact of FinTech adoption on individuals' likelihood of making risky purchases across various asset categories, following their initial purchase of risky assets. The dependent variables are the risky purchases within specific asset classes in month $t+1$. For instance, in column (3), the dependent variable is a binary indicator that equals one if the individual made any equity fund purchase in month $t+1$, and zero if not. The asset classes considered risky include bond, mixed, equity, index, QDII, and gold. The variable After1stPurc is a dummy that equals one in month t if an individual has purchased risky assets by month $t-1$, and zero otherwise. 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 effects in all the specifications. The last two rows report the mean and standard deviation of fund returns in each asset category over our sample period from January 2017 to March 2019. Standard errors are double-clustered at the time and user levels. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. See Internet Appendix IA1 for variable definitions.

	Bond	Mixed	Equity	Index	QDII	Gold
	(1)	(2)	(3)	(4)	(5)	(6)
Log(QRPay)	0.172***	0.667***	0.077**	0.172***	0.031**	1.153**
	(3.05)	(3.62)	(2.50)	(3.13)	(2.62)	(2.73)
Log(QRPay)×After1stPurc	0.029	0.838***	0.376***	0.679***	0.215***	-0.663**
	(0.34)	(3.22)	(5.90)	(8.46)	(6.39)	(-2.07)
After1stPurc	-0.086	2.101**	0.976***	1.050***	0.195***	-2.377**
	(-0.27)	(2.46)	(6.86)	(3.55)	(4.06)	(-2.61)
σ_{C}	-0.034	-0.055	-0.002	0.025	-0.016	0.052
	(-1.50)	(-0.95)	(-0.07)	(0.70)	(-1.03)	(1.64)
Log(C)	0.138***	0.653***	0.154***	0.335***	0.095***	-0.076**
	(4.58)	(9.88)	(5.01)	(6.99)	(5.00)	(-2.41)
Female	-0.093*	-1.327***	-0.442***	-0.899***	-0.208***	-0.640***
	(-1.89)	(-9.35)	(-7.10)	(-8.10)	(-6.39)	(-5.07)
Log(Age)	0.140***	0.825***	0.113***	0.144***	0.017	-0.186***
	(4.85)	(11.31)	(4.02)	(3.70)	(1.41)	(-2.86)
Time FE	Y	Y	Y	Y	Y	Y
Observations	1,300,000	1,300,000	1,300,000	1,300,000	1,300,000	1,300,000
R-squared	0.9%	1.3%	0.6%	1.1%	0.3%	2.8%
Mean	0.35%	0.39%	0.35%	0.25%	0.33%	0.33%
STD	1.54%	2.36%	2.46%	4.11%	3.11%	1.96%

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

- Section IA1. Definitions of Variables
- Section IA2. QRPay Implementation in the Shenzhen Transit Network
- Section IA3. Consumption Volatility and Individual Risk Preference
- Section IA4. Other Discussions
  - Section IA4.1 Sample Selection
  - Section IA4.2 Substitution from Banks and Extensive Margin
  - Section IA4.3 Access to Credit Provision
  - Section IA4.4 Alternative Measure of FinTech Penetration
  - Section IA4.5 Other Robustness Tests
- Section IA5. Survey of Mutual Fund Investment
  - Section IA5.1 Survey Design and Data Collection
  - Section IA5.2 Survey Results

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 $(1/\gamma)$.[34]

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 across individuals.

---

[34]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.

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 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.[35] 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 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

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

effective mutual fund accounts increased from 265 million at the end of 2016 to 793 million at the end of 2019.[36] 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.[37] 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 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

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

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

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.

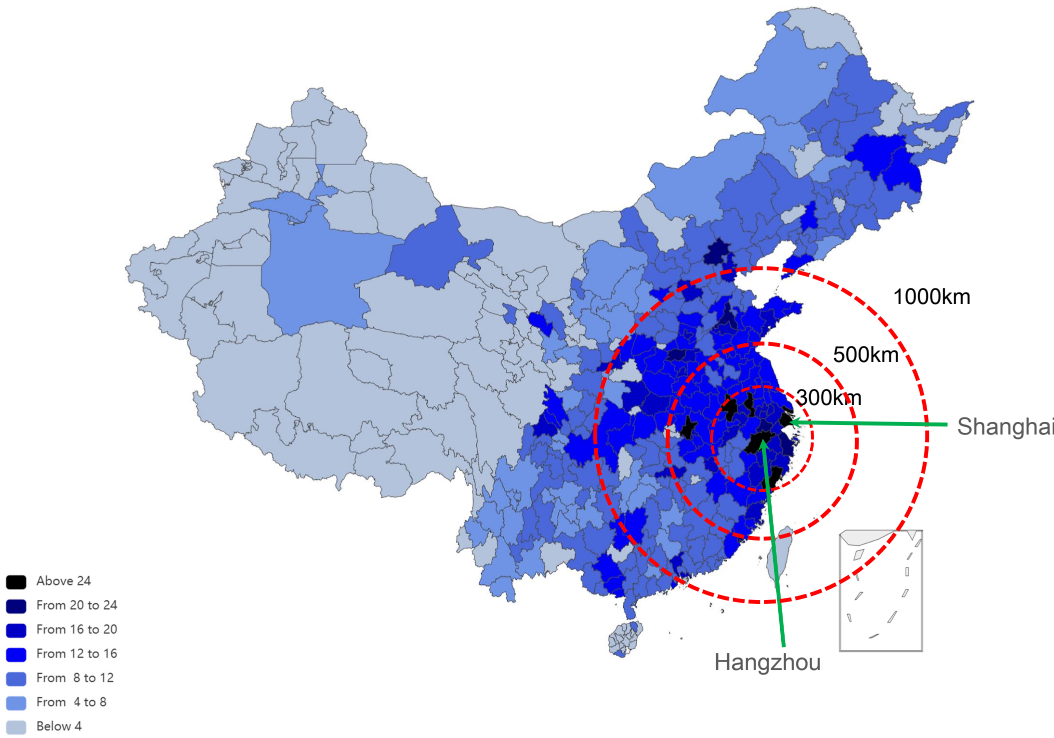
To enhance the representativeness of these findings, we apply similar weighting adjustments as described in Appendix Section IA4.1. The weighted estimates are 24.9% for the general population and 26.4% for the Ant sample, respectively, closely aligning with the unweighted figure. Overall, the survey 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.

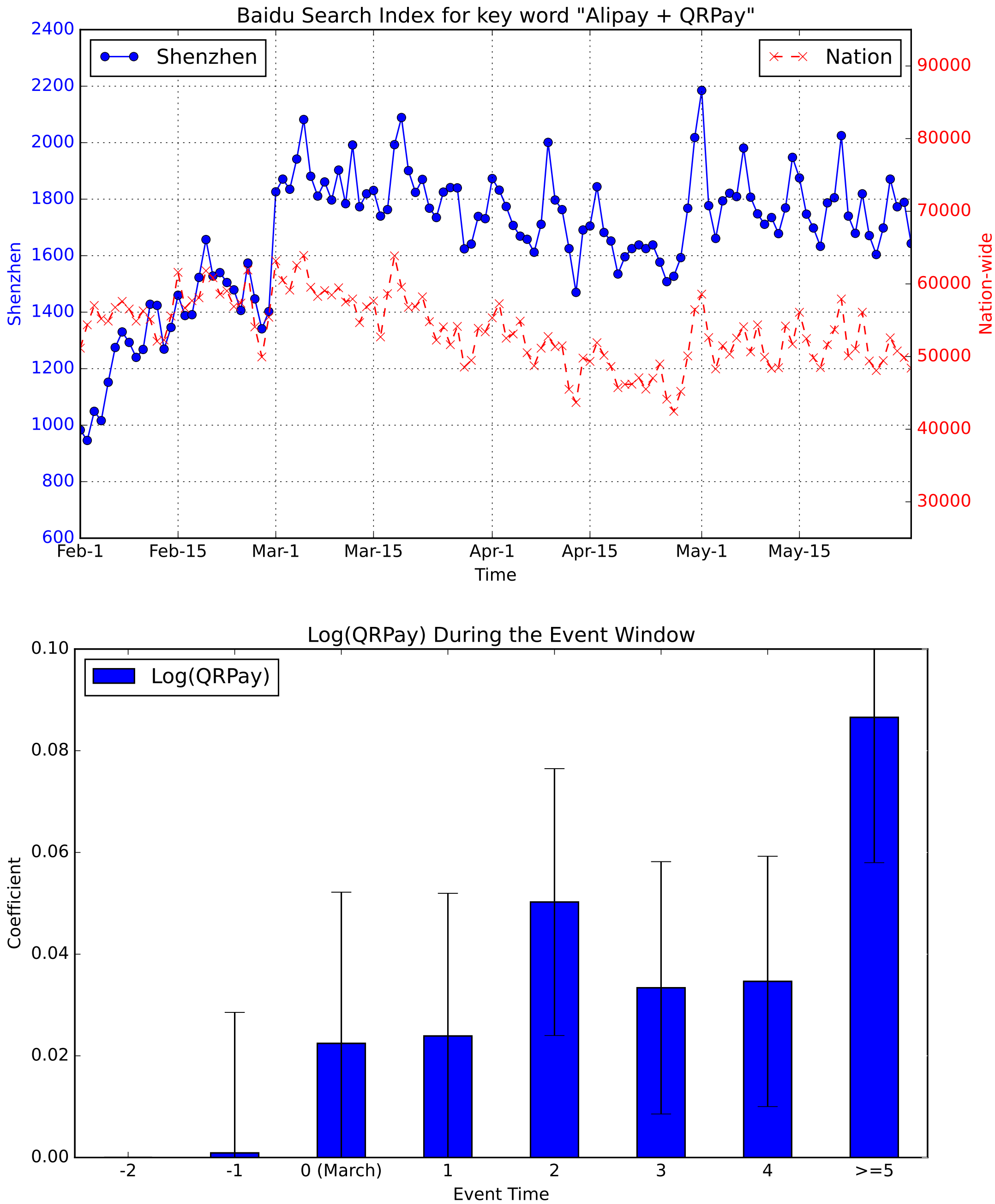
Taken together, the results from both questions suggest that non-monetary transaction costs have a greater influence than monetary costs when investors choose investment platforms.

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



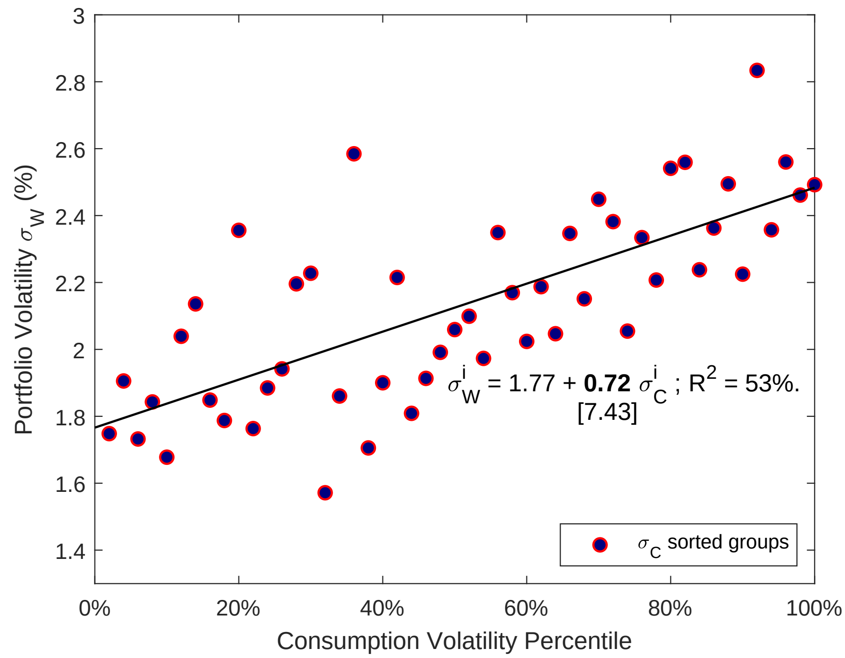
This figure shows the geographic distribution of prefecture-level average FinTech penetration for the sample period from 2017Q1 to 2019Q1. Prefecture FinTech penetration is calculated as the average QRPay for individuals in a given prefecture during our sample. Centering around the headquarters of Ant 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**

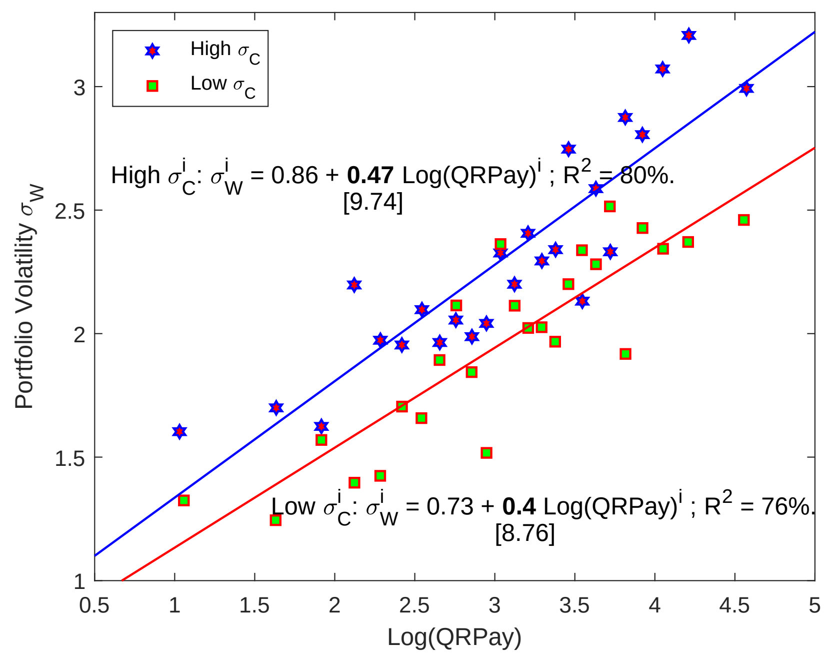


The upper graph illustrates the Baidu search index for the keywords "Alipay + QRPay." The blue solid line represents the search index for individuals in Shenzhen, while the red dotted line depicts the nationwide search index. The lower graph shows the change in Log(QRPay) relative to its value in month $t = -2$. 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($\widehat{\text{QRPay}}$)				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