Financial Inclusion via FinTech:

From Digital Payments to Platform Investments

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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 help break down households' participation barriers, particularly the psychological ones, ultimately leading to higher participation in the financial market. Taking advantage of an individual-level FinTech dataset, we find that higher FinTech adoption, both at the individual-level and the county-level instrumented by distance-from-Hangzhou, results in higher participation and more risk-taking in mutual-fund investments. Moreover, individuals who are otherwise more constrained, those with higher risk tolerance, or living in under-banked counties, stand to benefit more from the advent of FinTech.

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1 Introduction

In the constantly evolving FinTech sector, BigTech companies such as Amazon, Apple, Google, and PayPal in the US, alongside Alipay and Tencent in China, have ventured into the realm of financial services. They integrate digital payments, a cornerstone of modern finance, with other crucial household financial functions such as borrowing, lending, and investment within their digital ecosystems. This all-in-one approach, bolstered by their extensive user base, allows these tech giants to engage with a diverse spectrum of households and revolutionize financial practices.

A significant challenge in the field of household finance lies in the limited participation of individuals in financial markets. Despite the potential benefits of participation, existing research highlights that both physical costs (money, time, and effort) and psychological costs (familiarity and trust) play pivotal roles in hindering individuals from optimal risky asset investment.[1] Against this backdrop, our hypothesis is that FinTech, through their comprehensive all-in-one business model, can foster household risky asset participation. While the technological efficiency of FinTech platforms undoubtedly serve to reduce or even eliminate the physical costs of participation, the more profound impact may come from the reduction of psychological costs. Via FinTech adoptions, individuals can acquire familiarity through repeated usages of digital payments on the all-in-one super-apps. As familiarity breeds trust, repeated usage can gradually erode or even dismantle the psychological barriers that deter households from entering the market.

To test this hypothesis, we focus on the digital ecosystem of Alipay, which is primarily built around QR-Scan payments and encompasses a wide array of financial services, including mutual fund investments. We posit that the increased FinTech adoption via digital payments can help break down the participation barriers, particularly the psychological ones, faced by households in their participation of financial markets. Furthermore, it can promote financial inclusion by facilitating engagement in risky mutual fund investments, especially among households with limited access to conventional banking services.

Measuring FinTech Adoption – Our empirical study is based on an account-level dataset obtained from Ant Group, which tracks each individual's digital payments via Alipay, mutual fund investments made via Ant Group's investment platform, and online consumption via Taobao e-commerce platform. Importantly, all three activities can be initiated from Alipay,

[1]Haliassos and Bertaut (1995), Campbell (2006), and Vissing-Jørgensen and Attanasio (2003) show that a substantial fraction of households do not invest in risky assets, yet according to financial theory, all households, regardless of their risk aversion, should invest a fraction of their wealth in the risky asset as long as the risk premium is positive. Among others, Hong, Kubik, and Stein (2004) and Guiso, Sapienza, and Zingales (2008) document that familiarity and trust are important drivers of the low-participation puzzle.

China's pioneering super app. The dataset also contains individual basic information such as age, gender, and, important for our analysis, location. The data spans from January 2017 to March 2019, a period marked by a significant surge in offline digital payments through Alipay across China.

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. Individuals in our sample start using offline digital payments at different points in time and with varying frequency, creating significant heterogeneity in FinTech adoption both across individuals and over time. This heterogeneity is pivotal to our identification. Leveraging this swift technological advancement, we gauge 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.

Relative to the cross-individual variation, a significant and relatively exogenous variation emerges from the staggered penetration of QRPay in various regions of China. The FinTech penetration map of China, 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 household 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.[2] Individuals on this platform can choose from risk-free money market

[2]See Hong, Lu, and Pan (2022) for details on the development of FinTech platforms and their market-wide

funds and six types of risky mutual funds (bond, mixed, equity, index, QDII, and gold).[3] 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 a specific month, and "risky fraction", representing the proportion of the total purchase amount allocated to risky funds in a specific month.

Tracking households' participation in risky investments on platform along the dimension of their FinTech adoption, we find strong evidence that repeated usage of QRPay raises the probability of households investing through the FinTech platform. Focusing first on the relatively exogenous county-level evidence, we find that county-level FinTech penetration significantly predicts increases in both the probability of risky purchase and the fraction of risky investment for individuals living in the county, with a non-trivial economic magnitude. In particular, a one-standard-deviation increase in month-t county-level FinTech penetration, captured by the average Log(QRPay) of individuals living in the county, predicts a month-$t+1$ increase in the probability of risky fund purchase by 2.26% (t-stat=5.70).[4] Given that the probability of an average individual purchasing any risky fund in a given month is 9.16%, an improvement of 2.26% is sizable. Extending the analysis to risky fraction, we find similar evidence that a one-standard-deviation increase in county-level Log(QRPay) predicts an increase of 2.12% (t-stat=5.48) in the fraction of risky fund purchase the next month.[5]

To further establish the causal relationship from FinTech adoption to platform investment, we use a county's distance from Hangzhou as an instrumental variable (IV) to capture the exogenous variation in FinTech penetration. The rationale behind constructing this IV lies in Ant's ground promotion strategy during the early stages of QRPay development. To encourage adoption of QRPay among local merchants and governments, Ant's marketing teams communicated with them in person, starting from areas near Hangzhou and expanding gradually to more distant regions.[6] Consistently, we find Hangzhou is at the epicenter of the FinTech penetration map of China. Unlike the geographical restriction of QRPay promotion, the investment platform promotion primarily occurred online through the Alipay

impact on the Chinese mutual fund industry.

[3]Our data contains the fund purchase and redemption made by individuals in each month. Additionally, for a subset of the period from August 2017 to December 2018, we have detailed information about individuals' fund holdings and monthly returns on their portfolios.

[4]We control for county-level economic development, captured by GDP, income, population, and the access to financial infrastructure.

[5]This aligns with the nationwide trend. Concurrent with the rise in FinTech penetration, the number of mutual fund investors surged from 265 million in 2016 to 793 million in 2019.

[6]See "Ant Financial: The rise of a tech financial unicorn" by You Xi, for the development of Alipay.

app since 2014, without geographical limitations. Hence, a county's physical distance from Hangzhou provides unique information about FinTech penetration and is arguably independent of households' mutual fund investment motivations.[7] Using distance-from-Hangzhou as an instrument for FinTech penetration, we find that a one-standard-deviation increase in the instrumented county-level QRPay predicts a 2.34% (t-stat=2.11) increase in risky purchase and a 2.22% (t-stat=2.08) increase in risky fraction. Further allowing distance to have a time-varying effect on FinTech penetration in our IV estimation, we find qualitatively similar evidence.

Expanding our analysis from the county level to the individual level, we present additional evidence suggesting that frequent use of QRPay promotes participation in risky investments. Notably, this effect persists even when accounting for the net increase in purchases after redemptions, indicating that these findings are not driven by investors excessively shuffling their portfolios. Furthermore, by distinguishing individual self-initiated FinTech adoption from environmental-driven FinTech adoption, we uncover the distinctive influence of environmental factors in explaining the FinTech effect. In particular, for each individual, we regress individual-level Log(QRPay) on the average Log(QRPay) of peers in the same county. The environmental component, Sys Log(QRPay), is the predicted part of Log(QRPay) that can be explained by peers' adoption rate, while the discretionary component, Idio Log(QRPay), is the remaining part. We find that a one-standard-deviation increase in Sys Log(QRPay) leads to a 3.39% (t-stat=8.15) increase in risky purchase, whereas a one-standard-deviation increase in Idio Log(QRPay) corresponds to only a 1.05% (t-stat=5.00) increase in risky purchase. The magnitudes remain qualitatively the same when time and individual fixed effects are included, suggesting that unobserved individual characteristics and overall trend in household risk-taking cannot explain our findings. The dominant role of the systematic part, therefore, underscores the significant impact of environmental changes in shaping individuals' participation in risky investments.

The link between the adoption of digital payments and investments in high-risk funds can be attributed to the reduction of both physical and psychological costs. A decrease in the physical costs associated with FinTech platforms, such as fund purchase and redemption fee reduction, should predict an overall increase in participation. However, the increased participation associated with the use of digital payments, evident both across different individuals and across time, is more likely a result of the gradual build-up of familiarity and trust

[7] We restrict our IV analysis to counties located within the radius of 300 kilometers around Hangzhou, so as to disentangle the effects of distance-from-Hangzhou from distance-from-Shanghai. The details are discussed in Section 3.2.

throughout the process. To further pin down the role of psychological costs, we compare the impact of FinTech adoption on individuals' initial versus subsequent purchase of funds. We find that, benchmarking to the initial purchases, FinTech adoption has a larger impact on subsequent purchases for high-risk and unfamiliar fund styles. In other words, investors tend to favor familiar and low-risk assets initially, but become more open to unfamiliar and high-risk assets as trust and familiarity grow through digital payment usage. This underscores the crucial role of trust and familiarity in driving the impact of FinTech adoption on investment behavior.

Who Benefits More from FinTech Inclusion – To explore the impact of FinTech inclusion on individuals' welfare, we investigate whether FinTech has a stronger effect on investors who were more constrained before its introduction. If FinTech indeed breaks down investment barriers, it should particularly benefit those who are more risk-tolerant. To identify high-risk-tolerant individuals, following the classical consumption-based portfolio choice theory by Merton (1971), we use individual consumption growth volatility (σ_{C}) as a risk tolerance proxy.[8] Empirical findings support this theoretical framework: individuals with higher σ_{C} report a greater risk appetite in surveys conducted by the China Securities Regulatory Commission and exhibit higher levels of risk-taking in mutual fund investments. Using this risk tolerance proxy, we further examine FinTech's impact on individuals with varying risk tolerance. We document a significantly stronger effect of FinTech on risk-taking for individuals with high σ_{C}, suggesting that high risk-tolerant investors, with the advent of FinTech, become less constrained and can actively take more risk as desired.

From a geographical standpoint, FinTech has the potential to bridge the gap left by traditional banks, especially in under-banked regions. Our analysis, conducted in counties with above- and below-median bank coverage, reveals that the benefit of FinTech inclusion predominantly stems from counties with below-median banking 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 individuals in well-banked counties can invest through existing financial infrastructure, those in under-banked areas lack this privilege. FinTech advancement provides an alternative avenue for under-banked individuals to fulfill their investment needs. These findings support

[8] As per Merton (1971), the optimal portfolio weight is calculated as $w^* = \frac{\mu - r}{\gamma \sigma_R^2}$, where γ represents the risk aversion coefficient, and $\mu - r$ and σ_R denote the risk premium and volatility of the risky asset, respectively. Moreover, with the optimal consumption-to-wealth ratio being constant, we have consumption volatility σ_{C} equaling to portfolio volatility σ_{W}, and both are inversely proportional to γ.

the idea that FinTech, rather than replacing traditional banks, opens doors for individuals without access to financial opportunities, thereby serving as a complement to existing financial infrastructure.

Finally, we evaluate the performance of households' FinTech investments to answer the question of whether they indeed reap the benefits of FinTech inclusion. This assessment is crucial because potential investment losses could outweigh the gains from participation if households tend to make mistakes on FinTech platforms. For instance, Calvet, Campbell, and Sodini (2007) demonstrate that the cost of non-participation is significantly lower when considering that non-participants are likely to be inefficient investors. To evaluate the outcomes of individuals' FinTech investments, we focus on their portfolio performance and allocation. First, we find that, the mutual funds held by Ant investors tend to have slightly higher alphas compared to all funds in each fund category. Moreover, given that mutual funds in China typically outperform their passive benchmarks (e.g., Chi (2013)), investing with delegated portfolio management proves to be a welfare improvement for individuals willing to assume financial risks. Additionally, concerning asset allocation, FinTech adoption results in a more diversified portfolio across multiple funds and asset classes. This diversification also enhances the Sharpe ratio, underlining the benefits of FinTech adoption for investors.

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.[9] 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

[9]In a broader context, 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.

Pursiainen (2023)).

Our paper also adds to the emerging literature focuses 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. Recent works by Buchak, Hu, and Wei (2022), Chen and Jiang (2022), Ouyang (2021), Bian, Cong, and Ji (2023), and Liu, Lu, and Xiong (2022) highlight how digital payments facilitate the transformation of savings-like money market products, influence the liquidity premium of connected money market products, and enhance financial inclusion by expanding credit access for individuals and small businesses. Our research aligns with this prevailing trend by examining the synergy achieved through bundling digital payments with other financial services, but with a unique focus on individuals' investment behavior.[10]

Finally, our study is connected to the literature that explores the interplay between portfolio choices and risk preferences. Previous studies have back-engineered individual risk preferences by analyzing their portfolio allocations (Calvet et al. (2021)). Alternatively, some studies link survey-based investor beliefs and risk preferences to portfolio choices (Giglio et al. (2021), Jiang, Peng, and Yan (2021)). Household portfolio decisions are also influenced by personal experiences and attitudes, including past investments, macroeconomic encounters, and political affiliations (Choi et al. (2009), Malmendier and Nagel (2011), Meeuwis, Parker, Schoar, and Simester (2022)). Our work contributes to this literature by providing a measure of risk tolerance grounded in the theoretical framework of Merton (1971) and linking investor consumption growth volatility with portfolio choice. By offering direct empirical evidence on the relationship between consumption and investment behavior, our findings complement Mankiw and Zeldes (1991), who use aggregate food consumption data to show that stockholders' consumption is more volatile than that of non-stockholders.[11]

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 FinTech inclusion and welfare implications. Section 5 discusses potential economic mechanisms. Section 6 concludes.

[10]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), Chen et al. (2022), Agarwal et al. (2019), and Agarwal et al. (2020), among others).

[11]In contrast to Mankiw and Zeldes (1991), Chinco et al. (2022) find no significant relationship between participants' investment choices and an asset's correlation with aggregate consumption growth in a survey setting. Unlike these studies, our study explores the connection between individual-level consumption growth volatility and portfolio choices using investors' actual holdings and consumption data.

2 Data and Institutional Background

2.1 An All-in-One Ecosystem

In China, essential aspects of household finance, including consumption, investment, and payments, are now predominantly conducted via FinTech platforms. Ant Group initiated its all-in-one ecosystem, Alipay, as early as 2004. This ecosystem spans a diverse array of sectors, including finance, commerce, and everyday life services. Users not only enjoy access to financial services such as payments, investments, and credit facilities but also the convenience of participating in online shopping, food delivery, and various daily activities, all within a single application. Through the consolidation of these services into one comprehensive "super app," Alipay offers users a convenient and efficient experience, eliminating the need to navigate multiple applications for different purposes.

A key driving force of Alipay's development lies in its emphasis on digital payment, which serves as the foundation upon which a multitude of services are bundled. As shown in Panel A of Figure 1, the QR-Scan payment function appears on top of the front page of the Alipay app, and acts as a gateway to a wide range of financial and non-financial services offered in the ecosystem. By establishing a seamless connection between payment and a plethora of services, Alipay capitalizes on users' frequent interactions with the payment function to gradually build trust and familiarity, leading them to explore and adopt other services within the ecosystem. Alipay is a pioneer in exploiting the synergy effect between digital payment and other services. Nonetheless, other major tech giants operating platforms with substantial user bases are also capitalizing on the advantages of bundling.[12]

Our study focuses on evaluating the influence of household digital payment usage on their investments in platform mutual funds. Besides individual demographics, we are able to track the monthly investment activities, digital payment usage, and spending patterns of a randomly selected group of 50,000 individuals spanning from January 2017 to March 2019. The sample is drawn from the entire population of the Ant community, among investors 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 commencement of our study period. Given Alipay's extensive user base of 1.3 billion individuals, along with the fact that the overwhelming majority of Alipay users engage in risk-free MMF investments via Yu'ebao (Buchak, Hu, and Wei (2022)), our sample can be considered reasonably repre-

[12]For example, companies like Apple and Google also envision a similar development strategy which centers around payment and bundles other services with it. The prevalence of bundling is also evident from Stripe's cooperation with Klarna, SumUp's acquisition of Tiller, and Rapyd's acquisition of Valitor.

sentative of both the Alipay user community and the entire population of China. Table 1 illustrates that among the 50,000 individuals in our sample, 60% are female, with an average age of 30.4 years, and an average monthly e-commerce (Taobao) expenditure of 2,155 RMB. Approximately half of these individuals have engaged in substantial investments (risk-free and risky funds amounting to at least 100 RMB), and 17,406 individuals participate in risky mutual fund investments.

2.2 Measuring FinTech Adoption Using QR-Scan Payment

Digital payments in China started in 2004, which was initially developed to build trust between online buyers and sellers in the early days of e-commerce. In the category of digital payment, the prevalence of QR-Scan mobile payment is a more recent phenomenon, bringing China into a cashless society with over 852 million users now using mobile digital payments for daily activities. It permeates the entire country with each street vendor at every corner in China eager to accept QR-Scan payment offered by Alipay.[13]

We find a rapid increase in the penetration of QR-Scan payment during our sample period, based on both the statistics from the economy-wide data and our Ant sample. In just two years, QR-Scan payment exploded from 0.6 trillion yuan in Q1 of 2017 to 7.2 trillion yuan in Q4 of 2018. As shown in Panel B of Figure 1, the economy-wide ratio of QR-Scan pay to total offline consumption (red line) increased from around 8.0% in Q1 of 2017 to 85.3% in Q4 of 2018. The same trend is captured in our data by the rapid increase in the frequency of QR-Pay usage: The average number of monthly QR-Pay uses per person (blue line) increased from 12.6 times per month in January 2017 to 39.0 times per month in December 2018. The alignment of the two lines suggests that our Alipay payment data captures the penetration of QR-Scan mobile payment during our sample period.

Motivated by the fast-developing trend of QR-Scan payment in our sample, we capture each individual's FinTech adoption by their monthly Alipay usage frequency:

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

where QRPay_t^i is the total number of Alipay payments made by individual i in month t. As an alternative measure of FinTech adoption, we also compute QRFrac, the fraction of

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

Alipay consumption amount out of total consumption in the Ant ecosystem.[14] Over the long run, as mobile payments become the dominant payment method, the level of QRPay may stabilize. However, during our sample, which covers the period of a dramatic expansion in offline mobile payment, the level of QRPay contains valuable information about the speed and intensity with which individuals adopt the new technology.

Panel A of Table 1 demonstrates a large cross-sectional variation in FinTech adoption for individuals in our sample. An average user in our sample uses Alipay mobile payments 21.4 times per month, with a standard deviation of 19.2 times. Out of total consumption in the Ant ecosystem, 54% of the consumption is paid via Alipay mobile payment, with a standard deviation of 22%. The large variation in QRPay could be driven by an individual's own willingness to adopt the new technology as well as the exogenous penetration of FinTech across geographical areas in China. From individuals' perspective, Panel B of Table 1 shows that young and male individuals tend to have higher levels of Log(QRPay).

From a geographical perspective, how fast local governments and local vendors adopt the QR-Scan technology could have a large impact on local residents' adoption of the technology as well. Figure 2 exhibits the geographical distribution of FinTech penetration, measured as the monthly average QRPay for each prefecture from 2017Q2 to 2018Q4, computed using our sample of Alipay users.[15] As shown on the four maps, QRPay varies substantially across geographical areas and over time. Back in early 2017, the headquarters of Ant, Hangzhou, is the epicenter, leading the way in FinTech penetration. In 2017Q2, an average individual in Hangzhou already used Alipay 24.9 times per month to pay for consumption, the highest among all prefectures. In contrast, other prefectures had an average QRPay usage of 5.87 during the same period. Over time, we observed the gradual spread of FinTech from Ant headquarters to the inner regions of China. By 2018Q4, Hangzhou still led in FinTech penetration with a QRPay usage of 47.39, doubling its 2017Q2 level. In comparison, other prefectures saw their average QRPay usage increase to 18.85, more than three times their 2017Q2 average. Comparing Panel A and Panel D in Figure 2, we see that prefectures close to the Ant headquarters, equipped with high QRPay level in early 2017, enjoyed relatively less increase in FinTech penetration during 2018; while prefectures in the inner land of China witnessed a much larger increase in FinTech penetration during the same period. This

[14] $\text{QRFrac}_t^i = \text{QRpay Amount}_t^i / \text{Total Consumption Amount}_t^i$, 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).

[15] China's administrative divisions comprise several levels, ranging from provinces at the top level to prefectures and further down to granular county levels. In our figures, we use prefecture-level observations for clear graphical illustrations. For regression-based analysis, we use the most granular county-level observations.

staggered penetration of Alipay during our sample period suggests that a large proportion of the variations in QRPay is driven by relatively exogenous geographical factors. In our later empirical analyses, we will differentiate county-level FinTech penetration with individual-specific FinTech adoption to separately study their impact on risky fund investment.

2.3 Platform Investments of Mutual Funds

The evolution 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.

For the mutual fund investment data, we 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 return. 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 Panel A of 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 amounts (including both risk-free and risky funds) throughout our sample period, which leaves us with 28,393 users. These 28,393 users have on average a total investment amount of 41,080 RMB, equivalent to around 6,000 US dollars. The median value of investment 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 ($= 1-\text{MMF}/\text{Total}$). Portfolio volatility (σ_{W}) is the standard deviation of an individual's portfolio's monthly returns. The cross section of 28,393 users on average allocate 50.76% of their capital 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. Contrary to the common perception that investors tend to engage in excessive stock trading (e.g., Odean (1999)), our research reveals a different pattern. On average, individuals conduct approximately 8.9 transactions, and they engage in trading activities only during three out of the 27 months observed. This is because investors tend to exhibit reduced levels of speculative behavior in the context of delegated portfolio management, as opposed to trading individual stocks.

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 pairwise correlation of 0.48. In addition, individuals with higher risky share 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 male and younger users tend to have higher risky share and portfolio volatility.[16] Consistent with the theoretical prediction that consumption growth volatility captures individual risk tolerance (Merton (1971)), we find that consumption growth volatility (σ_C) is positively correlated with risky share and portfolio volatility. We discuss the details of the σ_C measure in Section 4.1. Overall, the evidence suggests that the investment variables indeed capture individuals' risk-taking outcomes.

3 FinTech and Risky Fund Investment

3.1 County-Level FinTech Penetration

We start by analyzing the impact of county-level FinTech penetration on individuals' risky mutual fund investments. Given that the investment function is bundled with digital payments in an all-in-one app, individuals who frequently use QRPay tend to cultivate familiarity and trust in Alipay, thereby increasing their inclination to explore the investment function within the ecosystem. Consequently, we anticipate that individuals living in areas with high FinTech penetration (i.e., QRPay) are more likely to use the same FinTech platform to fulfill their investment needs.

To capture county-level FinTech penetration in each month, we compute the logarithm of the equal-weighted average QRPay for all residents in a county. As shown in Figure 2, the cross-region as well as time-series variations in QRPay capture the staggered penetration of QRPay at the county level. To assess the impact of county-level QRPay on risky asset

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

investment, we conduct a panel regression, regressing the month-$t+1$ risky investment measures against the Log(QRPay) measure from month t:

$$\text{Risky Purchase}^c_{t+1}(\text{or Risky Fraction}^c_{t+1}) = \alpha + \beta_1 \cdot \text{Log(QRPay)}^c_t + \sum_j \gamma_j \cdot \text{Control}^c_{j,t} + \epsilon^c_t,$$

where Log(QRPay)^c_t represents the average Log(QRPay) for all residents in county c during month t. $\text{Risky Purchase}^c_{t+1}(\text{or Risky Fraction}^c_{t+1})$ denotes the average risky purchase (risky fraction) for all residents in county c in month $t+1$. We control for county-level economic factors, such as GDP, income, and population, as well as traditional financial service accessibility using LowBank (a dummy variable indicating below-median bank coverage). Time fixed effects, province fixed effects, and time×province fixed effects are included in different specifications.

In support of the hypothesis that FinTech penetration increases risky asset investment, Table 2 shows that month-t Log(QRPay) positively and significantly predicts month-$t+1$ risky purchase and risky fraction with a sizable magnitude. In particular, according to column (1), a one-standard-deviation increase in Log(QRPay) leads to an increase in risky purchase by 2.26% (t-stat=5.70) the next month. Given that the average monthly probability of individuals purchasing any high-risk fund stands at 9.16%, this enhancement of 2.26% is economically significant. When we include time fixed effects or province fixed effects in columns (2) and (3), the coefficient estimates remain robust. Finally, in column (4), we also include time×province fixed effects, utilizing cross-county variations within the same province at the same point in time to identify the impact of FinTech adoption. The coefficient estimate for Log(QRPay) remains significant, with a magnitude of 1.02% (t-stat=4.53), indicating that the impact of FinTech is unlikely to be solely driven by unobserved provincial factors or shared trends in FinTech and risky investments.

When considering risky fractions as an alternative measure of engagement in risky investments, the effect remains consistent. A one-standard-deviation increase in county-level Log(QRPay) results in a 2.12% rise (t-stat=5.48) in the average fraction of risky fund purchases in the following month. These results emphasize the significant influence of staggered QR-Scan technology adoption across various regions in China, notably shaping the investment choices of local residents.

3.2 Distance-from-Ant as an Instrument

To establish the causal impact of FinTech penetration on risky investment participation, we employ an instrumental variable approach. We utilize the distance from Ant headquarters to capture the plausibly exogenous variation in FinTech penetration. As detailed in Section 2.2, the expansion of Alipay QR-Scan technology originated from Ant's headquarters and gradually spread to more distant regions. This expansion involved a costly ground promotion process, where Ant's marketing team had to personally communicate with local merchants, convincing them to accept QRPay as a payment method. In contrast, the marketing of the mutual fund investment function was not geographically restricted.[17] Therefore, a county's physical distance from Ant headquarters has no direct effect on individuals' risky investment, other than through the penetration of QRPay.

Validity of the Instrument

We start by validating a county's distance from Ant headquarters as an instrument for FinTech penetration. A potential issue arises due to the proximity of the Ant headquarters in Hangzhou to Shanghai, China's economic center. Consequently, a county's distance from Ant often coincides with its distance from Shanghai. If proximity to metropolitan areas like Shanghai influences individuals' risky investment, our instrumental variable (IV) test might incorrectly attribute Shanghai's effect to Ant. To address this concern, we adjust the county subsamples based on their distance from Ant. Additionally, we conduct the first-stage IV regression using the distance from Shanghai as a placebo test.

The rationale behind this placebo test is illustrated in Figure 3, which depicts the locations of Ant headquarters and Shanghai on China's map, along with 1000km, 500km, and 300km radii around Ant headquarters. To distinguish the effects of Ant headquarters from those of Shanghai, we compare the first-stage estimation results for counties located within different radii around Ant. The underlying assumption is that, for counties far from Ant, distance from Ant and distance from Shanghai are highly correlated. Conversely, for counties closer to Ant, these distances can significantly differ. Panel A of Table 3 exhibits the first-stage IV regression results using Log(Dist from Ant) and Log(Dist from Shanghai) as the instrumental variables. We also control for county-level economic conditions, i.e., GDP, population, and income.

Table 3 shows a significantly negative relation between Log(QRPay) in a county and its distance from Ant. The coefficient on Log(Dist from Ant) is -0.25 with a t-stat of -13.79 for the whole sample. Zooming in on counties within a smaller radius around Ant, the effect remains qualitatively the same with a slightly smaller magnitude. For example, within 300km from Ant, the coefficient on Log(Dist from Ant) is -0.17 (t-stat $= -3.94$). This is partly due

[17] Ant's staff members have also verified that there were no on-site promotions or offline advertisements for the investment function throughout our sample period.

to the fact that counties near Ant already have relatively high FinTech penetration during our sample period, whereas distant counties have more potential for FinTech development. Moreover, the F-statistics of Log(Dist from Ant) is 190.04 for the whole sample and 15.53 for the subsample within 300km around Ant, passing the weak instrument test in Stock and Yogo (2002).

In contrast, as we zoom in on counties within a smaller radius around Ant, the coefficients on Log(Dist from Shanghai) become insignificant with a much smaller magnitude. Specifically, for counties within 300km, the coefficient on Log(Dist from Shanghai) in column (8) is -0.07 (t-stat = -1.14). This disparity between Shanghai and Ant headquarters is consistent with our intuition: for counties far from Ant, their distance from Ant and Shanghai highly overlap, leading to Log(Dist from Shanghai) capturing some of the effects of Log(Dist from Ant). Within smaller circles, however, only the distance from Ant correlates with FinTech penetration, while distance from Shanghai has no explanatory power.[18]

IV Estimation

To cleanly identify the effect of distance on FinTech penetration, we focus our IV analysis on the subset of counties within a 300km radius around the Ant headquarters. We adopt two model specifications here, as shown in Panel B of Table 3.

In the first specification, we regress county-level Log(QRPay) on Log(Dist from Ant) to obtain the instrumented value of FinTech penetration (reported in column (1)). Columns (3) and (5) present the corresponding second-stage results, where the risky investment measures, risky purchase and risky fraction, are regressed on the instrumented value of Log($\hat{\text{Q}}$RPay). The coefficient estimates indicate that a one-standard-deviation increase in Log($\hat{\text{Q}}$RPay) leads to a 2.39% (t-stat=2.14) increase in risky purchase and a 2.26% (t-stat=2.11) increase in risky fraction, respectively.

In the second specification, we further allow distance to have a time-varying effect on FinTech penetration. At the beginning of our sample period, counties closer to Ant had significantly higher FinTech penetration than distant counties. However, over time, the influence of distance diminishes as QR-Scan payment becomes widespread across all regions of China. To account for this evolving dynamic, we introduce an interaction term, Log(Dist from Ant)×Time, in our estimation, where time is measured as the number of years from January 2017. Consistent with our hypothesis, the coefficient estimate on the

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

interaction term in the first-stage estimation is significantly positive, indicating a decreasing influence of distance on FinTech adoption. Next, using the FinTech penetration instrumented by the Log(Dist from Ant)×Time, the second-stage estimations (columns (4) and (6)) show that a one-standard-deviation increase in $\text{Log}(\widehat{\text{QRPay}})$ leads to a 2.20% (t-stat=2.12) increase in next-month risky purchase and 2.09% (t-stat=2.09) increase in next-month risky fraction.

In summary, our IV analysis provides supporting evidence of the positive influence of digital payment penetration on participation in risky funds. This relationship is unlikely to be driven by unobserved wealth disparities or urban factors, as it is the proximity to Ant's headquarters in Hangzhou, rather than Shanghai, that plays a significant role. Moreover, for any latent variables to explain our findings, they must be linked to both the distance from Hangzhou and must display a declining association with distance over time. Hence, our IV analysis supports a causal interpretation of how county-level FinTech penetration affects participation in risky investments.

3.3 Individual-Level FinTech Adoption

At the individual level, we present additional micro-level evidence indicating that frequent use of QRPay encourages individuals to invest in risky funds. By distinguishing between self-initiated FinTech adoption and passive FinTech adoption influenced by environmental factors, we demonstrate the significant impact of these environmental factors in explaining the positive spillover effect from payment habits to investment decisions.

FinTech Adoption and Risky Fund Investment

To explore the cross-individual difference in risky investment participation associated with FinTech adoption, we estimate the following regression specification:

$$\text{Risky Purchase}^i_{t+1}(\text{or Risky Fraction}^i_{t+1}) = \alpha + \beta_1 \cdot \text{Log}(\text{QRPay}^i_t) + \sum_j \gamma_j \cdot \text{Control}^i_{j,t} + \epsilon^i_t,$$

where individual i's risk-taking in month $t+1$ is regressed against her Log(QRPay) in month t. Although adopting of digital payment to make risky investments is a plausible scenario, focusing on the lead-lag relationship here mitigates this reverse causality concern. We control for individual characteristics, including age, gender, monthly online consumption level, and quarterly consumption growth volatility (σ_C), as a proxy for individual risk tolerance.[19]

In the absence of fixed effects, Panel A of Table 4 reveals 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 risky mutual funds the next month. Including time fixed effects slightly reduces the coefficient to 2.21 (t-stat=8.13), indicating that the results are not solely driven by unobserved aggregate changes or time trends in risky investment participation. With individual fixed effects, the coefficient stands at 2.66 (t-stat=6.07), with an R-squared of 28.4%. This implies that for a given individual, the time-series variation in Log(QRPay) remains a significant determinant of risky investment participation over time. Finally, including both time and individual fixed effects, the coefficient on Log(QRPay) remains significant at 1.41 (t-stat=6.32). This suggests that FinTech, by bundling investment and payment functions, promotes financial inclusion – higher FinTech adoption leads to increased participation in risky investment.

Investors may be actively redeeming existing funds to purchase new ones, leading to an increase in risky purchase measure without acquiring additional risky assets. To address this concern, we employ the same regression framework using redemptions and net purchases as the dependent variables. In the specification with time and user fixed effects, a one-standard-deviation increase in Log(QRPay) leads to only a 0.36% rise in redemptions, as shown in Appendix Table IA1. In contrast, the corresponding effect on risky purchases is 2.72% in the same specification. Consequently, a one-standard-deviation increase in FinTech adoption results in a 1.21% increase in the probability of a net purchase of risky mutual funds in the subsequent month. This evidence indicates that the previous results on risky purchase are not driven by investors' excessive trading behavior. This is due to the fact that investors typically show lower levels of speculative behavior in the realm of delegated portfolio management, in contrast to trading individual stocks, as documented in Odean (1999) and Barber et al. (2022), among others.

Systematic vs. Idiosyncratic Adoption

Having established a positive relationship between Log(QRPay) and risky asset investment, an important question arises: What factors influence an individual's adoption of FinTech? At the individual level, FinTech adoption can be driven by environmental factors and individual-specific factors. Environmental factors entail the passive adoption of QRPay due to changes in the individual's residing county. If local merchants, friends, and neighbors all embrace

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

QRPay, the individual is likely to adopt it too. Individual-specific factors refer to an individual's willingness to adopt technology unrelated to environmental changes, possibly driven by tech-savviness and risk appetite, among other factors.

Guided by this intuition, we decompose FinTech adoption into two components, a systematic component and an idiosyncratic component. For each person, we calculate her Peer Log(QRPay)$_t^i$, which represents the equal-weighted average Log(QRPay) of all individuals in the same county as individual i, excluding the focal individual i herself. We then estimate the following regression specification for each individual in our sample: Log(QRPay)$_t^i$ = $a^i + b^i *$Peer Log(QRPay)$_t^i$ $+\epsilon_t^i$. Here, Sys Log(QRPay)$_t^i$ is calculated as $\hat{b}^i *$Peer Log(QRPay)$_t^i$, and Idio Log(QRPay)$_t^i$ is calculated as Log(QRPay)$_t^i$ - Sys Log(QRPay)$_t^i$. The systematic component reflects the predicted portion of individual i's Log(QRPay) explained by her peers' FinTech adoption, capturing the influence of environmental changes on her FinTech adoption. In contrast, the idiosyncratic component represents the portion not explained by her peers' FinTech adoption and is primarily determined by individual-specific factors.

Panel B of Table 4 presents the impact of systematic and idiosyncratic FinTech adoption on individual risky fund investment using a similar regression framework as in Panel A. In the absence of fixed effects, the coefficient estimate on Sys Log(QRPay) is 3.39, with a t-stat of 8.15, whereas the coefficient estimate on Idio Log(QRPay) is only 1.05, with a t-stat of 5.00. Both variables are standardized with a mean of zero and a standard deviation of one. Hence, the relative magnitude of these coefficients indicates that variation in Sys Log(QRPay) has a significantly larger impact on risky purchases than variation in Idio Log(QRPay). In other words, risky fund investment decisions are more influenced by environmental factors, which are relatively exogenous to individual choices. When controlling for user fixed effects, time fixed effects, or both, the coefficient estimates for Sys Log(QRPay) remain larger than those of Idio Log(QRPay). In particular, when individual fixed effects are included, the coefficient estimate for Sys Log(QRPay) increases to 4.81 (t-stat=5.74), indicating that environmental factors play a dominant role in shaping an individual's risky fund investment decisions over time. Similar patterns are observed for risky fraction.

In summary, both environmental and individual-specific components of FinTech adoption play significant roles in explaining participation in risky fund investments. Yet, the influence of environmental factors is particularly crucial, emphasizing the importance of county-level FinTech penetration in driving risky fund investment, as discussed in Sections 3.1 and 3.2.

4 FinTech Inclusion and Welfare Implications

Our empirical results have shown that FinTech adoption promotes financial inclusion by encouraging individuals to engage in risky asset investments. Considering that existing literature often highlights the welfare losses due to individuals' non-participation and under-risk-taking, the rise in risky fund participation signifies an improvement in welfare. In this section, we further explore the individual heterogeneity within our sample to understand who gains the most from FinTech inclusion. We specifically focus on investors who faced more constraints before the advent of FinTech, including those with higher risk tolerance and individuals residing in counties underserved by traditional financial infrastructure. Beyond examining risky investment participation, we also evaluate the outcomes and efficiency of investments on FinTech platforms, focusing on measures of portfolio performance, Sharpe ratio, and portfolio diversification.

4.1 Benefits for Individuals with Higher Risk Tolerance

We first examine the dimension of risk aversion, a fundamental characteristic differentiating one investor's risk-taking behavior from another's, according to financial theory. In general, more risk-tolerant individuals should invest more in risky assets. 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. In the extreme case of zero risky participation ($w = 0$), investors with lower risk-aversion coefficient γ (i.e., higher risk tolerance $1/\gamma$) face more severe constraints and experience larger utility losses. Consequently, the benefits of FinTech inclusion would be higher for the more risk-tolerant investors. If FinTech can indeed remove barriers and alleviate constraints, both physically and psychologically, then it is the more risk-tolerant investors who stand to benefit the most from FinTech advent, as they are otherwise more constrained in the absence of FinTech.

Consumption Volatility as a Proxy of Risk Tolerance

Measuring individual-level risk aversion has always been a critical yet challenging task in the literature of household portfolio choice.[20] Leveraging consumption data available to us, we propose using individual-level consumption growth volatility as a proxy for risk tolerance. The theoretical basis of our approach lies in the Merton's optimal consumption and portfolio choice problem. As solved by Merton (1971) and expressed in Equation (1), 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 $(1/\gamma)$. This result allows us to use the cross-sectional variation in σ_{C} to capture the cross-sectional variation in risk tolerance.[21]

Our empirical findings support 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)), we observe that male, mature investors, and investors with higher consumption levels exhibit higher σ_{C} on average. Secondly, individuals with higher self-reported risk tolerance ratings, as collected and classified by China Securities Regulatory Commission, tend to have a higher average σ_{C}, and this association remains significant even after accounting for other personal characteristics in a multivariate regression setting (see Appendix Table IA3). Lastly, 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 Figure 4. 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%. Overall, in line with the conclusions drawn in Mankiw and Zeldes (1991), we demonstrate, based on micro-level evidence, that the volatility of consumption growth can effectively capture variations in risk tolerance across individuals.

[20] One approach to eliciting risk aversion is through lottery-type questions; however, the reliability of the survey data and their connection to investors' risk-taking remain debatable (e.g., Ameriks et al. (2020)). Alternatively, researchers have inferred individual-level risk aversion through their investment portfolio choice (e.g., Calvet et al. (2021)). However, since households' investment choice is our outcome variable here, such a methodology is not appropriate in our analysis.

[21] 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.

FinTech and Risky Investment, Conditional on Risk Tolerance

After establishing σ_C as a valid proxy for risk tolerance, we examine the effect of FinTech on individuals' risky investment outcomes, conditional on their risk appetite. To construct valid investment outcome measures, we focus on individuals with meaningful investment amounts, defined as users with at least 100 RMB total purchase amounts (including both risk-free and risky funds) on the Ant platform. Individuals' investment outcomes are assessed through their portfolio risky share and portfolio volatility. Risky share is defined as the average fraction of risky fund investment, whereas portfolio volatility represents the standard deviation of realized monthly portfolio return for each individual.[22]

Table 5 reports the cross-sectional regression results using risky share and portfolio volatility as the dependent variables. We first verify that FinTech adoption correlates positively with the two investment outcome variables, risky share and portfolio volatility. Consistent with previous panel regression estimates, a one-standard-deviation increase in the level of Log(QRPay) corresponds to a 1.83% (t-stat=6.33) increase in risky share and a 0.26% (t-stat=9.46) increase in portfolio volatility.

To answer the question of who benefits more from FinTech inclusion, we next include the interaction term of Log(QRPay) with risk tolerance proxy σ_C in the regression framework. Focusing first on risky share, we see that the coefficient for the interaction term is positive and statistically significant in column (2). This implies that FinTech adoption indeed increases risky share more for individuals with higher risk tolerance. Moreover, column (3) incorporates interaction terms between FinTech adoption and other investor characteristics, such as gender, age, and wealth. Even when accounting for heterogeneity along these dimensions, Log(QRPay)$\times\sigma_C$ remains significant. It is noteworthy that the coefficient on Log(QRPay)$\times\sigma_C$ slightly diminishes in magnitude (decreasing from 0.58 to 0.49). This suggests that σ_C and other individual characteristics, including gender, age, and wealth, contain overlapping information concerning individual-level risk tolerance. Nevertheless, conditioning on these individual traits, σ_C remains essential and informative, indicating that σ_C offers insights into risk tolerance that go beyond the information captured by these individual traits.

Finally, the right panel of Table 5 reports the corresponding results for portfolio volatility. The heterogeneous effect of risk tolerance, captured by the coefficient on Log(QRPay)$\times\sigma_C$, is similar to that for risky share. Overall, these findings align with our hypothesis that investors with higher risk tolerance, who would otherwise be more constrained in the absence

[22]Here, we focus on individuals' final portfolio allocation and riskiness, not their monthly participation decisions, because risk tolerance is not directly related to individuals' portfolio-building process.

of FinTech, benefit more from FinTech inclusion.

4.2 Benefits for Individuals in Under-Banked Counties

Incorporating FinTech into the financial landscape provides substantial advantages for individuals who have historically been underserved by traditional financial systems. For example, as demonstrated by Suri (2017), mobile money in developing economies facilitates digital transactions for unbanked individuals. In this section, we delve into the impact of FinTech in Chinese counties that exhibit diverse levels of financial services. In the pre-FinTech era, mutual funds were predominantly distributed through banks, which restricted access in areas with limited branch coverage. We posit that residents in under-banked counties, historically constrained, should gain the most from FinTech inclusion.

County-Level Evidence

We start by analyzing the impact of county-level FinTech penetration on risky purchase and risky fraction, conditioning on bank coverage levels. We measure bank service coverage by counting the total number of bank branches within the county's prefecture.[23] To identify under-banked regions, we introduce a dummy variable called LowBank, which is assigned a value of one for counties located in prefectures with bank branches below the median, and zero otherwise. The additional impact of FinTech in these areas is reflected in the coefficient of the interaction term, Log(QRPay)×LowBank. We control for local economic factors, including county-level GDP, population, and income.

Across all specifications in Table 6, 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 by 2.13% (t-stat=5.15) the following month. In counties with below-median bank coverage, the same increase boosts risky purchases by an extra 0.41% (t-stat=2.30), leading to a combined effect of 2.54%. Similar results are observed in the regression settings using risky fraction as the dependent variable, shown in columns (4) to (6). These results suggest that FinTech inclusion is more impactful, both statistically and economically, for individuals in under-banked areas.

Graphical representation in Figure 5 confirms that FinTech predominantly benefits areas 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-

[23]Figure IA1 provides a geographical representation of banking coverage, exhibiting a distinct pattern compared to the FinTech penetration depicted in Figure 2.

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.

Individual-Level Evidence: Matched Samples

We further investigate the individual-level effects of FinTech adoption using a matched sample approach. Among the 28,393 investors with substantial investments, 4,053 reside 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, considering factors such as gender, birth year, consumption levels, and volatility. As displayed in Panel A of Table 7, the matched individuals from low-bank and high-bank areas exhibit highly similar characteristics.

We first assess the impact of Log(QRPay) on portfolio volatility (σ_{W}) for both low- and high-bank groups, while controlling for individual characteristics as specified in Table 5. As illustrated in the top row of Panel B, 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 of 0.26 (t-stat=2.01) highlights the heightened FinTech advantages for under-banked individuals, reaffirming the findings from our county-level analysis.

Employing matched samples, we further delve into the impact of FinTech on individuals with varying characteristics. To this end, within both high- and low-bank groups, we classify individuals into two subgroups based on median risk tolerance (σ_{C}), consumption, gender, and age. As outlined in Section 4.1, FinTech benefits individuals with higher risk tolerance by providing an alternative option. This effect should be especially pronounced for high-risk-tolerant investors in low-bank areas, where their limitations were more severe compared to high-bank regions. Our findings align with this expectation. For high-risk-tolerant (σ_{C}) investors in low-bank regions, Log(QRPay) significantly impacts portfolio volatility (σ_{W}) with a coefficient of 0.70 (t-stat=4.60), contrasting with 0.36 (t-stat=3.02) for high-bank counterparts. Conversely, the difference is insignificant for the low-risk-tolerance group.

Furthermore, individuals who are mature and financially well-off tend to have greater investment capabilities. While such individuals can typically rely on traditional banking services in high-bank areas, FinTech serves as a viable alternative for those residing in low-bank regions. Our findings provide support for this hypothesis: for mature individuals (aged between 30 and 55), the coefficient 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.[24] Likewise, 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, we observe that females in low-bank areas benefit more from FinTech inclusion compared to their counterparts in high-bank regions. In summary, FinTech inclusion proves to be particularly advantageous for high-risk-tolerant, mature, female, and affluent investors residing in underserved regions.

4.3 Implications on Portfolio Performance

Lastly, can investors genuinely capitalize on FinTech inclusion and experience improved investment outcomes? This question hinges on two contrasting factors. On one side, academic research advocates participating in risky assets to harness the positive equity risk premium. Conversely, individual investors often display behavioral biases, potentially offsetting the benefits of such participation.[25] To evaluate the welfare implications of platform investments, this section examines portfolio performance and allocation outcomes for Ant investors.

Performance of Platform Funds

We compare 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. The equity factor is calculated as value-weighted China A-share stock returns minus the risk-free rate, while the bond factor is calculated as China's aggregate comprehensive bond index returns minus the risk-free rate.

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

[24]We use 30 and 55 as the cutoff points of age, because 30 is the median age in our sample and 55 is the retirement age for females in China.

[25]For example, Calvet, Campbell, and Sodini (2007) demonstrate that the cost of non-participation decreases significantly when considering that non-participants might be inefficient investors.

that of the overall market funds. 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. In summary, Ant investors tend to select funds with slightly higher performance, suggesting their investment decisions are sound on average. Moreover, given the overall capacity of Chinese actively-managed mutual funds to outperform passive benchmarks, delegated portfolio management proves advantageous for investors willing to embrace some financial risk.

Portfolio Diversification

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. 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. We use historical data spanning from 2005 to 2019 to estimate expected returns and variance-covariance matrix.[26]

In cross-sectional regression analysis, we find that individuals with higher FinTech adoption tend to diversify their investments across more funds and asset classes. A one-standard-deviation increase in Log(QRPay) results in a 10.6% rise in the number of funds and a 6.7% increase in the number of asset classes an individual invests in, indicating a significantly more diversified portfolio. Moreover, increased diversification leads to improved Sharpe ratio. A one-standard-deviation increase in FinTech penetration is associated with a 0.96% increase in the monthly Sharpe ratio. Overall, FinTech adoption consistently enhances the diversification benefits of investing.

[26]Sharpe ratios are set as 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, considering that our investment context is already at the factor level, we directly estimate expected returns from historical mutual fund performance.

5 Economic Mechanism

5.1 Familiarity and Trust as Key Economic Mechanisms

Our empirical findings reveal a positive spillover effect stemming from digital payment utilization to platform-based investments. We hypothesize that frequent use of digital payment services nurtures a sense of familiarity and trust, which in turn, empowers individuals to overcome the obstacles associated with engaging in the investment functions offered by the platform. To confirm this mechanism, we examine the likelihood of individuals purchasing unfamiliar and high-risk funds when they invest for the first time and when they conduct subsequent purchases. If investors initially avoid investing in risky assets due to a lack of trust or familiarity but gradually develop trust and familiarity through frequent digital payment use, we should observe a gradual transition from low-risk to higher-risk funds and from familiar to unfamiliar assets as the level of FinTech adoption 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 4. 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 9, 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.

5.2 Survey Evidence

We further conduct an online survey to directly gather insights into the factors influencing individuals' platform-based investments.[27] Specifically, we ask two questions to survey participants. 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: "The availability of additional platform functions, such as payment, etc." (37.7%), "The ease of use of the operating system" (21.1%), and "The convenience 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 investors who had used Alipay for mutual fund purchases, the predominant reasons for selecting the Alipay platform were: "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.

5.3 Other Alternative Channels

Substitution from banks: Since our data solely comes from the Ant Group, a valid concern is whether some investors may have transferred their existing mutual fund investments from banks to Alipay. Although it is challenging to entirely rule out this possibility, our discussion in Section 4.2 suggests that this is unlikely to be the main driver. Investment of mutual

[27] A detailed description of the survey is provided in the Internet Appendix.

funds via banks typically rely on the promotion by financial advisors at local bank branches. Therefore, residents of low-bank counties are less likely to be exposed to and have pre-existing investments in risky mutual funds through traditional financial institutions. As a result, any rise in risky participation is more likely to stem from incremental investments driven by frequent digital payment usage rather than portfolio shifts from banks to Alipay.

In particular, according to Table 6, within the low-bank counties, a one-standard-deviation rise in month-t Log(QRPay) corresponds to a 2.51% increase in the average local individual risky purchases the following month. In contrast, the same increase in Log(QRPay) is associated with a 2.15% increase in risky purchases for residents in high-bank counties. This implies that the impact of FinTech penetration not only exists but is also more pronounced among individuals residing in low-bank counties, who are more likely to initiate investments in risky assets for the first time.

Additionally, at the aggregate level, we observe a concurrent increase in the value of mutual fund holdings and the number of mutual fund investors alongside the growth of FinTech penetration. The total net assets of non-money-market mutual funds rose from 4.6 billion RMB at the end of 2016 to 7.2 billion RMB at the end of 2019. The total number of effective mutual fund accounts increased from 265 million at the end of 2016 to 793 million at the end of 2019.[28] This trend aligns with our hypothesis that the integration of FinTech facilitates a widespread increase in participation in risky asset investments across the nation.

Furthermore, findings from our survey indicate that a significant portion of respondents initiated their mutual fund investments using Alipay.[29] To be precise, we directly inquired about this in our survey: "Through which channel did you first purchase risky mutual fund products?" The responses revealed that 26% of the participants made their initial purchases through Alipay. In essence, one out of every four investors had no prior exposure to risky asset investments before utilizing Alipay, marking their inaugural venture into the world of risky fund investments through this platform. In summary, the evidence from the three perspectives above suggests an increase in risky asset participation at the extensive margin, driven by frequent usage of digital payments.

Access to credit provision: Ouyang (2021) and Bian, Cong, and Ji (2023) show 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

[28]The numbers include both money market fund and risky mutual fund investors.

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

is unlikely to be 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 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. Table 10 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 1.74% 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.

Other channels: There are several alternative channels that could complement the economic mechanism we propose. One such channel is the reduction in the physical cost of participation. Mutual funds often impose minimum one-time purchase requirements, typically set at 1,000 RMB. Alipay, in collaboration with many mutual funds, has lowered the minimum investment amount to as low as 100 RMB. While the reduction in participation cost could explain a general increase in platform investment, it is important to note that this reduction applies to all individuals and cannot solely account for the positive relationship between payment usage and platform investment. Another alternative perspective is the role of the robo-advising service offered by Alipay in boosting risky asset participation. During our sample period, the development of Alipay's robo-advising service was in its early stages (Ge, Wu, and Zhang (2022)). However, this perspective aligns with our interpretation: frequent use of the digital payment feature encourages investors to explore and embrace additional services. In this context, robo-advising is one such service within Alipay's ecosystem that pertains to the realm of risky asset investment. Moreover, frequent use of digital payment may also encourage investors to explore the information available on the investment platform, enhancing their financial literacy and ultimately leading to participation in riskier investments. This perspective resonates with our standpoint as well.

6 Conclusions

Tech firms entering the financial sector has dismantled physical barriers and unshackled 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 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. Regulatory issues, exemplified by Ant Group's IPO suspension, underscore the need for studying FinTech's impact on household finance. 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 (2022). 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.

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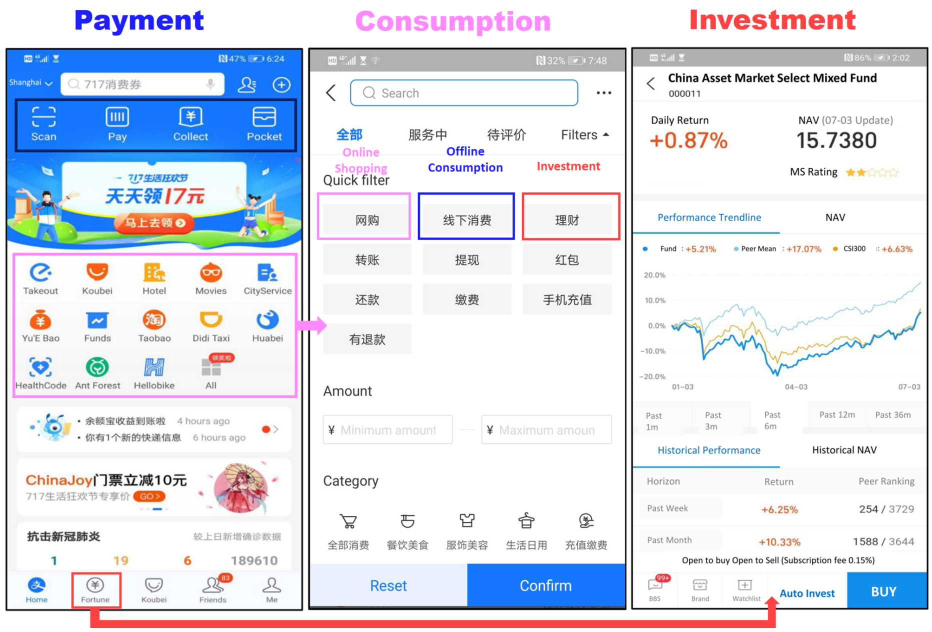
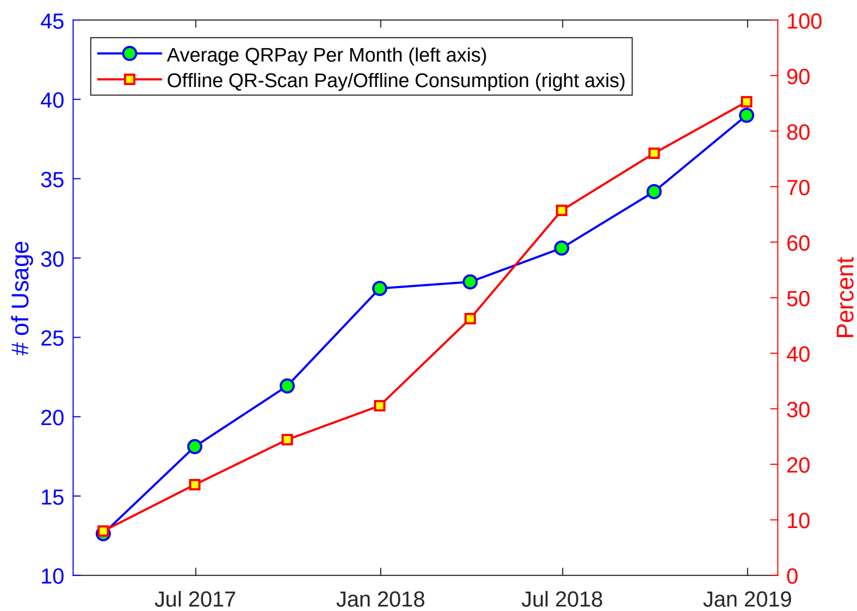
Appendix A. Variable Definitions

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
Peer 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
Sys Log(QRPay)_t^i	The predicted component of individual i's Log(QRPay) that can be explained by her Peer Log(QRPay)_t^i, estimated for each individual using the regression specification: Log(QRPay)_t^i=a+b*Peer Log(QRPay)_t^i $+\epsilon_t^i$. Sys Log(QRPay)_t^i is calculated as $\hat{b}^i$*Peer 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 - Sys 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.

Figure 1. FinTech in China — Payment, Consumption, and Investment



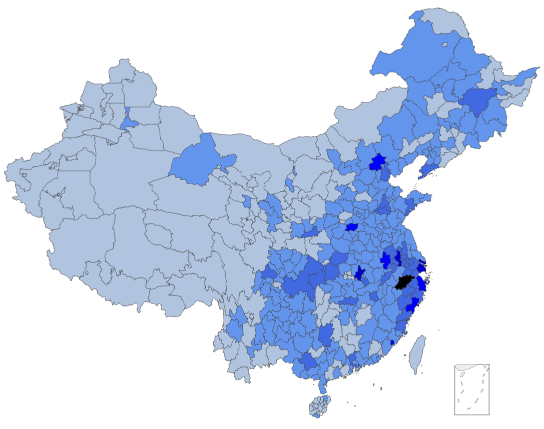
A: **Alipay User Interface**



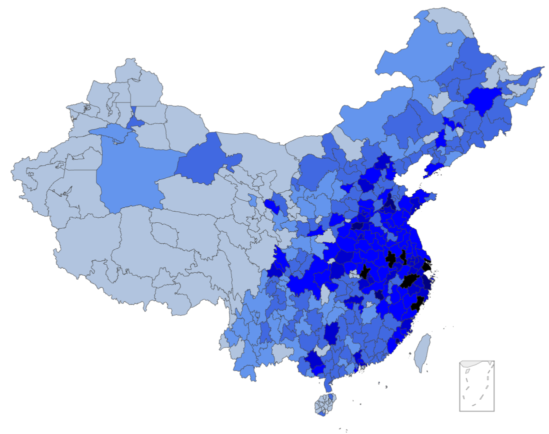
B: **Offline QR-Scan Payment and Alipay Payments**

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.

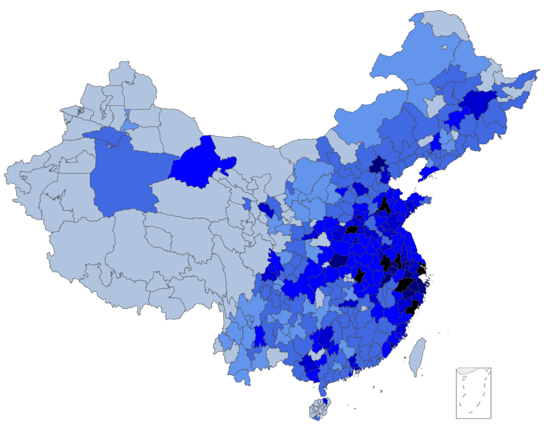
Figure 2. Geographic Distribution of FinTech Penetration



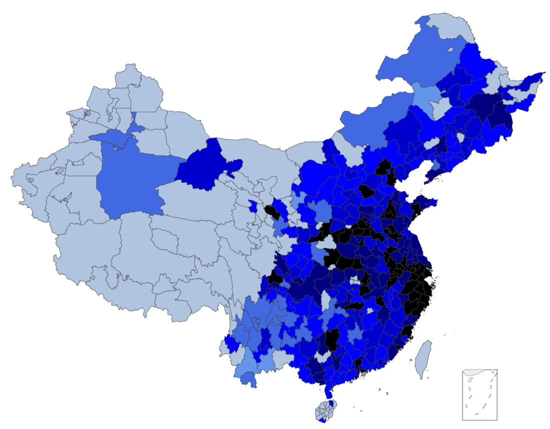
A: **2017Q2**



B: **2017Q4**



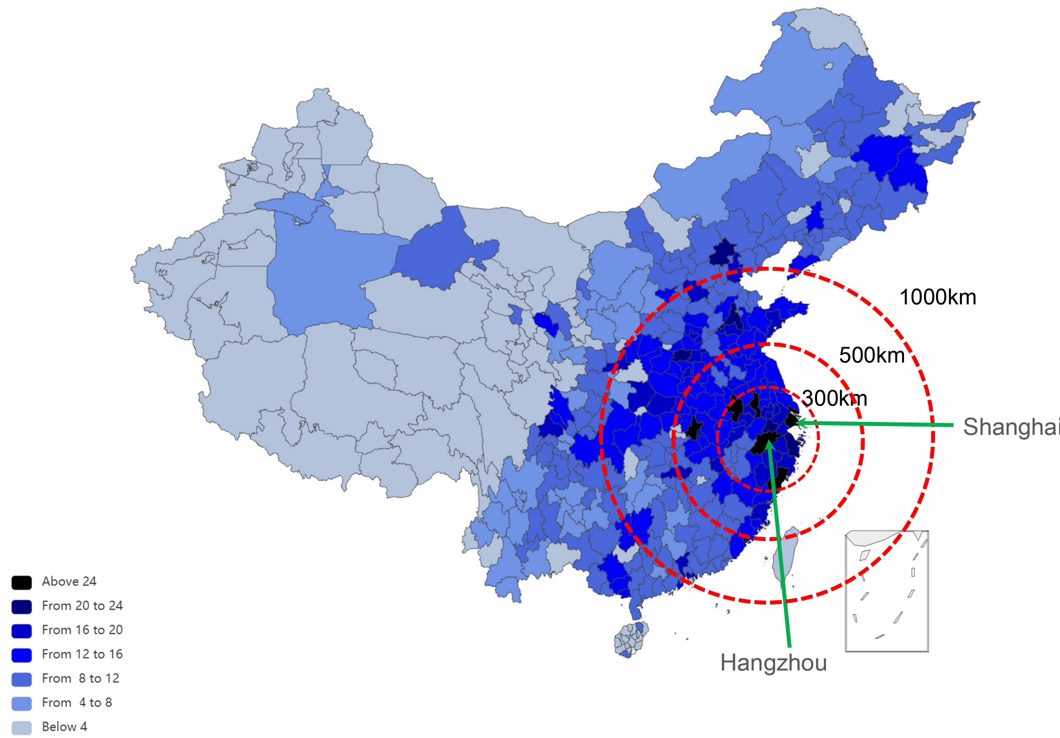
C: **2018Q2**



D: **2018Q4**

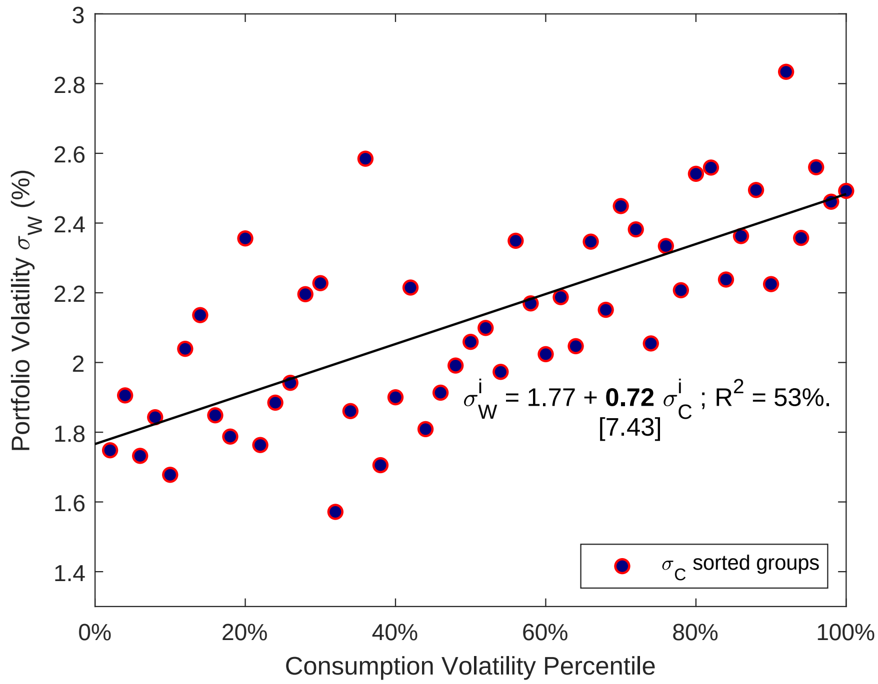
Panels A to D display the geographic distribution of prefecture-level FinTech penetration from 2017Q2 to 2018Q4. Prefecture-level FinTech penetration is calculated as the average QRPay for individuals within a given prefecture. The darker the color, the higher the FinTech penetration.

Figure 3. FinTech Penetration: Distance from Ant Headquarters as an Instrument

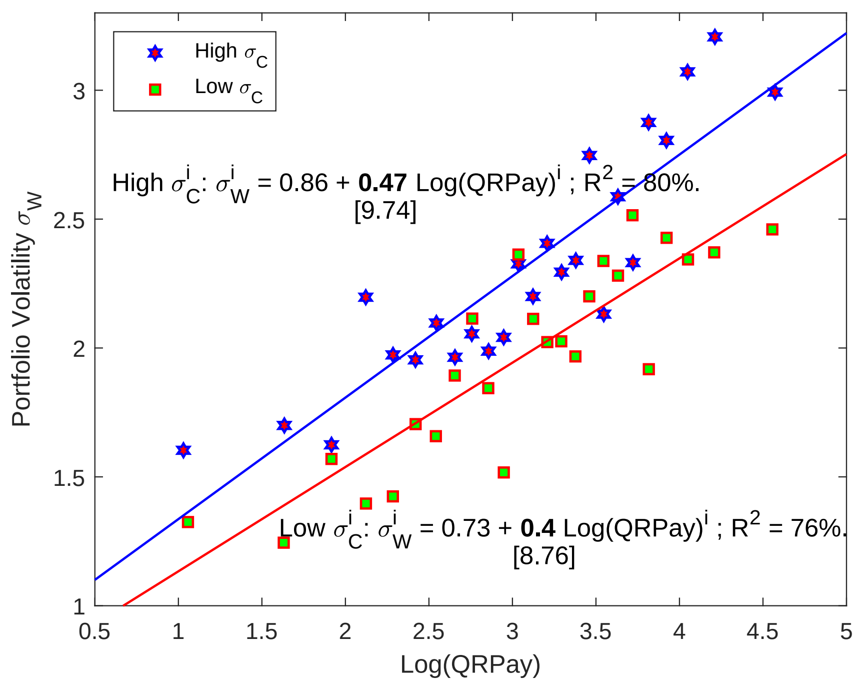


This figure shows the geographic distribution of prefecture-level average FinTech penetration for the sample period from 2017Q1 to 2019Q1. Prefecture FinTech penetration is calculated as the average QRPay for individuals in a given prefecture during our sample. Centering around the headquarters of Ant 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 4. FinTech Adoption and Risk-Taking by σ_{C} Groups



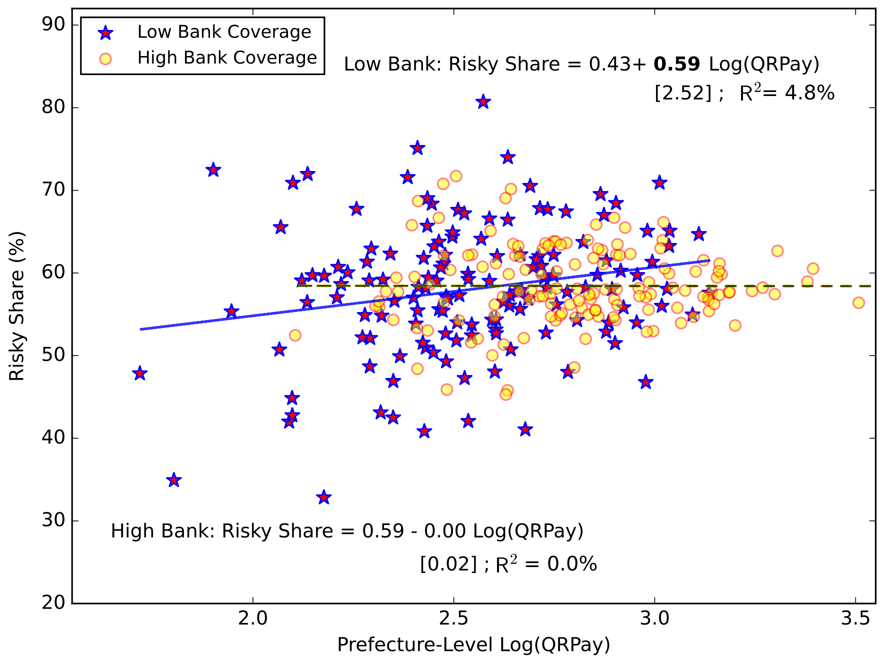
A: **Portfolio Volatility vs. Consumption Volatility**



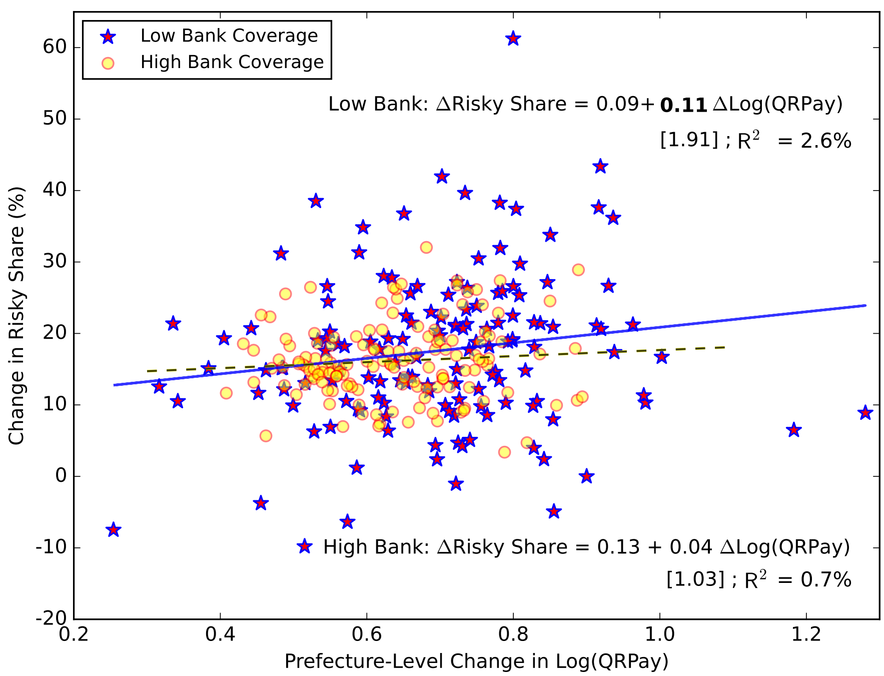
B: **Portfolio Volatility vs. QRPay: By σ_{C} Groups**

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.

Figure 5. 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.

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 Appendix A 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. County-Level FinTech Penetration and Risky Fund Investment

The table reports the panel regression estimates of county-level FinTech penetration on individuals' next-month risky fund investment. In columns (1) to (4), the dependent variable is the average risky fund purchase probability for individuals residing in a county in month $t+1$. In columns (5) to (8), the dependent variable is the average fraction of risky fund purchase in month $t+1$. Log(QRPay) is the natural logarithm of the number of Alipay QR-Scan payments in month t, averaged across individuals in the county. We control for the natural logarithm of county GDP, population, and income per person. LowBank is a dummy variable that equals one if the county belongs to prefectures with below-median bank coverage, and zero otherwise. We include time fixed effects, province fixed effects, and time*province fixed effects as indicated. 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 Appendix A for variable definitions.

	Y= Risky Purchase$_{t+1}$				**Y=Risky Fraction$_{t+1}$**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(QRPay)	2.259***	0.826***	1.050***	1.018***	2.119***	0.770***	0.958***	0.921***
	(5.70)	(4.44)	(4.84)	(4.53)	(5.48)	(4.41)	(4.76)	(4.42)
LowBank	-0.395**	-0.042	-0.282**	-0.275*	-0.370**	-0.037	-0.261*	-0.254*
	(-2.71)	(-0.35)	(-2.07)	(-2.01)	(-2.66)	(-0.33)	(-2.02)	(-1.96)
Log(GDP)	0.270**	0.429***	0.213	0.217	0.234**	0.384***	0.178	0.184
	(2.27)	(4.02)	(1.63)	(1.68)	(2.07)	(3.77)	(1.44)	(1.50)
Log(Income)	-0.063	0.044	0.036	0.038	-0.070	0.031	0.018	0.020
	(-0.71)	(0.49)	(0.36)	(0.38)	(-0.79)	(0.37)	(0.19)	(0.21)
Log(Population)	0.704***	0.309	0.018	0.012	0.646**	0.274	-0.004	-0.011
	(2.80)	(1.34)	(0.07)	(0.05)	(2.69)	(1.23)	(-0.02)	(-0.04)
Time FE	N	Y	Y	N	N	Y	Y	N
Province FE	N	N	Y	N	N	N	Y	N
Time*Province FE	N	N	N	Y	N	N	N	Y
Observations	20,202	20,202	20,202	20,176	20,202	20,202	20,202	20,176
R-squared	13.3%	35.8%	37.3%	39.9%	12.4%	34.9%	36.4%	39.1%

Table 3. Distance from Ant as Instruments for FinTech Penetration

This table reports the 2SLS estimation using the physical distance from Ant headquarters as an instrument for FinTech penetration. Panel A reports the effect of distance on FinTech penetrations for subsamples of counties within the 1000km, 500km, and 300km radius from the Ant headquarters. Log(Dist from X) is the natural logarithm of distance from Ant headquarters in columns (1) to (4) and distance from Shanghai in columns (5) to (8). We include the same set of controls as in Table 2. Panel B reports the first and second stage IV estimates for the region within the 300km radius from the headquarters of Ant. To capture time-varying effect 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) and (2) report the first-stage estimates of Log(QRPay) and columns (3) to (6) report the second stage estimates for risky purchase and risky fraction. Time fixed effects are included in all the specifications. The sample period is from January 2017 to March 2019. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively. See Appendix A 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)	-0.253***	-0.180***	-0.136***	-0.166***	-0.224***	-0.132***	-0.051	-0.071
	(-13.79)	(-6.46)	(-3.45)	(-3.94)	(-12.14)	(-4.62)	(-1.03)	(-1.14)
LowBank	-0.216***	-0.180***	-0.152*	-0.012	-0.236***	-0.195***	-0.185**	-0.117
	(-5.87)	(-3.61)	(-1.86)	(-0.08)	(-6.23)	(-3.79)	(-2.22)	(-0.73)
Log(GDP)	0.202***	0.110***	0.062	0.041	0.188***	0.091***	0.057	0.021
	(9.00)	(4.15)	(1.41)	(0.76)	(8.20)	(3.20)	(1.26)	(0.36)
Log(Income)	0.082***	0.172***	0.223***	0.259***	0.068***	0.178***	0.235***	0.240***
	(4.18)	(6.67)	(4.68)	(4.59)	(3.44)	(6.42)	(4.08)	(3.36)
Log(Population)	0.014	0.019	0.056	0.057	0.057***	0.073***	0.107**	0.128**
	(0.94)	(0.83)	(1.58)	(1.32)	(3.15)	(2.79)	(2.59)	(2.48)
Time FE	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	73.9%	72.3%	71.6%	69.3%	72.8%	71.3%	70.5%	67.2%
F-stat of (a)	190.04	41.79	11.87	15.53	147.46	21.36	1.06	1.31

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)
Log($\hat{\text{QRPay}}$)			2.387**	2.196**	2.259**	2.090**
			(2.14)	(2.12)	(2.11)	(2.09)
Log(Dist from Ant)	-0.166***	-0.230***				
	(-3.94)	(-4.80)				
Log(Dist from Ant)*Time		0.071***				
		(8.03)				
Controls	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	4,212	4,212	4,212	4,212	4,212	4,212
R-squared	69.4%	83.2%	38.7%	38.7%	37.8%	37.7%

Table 4. 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 $t+1$. Risky Fraction is the fraction of risky fund purchase 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 systematic and idiosyncratic components by estimating the following regression for each individual i: $\text{Log(QRPay)}_t^i = a^i + b^i {*}\text{Peer Log(QRPay)}_t^i + \epsilon_t^i$. Sys Log(QRPay) is the predicted component of individual i's Log(QRPay) that can be explained by her Peer Log(QRPay) ($= \hat{b}^i {*}\text{Peer Log(QRPay)}_t^i$). Idio Log(QRPay) is calculated as Log(QRPay) minus Sys 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. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. See Appendix A 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
Time FE	N	Y	N	Y	N	Y	N	Y
User FE	N	N	Y	Y	N	N	Y	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%

Panel B. Systematic vs. Idiosyncratic FinTech Adoption

	Y=Risky Purchase$_{t+1}$				Y=Risky Fraction$_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sys Log(QRPay)	3.387***	2.786***	4.811***	2.743***	3.168***	2.611***	4.520***	2.644***
	(8.15)	(8.57)	(5.74)	(6.18)	(8.12)	(8.73)	(5.52)	(6.23)
Idio Log(QRPay)	1.047***	0.991***	1.058***	1.009***	0.999***	0.947***	1.011***	0.965***
	(5.00)	(5.09)	(5.04)	(5.25)	(5.03)	(5.14)	(5.07)	(5.29)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y
User FE	N	N	Y	Y	N	N	Y	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%

Table 5. Individual FinTech Adoption and Portfolio Risk Taking

The table reports the cross-sectional regression estimates of individual FinTech adoption on portfolio risk taking. To capture individuals' portfolio risk taking, risky share is the average fraction of risky funds investment in the entire sample period; σ_{W} is the standard deviation of individual portfolio monthly return in percent. Log(QRPay) is the monthly natural logarithm of QRPay, averaged month by month for each individual. We control for individual characteristics, including Log(Age), Female, Log(C), and σ_{C}. In columns (2), (3), (5) and (6), we further include the interactions of Log(QRPay) with individual characteristics. All continuous independent variables are standardized with a mean of zero and a standard deviation of one. The sample excludes individuals with less than 100 RMB purchase of funds (including both risk-free and risky mutual funds). *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. See Appendix A for variable definitions.

	Risky Share			$\sigma_{\mathbf{W}}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(QRPay)	1.826***	1.840***	2.255***	0.261***	0.263***	0.383***
	(6.33)	(6.37)	(5.24)	(9.46)	(9.49)	(7.87)
Log(QRPay)*σ_{C}		0.581**	0.486*		0.083***	0.079***
		(2.25)	(1.86)		(2.82)	(2.67)
Log(QRPay)*Log(C)			0.067			-0.007
			(0.25)			(-0.29)
Log(QRPay)*Female			-1.217**			-0.166***
			(-2.20)			(-2.98)
Log(QRPay)*Log(Age)			1.129***			-0.092***
			(4.23)			(-3.41)
Controls	Y	Y	Y	Y	Y	Y
Observations	28,393	28,393	28,393	28,393	28,393	28,393
R-squared	3.4%	3.5%	3.5%	1.7%	1.7%	1.8%

Table 6. FinTech Penetration Conditional on Local Bank Coverage

The table reports the effect of county-level FinTech penetration on risky fund participation, conditional on local bank coverage. In columns (1) to (3), the dependent variable is the average risky fund purchase probability in month $t+1$. In columns (4) to (6), the dependent variable is the average risky fund purchase fraction in month $t+1$. Log(QRPay) is the natural logarithm of the number of Alipay QR-Scan payments in month t, averaged across individuals in the county. LowBank is a dummy variable that equals one for counties with a below-median number of bank coverage, and zero otherwise. The coefficients of interest are the interaction between LowBank and Log(QRPay). We also control for the natural logarithm of county GDP, population, income per person, and their interactions with Log(QRPay). 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 Appendix A for variable definitions.

	Y=Risky Purchase$_{t+1}$			**Y=Risky Fraction**$_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(QRPay)	2.154***	2.134***	0.875***	2.009***	1.994***	0.779***
	(5.31)	(5.15)	(3.78)	(5.07)	(4.93)	(3.61)
Log(QRPay)*LowBank	0.364**	0.410**	0.427**	0.383**	0.414**	0.435**
	(2.09)	(2.30)	(2.11)	(2.31)	(2.41)	(2.25)
Log(QRPay)*Log(GDP)		-0.005	0.024		-0.010	0.021
		(-0.06)	(0.24)		(-0.12)	(0.21)
Log(QRPay)*Log(Income)		0.049	0.269**		0.039	0.260**
		(0.55)	(2.61)		(0.44)	(2.61)
Log(QRPay)*Log(Population)		0.085	0.087		0.070	0.073
		(1.23)	(1.13)		(1.05)	(0.99)
Controls	Y	Y	Y	Y	Y	Y
Province*Time FE	N	N	Y	N	N	Y
Observations	20,202	20,202	20,176	20,202	20,202	20,176
R-squared	13.3%	13.4%	40.1%	12.5%	12.6%	39.3%

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 and consumption growth volatility. Panel A reports the summary statistics for the low- and high-bank coverage individuals in the matched sample, as well as the difference between the two. Panel B reports the regression estimates for the effect of FinTech on portfolio risk taking (σ_W). Following the specification in column (4) of Table 5, we regress individual σ_W on Log(QRPay), controlling for individual characteristics. The coefficients on Log(QRPay), estimated separately for high- and low-bank coverage individuals, are reported. The last column further reports the coefficient estimate difference between the low- and high-bank coverage groups. We report the results estimated using all the observations in the matched sample, as well as subsamples defined based on the median cutoff of risk tolerance (σ_C), gender, mature individuals with an age between 30 and 55 years old, and median cutoff of consumption level. *, **, 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
σ_C	4,053	1.10	1.01	1.09	1.01	0.01	(0.33)
Log(C)	4,053	7.25	0.82	7.25	0.81	0.00	(0.12)
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(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)				
High Risk Tolerance (σ_C)	0.701***	0.359***	0.342*	Low Risk Tolerance (σ_C)	0.339***	0.122	0.217
	(4.60)	(3.02)	(1.78)		(2.86)	(0.96)	(1.25)
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)
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)

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.

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. Diversification Benefit

	Log(#Funds) (1)	Log(#Assets) (2)	Sharpe Ratio (3)
Log(QRPay)	0.106***	0.067***	0.955***
	(19.46)	(17.96)	(11.87)
σ_C	0.019***	0.010***	0.082
	(3.92)	(3.15)	(1.39)
Log(C)	0.001	-0.006**	0.068
	(0.30)	(-2.28)	(1.19)
Female	-0.155***	-0.109***	-1.393***
	(-15.89)	(-17.86)	(-11.20)
Log(Age)	-0.068***	-0.052***	-0.640***
	(-12.96)	(-14.78)	(-10.38)
Constant	1.494***	1.111***	11.690***
	(161.27)	(173.01)	(81.77)
Observations	20,033	20,033	20,033
R-squared	6.2%	7.1%	3.4%

Table 9. Initial and Subsequent Purchase of Each Asset Class

This table reports the effect of FinTech adoption on individuals' propensity for risky purchases across different asset categories, subsequent to their initial risky asset purchase. After1stPurc is a dummy that is equal to one in month t if an individual has purchased risky assets as of month $t-1$, and zero otherwise. Log(QRPay)×After1stPurc is the interaction term between Log(QRPay) and After1stPurc. The dependent variables are the risky purchase within specific asset classes in month $t+1$. For example, in column (3), the dependent variable is a binary indicator, taking the value of one if the individual made any equity fund purchase in month $t+1$, and zero otherwise. Risky fund asset classes include bond, mixed, equity, index, QDII, and gold. 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 sample period is 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 Appendix A 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%

Table 10. FinTech Adoption and Risky Investment, Conditional on Credit Access

This table reports the effect of FinTech conditional on the investors' credit access information. We divide the entire sample into two groups based on whether individuals have access to credit cards in their Alipay account or not. Subsequently, we examine how FinTech adoption influences an individual's next-month risky purchase and risky fraction for both subgroups. We control for individual characteristics, including Log(Age), Female, Log(C), and σ_C. All continuous 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 sample period is 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 Appendix A for variable definitions.

	Y= Risky Purchase$_{t+1}$							
	With Credit Card				No Credit Card			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(QRPay)	3.070***	2.595***	2.983***	1.741***	2.432***	1.859***	2.515***	1.252***
	(7.52)	(7.82)	(5.87)	(6.33)	(7.31)	(7.33)	(6.07)	(5.99)
σ_C	-0.095	-0.134			0.063	0.029		
	(-0.72)	(-1.01)			(0.69)	(0.32)		
Log(C)	0.605***	0.665***			0.521***	0.592***		
	(4.08)	(4.43)			(5.47)	(6.56)		
Female	-2.207***	-2.270***			-2.173***	-2.256***		
	(-6.40)	(-6.50)			(-10.21)	(-10.32)		
Log(Age)	0.697***	0.622***	0.000		0.748***	0.613***		
	(3.94)	(3.60)	(0.00)		(5.76)	(4.87)		
Time FE	N	Y	N	Y	N	Y	N	Y
User FE	N	N	Y	Y	N	N	Y	Y
Observations	470,314	470,314	470,314	470,314	829,686	829,686	829,686	829,686
R-squared	0.011	0.02	0.345	0.354	0.01	0.021	0.237	0.249

Internet Appendix to

"Financial Inclusion via FinTech:

From Digital Payments to Platform Investments"

Claire Yurong Hong, Xiaomeng Lu, and Jun Pan

IA1. Alternative Measure of FinTech Penetration

Our main measure of FinTech adoption is the natural logarithm of the number of Alipay QR-Scan payments made by each individual during each month. One may be concerned that high-income individuals tend to consume more, and they tend to use mobile payment more frequently. To alleviate this concern, we also compute QRFrac, the fraction of Alipay QR-Scan consumption out of total Alipay and Taobao consumption for each user, as an alternative measure of FinTech adoption. Similarly, county-level FinTech penetration is computed as the average QRFrac for individuals living in the county. Using this alternative measure of FinTech penetration and FinTech adoption, we repeat our analyses using the same regression settings in Section 3.

Panel A of Appendix Table IA2 reports the results using the instrumental variable approach, similar to the setting in Panel B of Table 3. Across all specifications, the results are qualitatively the same as those for the Log(QRPay) measure. For example, when we only include Log(Dist to Ant) in the first stage estimation, one-standard-deviation increase in $\widehat{\text{QRFrac}}$ implies a 2.44% increase in risky purchase and a 2.32% increase in risky fraction. The magnitudes are close to the corresponding coefficients estimates in Panel B of Table 3 (2.39% for risky purchase and 2.26% for risky fraction, respectively). For the first-stage estimation that allows for the time-varying effect of distance, we also observe a similar economic magnitude and statistical significance as the results in Panel B of Table 3 in the second stage. For example, the effect of one-standard-deviation increase in $\widehat{\text{QRFrac}}$ on risky purchase in this setting is 2.30%, close to the corresponding value of 2.44% in column (4).

Panel B of Appendix Table IA2 reports the corresponding results at the individual level, similar to the panel regression setting in Panel A of Table 4. We also find that a higher level of FinTech adoption in month t is associated with higher risk taking in month $t+1$ across all model specifications. In summary, the effect of FinTech penetration and FinTech adoption on investors' risk-taking behavior is robust to this alternative measure.

IA2. 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.

Survey Design and Data Collection

We administer the survey through a third-party survey company. The survey took place in July 2022. Respondents could open the survey using their personal computers or their smartphones. The survey is consisted 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 distribution channels.

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.

Survey Results

Appendix Table IA4 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. This result supports the notion that FinTech penetration leads to increased investments in risky assets.

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: "The availability of additional platform functions, such as payment, etc." (37.7%), "The ease of use of the operating system" (21.1%), and "The convenience 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 investors who had used Alipay for mutual fund purchases, the predominant reasons for selecting the Alipay platform were: "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.

Figure IA1. Geographic Distribution of Banking Coverage

This figure shows the geographic distribution of banking coverage in each prefecture. We rank all prefectures in our sample into percentiles based on the total number of traditional bank branches. The darker the color, the higher the traditional bank coverage.

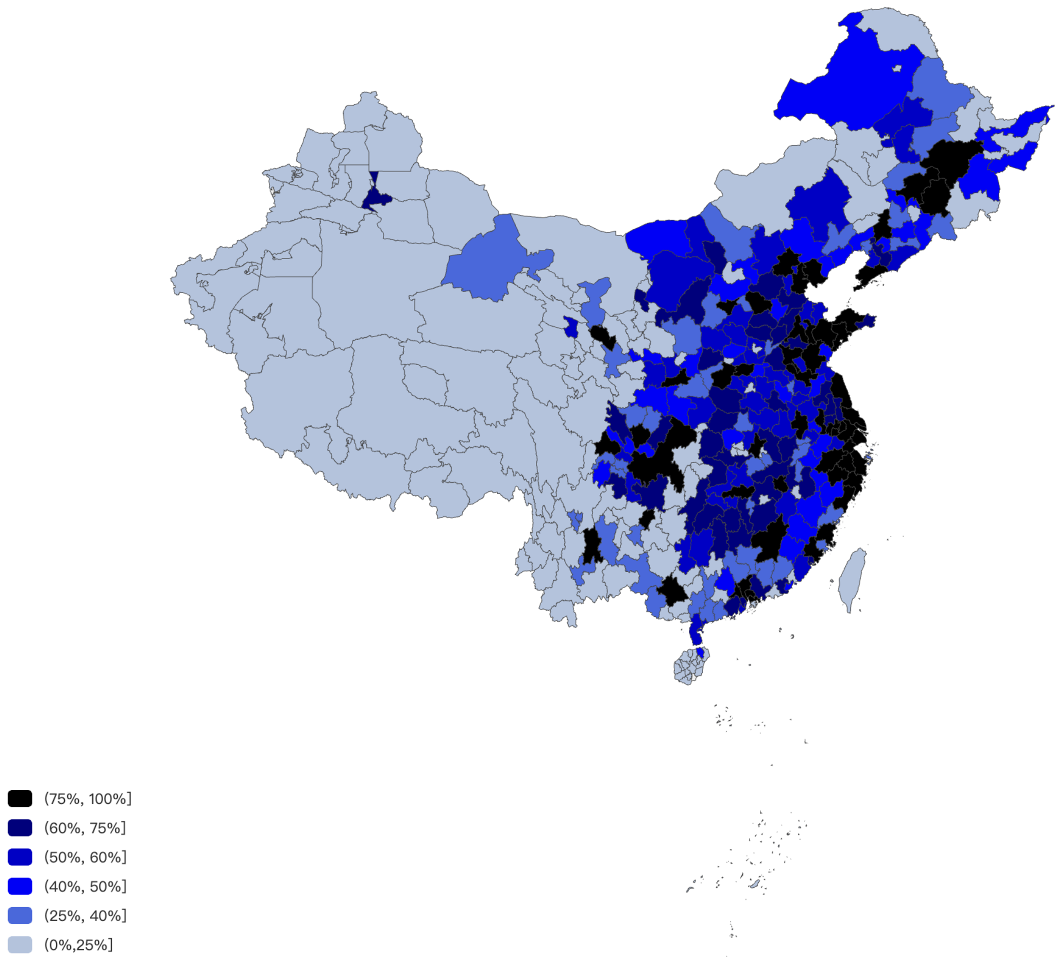


Table IA1. Redemption and Net Purchase

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. 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 A for variable definitions.

	Y=Risky Redemption$_{t+1}$				Net Purchase$_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(QRPay)	0.479***	0.490***	0.370***	0.356***	2.444***	1.918***	2.459***	1.210***
	(8.90)	(7.96)	(5.92)	(7.28)	(7.49)	(7.77)	(6.05)	(6.02)
σ_C	0.091***	0.091***			-0.055	-0.092		
	(2.95)	(2.91)			(-0.75)	(-1.25)		
Log(C)	0.055**	0.053**			0.665***	0.744***		
	(2.19)	(2.18)			(8.02)	(9.18)		
Log(Age)	-0.184***	-0.182***			1.026***	0.930***		
	(-4.66)	(-4.58)			(10.73)	(10.20)		
Female	-0.921***	-0.919***			-1.671***	-1.747***		
	(-11.19)	(-11.27)			(-9.16)	(-9.24)		
Time FE	N	Y	N	Y	N	Y	N	Y
User FE	N	N	Y	Y	N	N	Y	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	0.3%	0.5%	13.3%	13.5%	1.1%	2.0%	26.4%	27.4%

Table IA2. Alternative Measure of FinTech Penetration

This table reports the effect of FinTech on individual risk taking using alternative measure of FinTech penetration. FinTech penetration is measured by QRFrac, computed for each individual in each month as the fraction of consumption paid via Alipay out of total consumption paid via Alipay and Taobao. Panel A reports the county-level results following the specification in Table 3. Panel B reports the individual-level results following the specification in Table 4. See Appendix A for detailed variable definitions. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Panel A. IV Regression using QRFrac

	First Stage		Second Stage			
	Y=AliFrac		Y=Risky Purchase$_{t+1}$		Y=Risky Fraction$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{QRFrac}$			2.444**	2.302**	2.321**	2.196**
			(2.11)	(2.09)	(2.08)	(2.07)
Log(Dist from Ant)	-0.159***	-0.209***				
	(-4.72)	(-4.50)				
Log(Dist from Ant)*Time		0.056**				
		(2.35)				
Controls	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	4,212	4,212	4,212	4,212	4,212	4,212
R-squared	58.7%	58.8%	38.7%	38.7%	37.7%	37.7%

Panel B. Individual QRFrac and Risky Fund Purchase

	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
Time FE	N	Y	N	Y	N	Y	N	Y
User FE	N	N	Y	Y	N	N	Y	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%

Table IA3. Consumption Growth Volatility and Individual Risk Tolerance

This table reports the summary statistics and determinants of consumption growth volatility (σ_C). σ_C is calculated for each individual as the standard deviation of her quarterly consumption growth in our sample period. Panel A reports the distribution of σ_C conditional on individual characteristics. In row "Risk Appetite", we divide individuals into three groups based on their risk tolerance ratings classified by the China Securities Regulatory Commission. "Low" denotes very conservative individuals and "High" denotes very aggressive individuals. Row "Gender" and "Age" report the statistics for individuals with different gender and age categories. In row "Consumption Level", we divide individuals into three groups based on their monthly online consumption amount, where 'High" denotes individuals with the highest consumption level. Panel B reports the determinants of σ_C), estimated under a regression framework. High Risk Appetite and Medium Risk Appetite are dummy variables equal to one for individuals within "High" and "Medium" risk categories, respectively. We control for Log(Age), Female, and Log(C). See Appendix A for detailed variable definitions. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively.

Panel A. σ_C by Personal Characteristics

Risk Appetite	Low	Medium	High	
Mean	1.00	1.06	1.12	
Median	0.73	0.76	0.78	
Std	0.91	0.99	1.08	
Gender	Male	Female		
Mean	1.12	0.94		
Median	0.80	0.69		
Std	1.02	0.85		
Age	<22	22-30	30-55	>55
Mean	0.87	1.01	1.05	1.14
Median	0.66	0.73	0.75	0.75
Std	0.78	0.93	0.95	1.15
Consumption Level	Low	Medium	High	
Mean	0.94	0.98	1.10	
Median	0.67	0.74	0.79	
Std	0.90	0.85	1.00	

Panel B. Determinants of σ_C

High Risk Appetite	0.138***				0.078**
	(3.86)				(2.20)
Medium Risk Appetite	0.055**				0.019
	(2.11)				(0.74)
Female		-0.190***			-0.192***
		(-19.83)			(-20.08)
Log(Age)			0.058***		0.039***
			(12.71)		(8.45)
Log(C)				0.105***	0.101***
				(18.82)	(17.65)
County FE	Y	Y	Y	Y	Y
Observations	50,000	50,000	50,000	50,000	50,000
R-squared	2.5%	3.2%	2.7%	3.5%	4.5%

Table IA4. 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
Gender	
Male	64.04
Female	35.96
Age	
Below 18	0.97
18-25	21.38
26-30	39.09
31-40	34.13
21-50	4.32
Above 50	0.11
Education	
Junior college	21.68
College	63.24
Master	13.85
PhD	1.23
Have you received an education related to finance?	
My major is related to economics (such as economics, finance, management, international trade, etc.).	38.77
I have learnt some finance by myself from textbooks and books	28.73
I have obtained some financial knowledge through the Internet.	28.08
No, I have not received any education related to finance at all.	4.10
Others	0.32
Occupation	
Ordinary employees	32.94
Government officials/civil servants	11.77
Enterprise managers (including junior and senior managers)	23.22
Financial practitioner	13.82
Freelancer	11.23
Student	6.80
Retired	0.11
Other	0.11
Willingness to take risk	
Not willing to take any risk	2.16
Low risk, low return	20.63
Moderate risk, stable return	67.17
High risk high return	10.04
At what point of investment loss do you experience significant anxiety?	
Below 10%	7.34
10%-30%	43.63
30%-50%	39.96
50%-70%	5.94
Above 70%	1.08
Will not experience anxiety	2.05

	% of Respondents
Income (RMB) per month	
Below 3000	5.94
3001-5000	15.55
5001-10000	43.63
10001-15000	24.95
15001-20000	6.70
20001-50000	3.02
Above 50000	0.22
Total amount of financial investment, including bank deposit, stocks, mutual fund, wealth management products, future, options, etc.	
Below 50,000	13.28
50,000-100,000	31.21
100,000-500,000	44.06
0.5-1 million	9.50
Above 1 million	1.94
What is the total scale of your mutual fund investment (excluding money market funds)	
Below 50,000	34.67
50,000-100,000	40.71
100,000-500,000	21.17
0.5-1 million	2.70
Above 1 million	0.76
Through which channel did you first purchase risky mutual fund products	
Banks	18.14
Brokers	25.81
Fund Companies	25.70
Alipay (Ant Fortune)	25.59
Other third-party distribution channels (including Tiantian, Tencent)	4.75
What is the main reason influencing your decision to purchase mutual funds through various platforms?	
The availability of additional platform functions, such as payment, etc.	37.69
The ease of use of the operating system	21.06
The convenience of accessing fund-related information	16.74
Fund security	9.50
Fund variety	7.24
Fees	7.24
Other factors	0.54
What are the top three reasons for choosing Alipay? (Alipay investment users only)	
Ease of managing investments, payments, and consumption all in one app	52.38
Convenient access to information	41.79
User-friendly platform interface	49.03
Discounted fees	24.73
Trust in Alipay’s safety and the safety of investment funds	38.01
A wide range of mutual fund choices	18.90