FinTech Adoption and Household Risk-Taking:

From Digital Payments to Platform Investments

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Abstract

We study household finance in the age of FinTech, where consumption, payments, and investments take place via all-in-one super-apps. We hypothesize that FinTech adoption can improve household risk-taking by breaking down the traditional physical and psychological barriers and enhance financial inclusion. 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

This paper studies the extent to which widespread adoptions of financial technology (FinTech) can reshape household finance and enhance financial inclusion. To understand why many households do not invest in risky assets despite the obvious utility enhancement, the existing literature finds that fixed physical costs (money, time, and effort) and psychological costs (familiarity and trust) are important factors hindering individuals from optimal risk-taking.[1] Against this backdrop, our hypothesis is that FinTech adoption can improve household risk-taking by helping break down the traditional barriers, physical as well as psychological, faced by households in their participation of financial markets.

To test this hypothesis, our focus is placed on the digital ecosystem created by BigTechs, which, through the deployment of all-in-one super-apps, bundle activities that are central to household finance into one integrated platform. China's super-app Alipay created by the Ant Group is one such example, which hosts functions including the e-commerce shopping platform of Taobao, QR-Scan based digital payments, and mutual-fund investment platform. As such BigTechs typically enter the financial-service industry by first offering digital payments and then expanding into the distributions of financial products including mutual funds, our research design follows the same trajectory. Specifically, from digital payments to platform investments, we examine the extent to which increased FinTech adoption via digital payments can lead to higher participation and more risk-taking in mutual-fund investments on the same platform.

While the technological efficiency of the FinTech platforms can clearly help minimize or even eliminate the physical costs of participation, the reduction of the psychological barriers can have a more profound impact. Via FinTech adoptions, individuals can acquire familiarity through repeated usages of digital payments on the all-in-one super-apps. As familiarity leads to trust, repeated usage can then help lessen or even break down the psychological barriers that prevent households from market participation. It is from this vantage point that we study how FinTech advancement can help households lower investment barriers and improve risk-taking.

Measuring FinTech Adoption – Our empirical study is based on an account-level dataset from Ant Group, which tracks each individual's digital payments via Alipay, online mutual-fund investments via Ant Group's investment platform, and online consumption via Taobao

[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.

e-commerce platform. Importantly, all three activities can be initiated from Alipay, the first super app in China. Also included in the data are the individual characteristics including age, gender, and, important for our purpose, location. The data are of monthly frequency from January 2017 to March 2019, when China experienced the most dramatic expansion in offline digital payments via Alipay.

From 2017 to 2018, offline digital payments in the form of quick response (QR) scan exploded ten-fold in China to a total of 7.2 trillion RMB by 2018Q4. This unique window of offline expansion is central to our empirical design, as it captures the process of FinTech adoption from zero to one. Different individuals in our sample pop up as offline digital payers at different points in time and, importantly, with different intensity. This rich heterogeneity in FinTech adoption, both cross individual and over time, is key to our identification. Seizing on this rapid technological development, we measure individual-level FinTech adoption by how much and how fast an individual adopts this new technology. Specifically, our FinTech adoption measure, QRPay_t^i, is the number of Alipay digital payments, made by individual i in month t. Over the long run, as digital payments become the dominant payment method, the level of QRPay may stabilize and lose its information value. Within our sample period, however, as digital payment is being adopted with varying speed and intensity by individuals in different areas, the level of QRPay contains valuable information about an individual's FinTech adoption.

Relative to the cross-individual variation, an important and more exogenous variation emerges from the staggered penetration of this new QR technology across geographical locations in China. The FinTech penetration map of China, captured at time, demonstrates a gradual spread of the new QR technology from Hangzhou, the headquarters of Ant, to the rest of China. Indeed, back in 2016, street vendors accepting QR-code scanning payments were a novelty sight spotted mostly near Hangzhou. By 2020, it had become part of everyday life for most people living in China. While the individual-level variation might be driven by personal characteristics and experiences, this county-level variation is plausibly more exogenous, owing to the gradual spread of the new technology across China.

From FinTech Adoption to Platform Investments – By examining the difference in risk-taking across variations in FinTech adoption, both at the individual level and across geographical locations in China, we aim to offer evidence of how FinTech can improve household risk-taking and encourage financial inclusion. We hypothesize that with the familiarity and trust built from repeated use of the Alipay app, individuals of high QRPay are more likely to use the mutual-fund platform bundled with Alipay to fulfill their investment needs, while individuals with low QRPay have not yet bought into the FinTech revolution. Moreover, if FinTech can indeed lower investment barriers for households, we would also expect to see FinTech penetration leading the way to improved risk-taking across geographical areas in China. Importantly, the more constrained counties with lower financial-service coverage should benefit more from FinTech penetration.

To capture households' risk-taking behavior, 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, and Ant Group is the largest FinTech player, accounting for over half of the FinTech distribution market share.[2] Individuals have access to risk-free money market funds, as well as six types of risky mutual funds (bond, mixed, equity, index, QDII, and gold) on the FinTech platform.[3] We measure households' risk-taking by their risky mutual fund investments behavior: risky purchase is a dummy variable that equals to one if the individual purchases any risky fund in a given month; and risky fraction is the proportion of risky fund purchase amount to total purchase.

Tracking households' platform risk-taking along the dimension of their FinTech adoption, we find strong evidence that repeated usage of QR-Pay increases the likelihood that households will invest via 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.

To further establish the causal relationship of the adoption of FinTech 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 construction of the IV is motivated by

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

[3]Our data contains the fund purchase and redemption made by individuals in each month. For a sub-sample period from August 2017 to December 2018, we also have detailed information on individuals' fund holdings and portfolio monthly returns.

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

the ground promotion strategy of Ant in the early development stage of QR technology. To convince local merchants and local governments to massively adopt the QR payment, the marketing teams of Ant have to pitch and showcase the usage of QR-Scan Pay in person, and it naturally starts from areas near Hangzhou, and then gradually expands to more distant areas.[5] Consistently, we find Hangzhou is at the epicenter of the FinTech penetration map of China. By contrast, the promotion of the investment platform is not restricted to a geographical perspective, as it was conducted mostly online via the Alipay app since 2014. Therefore, a county's physical distance from Hangzhou contains unique information about FinTech penetration, but is arguably orthogonal to households' mutual fund investment incentive.[6] Using distance-from-Hangzhou as an instrument for FinTech penetration, we find consistent evidence 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.

Extending the analysis from county level to individual level, we provide further micro-level evidence that repeated use of QR-Scan encourages household risk-taking. Moreover, by differentiating individual self-initiated FinTech adoption from environmental-driven FinTech adoption, we uncover the unique role played by 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 residual 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 aggregate time trend in household risk-taking cannot explain our findings. The dominant role of the systematic part, therefore, points to the profound impact of environmental change in shaping individuals' risk-taking behavior.

Who Benefits More from FinTech Inclusion – To further explore the welfare implications of FinTech inclusion, we next study whether the effect of FinTech is stronger for investors

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

[6] 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.

who are otherwise more constrained prior to the advent of FinTech. If the advent of FinTech can indeed break down the barriers of investments, it should be the more risk-tolerant investors who stand to benefit the most. To identify the high risk-tolerant individuals, motivated by the classical consumption-based portfolio choice problem of Merton (1971), we use individual consumption growth volatility σ_{C} as a proxy for risk tolerance.[7] Consistent with the theoretical implications of σ_{C}, empirically, we find that σ_{C} contains unique information about cross-individual variations in risk aversion. Individuals with higher σ_{C} self-report a higher level of risk appetite based on the surveys conducted by China Securities Regulatory Commission, and they also exhibit a higher risk taking in mutual fund investments. Armed with our proxy for risk tolerance, we further examine the effect of FinTech for individuals with different tolerance for risk. 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 they want.

From a geographical perspective, FinTech also has the potential to fill in the vacuum left out by traditional banks and better serve the individuals living in under-banked areas. Performing our analysis for counties with above- and below-median bank coverage, we find that the benefit of FinTech inclusion in fact comes mostly from counties with below-median banking coverage. Moreover, focusing on the under-banked individuals, we compare and contrast their risk-taking sensitivity to FinTech adoption with a matching sample of high-bank-coverage individuals. We find that mature, high-wealth, and high risk appetite individuals, living in low-bank coverage areas, increase their risk-taking much more readily with FinTech adoption, when compared with the same-characteristic individuals living in high-bank-coverage areas. Living in high-bank-coverage counties, individuals with high risk capacities can invest via the existing financial infrastructure, but their counterparts living in low-bank-coverage counties do not have that privilege. With FinTech advancement, the under-banked individuals are given an alternative channel to fulfill their investment needs. Overall, these results are consistent with the interpretation that FinTech, instead of serving as a substitution to traditional banks, indeed opens the door for individuals who lack access to financial investment opportunities and would otherwise remain unbanked. Our finding, therefore, provides compelling evidence for the complementary role of FinTech to the existing financial infrastructure.

Finally, to answer the question whether investors truly benefit from FinTech inclusion,

[7]According to Merton (1971), the optimal portfolio weight is $w^* = \frac{\mu - r}{\gamma\, \sigma_R^2}$, where γ is the risk aversion coefficient, and $\mu - r$ and σ_R are the risk premium and volatility of the risky asset, respectively. Moreover, with 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 risk aversion coefficient γ.

we examine the performance of their FinTech investments. Investment loss could potentially erase the gain of participation if households tend to make investment mistakes on FinTech platforms. For example, Calvet, Campbell, and Sodini (2007) show that the cost of non-participation is smaller by almost one-half when taking into account the fact that non-participants would likely be inefficient investors. To examine households' FinTech investment outcome, we focus on their portfolio performance and portfolio allocation. Comparing Ant investors' holdings of mutual funds with the distribution of funds in the aggregate mutual fund industry, we find that Ant investors' choice of funds, on average, exhibit higher alphas than an average fund in the industry. Since mutual funds in China tend to outperform their passive benchmarks, investing with delegated portfolio management is clearly a welfare improvement for individuals who do want to take financial risk. Moreover, from the perspective of asset allocations, we find that FinTech adoption also leads to a more diversified portfolio allocation with investments over more funds and across multiple asset classes, the benefit of which is a reduction in portfolio volatility and an enhancement in Sharpe ratio.

Related Literature – Our paper contributes to the literature on how the development of technology helps solve the low-participation rate puzzle. Choi, Laibson, and Metrick (2002), Bogan (2008), and Reher and Sokolinski (2021) document that the use of web-based trading platform and the introduction of robo advisory service help encourage active participation in financial markets. Focusing on the performance of households, Barber and Odean (2002) show that adopters of online platforms experience a reduction in performance, and D'Acunto, Prabhala, and Rossi (2019) show that robo-advising helps mitigate households' behavioral bias. We contribute to this literature by investigating the impact of digital payments on households' incentive to invest in risky mutual funds. Unlike the technologies studied in these papers, digital payments have no direct impact on households' access to investment services. Instead, the positive externality of digital payments on investments stems from the trust and familiarity, accumulated when households frequently use FinTech platform for payments.[8]

Our paper also adds to the growing literature on the development of digital payments on households' behaviors. Existing literature mostly focuses on studying the adoption of mobile payments and its impact on households' saving and consumption.[9] For example,

[8]Our argument is consistent with Hong, Kubik, and Stein (2004) and Guiso, Sapienza, and Zingales (2008), who document that familiarity and trust are important drivers of the low-participation puzzle. More generally, Christiansen, Joensen, and Rangvid (2008), Calvet, Campbell, and Sodini (2009), Calvet and Sodini (2014), and Calvet et al. (2020) find that lower participation cost, higher income, better education, and higher financial sophistication are associated with increase in participation rate.

[9]Focusing on the effect of payments on merchants, Chen et al. (2021) and Agarwal et al. (2020) show that the development of digital payment reduces sales volatility, fosters sales growth and entrepreneurship.

Jack and Suri (2011) document the adoption of mobile money in Kenya and Higgins (2019) emphasizes the network effect in the adoption of debit cards in Mexico. Buchak, Hu, and Wei (2022), Suri, Bharadwaj, and Jack (2021), Ouyang (2021), and Agarwal et al. (2019) further show that digital payments help revolutionize savings-like money market products, improve financial resilience for the underprivileged, but could at the same time induce excessive consumption. Unlike these studies, we examine the externality of digital payments on households' investment behavior, with a special emphasis on the bundling feature of FinTech platform. Digital payment, in the form of Alipay QR-Scan, is different from a mobile-based banking account, as it lies outside the banking system. It also differs from the mobile money in Kenya (e.g., M-PESA), as it provides a "one-stop-shop" for customers with a wide range of services apart from money transfer. This bundling business model, where companies package payment function with several other services as a single unit, is becoming prevalent across FinTech companies around the globe, and is the focus of our paper.[10]

Finally, our paper is related to the literature that connects portfolio choices with risk preferences. For example, individual risk preference can be back-engineered via an examination of their portfolio allocation (e.g., Calvet et al. (2021)). Alternatively, a growing literature links survey-based investor beliefs and risk preferences to portfolio choices (Giglio et al. (2021), Jiang, Peng, and Yan (2021)). Household portfolio choice is also related to personal experiences and attitudes, such as past investment, macroeconomic experiences, and political affiliation (e.g., Choi et al. (2009), Malmendier and Nagel (2011), and Meeuwis, Parker, Schoar, and Simester (2018)). Our work contributes to this literature by providing a measure of risk tolerance based on the theoretical framework in Merton (1971) and connecting it with portfolio choice. In particular, we use consumption growth volatility to infer cross-individual variations in risk attitudes, and establish a positive link between individual consumption growth volatility, portfolio risk-taking, and survey-based risk tolerance. By providing direct empirical evidence of the connection between consumption and investment behavior, our finding also complements Mankiw and Zeldes (1991), who use aggregate series of food consumption data to show that the consumption of stockholders is more volatile than that of non-stockholders.[11]

[10]The prevalence of bundling is evident from Stripe's cooperation with Klarna, SumUp's acquisition of Tiller, Thunes' acquisition of Limonetik, and Rapyd's acquisition of Valitor. See Finextra's study, titled "Rebundling: The next stage of the FinTech evolution" for more details. https://www.finextra.com/researcharticle/251/rebundling-the-next-stage-of-the-fintech-evolution Accessed October 24 2022.

[11]Contrary to Mankiw and Zeldes (1991), Chinco et al. (2022) find that, in a survey setting, participants' investment choice is not related to an asset's correlation with aggregate consumption growth. Unlike these two papers, we study the relation between individual-level consumption growth volatility and portfolio choice

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 risk-taking. Section 4 focuses on FinTech inclusion and welfare implications. Section 5 presents further evidence and robustness tests. Section 6 concludes.

2 Data and Institutional Background

In China, activities central to household finance — consumption, investment, and payment — are all taking place on FinTech platforms. In this section, we provide detailed description of the all-in-one ecosystem of Ant platform, as well as the Ant data used in this paper.

2.1 An All-in-One Ecosystem with Payment and Investment

Ant Group is an integrated corporation that provides products ranging across various sectors, all through its all-in-one ecosystem. On the consumer business side, Ant's ecosystem consists of five major components: online consumption, mobile payment, investment, consumer credit, and healthcare insurance. Empowered by technological development, the company takes advantage of cross-selling opportunities via a sophisticated network of interconnected functions. For the purpose of our study, we mainly focus on the mobile payment function and the mutual fund investment function.

The mobile payment function was initially developed to build trust between online buyers and sellers in the early days of e-commerce. In 2011, the technology of QR-code scan payment was introduced to further facilitate the development of mobile payment. It allows offline partnering merchants to settle for payment by scanning a customer's QR code. The development of investment function can be traced back to 2013 when Alipay launched Yu'ebao, by far the largest risk-free money market fund in the world. It allows customers to invest with their pocket money inside the ecosystem. Beginning in 2014 Ant further offered mutual fund distribution service, allowing investors to access a wide range of risky mutual funds in its ecosystem. A key feature of the Ant business model is the bundling of services, that is, packaging related products and services into a single offering for the customer. By integrating the needs of customers into a single app, this all-in-one business model has the potential to encourage cross use of functions, establish greater customer connection, and secure long-term loyalty. Among all the functions in the ecosystem, the mobile payment function is at the core of this bundling practice.

using investors' actual holding and consumption data.

As shown in the left panel of Appendix Figure IA1, the Alipay app contains access to a spectrum of services, with the QR-Scan mobile payment function appearing on top of the front page. The mobile payment function is bundled with other financial services, such as investment and credit provisions, as well as everyday life services such as online shopping, food deliveries, and so on. With frequent use of the payment function, customers can gradually build trust with Ant, and start to manage their money using instruments from the Ant platform as well. This synergy effect makes payment function a door to other services offered in the ecosystem. Alipay is a pioneer in this process partially due to the urge for convenient and low cost payment service in an emerging market and to a relatively loose regulation environment in the early years. Nonetheless, other BigTech firms that operate platforms with large customer bases are also actively exploiting the benefit of bundling. 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.

Taking advantage of this bundling business model, we are able to access data along multiple dimensions of individuals' activities occurring on the Ant ecosystem. In addition to individuals' personal characteristics, we are able to track the monthly investment, payment, and consumption behavior for a sample of 50,000 randomly selected investors for the period from January 2017 to March 2019. The sample is randomly selected from the entire population of the Ant platform, among investors who have had at least one purchase or redemption of a money market fund, or a risky mutual fund, or a short-term wealth management product on the Ant platform. Based on statistics from Table 1, 60% of investors on the Ant platform are female with an average age of 30.4 years old. They entail a monthly e-commerce (Taobao) consumption of 2,155 RMB and a quarterly total consumption growth volatility of 1.01 (or 101%).[12] Below, we describe activities related to investment and FinTech in more detail.

2.2 Measuring FinTech Adoption Using QR-Scan Payment

Digital payments in China started in 2004, bringing China into a cashless society with over 852 million users now using mobile digital payments for daily activities. In the category of digital payment, the prevalence of QR-Scan mobile payment is a more recent phenomenon. It permeates the entire country with each street vendor at every corner in China eager to

[12] We use quarterly total consumption growth volatility, σ_C, as a theory-motivated proxy for individual tolerance. The details are explained in Section 4.1.

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 A 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 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).

[13] As the undisputed leaders 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.

[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-commence platform of Alibaba).

From a geographical perspective, how 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. Among all prefectures, Hangzhou has the highest QRPay of 24.9 times per month. In other words, an average individual in Hangzhou already used Alipay 24.9 times per month to pay for consumption in 2017Q2. Other prefectures at that time only have an average QRPay of 5.87. With the passage of time, we observe a gradual penetration of FinTech from the Ant headquarters to the inner region of China. Hangzhou still leads other prefectures in FinTech penetration with a QRPay of 47.39 in 2018Q4, which doubled the level of QRPay for Hangzhou in 2017Q2. In comparison, the average QRPay for other prefectures increases to 18.85, which is more than three times the level of their average QRPay in 2017Q2. 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 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 risk taking.

2.3 Platform Investments of Mutual Funds

In 2014, Ant started to offer mutual fund distribution service, enabling investors to access and invest in almost the entire universe of mutual funds in China. For the mutual fund investment data, we are able to obtain the detailed monthly purchase and redemption transactions made by each investor on the Ant investment platform. For a sub-sample period from August 2017 to December 2018, we also obtain information on their detailed fund holdings and portfolio monthly 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

[15]The administrative divisions of China is consisted of multiple levels, from the top-level of province, to prefecture, and to the granular county-level. In our figures, we use prefecture-level observations for clear graphical illustrations. For regression-based analysis, we use the most granular county-level observations.

funds. Panel B of Figure 1 plots the aggregate purchase of money market funds and risky mutual funds of all users in our sample. As the development of investment platform had already passed its fast-developing stage in early 2014, compared with the increasing trend observed for Alipay payment, the total purchase amount of money market fund and risky mutual funds remain relatively stable during our sample period.

To capture each individual's risky mutual fund investment behavior, 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 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−MMF/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.

Panel B of Table 1 further reports the correlation among the key variables. Consistent with our intuition, risky share and portfolio volatility are positively correlated, with a pair-wise correlation of 0.48. In addition, individuals with higher risky 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 (e.g., Sunden and Surette (1998), Jianakoplos and Bernasek (1998), Barber and Odean (2002), etc.) that male and younger users tend to have higher risky share and portfolio volatility. 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. Overall, this evidence gives us confidence that our investment variables indeed capture individuals' risk-taking outcomes.

3 FinTech and Risky Fund Investment

3.1 County-Level FinTech Penetration

We start by examining the effect of county-level FinTech penetration on households' decision to invest in risky mutual funds. Our hypothesis is that, by bundling the investment function with the digital payment function in an "all-in-one" app, individuals living in areas with high FinTech penetration (i.e., QR-Scan Pay) are more likely to use the same FinTech platform (i.e., mutual-fund investment platform) to fulfill their investment needs. Put differently, we are utilizing the county-level variation in the speed of QR-Scan penetration to identify the effect of FinTech on households' risk-taking.

To capture county-level FinTech penetration in each month, we compute the equal-weighted average Log(QRPay) for all individuals living in a county. As shown in Figure 2, as local merchants gradually adopt the Alipay scan-to-pay QR code, the cross-region as well as time-series variations in Log(QRPay) can capture the staggered penetration of QR-Scan technology at the county level. To examine whether the penetration of QR-Scan encourages risky asset investment, we regress the month-$t+1$ risk-taking measures on the Log(QRPay) measure observed for month t in a panel regression setting as follows:

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

where Log(QRPay)^c_t is the equally-weighted average Log(QRPay) for all the individuals living in county c in month t, and $\text{Risky Purchase}^c_{t+1}(\text{Risky Fraction}^c_{t+1})$ is the month-$t+1$ average risky purchase (risky fraction) for all the individuals living in county c. As local economic conditions can be important determinants of an individual's investment choice, we control for county-level economic variables, including the natural logarithm of GDP, income, and population. We also control for the accessibility to traditional financial infrastructure using LowBank, a dummy variable that equals one if the county belongs to prefectures with below-median bank coverage. Time fixed effects, province fixed effects, as well as time$\times$province fixed effects are included as indicated.

Consistent with the hypothesis that FinTech penetration increases risk-taking, 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 probability for an individual to purchase any risky fund in a given month is 9.16%, an improvement of 2.26% is sizable. When time fixed effects or province fixed effects are included, the coefficient estimates on Log(QRPay) reduce to 0.83% (t-stat=4.44) and 1.05% (t-stat=4.84) respectively. When we further include time×province fixed effects in column (4), the coefficient on Log(QRPay) remains significant with a magnitude of 1.02% (t-stat=4.53). In the case of time×province fixed effects, we are utilizing the cross-county variations in the same province at the same time to identify the effect of FinTech on risk taking. Hence, the positive relationship between FinTech and risky fund participation is unlikely to be fully driven by some unobserved factors at the province level or some common time trend in the variations of FinTech and risk taking.

Turning to risky fraction as an alternative measure of risk-taking, the effect is similar: a one standard deviation increase in county-level Log(QRPay) enhances the average risky fund purchase fraction in the county by 2.12% (t-stat=5.48) the next month. The coefficients remain significant when we further include time fixed effect, province fixed effect, and time×province fixed effect. Overall, these results suggest that the staggered penetration of QR-Scan technology, across geographical locations in China, plays an important role in driving local residents' investment decisions.

3.2 Distance-from-Ant as an Instrument

To further pin down the causal impact of FinTech penetration on household risk-taking, we employ an instrumental variable approach, using the distance from Ant headquarters to capture the plausibly exogenous variation in FinTech penetration. As discussed in Section 2.2, the expansion footprint of the Alipay QR-Scan technology was initiated from the headquarters of Ant, and then gradually penetrated into more distant areas. This is because the penetration of the QR-scan technology is associated with a costly ground promotion process, in which the marketing team of Ant has to communicate with local merchants in person and convince them to accept the QR-Scan pay function as a payment method. However, the marketing of the mutual fund investment function is not restricted from a geographical perspective.[16] Therefore, a county's physical distance from Hangzhou has no direct effect on households' risk-taking, other than through the promotion of QR-Scan payment.

[16]Staff members at Ant also confirm that Alipay did not implement a ground promotion or offline advertisement for the investment function during our sample period.

Validity of the Instrument

We start by validating a county's distance from Ant headquarters as an instrument for FinTech penetration. One immediate problem emerges in that the Ant headquarters, located in Hangzhou of Zhejiang province, is geographically close to Shanghai, which is the economic center of China. A county's distance from Ant, therefore, largely correlates with its distance from Shanghai. If being closer to metropolitan areas like Shanghai encourages individual risk-taking, our IV test may mistakenly attribute the effect of Shanghai to Ant. To alleviate this concern, we vary the subsample of counties according to their distance from Ant and meantime conduct the first-stage IV regression using distance from Shanghai as a placebo test.

The intuition of this placebo test can be illustrated using Figure 3, which shows the location of Ant headquarters and Shanghai on the map of China, as well as the 1000km, 500km, 300km radius around Ant headquarters. To distinguish the Ant headquarters effect from the Shanghai effect, we compare the first-stage estimation results for counties located within a different radius around Ant. The underlying assumption is that for counties located far from Ant, distance from Ant and distance from Shanghai are highly correlated. In contrast, for counties closer to Ant, distance from Ant and distance from Shanghai can be rather different. To ensure that the effect of distance is not driven by county wealth effect, we further control for county-level economic conditions, i.e., GDP, population, and income. The left four columns in Panel A of Table 3 report the results of the first stage IV regression, in which county-level FinTech penetration is regressed on Log(Dist from Ant), and the right four columns exhibit the corresponding results using Log(Dist from Shanghai) as the placebo instrument.

Focusing first on the effect of distance from Ant, we find strong evidence that Log(QRPay) in a county is negatively related to the county's distance from Ant. The coefficient on Log(Dist from Ant) is -0.25 with a t-statistic of -13.79 for the whole sample. When we zoom in to the counties within a smaller radius around Ant, the effect is qualitatively the same with a sightly smaller economic magnitude. For example, focusing on counties located within 300km from Ant, the coefficient on Log(Dist from Ant) is -0.17 with a t-statistic of -3.94. This is partially due to the fact that, in our sample period, counties near Ant already have a relatively high level of FinTech penetration, whereas counties far away from Ant have more room to develop in terms of FinTech penetration. 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 comparison, for the placebo estimation using distance from Shanghai as the IV, the coefficients on Log(Dist from Shanghai) are only significant when we include counties far from Ant in the regression. Within a small radius (300km) around Ant, the coefficients on distance from Shanghai are statistically insignificant, and also have a much smaller magnitude. Specifically, for counties within 300km radius, the coefficient on Log(Dist from Shanghai) in column (8) is insignificant (-0.07 with a t-stat of -1.14). This contrast between Shanghai and Hangzhou is consistent with our intuition: For counties far from Ant, their distance from Ant and Shanghai highly overlap. Therefore, the coefficients on Log(Dist from Shanghai) partially capture the effect of Log(Dist from Ant). Within smaller circles, however, only the distance from Ant is related to FinTech penetration, whereas distance from Shanghai has no explanatory power.[17]

IV Estimation

To cleanly identify the effect of distance on FinTech penetration, we then conduct the IV test focusing on the subsample within a 300km radius around the Ant headquarters. We adopt two model specifications for the IV analyses. The first specification exploits only the cross-county variation in Log(Dist from Ant), whereas the second specification exploits both the cross-county and the time-series variation in the effect of distance on FinTech penetration.

In particular, in the first specification, we regress county-level Log(QRPay) on Log(Dist from Ant) to get the instrumented value of FinTech penetration (column (1) in Panel B of Table 3). Columns (3) and (5) report the corresponding second-stage results, in which the two risk-taking measures, risky purchase and risky fraction, are regressed on the instrumented value of $\text{Log}(\hat{\text{Q}}\text{RPay})$. The coefficient estimates suggest that a one standard deviation increase in $\text{Log}(\hat{\text{Q}}\text{RPay})$ 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. As discussed in Section 2.2, at the beginning of our sample period, counties that are closer to Ant tend to have a much higher level of FinTech penetration than counties that are far away from Ant. With the passage of time, however, the effect of distance is attenuated, as QR-Scan payment becomes prevalent in every corner of China. This pattern motivates us to further incorporate the time-series variation to enhance the measurement accuracy of distance on FinTech penetration. In particular, in the first-stage regression reported in column (2), we include the interaction term, Log(Dist from Ant)$\times$Time, to capture

[17] In untabulated analyses, we also conduct placebo tests using distance from the other tier-one cities, Beijing, Shenzhen, and Guangzhou in the first stage regression. The regression coefficients on these placebo distance measures are also insignificant.

the time-varying effect of distance, where Time denotes the number of years from January 2017. Consistent with our intuition, the coefficient estimate on Log(Dist from Ant)×Time is indeed significantly positive. Using the Log(Dist from Ant)×Time instrumented FinTech penetration, the second-stage estimations, reported in columns (4) and (6), show that a one standard deviation increase in $\widehat{\text{Log(QRPay)}}$ 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, the IV analysis lends support to a causal relation between county-level FinTech penetration and household platform risk taking. Importantly, distance from the Ant headquarters, instead of distance from an economic center, matters in terms of explaining the level of FinTech penetration in each county. Moreover, the effect is qualitatively the same when taking into consideration the time-varying effect of distance in driving the variations in FinTech penetration.

3.3 Individual-Level FinTech Adoption

At the individual level, we next provide further micro-level evidence that repeated usage of QR-Scan payments encourages household risk taking. By differentiating individual self-initiated FinTech adoption from environmental-driven passive FinTech adoption, we further show that environmental factors play an important role in explaining the positive spillover effect from payments to investments.

FinTech Adoption and Risk-Taking

To explore the cross-individual difference in risk-taking along the dimension of FinTech adoption, we estimate the following regression specification:

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

where individual i's risky taking in month $t+1$ is regressed against the Log(QRPay) for individual i in month t. It is possible that individuals might adopt digital payment early on for the purpose of making risky investment. Since we focus on the lead-lag relationship between Log(QRPay) and risk taking, this reverse causality is less of a problem. We control for individual characteristics, including age, gender, monthly online consumption level, and quarterly consumption growth volatility in all the regression specifications.[18] Quarterly

[18]We use online consumption as a control for individual's consumption (wealth) level, because the offline consumption would capture the effect of QR-Scan pay.

consumption growth volatility σ_C, calculated as the standard deviation of quarterly total consumption growth, is a proxy for individual risk tolerance.

In the regression setting without any fixed effects, Panel A of Table 4 shows 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. When we include time fixed effects, the coefficient decreases slightly to 2.21 (t-stat=8.13), suggesting that the results cannot be purely explained by some unobserved aggregate economic change or any time trend in household risk-taking. With individual fixed effects, the coefficient becomes 2.66 (t-stat=6.07), with an R-squared of 28.4%. It suggests that for a given individual, the time-series variation in Log(QRPay) remains strong as an important determinant of time-series risk-taking. Finally, when we include both time and individual fixed effects, the coefficient on Log(QRPay) remains significant with a magnitude of 1.41 (t-stat=6.32). Our empirical results therefore offers supporting evidence that, by bundling investment function with the payment function, FinTech fosters financial inclusion – higher FinTech adoption results in higher risk-taking.[19]

Systematic vs. Idiosyncratic Adoption

After documenting a positive relationship between Log(QRPay) and risky asset investment, an important question is what drives an individual's FinTech adoption. In particular, FinTech adoption at the individual level could be driven by both environmental factors and individual-specific factors. Environmental factors refer to the passive adoption of QR-Scan pay, driven by the environmental change in the county that the individual lives in. If local merchants, friends, and neighbors are all using QR-Scan as the default payment method, that individual is likely to adopt the QR-Scan payment as well. Individual-specific factors refer to an individual's own willingness to adopt the technology that is unexplained by the environmental change, possibly driven by their tech-savviness and risk appetite, etc.

Guided by this intuition, we decompose FinTech adoption into two components, a systematic component and an idiosyncratic component. In particular, for each person, we first compute her Peer Log(QRPay)_t^i, which is the equal-weighted average Log(QRPay) of all individuals living in the same county as individual i, excluding the focal individual i herself. Next, we estimate the following regression specification for each individual in our sample:

[19] Though empirically we do not differentiate between the effect of psychological cost and physical cost of participation, the reduction in the physical cost alone, e.g., improved convenience and lower transaction cost, cannot explain the positive relationship between Log(QRPay) and risky investment. This is because, for a given individual, the physical cost of participation would not vary with the repeated usage of payment service, while the psychological cost does.

$\text{Log(QRPay)}_t^i = a^i + b^i {*}\text{Peer Log(QRPay)}_t^i + \epsilon_t^i$. 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. In other words, the systematic component of FinTech adoption is the predicted component of individual i's Log(QRPay) that can be explained by her peers' FinTech adoption. It captures the effect of environmental change in driving her FinTech adoption. The idiosyncratic component, however, is the part that cannot be explained by her peer's FinTech adoption, and is mainly determined by individual-specific factors related to her own intention to use the digital payment.

Panel B of Table 4 reports the effect of systematic and idiosyncratic FinTech adoption on individual risk taking. We follow similar regression framework as in Panel A. For the setting without any fixed effects, the coefficient estimate on Sys Log(QRPay) is 3.39, with a t-statistic of 8.15, whereas the coefficient estimate on Idio Log(QRPay) is only 1.05, with a t-statistic of 5.00. Given that both variables are standardized with a mean of zero and standard deviation of one, the relative magnitude of the two coefficients suggests that the variation in the Sys Log(QRPay) has a much larger impact on risky purchase than the variation in Idio Log(QRPay). In other words, risk-taking decision making is impacted more by the environmental factors that are relatively exogenous to each individual's own choice. Controlling for user fixed effects, or time fixed effects, or both, we find that the coefficient estimates of Sys Log(QRPay) remain bigger than those of Idio Log(QRPay). In particular, the coefficient estimate of Sys Log(QRPay) increases to 4.81 (t-stat=5.74) when individual fixed effect is included. It suggests that, for a given individual, environmental factors play a dominant role in driving her risk-taking decision over time. The results for risky fraction largely resemble the patterns for risky purchase.

In summary, by decomposing an individual's FinTech adoption into systematic and idiosyncratic components, we confirm that both the environmental factors and individual-specific factors are important in explaining risk-taking behavior. Moreover, the effect of environmental factors is especially important in explaining the time-series variation in risk taking. These results echo the importance of county-level FinTech penetration on risky asset investment in Section 3.1 and 3.2.

4 FinTech Inclusion and Welfare Implications

Our empirical results have so far shown that FinTech fosters financial inclusion – higher FinTech penetration and adoption is associated with more risky fund participation. This finding is itself welfare-improving as the literature has in general documented the welfare losses due to the non-participation and under risk-taking by households, which, according to financial theory, are apparently against their own best interests. Exploring the individual heterogeneity in our sample, we provide in this section further evidence of welfare improvement by focusing on investors who are otherwise more constrained prior to the advent of FinTech. This includes investors who are more risk tolerant and investors that live in counties under-served by the traditional financial infrastructure. Moving beyond the risky purchase and risky fraction measures, we also examine the outcome and efficiency of the investments on FinTech platforms, focusing on measures of portfolio volatility, portfolio performance, Sharpe ratio, and portfolio diversification.

4.1 Benefits for Individuals with Higher Risk Tolerance

As FinTech expands its sphere of influence and includes more investors in its platforms, who benefits more from FinTech inclusion? In this section, we focus on the dimension of risk aversion, which, according to financial theory, is the sole characteristics differentiating one investor's risk-taking from that of another.

In general, more risk-tolerant individuals should invest more in risky assets. In the case of a mean-variance investor (Markowitz (1952) and Tobin (1958)) or Merton's portfolio problem (Merton (1969, 1971)), the optimal risky portfolio weight w^* of an investor is inversely proportional to her risk-aversion coefficient γ:

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

where $\mu - r$ is the risk premium of the risky asset and σ_R its volatility. If we consider the extreme case of zero risky participation ($w = 0$), the constraint faced by investors with lower risk-aversion coefficient γ (i.e., higher risk tolerance $1/\gamma$) would be more severe and their utility loss larger. Consequently, the benefits of FinTech inclusion would be higher for the more risk-tolerant investors. In other words, if the advent of FinTech can indeed break down barriers and unshackle constraints, both physically and psychologically, then it is the more risk-tolerant investors who stand to benefit the most, 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 an important and yet daunting task in the literature of household portfolio choice. One approach to eliciting risk aversion is through lottery-type questions, yet the reliability of the survey data and their connection to investors' risk-taking have yet to be established (e.g., Ameriks et al. (2020)). Alternatively, the literature has approached the task by inferring individual-level risk aversion through their investment portfolio choice. For example, using a large administrative panel of Swedish households, Calvet et al. (2021) estimate the cross-sectional distribution of preference parameters, including households' risk appetite.[20] However, since households' investment choice is our outcome variable here, we cannot apply such a methodology in our analysis.

Taking advantage of the consumption side of our data, we propose to use individual-level consumption growth volatility as a proxy for risk tolerance. The theoretical foundation of our approach is 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 inversely proportional to the risk-aversion coefficient γ and linear in risk tolerance $1/\gamma$. Moreover, with the optimal consumption-to-wealth ratio being constant, the consumption volatility σ_{C} equals the 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 aversion.

While σ_{C} as a function of risk aversion γ is exactly specified in the complete market setting of Merton, in the more general setting σ_{C} should still be a decreasing function of risk aversion and increasing function of risk tolerance. The consumption volatility is a measure of 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 is a result of the individual's consumption choice (to maximize utility with available albeit incomplete financial instruments), then, even when markets are incomplete, a more volatile consumption should correspond to less risk aversion.

Empirically, we also validate the effectiveness of σ_{C} as a proxy for risk aversion. We first examine the cross-sectional determinants of σ_{C} in Appendix Table IA1. Consistent with the existing literature (e.g., Ameriks et al. (2020), Calvet et al. (2021)), we find that male, mature investors, and investors with higher consumption levels on average have higher σ_{C}. Moreover, we connect σ_{C} with individuals' self-reported risk tolerance ratings, as collected and classified by China Securities Regulatory Commission. We find that individuals with more aggressive risk appetite on average exhibit a higher level of σ_{C}, and the relation remains significant when controlling for other personal characteristics in a multivariate regression setting in Panel B of Appendix Table IA1.

To further validate the effectiveness of σ_{C}, we directly link investors' realized risk-taking

[20]See also Meeuwis, Parker, Schoar, and Simester (2018) and Giglio et al. (2021) on the connection between individual risk-taking and variations in preferences and beliefs.

to their consumption volatility. If σ_C carries information about cross-sectional distribution in risk appetite, we expect individuals with higher σ_C to invest more in risky assets and obtain a higher realized portfolio volatility. Specifically, we sort individuals by their consumption volatility into 50 groups, and plot the average portfolio volatility for each group against the consumption volatility percentile in the upper panel of Figure 4. The figure shows a rather strong positive relation between consumption volatility and portfolio volatility. As indicated in the fitted lines, regressing portfolio volatility on the consumption volatility percentile across the 50 groups, the coefficient is 0.72 (t-stat=7.43) and the R-squared is 53%. Overall, the empirical evidence is consistent with the interpretation that consumption volatility reveals the cross-individual variations in risk tolerance.

FinTech and Risk Taking, Conditional on Risk Tolerance

Having identified σ_C as a valid proxy for individual risk tolerance, we next examine the effect of FinTech on households' ultimate risk-taking, 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. Households' investment outcome is captured by their portfolio risky share and portfolio volatility. In particular, risky share is defined as the average fraction of risky fund investment, whereas portfolio volatility is the standard deviation of realized portfolio return for each individual.[21]

Table 5 reports the cross-sectional regression results using risky share and portfolio volatility as the dependent variables. We first verify that FinTech adoption is positively associated with the two investment outcome variables, risky share and portfolio volatility. As shown in columns (1) and (4), one standard deviation increase in the level of Log(QRPay) corresponds to 1.83% (t-stat=6.33) increase in risky share and 0.26% (t-stat=9.46) increase in portfolio volatility, which are of reasonable economic magnitude compared to their respective sample averages of 50.76% for risky share and 2.13% for portfolio volatility. These results confirm the effect of FinTech adoption in encouraging the intensity of risk-taking.

The next question is, who benefits more from FinTech inclusion? To answer this question, we 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), indicating that FinTech adoption

[21]Here, we focus on households' ultimate portfolio allocation and riskiness, instead of their monthly participation decisions. This is because risk tolerance has no implications for households' intermediate portfolio-building process.

indeed increases risky share more for individuals with higher risk tolerance. This finding is consistent with our hypothesis that investors with higher risk tolerance, who are otherwise more constrained in the absence of FinTech, benefit more from FinTech inclusion.

In addition to consumption growth volatility, column (3) further includes the interaction terms between FinTech adoption and other investor characteristics, including gender, age, and wealth. Controlling for heterogeneity along these dimensions, the interaction term between Log(QRPay) and σ_{C} is still significant. It is also interesting to see that the coefficient on the interaction term, Log(QRPay)$\times\sigma_{\mathrm{C}}$, reduces slightly in magnitude (decreases from 0.58 to 0.49). This is consistent with the interpretation that σ_{C} and the other individual characteristics contain overlapping information with respect to individual-level risk tolerance. Nevertheless, conditioning on such individual characteristics, σ_{C} remains important and informative, indicating that σ_{C} is informative with respect to risk tolerance above and beyond the individual characteristics of gender, age, and wealth. Finally, the right panel of Table 5 reports the corresponding results for portfolio volatility. The results for the heterogeneous effect of risk tolerance, captured by the coefficient on Log(QRPay)$\times\sigma_{\mathrm{C}}$, are similar to those for risky share.

4.2 Benefits for Individuals in Under-Banked Counties

The benefits of FinTech inclusion are without any doubt stronger for individuals underserved by traditional financial infrastructures. As reviewed by Suri (2017), mobile money in developing economies has allowed individuals without bank accounts to digitally transact money. Motivated by this important trend, we examine the benefits of FinTech inclusion across Chinese counties with varying levels of financial services. Before the development of FinTech platforms, banks were the predominant distribution channel of mutual funds. As a result, investors living in areas with fewer bank branches had limited access to mutual fund investments. Based on these observations, our hypothesis is that investors living in such under-banked counties, who are otherwise more constrained prior to the arrival of FinTech platforms, would benefit more from FinTech inclusion.

County-Level Evidence

We measure the coverage of bank service using the total number of bank branches in the prefecture that the county belongs to. Figure IA2 plots the geographic distribution of banking coverage in each prefecture. Comparing the bank-coverage map with the FinTech penetration maps in Figure 2, we can see that the distribution of bank coverage is uniquely different from that of FinTech penetration. The richness of the cross-region variations in FinTech penetration and bank coverage provide a fertile ground for us to study the benefits of FinTech inclusion. Moreover, as the number of bank branches in each prefecture itself can be influenced by the local economic and demographic conditions, we include the county-level GDP, population, and income per capita as controls in our analysis.

We start by investigating the effect of FinTech penetration on risk-taking, conditioning on the level of bank coverage. The results are summarized in Table 6. In particular, we conduct panel regression analyses similarly to Table 2, using county-level risky purchase and risky fraction as the dependent variables. To identify the under-banked areas, we use a dummy variable, LowBank, which equals one for the subsample of counties located in prefectures with below-median number of bank branches, and zero otherwise. The extra effect of FinTech on risk-taking in under-banked areas is captured by the coefficient estimate of the interaction term, Log(QRPay)$\times$LowBank.

Across different specifications in Table 6, we find that the coefficients on the interaction term are significantly positive. Taking the estimation for risky purchase in column (2) as an example, when the Log(QRPay) of a county increases by one standard deviation, it drives up the average local individual risky purchase by 2.13% (t-stat=5.15) the next month. For a county whose bank coverage is below the median, the same one standard deviation increase in Log(QRPay) would increase risky purchase by an extra 0.41% (t-stat=2.30), leading to a combined effect of 2.54%. In other words, the benefit of FinTech inclusion is more significant, both statistically and economically, for individuals living in under-banked areas. The results are similar for the corresponding regression settings using risky fraction as the dependent variable, as shown in columns (4) to (6).

Figure 5 provides a more intuitive graphical demonstration of our results. In the top panel, each prefecture's risky share is plotted against its Log(QRPay). The 287 prefectures are divided into two groups according to their bank coverage – the below-median prefectures plotted in red stars and above-median prefectures in orange circles. The solid fitted line indicates that among prefectures with low bank coverage, a 10% increase in prefecture-level Log(QRPay) increases risky share by 5.9% (t-stat=2.52). By contrast, the FinTech benefits among prefectures with high bank coverage are close to zero. In other words, the benefit of FinTech inclusion comes mostly from areas less served by traditional banks.

Similar evidence can be observed in the bottom panel of Figure 5, where changes in risky share are plotted against changes in FinTech penetration. Plotting the relationship between change in FinTech penetration and change in risk taking is equivalent to a regression specification with prefecture fixed effect. Essentially, as discussed in Section 2.2 and Section

3.1, we are using the staggered penetration of QR-Scan across different prefectures to identify the FinTech effect. The contrast between low-bank and high-bank areas remains strong: For areas with below-median bank coverage, a 1% increase in ΔLog(QRPay) leads to a 0.11% (t-stat=1.91) increase in risky share, while for areas with above-median bank coverage, the relation is much weaker with a coefficient estimate of 0.04% (t-stat=1.03).

Individual-Level Evidence

Out of the 28,393 investors with meaningful investments in our sample, there are 4,053 individuals living in counties with below-median bank coverage. Not surprisingly, the population distribution of our data, which is randomly selected from the entire population of the Ant platform, is tilted toward the larger and richer counties. We pair each of the 4,053 individuals with a counterpart living in counties with above-median bank coverage, requiring the pair to share the same gender, same year of birth, and have the closest values in consumption level and consumption volatility. Panel A of Table 7 summarizes the distributions of these two samples, with the low-bank sample as treatment and high-bank as control. Given the abundance of individuals living in areas of high-bank coverage, the matching is quite effective and the distributions of these two samples are very close.

Using these two matching samples, we compare and contrast the impact of Log(QRPay) on portfolio volatility (σ_{W}) between the low- and high-bank groups. In particular, we follow the specification in Table 5, and 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.

As shown in the first row of Panel B of Table 7, the impact of Log(QRPay) is significant for both groups, indicating the importance of FinTech adoption on individuals' risk-taking behavior. The magnitude of Log(QRPay), however, varies between the two groups – the regression coefficient is 0.51 (t-stat=5.26) for the low-bank sample and 0.25 (t-stat=2.82) for the high-bank group, and the difference between the two is 0.26 with a t-stat of 2.01. Similar to the county-level results, the benefits of FinTech inclusion are stronger in magnitude as well as statistical significance for the under-banked individuals.

Individual Heterogeneity: Matched Samples

Taking advantage of the two matched samples, we can further investigate what type of individuals in under-banked areas benefit more from FinTech inclusion. For example, do mature and risk-tolerant individuals living in under-banked counties react to FinTech advancement differently from their high-bank counterparts? To answer such questions, we focus on the individual characteristics. Within each subsample, we further classify individuals into two groups, based on the median cutoffs of risk tolerance (σ_{C}), consumption level, gender, and age. The lower four rows in Panel B of Table 7 present the differential effect of FinTech adoption across different types of individuals.

We start with the dimension of risk tolerance, proxied by σ_{C}. As shown in Section 4.1, the benefits of FinTech inclusion are higher for individuals with higher risk tolerance, as, prior to the arrival of FinTech, the more risk-tolerant investors are more constrained. Compounding this effect with bank coverage, high risk-tolerant investors living in counties with low-bank coverage are more constrained than their high-bank counterparts. The results in Panel B of Table 7 are strongly supportive of this hypothesis. For investors with high σ_{C}, the coefficient of portfolio volatility (σ_{W}) on Log(QRPay) is 0.70 (t-stat=4.60) for the low-bank group, while that for the high-bank group is 0.36 (t-stat=3.02). The difference is 0.34 with a t-stat of 1.78. In comparison, for the low risk tolerance group, the coefficient of σ_{W} on Log(QRPay) is only 0.34 (t-stat=2.86) for the low-bank group, while that for the high-bank group is only 0.12 (t-stat=0.96). The difference between the low and high-bank groups is also insignificant. Overall, the benefits of FinTech inclusion is the strongest for those high risk-tolerant investors under-served by the traditional financial infrastructure.

Turning to other individual characteristics, we find that mature investors between the ages of 30 and 55,[22] as well as investors with higher consumption level (wealth), tend to benefit more from FinTech inclusion in areas under-served by traditional banks. Compared with young and low-wealth individuals, mature and high-wealth individuals have higher investment capacities and needs. Living in counties with high-bank coverage, such investors can invest in mutual funds via the traditional channels such as banks, but their counterparts living in counties with low-bank coverage do not have that privilege. With FinTech penetration, such under-banked individuals are given an alternative channel and they jump on the FinTech bandwagon more readily than their high-bank counterparts. In particular, for mature individuals, the coefficient of σ_{W} on Log(QRPay) is 0.49 (t-stat=4.37) for the low-bank group, 0.41 (t-stat=2.66) higher than their high-bank counterparts. For high-wealth individuals, the coefficient on Log(QRPay) is 0.65 (t-stat=4.69) for the low-bank group, 0.48 (t-stat=2.57) higher than for their high-bank counterparts. Overall, the evidence suggests that FinTech inclusion benefits more those investors most in need of such technology.

[22]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.

4.3 Performance and Diversification Benefit

Finally, can investors truly benefit from this FinTech inclusion? Does increased probability of participation ultimately lead to better investment outcomes? To answer such questions, we examine the portfolio performance and portfolio allocation outcome for investors that make meaningful investments via the Ant platform.

Portfolio Performance

To assess the welfare implications of platform investments, the most straightforward question is how do Ant investors actually perform. On the one hand, academic research in general advocates for risky asset participation because investors can capture the positive equity risk premium by investing in risky asset. On the other hand, individual investors tend to make a variety of investment mistakes due to their behavioral biases, which could potentially undermine the benefit of risky participation. For example, Calvet, Campbell, and Sodini (2007) show that the cost of non-participation is smaller by almost one-half when taking account of the fact that non-participants would likely be inefficient investors.

To provide direct evidence on this issue, we compute and compare returns for three sets of fund samples: all mutual funds in the market, the funds available for sale on the Ant platform, and the funds held by Ant investors according to their actual portfolio weights in each fund. 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. To capture the excess returns of these three sets of funds, we estimate fund alphas using a two-factor model (equity factor and bond factor), where equity factor is the value weighted China A-share stock return minus risk-free rate, and the bond factor is the China aggregate comprehensive bond index return minus risk free rate. Fund returns are computed net of management fee, but before subscription and redemption fee.

Panel A of Table 8 reports the corresponding results. Focusing first on the value-weighted monthly alphas for all mutual funds in the market (weights given by fund total net assets as of April 2019), the average monthly alpha for mixed, equity, and bond funds in the market are 1.00% (t-stat=1.72), 0.46% (t-stat=1.01), and 0.02% (t-stat=0.88) respectively. Despite of a relatively short sample period, we find suggestive evidence on the outperformance of mutual funds in China. This result is consistent with the findings in the literature that Chinese actively-managed mutual funds on average yield a positive alpha (Chi (2013), Jiang (2019)). Overall, by investing in risky assets indirectly through delegated portfolio management, Chinese investors have the potential to outperform a passive benchmark. Turning to the value-weighted monthly alphas for funds available on the Ant platform, we find that the monthly alphas for bond, mixed, and equity funds are all close to their counterparts for all funds in the market. Given that the Ant investment platform covers the vast majority of funds in the market, it is natural that the average returns of the Ant funds are similar to those for the whole mutual fund market.

The more interesting results are for the funds held by Ant investors. Using Ant investors' portfolio holdings at the end of March 2019, we find that Ant investors' choice of funds on average outperforms that of an average fund in the market. The average monthly alpha of mixed funds held by Ant investors is 1.18%, slightly higher than the alpha of 1% estimated for all mixed funds in the market. For equity and bond funds, Ant investors' average monthly alpha is 1.00% and 0.05% respectively, also higher than the average alpha of 0.46% and 0.02% for all the equity and bond funds in the market. Taken together, the evidence suggests that Ant investors on average are not making inferior investment decisions, as their portfolio weights tilt slightly toward the outperforming funds. Moreover, given that Chinese mutual funds in general are able to outperform their passive benchmarks, participation via delegated portfolio management is beneficial for investors that do want to take financial risk.

Portfolio Diversification

Next, by examining the portfolio allocation decisions of platform investors, we uncover another potential benefit of investing from the dimension of diversification. By optimally diverting capital across different styles of funds, investors can potentially obtain the same expected return under a lower portfolio volatility, as long as the asset returns are not perfectly correlated. If FinTech can indeed lower the barrier of investment, we might expect to observe a more balanced portfolio built up with the familiarity and trust from repeated payment usage.

To capture this potential diversification benefit, we construct four measures: the number of funds, the number of asset classes, variance improvement, and the Sharpe ratio. Log(#Funds) and Log(#Assets) are the natural logarithm of the number of unique funds and number of unique asset classes invested in by investors during our sample period. Variance improvement and Sharpe ratio are calculated based on investors' portfolio allocation weights (w_i) across the six styles of assets and the variance-covariance matrix (Σ) of asset returns. In particular, variance improvement ratio is the percentage difference between the portfolio variance computed using the actual variance-covariance matrix, and the portfolio variance computed assuming all the assets are perfectly correlated. Sharpe ratio is estimated by the expected portfolio return divided by the expected portfolio volatility, where expected return and variance-covariance matrix are all estimated using historical data from 2005 to 2019.[23]

Examining the relation between these four measures and FinTech adoption in a cross-sectional regression setting, we find that investors with higher FinTech adoption tend to diversify their investments across different funds and among multiple asset classes. In particular, a one standard deviation increase in Log(QRPay) leads to a 10.6% increase in the number of funds and a 6.7% increase in the number of asset classes invested in by the individual, resulting in a much more diversified portfolio. Moreover, increased diversification leads to reduction in portfolio volatility and enhancement in Sharpe ratio. One standard deviation increase in FinTech penetration is associated with a reduction of 1.43% in portfolio variance, and an increase of 0.96% in monthly Sharpe ratio. Overall, we observe a uniformly positive effect of FinTech penetration on the diversification benefit of investing.

5 Conclusions

The entry of tech firms into the financial industry has substantially broken down the physical barrier and unshackled the mental constraints for individual investors participating in the financial markets. As FinTech platforms open up new channels of financial services, and threaten to dominate and even replace conventional financial institutions, it raises a critical need for researchers and policy makers to understand and protect those early adopters of FinTech platforms and study the long-term impact of FinTech penetration on household finance.

Our findings shed light on the potential benefits of tech firms in the provision of financial services through an all-in-one ecosystem. Unlike traditional financial institutions, one distinct feature of FinTech in China and other emerging markets is the integration of payment function with other financial services and non-financial services via "super apps" like Alipay. As these super apps become one-stop shops for living, households build familiarity and trust through repeated usages and exhibit less psychological aversion to risky investment. Despite the extensive concerns over the monopoly power of big FinTech platforms, improving risky asset participation is one area where an integrated model is indeed desirable. This is especially true for investors in emerging markets who are in urgent need of financial services due

[23]Sharpe ratio for individuals without risky asset investment are set to zero, as these investors will not earn any risk premium. One alternative way to estimate Sharpe ratio is to impose a CAPM model, similar to the approach in Calvet, Campbell, and Sodini (2007). Given that the investment opportunity in our setting is already at the factor level, we opt to estimate the expected return directly from the historical mutual fund performance.

to the rapid growth of their household income. Given the lack of financial infrastructure in these markets, tech-based options, less expensive and highly scalable, are the most promising business model to fill the vacuum left behind by traditional financial institutions.

The FinTech development, however, is not without challenges. When we finished the first draft of our paper in October 2020, the IPO of Ant Group was all the rage. One year later, with the suspension of Ant's IPO and the recent sweeping tech crackdown in China, the future of FinTech might look uncertain. Indeed, events like this exemplify the pressing need to study the impact of FinTech on household finance. Only through better understanding will more effective and productive FinTech regulations emerge. As with any new technologies, a dark side always accompanies the bright side, and FinTech innovations are no exception. FinTech platforms, such as the one studied in this paper, grew from non-existence in 2012 to capture an estimated 30% of the total market share of mutual-fund distribution in China. Focusing on this episode of rapid FinTech development, Hong, Lu, and Pan (2022) find that the emergence of FinTech platforms has a rather dramatic impact on the behavior of mutual-fund investors and managers. In particular, as an example of how FinTech innovations can inadvertently strengthen investors' behavioral biases, they document a strong platform-induced amplification of investor's heuristics in chasing top-performing mutual funds.

The above discussion points to the complexity and subtlety of FinTech regulation. There is no uniform solution. Policy makers have to accept and understand the multifaceted nature of FinTech development, mindful of the specific biases and frictions that FinTech could amplify or alleviate. To develop welfare-improving policies, much remains to be understood about how FinTech can improve or worsen the household financial decision makings. This is where further academic research on FinTech can be of value.

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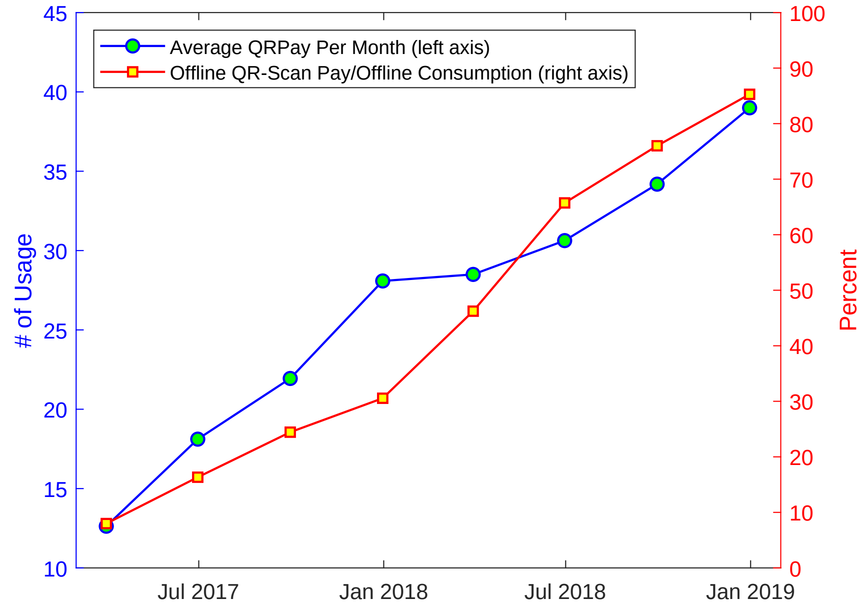
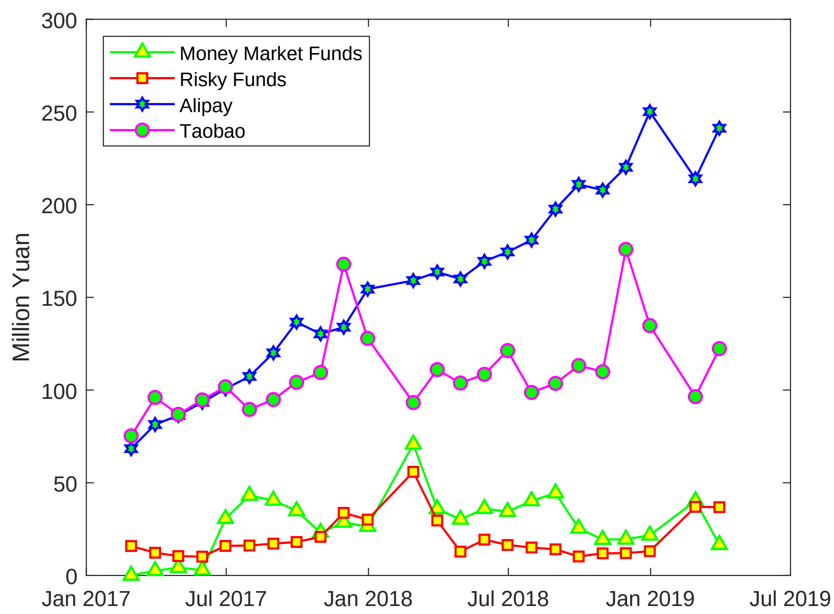
Appendix A. Variable Definitions

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 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



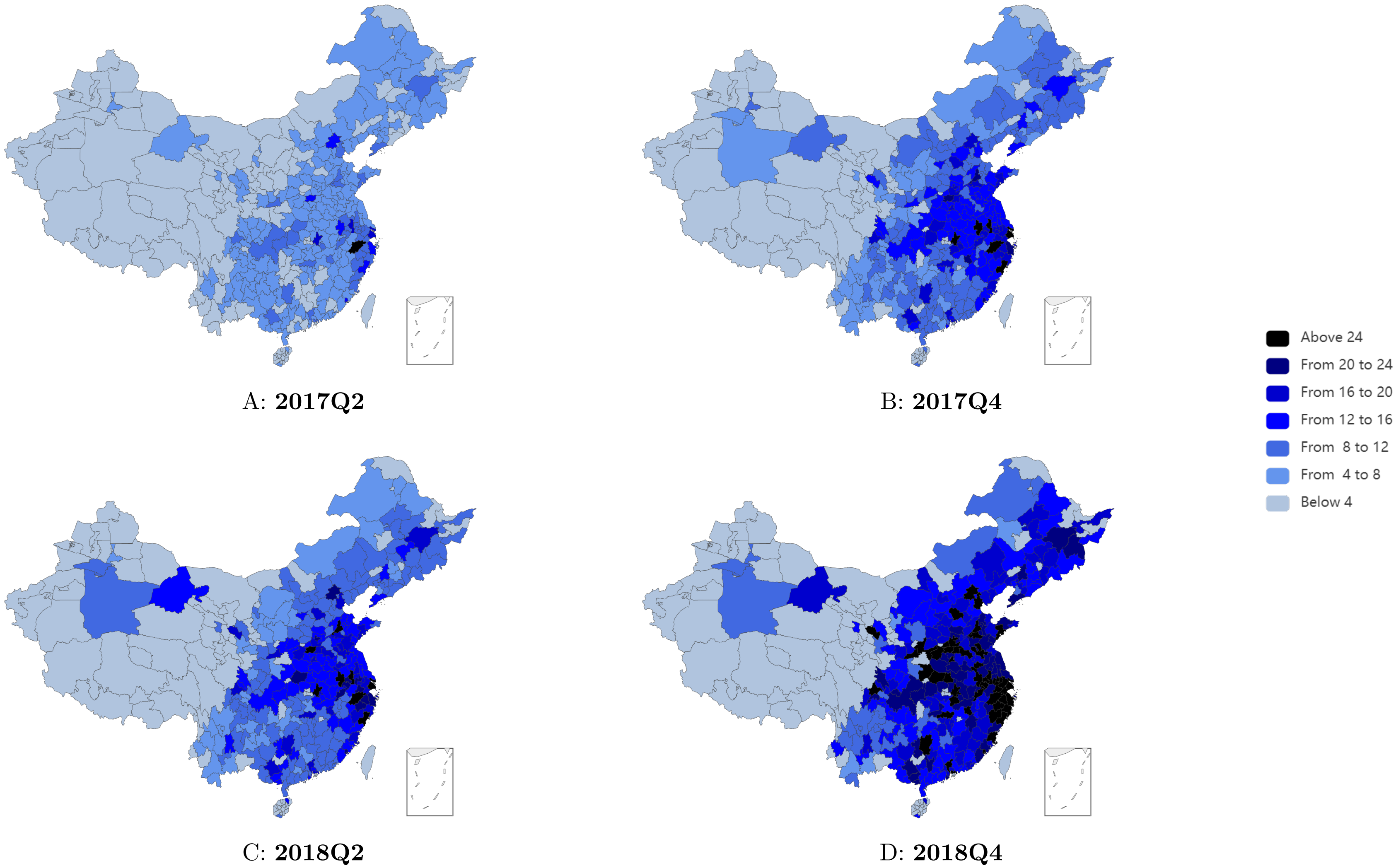
A: **Offline QR-Scan Payment and Alipay Payments**



B: **Mutual Fund Purchases and Consumption**

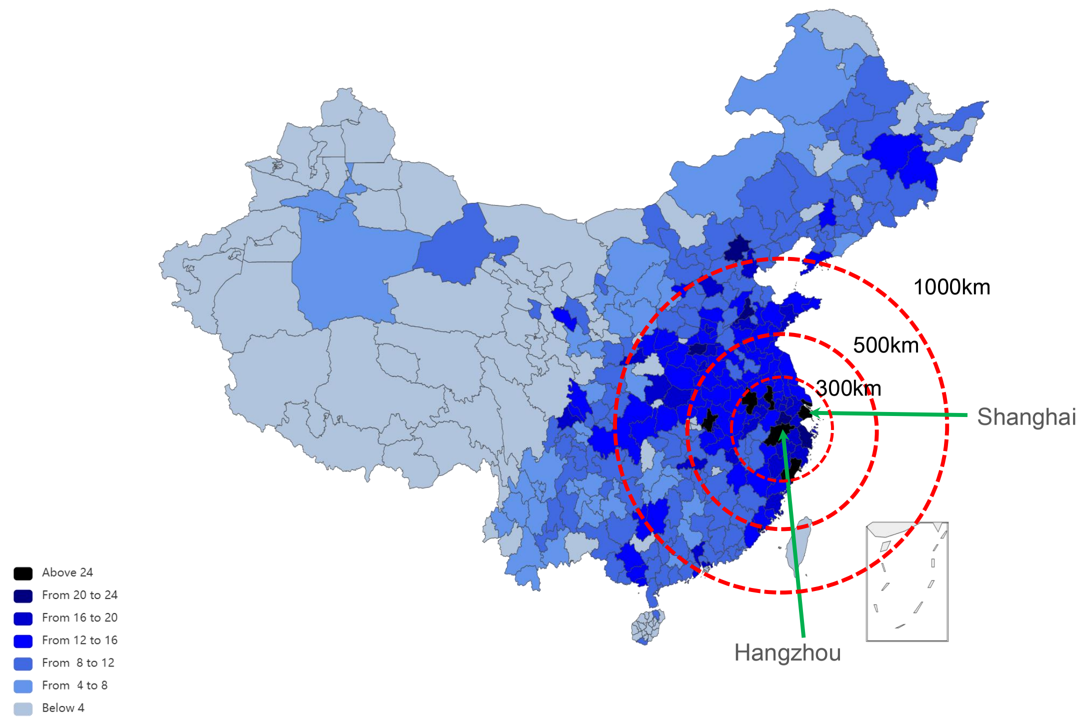
Data is aggregated across 50,000 randomly sampled individuals from January 2017 through March 2019. In Panel A, we plot two time series: the average number of Alipay payment usage per person during each month in our sample, and nation-wide total offline QR-Scan payment out of total offline consumption in China. Panel B reports the time series variation of mutual-fund purchases on Ant's investment platform, together with the aggregate consumption via Alipay QR-Scan payment and consumption via Ant e-commerce platform for the randomly selected 50,000 sample.

Figure 2. Geographic Distribution of FinTech Penetration



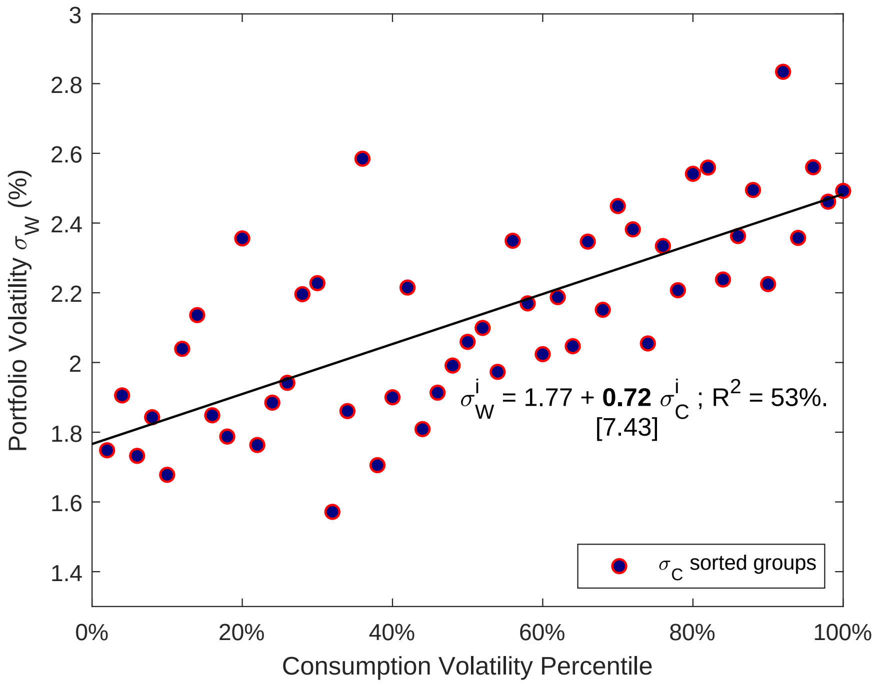
Panels A to D display the geographic distribution of prefecture-level FinTech penetration from 2017Q2 to 2018Q4. Prefecture-level FinTech penetration is calculated as the average QRPay for individuals within a given prefecture. The darker the color, the higher the FinTech penetration.

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

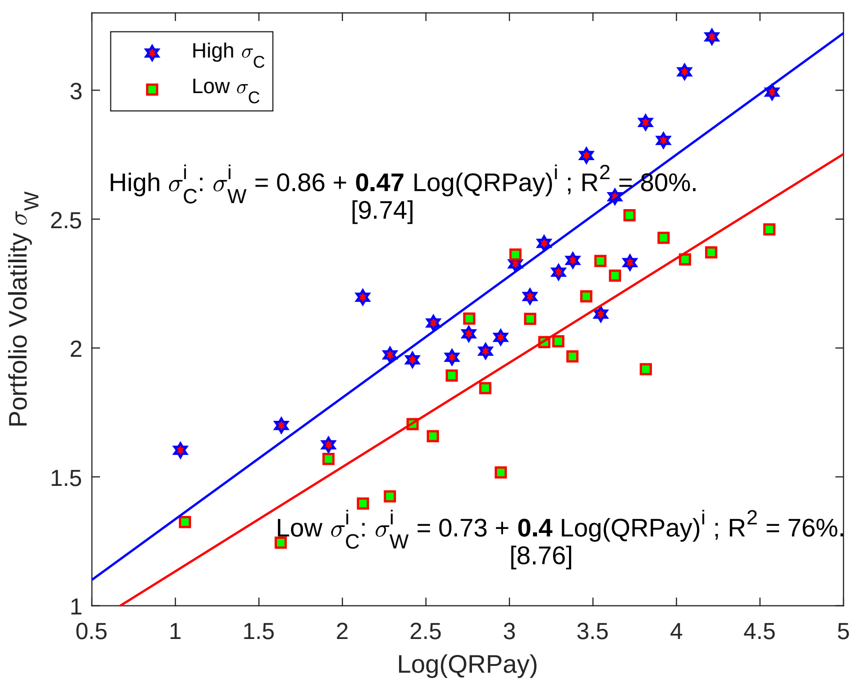


This figure shows the geographic distribution of prefecture-level average FinTech penetration for the sample period from 2017Q1 to 2019Q1. Prefecture FinTech penetration is calculated as the average QRPay for individuals in a given prefecture during our sample. Centering around the headquarters of Ant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

Figure 4. FinTech Adoption and Risk-Taking by σ_C Groups



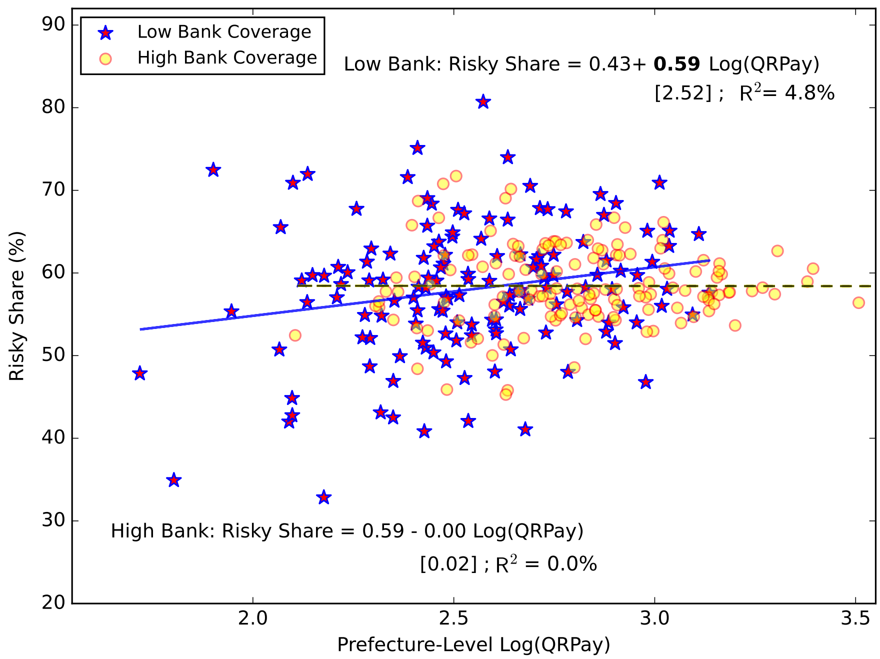
A: **Portfolio Volatility vs. Consumption Volatility**



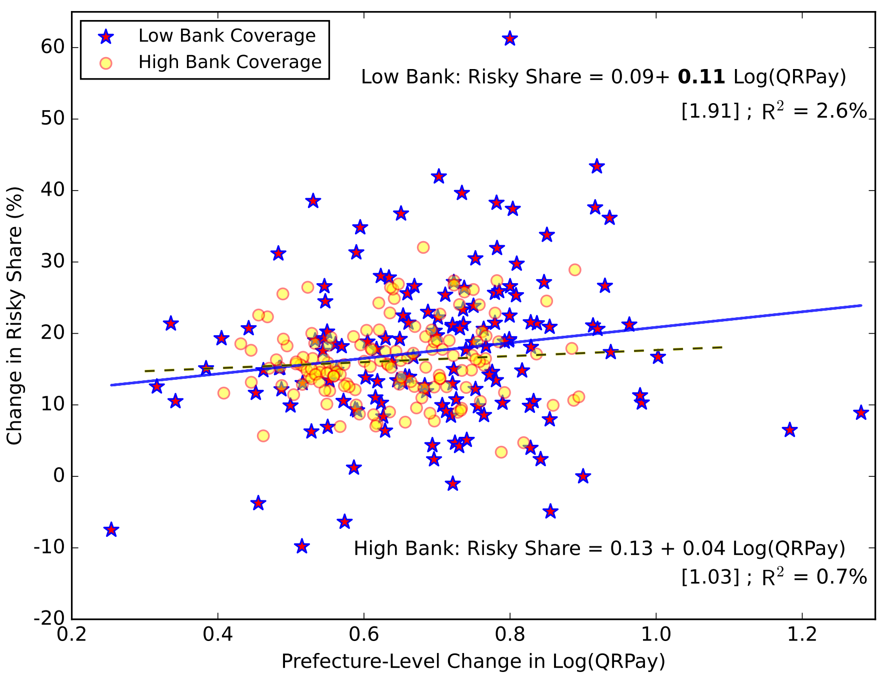
B: **Portfolio Volatility vs. QRPay: By σ_C Groups**

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 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. 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 outcome, 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 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 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 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 (3) report the first-stage estimates of Log(QRPay) and columns (4) to (9) report the second stage estimates for risky fund 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 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 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 portfolio risk taking conditional on individual FinTech adoption. To capture individuals' portfolio risk taking, risky share is the 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 the 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			σ_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 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 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 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 group. 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	4053	1.10	1.01	1.09	1.01	0.01	(0.33)
Female	4053	0.59	0.49	0.59	0.49	0.00	
Log(Age)	4053	3.43	0.24	3.43	0.24	0.00	(0.03)
Log(C)	4053	7.25	0.82	7.25	0.81	0.00	(0.12)
Log(QRPay)	4053	2.25	0.86	2.77	0.88	-0.52	(-26.91)
σ_W (%)	4053	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)
Male	0.610***	0.322**	0.288	Female	0.416***	0.158	0.258*
	(3.46)	(2.20)	(1.26)		(3.96)	(1.49)	(1.73)
Age [30,55]	0.486***	0.077	0.409***	Age<30 or Age>55	0.529***	0.467***	0.062
	(4.37)	(0.73)	(2.66)		(3.22)	(3.26)	(0.28)
High Consumption (C)	0.651***	0.176	0.475**	Low Consumption (C)	0.356***	0.305**	0.05
	(4.69)	(1.43)	(2.57)		(2.68)	(2.48)	(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 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 outcome. 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. Variance improve (in percent) is defined as $1 - \frac{\sigma_i^2}{\sigma_{i,B}^2}$, where σ_i^2 is individuals' actual portfolio variance, and $\sigma_{i,B}^2$ is the variance of a hypothetical benchmark portfolio when all asset classes are perfectly correlated. In particular, $\sigma_i^2 = w_i' \sum w_i$, where w_i is individual i's vector of portfolio weights in each asset class and the variance-covariance matrix ($\sum$) is estimated using historical data from 2005 to 2019. 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)	Variance Improve (3)	Sharpe Ratio (4)
Log(QRPay)	0.106***	0.067***	1.432***	0.955***
	(19.46)	(17.96)	(14.91)	(11.87)
Log(Age)	-0.068***	-0.052***	-0.782***	-0.640***
	(-12.96)	(-14.78)	(-9.49)	(-10.38)
Female	-0.155***	-0.109***	-1.347***	-1.393***
	(-15.89)	(-17.86)	(-7.17)	(-11.20)
Log(C)	0.001	-0.006**	-0.159**	0.068
	(0.30)	(-2.28)	(-2.20)	(1.19)
σ_C	0.019***	0.010***	0.156**	0.082
	(3.92)	(3.15)	(2.19)	(1.39)
Constant	1.494***	1.111***	5.662***	11.690***
	(161.27)	(173.01)	(28.26)	(81.77)
Observations	20,033	20,033	20,033	20,033
R-squared	6.2%	7.1%	3.3%	3.4%

Internet Appendix to

"FinTech Adoption and Household Risk-Taking:

From Digital Payments to Platform Investments"

Claire Yurong Hong, Xiaomeng Lu, and Jun Pan

In this Appendix, we provide further evidence and robustness tests on the effect of FinTech adoption on the risk-taking behavior of individual investors.

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 2.44% increase in risky purchase and 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. Risky Participation by Asset Class

Investors in our sample have access to six types of risky mutual funds: bond, equity, mixed, index, QDII, and gold, which we treat as six risky assets. To explore investors' investment decision in more detail, we examine the effect of FinTech adoption on the probability of fund purchase in each asset class separately. For example, bond purchase is set as one if an individual invests a positive amount in a bond fund in a given month, and zero otherwise. The results are shown in Table IA3, using a similar panel regression setting as Panel A of Table 4.

We find that FinTech adoption has a positive and significant impact on the purchase of all six risky assets, but the magnitude of the impact varies across the asset classes. Risky purchase in the mixed fund category is most sensitive to FinTech adoption with a coefficient estimate of 1.13 (t-stat=12.76) on Log(QRPay), indicating that a one standard deviation increase in Log(QRPay) corresponds to an increase of 1.13% in the probability of mixed fund purchase the next month. This result is to be expected, as mixed mutual funds are the largest fund category, accounting for 65% of the total mutual fund holdings by retail investors. What is unusual, however, is the impact of FinTech on gold fund purchase, whose overall market share is a mere 0.6% for all retail investors. And yet a one standard deviation increase in Log(QRPay) corresponds to an increase of 0.79% (t-stat=2.78) in the probability of gold fund purchase the next month.

In terms of the effect of individual personal characteristics on risky purchase, the results are mostly consistent across asset classes. For example, female investors tend to have a lower probability of purchase across all risky assets. Mature investors and investors with high consumption level exhibit a higher probability of purchase for all asset classes, except for gold. In comparison, young investors and investors with lower consumption level tend to have a higher probability of purchasing gold funds. These results indicate that the purchase motives for gold funds could be different.[24]

[24]Our evidence on gold investment is consistent with Badarinza, Balasubramaniam, and Ramadorai (2019), who document that individuals tend to invest in tangible assets in emerging markets.

Figure IA1. Alipay User Interface

This figure exhibits a few sample pages from the Alipay user interface. The left panel shows the front page of the app. The middle panel shows the category of payments, including online shopping, offline consumption, and investment. The right panel shows the page display for one example of mutual fund in the investment function.

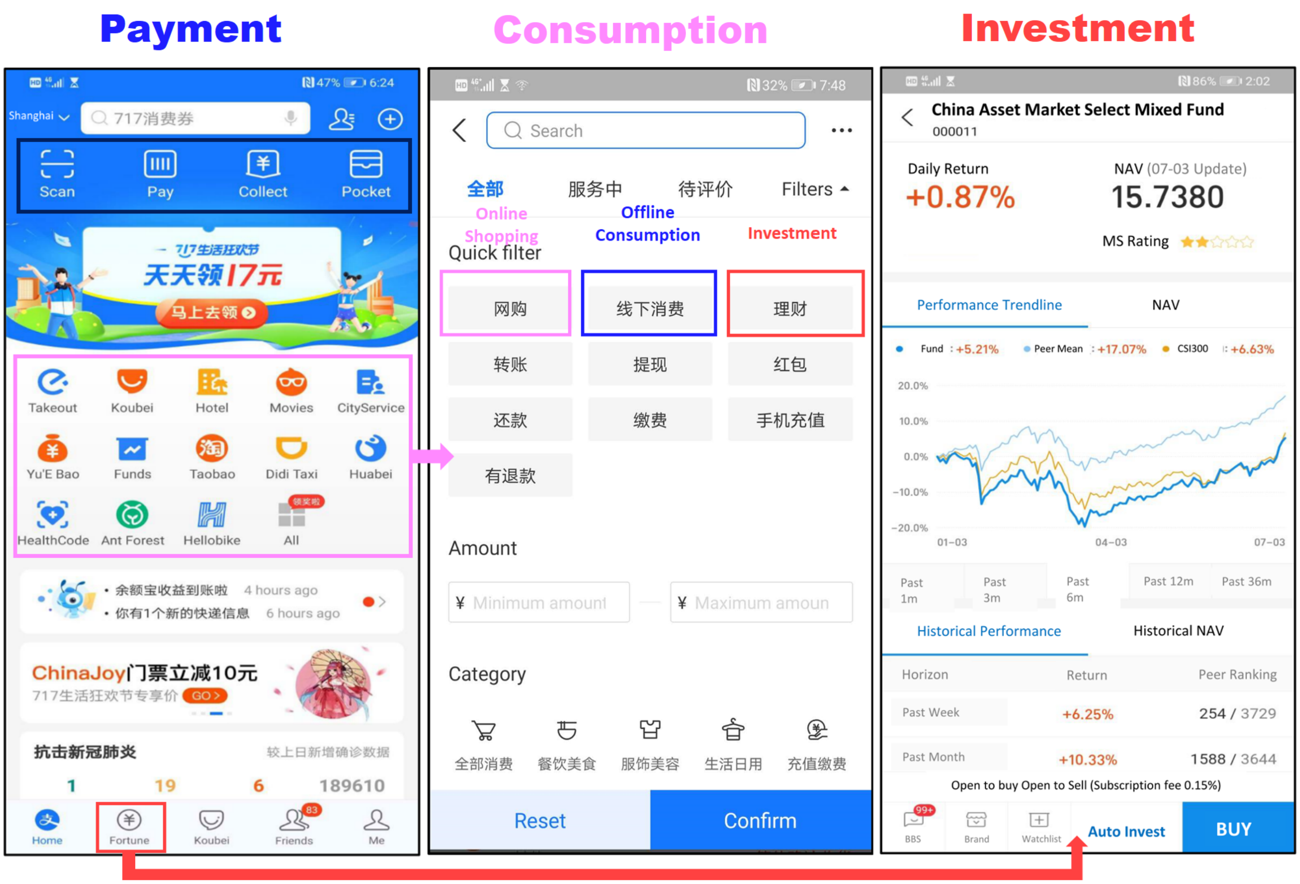


Figure IA2. Geographic Distribution of Banking Coverage

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.

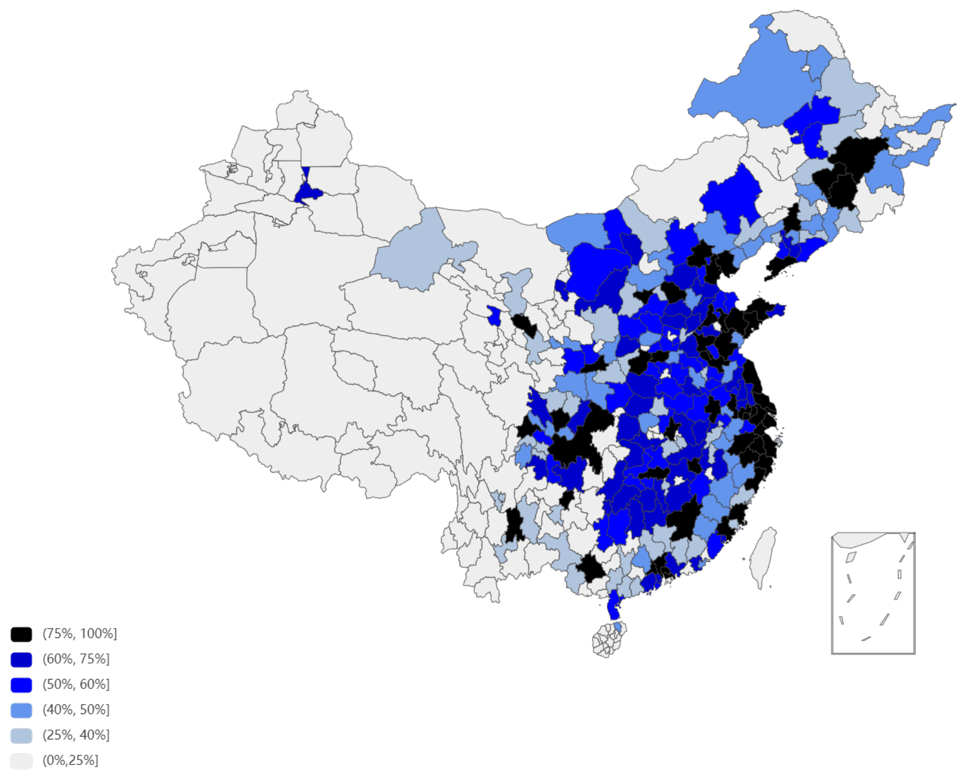


Table IA1. Consumption Growth Volatility and Individual Risk Tolerance

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 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 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 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. FinTech Adoption and Risky Participation by Asset Class

The table reports the effect of FinTech adoption on individual risky purchase in each asset class. We follow similar model specification as in Panel A of Table 4. The dependent variable is risky purchase in month $t+1$, a dummy variable that equals one if the individual purchased any risky fund in the specific asset class in month $t+1$, and zero otherwise. Log(QRPay) is the natural logarithm of number of Alipay QR-Scan payments in month t. Risky fund asset classes include bond, mixed, equity, index, QDII, and gold. 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.

	Risky Purchase for Each Type of Asset					
	Bond	Mix	Equity	Index	QDII	Gold
Log(QRPay)	0.188***	1.127***	0.283***	0.544***	0.148***	0.787**
	(4.94)	(12.76)	(9.20)	(8.86)	(5.65)	(2.78)
σ_{C}	-0.034	-0.038	0.006	0.035	-0.014	0.034
	(-1.48)	(-0.65)	(0.23)	(0.95)	(-0.90)	(0.98)
Female	-0.095*	-1.315***	-0.436***	-0.899***	-0.211***	-0.661***
	(-1.86)	(-9.08)	(-6.98)	(-7.85)	(-6.41)	(-5.18)
Log(Age)	0.135***	0.913***	0.155***	0.186***	0.024*	-0.289***
	(5.10)	(14.40)	(5.48)	(5.07)	(1.97)	(-3.62)
Log(C)	0.137***	0.667***	0.160***	0.340***	0.096***	-0.093**
	(4.73)	(10.08)	(5.19)	(7.21)	(5.10)	(-2.63)
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%	1.1%	0.4%	0.9%	0.2%	2.3%