FinTech Adoption and Household Risk-Taking

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Abstract

Using a unique FinTech data containing monthly individual-level consumption, investments, and payments, we examine how FinTech can lower investment barriers and improve risk-taking. Seizing on the rapid expansion of offline usages of Alipay in China, we measure individuals' FinTech adoption by the speed and intensity with which they adopt the new technology. Our hypothesis is that individuals with high FinTech adoption, through repeated usages of the Alipay app, would build familiarity and trust, reducing the psychological barriers against investing in risky assets. Measuring risk-taking by individuals' mutual-fund investments on the FinTech platform, we find that higher FinTech adoption results in higher participation and more risk-taking. Using the distance to Hangzhou as an instrument variable to capture the exogenous variation in FinTech adoption yields results of similar economic and statistical significance. Focusing on the welfare-improving aspect of FinTech inclusion, we find that individuals with high risk tolerance, hence more risk-taking capacity, and those living in under-banked cities stand to benefit more from the advent of FinTech.

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1 Introduction

On household finance, Campbell (2006) opens his AFA presidential address with, *"The study of household finance is challenging because household behavior is difficult to measure, and households face constraints not captured by textbook models."* Over the past decade, widespread adoptions of financial technology (FinTech) are breaking down many of the traditional barriers faced by households and reshaping the practice of household finance. Increasingly, activities central to household finance such as consumption, investments, and payments are taking place on FinTech platforms, where traditionally time-consuming financial-service needs can be fulfilled with the ease and convenience of a few mobile apps.[1] The advent of FinTech is also revolutionizing the study of household finance, as big data from FinTech platforms are made available to researchers, significantly reducing the measurement difficulty elaborated by Campbell (2006).

This paper is a study of household finance in the age of FinTech. Our hypothesis is that FinTech fosters financial inclusion by providing financial services to individuals who are otherwise unable or unwilling to invest in capital markets. In explaining why many households do not invest in risky assets against the obvious welfare gains, the household finance literature has shown that fixed physical costs (money, time, and effort) and psychological costs (familiarity and trust) are important factors hindering individuals from optimal risk-taking.[2] Indeed, this is where FinTech can help. Compared with the traditional venues, the technological efficiency of FinTech platforms can significantly reduce the physical costs associated with investing. Their brand recognition and the repeated usage of FinTech apps by individuals (e.g., via digital payments) can also help build familiarity and trust, lowering the psychological barriers associated with investing in risky financial assets.[3]

We study how FinTech advancement can help households lower investment barriers and improve risk-taking, using an account-level data from Ant Group, which allows us to track individuals' online consumption via Taobao, online investment in mutual funds via Ant Group's FinTech platform, third-party digital payments, both online and offline, via Ali-

[1]In China, online consumption took off around 2003 and has since increased to account for about 25% of the total consumption in 2020; Mutual-fund distributions via FinTech platforms grew from non-existence in 2012 to capture an estimated 30% of the total market share; Digital payments began in 2004, and are now accounting for over 80% of the total offline payment.

[2]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. And yet, a substantial fraction of households do not invest in risky assets (e.g., Haliassos and Bertaut (1995), Campbell (2006), and Vissing-Jørgensen and Attanasio (2003)). Among others, Hong, Kubik, and Stein (2004) and Guiso, Sapienza, and Zingales (2008) document that familiarity and trust are important drivers for the low-participation puzzle.

[3]As the consumer-tech oriented FinTech platforms use "super apps" to deliver both financial and non-financial services to their consumers, such an integrated model of "one-stop shop for living" can further facilitate financial inclusion, especially for those under-served by the existing financial infrastructures.

pay, and other individual characteristics including age, gender, and location. The data is of monthly frequency from January 2017 to March 2019, when China experiences the most dramatic expansion in offline digital payments. Taking advantage of this rapid technological development, we construct a unique measure of FinTech adoption that differentiates individuals by their tech-savviness. Those with low FinTech adoption are at an early stage, while those with high FinTech adoption in our sample are taking full advantage of what FinTech has to offer. It is through exploring the difference in risk-taking across this dimension of FinTech adoption, both at the individual level and across geographical locations in China, that we offer evidence that FinTech improves household risk-taking and financial inclusion via FinTech can be welfare improving.

Measuring FinTech Adoption: Central to our study is the measurement of the penetration as well as the adoption of the new technology. Over our sample period, China experiences a rapid increase in offline digital payments via QR-code scanning, of which Alipay is the pioneer adopter. From 2017 to 2018, over the span of just two years, quarterly amounts of offline digital payments explode by over ten-fold to a total of 7.2 trillion yuan by 2018Q4. The Alipay component of our data captures this explosion not only in aggregate, but also across individuals. Seizing on this rapid technological development, we measure FinTech adoption by how much and how fast an individual adopts to the new technology. Specifically, for each individual and for each month, AliFrac=Alipay/(Alipay+Taobao), where Alipay is the third-party consumption paid through Alipay, including the offline consumption, and Taobao is the online consumption via Taobao.[4]

Over the long run, as digital payments become the dominant payment method, AliFrac would reflect the individual's preference for offline versus online shopping. Within our sample period, however, as digital payment is being adopted with varying speed and intensity by individuals, the level of AliFrac and the change in AliFrac contain valuable information of an individual's FinTech adoption. Either by their personal inclinations or the familiarity and trust built from repeated usages of the Alipay app, individuals of high AliFrac or large increase in AliFrac are more likely to use the existing FinTech platforms (e.g., Ant Group's mutual-fund platform) to fulfill their investment needs, while low AliFrac indicates that the individual has not yet bought into the FinTech revolution. It is through exploring the cross-individual difference in risk-taking along such dimensions of FinTech adoption that we offer

[4]While online Taobao consumption also increases from 2017 to 2018, it has become "yesterdays technology" in the sense that most individuals in China have already adopted this technology. During our time period, the FinTech savviness of an individual is captured not by his online consumption, but by the FinTech penetration of his offline consumption. As such, AliFrac measures an individual's usage of the new technology (Alipay) relative to the old technology (Taobao). It should also be emphasized that the third-party nature of the Alipay consumption means that consumption on Taobao and investments on Ant's FinTech platform do not count toward Alipay consumption.

evidence on how FinTech can improve household risk-taking.

In addition to cross-individual variation, another important and more exogenous variation in FinTech adoption emerges as we use individual-level location information and aggregate the FinTech adoption measures to the city-level. Our FinTech adoption maps of China, plotted over different points in time, capture the gradual spread of the new technology from Hangzhou, the headquarter of Alibaba and Ant Group, to the rest of China. Indeed, back in 2016, street vendors accepting QR-code scanning payments are a novelty sight spotted mostly near Hangzhou. By 2020, it has become part of the everyday life for most people living in China. While the individual-level variation might be driven by personal characteristics and experiences, this city-level variation is exogenous, owing to the gradual spread of the new technology across China. If FinTech can indeed lower investment barriers for households, we would expect to see FinTech penetration to lead the way of improved risk-taking across cities in China. More importantly, the more constrained cities with lower financial-service coverage should benefit more from FinTech penetration.

FinTech Improves Risk-Taking: We measure risk-taking using our data from Ant Group, which tracks the monthly mutual-fund investments made by individuals in our sample via Ant Group's FinTech platform.[5] In China, FinTech platforms are given permission to distribute mutual fund since 2012 and have grown substantially in market share.[6] Ant Group, a top player in this space, begins to distribute mutual funds via the one-stop Alipay app since 2014, offering a near complete coverage of mutual funds in China. Individuals in our sample have access to six types of risky mutual funds (bond, mixed, equity, index, QDII, and gold) and risk-free money market funds. Their portfolio choices are measured along three dimensions. As a zero-one variable, "risky participation" measures the individual's participation in the risky funds. Conditioning on participation, "risky share" measures the portfolio weight on the risky funds, and "portfolio volatility" is estimated using the individual's monthly holding-period returns.

To show that FinTech improves risk-taking, we provide empirical evidences from the following three perspectives. First, focusing on the cross-individual variation in the level of AliFrac, we find that all three risk-taking measures are positively and significantly related to AliFrac, consistent with the hypothesis that FinTech increases risk-taking. A unit change of AliFrac from 0 to 1 corresponds to an increase of 13.6% in risky participation, 14% in risky share and 0.52% in portfolio volatility. Compared with their respective sample averages,

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

[6] See Hong, Lu, and Pan (2019) for details on the development of FinTech platforms and their market-wide impact on the Chinese mutual fund industry.

37.5% for risky participation, 45% for risky share, 1.77% for portfolio volatility, the economic significance of the FinTech impact is rather large. Controlling for individual characteristics such as age, gender, location, consumption level and volatility, the results remain strong and significant, both economically and statistically.

Using panel regressions with high dimensional fixed effects, we further decompose the economic magnitude into individual and environmental factors. We find that while individuals allow the outside environment to influence their decision on whether to participate in risky assets, the decision on the intensity of risk-taking is largely kept under their own control. Specifically, including city-times-month fixed effects cuts the original economic significance of AliFrac in explaining risky participation by 45%, compared with 17.5% for risky share, indicating that outside environmental factors such as time and place play an important role in explaining risky participation. By contrast, including individual fixed effects cuts the economic significance of AliFrac in explaining risky share by 65%, compared with 24% for risky participation, reflecting the importance of individual factors in explaining risky share. The impact of AliFrac on risk-taking remains statistically significant, though with smaller economic magnitudes, if we include both the individual and city-times-month fixed effects. In other words, relying exclusively on the individual-specific time-series variation, AliFrac can still impact risk-taking in a meaningful way.

Second, we explore the cross-individual variation in ΔAliFrac, which measures each individual's change in AliFrac from 2017 to 2018. Although individual characteristics are used as controls in establishing the positive relation between risk-taking and AliFrac, both variables can still be influenced by some unobserved, hence uncontrolled, factors, giving rise to the positive relation. This is where the information contained in ΔAliFrac can be helpful. Unlike other individual characteristics, which remain stable or unchanged from 2017 to 2018, ΔAliFrac is unique and highly informative as it is measured during the most dramatic expansion in the new technology. The aforementioned unobserved factors might drive both the level of AliFrac and risk-taking (e.g., openness to new experiences), but it is highly unlikely that such factors will drive both ΔAliFrac and changes in risk-taking at the same time. This is especially true given that Ant's mutual-fund platform has already been well established prior to 2017. And yet, regressing changes in risk-taking on ΔAliFrac, we find a significant relation between the two, affirming that the increase in risk-taking is indeed the result of the increase in AliFrac, not some unobserved common factors.

Third, to further establish the causal impact of FinTech on risk-taking, we use the distance to Hangzhou as an instrument variable to capture the exogenous variation in FinTech adoption. As discussed early, Hangzhou is at the epicenter of the map of FinTech penetration – cities closer to Hangzhou have higher levels of FinTech penetration. This is in fact a result of how Ant Group initially implements the QR code-based digital payments. They first cooperate with local governments and local vendors in Hangzhou and then expand to other cities in Zhejiang province, the nearby cities, and distant cities. This pattern of expansion is necessary for Ant Group because their marketing teams have to communicate with local merchants in person to convince them to accept the new technology. By contrast, promoting mutual funds on Ant's FinTech platform is mostly an online effort without an epicenter, and, more importantly, Ant Group has already established itself as a top player in mutual-fund distribution prior to 2017.

Given the closeness of Hangzhou to Shanghai (SH), distance-to-HZ can be highly correlated with distance-to-SH, which, given Shanghai's economic importance in China, reflects the proximity to affluence, a variable that can be easily linked to investment behavior. To disengage these two measures, we take advantage of the fact that the difference between Hangzhou and Shanghai (160 kilometers apart) is meaningful for cities within a small enough radius around Hangzhou and Shanghai. Indeed, using a radius of 500 kilometers around Hangzhou, we find that only distance-to-HZ can strongly predict FinTech penetration in the first stage regression. Using this instrument in the second stage estimation, we find that a one standard deviation increase in instrumented city-level AliFrac predicts a 2.55% (t-stat=3.13) increase in risky participation and a 4.10% (t-stat=5.26) increase in risky share. Expanding to all cities in China, the instrumental variable approach using distance-to-HZ still works but with smaller economic significance. Using distance to the other tier-one cities as placebo tests, however, we find no results.

Welfare Implications: Our empirical results have so far shown that FinTech fosters financial inclusion – higher FinTech adoption results in higher participation and risk-taking. 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. We can provide further evidences 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 live in cities under-served by the traditional financial infrastructure. These findings can also speak to the nature of FinTech inclusion in that it is not simply a zero-sum game with FinTech platforms competing for customers against the traditional channels. Instead, FinTech inclusion is welfare improving by providing financial services to individuals who are otherwise unable, both physically and psychologically, to invest in financial markets.

First, we document the benefits of FinTech inclusion for investors with high risk tolerance. To identify the high risk-tolerant individuals in our sample, we use the consumption side of the data and proxy for risk tolerance by consumption volatility σ_{C} – individuals with higher σ_{C} are more risk tolerant. Our immediate theoretical foundation is from the Merton model, where, under complete markets, σ_C as a function of risk aversion is exactly specified.[7] In the more general setting, as long as the state dependence of consumption is a result of the individuals consumption choice using available albeit incomplete financial instruments, then, even when markets are incomplete, more volatile consumption should correspond to less risk aversion. Empirically, we validate the effectiveness of σ_C as a proxy for risk tolerance in two dimensions. First, examining the cross-sectional determinants of σ_C, we find that male and young investors on average have higher σ_C, consistent with the perception that such investors are relatively more risk tolerant. Second, we find that although consumption and risk-taking occur on two different FinTech platforms, there is a significant connection between the two. Consistent with our hypothesis that σ_C is a good proxy for risk tolerance, individuals with higher σ_C exhibit higher levels of financial risk-taking.

According to financial theory, the optimal risk-taking is higher for less risk averse investors. If the advent of FinTech can indeed break down the barriers and unshackle the 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. We find that this is indeed the case. Armed with our proxy for risk tolerance, we sort individuals in our sample by σ_C into high and low risk tolerance, and compare their risk-taking behaviors as a function of their FinTech adoption. When the FinTech adoption level is low, the high risk-tolerant investors behave not that differently from their low risk-tolerant counterparts. This, of course, is counter to financial theory and speaks to the fact that such high risk-tolerant investors are constrained and their utility not optimized. With the increase in FinTech adoption, however, this gap in risk-taking widens, indicating that, with the increase in FinTech adoption, such high risk-tolerant investors are less constrained and are taking more risk. Utilizing regression based analysis by adding σ_C as an conditioning variable in the previous regression specification, we find similar results.

Second, we document the benefits of FinTech inclusion for individuals living in cities with low bank coverage, using the number of local bank branches as a proxy for bank coverage. With respect to how FinTech can be welfare improving, this line of analysis is of the first order importance as the future for FinTech inclusion is without any doubt brighter for individuals under-served by the existing financial infrastructure. Before the development of FinTech platforms, banks are the predominant distribution channel of mutual funds. As a result, investors living in areas with fewer bank branches have limited access as well as limited exposures to mutual fund investments. With FinTech advancement, such under-

[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.

banked individuals can pursue what they want. Performing our analysis at the city level, we find that the benefit of FinTech inclusion in fact comes mostly from cities less served by banks, suggesting that, in the provision of financial services, FinTech could add to the vacuum left behind by the traditional financial institutions.

FinTech inclusion can take place through two channels. One is at the expense of the existing financial infrastructure, while the other takes place when FinTech opens the door for individuals who are unaware of financial investment opportunities and would otherwise remain unbanked. This is financial inclusion in the real sense of the word. For FinTech platforms to have a bright future in our society, the welfare improving aspect of their service is essential. The fact that the benefits of FinTech inclusion are stronger for individuals who are otherwise more constrained individuals with more risk-taking capacity and individuals under-served by banks, provides a compelling evidence for the welfare-improving channel.

To further illustrate the welfare improving aspect of FinTech inclusion, we focus on the under-banked individuals and compare and contrast their risk-taking sensitivity to FinTech adoption against a matching sample of individuals with above-median bank coverage. We find that, within the under-banked sample, individuals who are more mature (above 30 in age), hence with higher investment capacities and needs, increase their risk-taking much more readily with FinTech adoption. By contrast, the matching sample of high-banked individuals do not exhibit this pattern. Living in cities with high-bank coverage, such mature investors can invest in mutual funds via the traditional channels such as banks, but their counterparts living in cities with low-bank coverage do not have that privilege. With FinTech advancement, such under-banked individuals are given an alternative channel to fulfill their investment needs. Using σ_{C} as a proxy for risk tolerance, we find the same pattern. High risk tolerant individuals increase their risk-taking more readily with FinTech adoption in the under-banked sample, but not in the matching sample of above-median bank coverage.

Finally, in addition to non-participation, welfare costs could also incur due to the investment mistakes made by households. Investigating the investment efficiency of Swedish households, Calvet, Campbell, and Sodini (2007) show that the return cost of non-participation is smaller by almost one-half when taking account of the fact that non-participants would likely be inefficient investors. Motivated by this observation, we further study how FinTech adoption can affect the investment efficiency. We find that individuals with higher FinTech adoption tend to have more diversified portfolio, larger reduction in portfolio variance, and higher Sharpe ratio. The effect of AliFrac on diversification benefit is universal across all investors, whereas the effect on Sharpe ratio is particularly concentrated on the subsample of investors with low risky share, consistent with the benefit of risky participation. For the sample of investors with high risky share, we find evidence of mean-variance inefficiency among investors with high FinTech adoption.

Related literature: Our paper contributes to the literature on household finance (Campbell (2006), Guiso and Sodini (2013) and Beshears et al. (2018)) by helping shed light on the long standing puzzle of low-participation and under risk-taking. Our results show that FinTech adoption can increase not only risky participation, but also the level of risk-taking (i.e., higher risky share and portfolio volatility). Better access via FinTech can explain the increase in participation, but not the increase in the level of risk-taking, indicating that there are other channels through which FinTech improves risk-taking. Indeed, using our FinTech adoption measure, which captures individuals' FinTech usage, we show that repeated usages of FinTech apps (e.g., Alipay) can build familiarity and trust and reduce the psychological barriers against investing in risky financial assets. Our findings are therefore consistent with Hong, Kubik, and Stein (2004) and Guiso, Sapienza, and Zingales (2008), who document that familiarity and trust are important drivers for the low-participation puzzle.[8]

Our paper also contributes to the growing literature on the impact of technology on household finance. This includes Barber and Odean (2002), Choi, Laibson, and Metrick (2002), and Bogan (2008), who examine how Internet improves stock participation in the early 2000s. Throughout history, the financial industry has always been on the forefront of adopting new technologies, but the current wave of FinTech is unique in that the large FinTech platforms are run by technology firms. Bypassing the traditional financial institutions, FinTech platforms are delivering financial products and services directly to households via mobile apps.[9] As reviewed by Suri (2017), mobile money in developing economies has allowed individuals without bank accounts to digitally transact money. Households in Kenya, with the help of digital loans, are able to enhance their financial resiliency to shocks (Suri, Bharadwaj, and Jack (2021)).[10] Our finding on how FinTech can benefit individuals less served by traditional banks has profound implications for the future of FinTech. Indeed, for emerging-market countries with less developed financial infrastructures (e.g., Badarinza, Balasubramaniam, and Ramadorai (2019)), the future of FinTech is the brightest.

Finally, our paper is related to the literature of household portfolio choice that stud-

[8]Among others, Christiansen, Joensen, and Rangvid (2008), Calvet, Campbell, and Sodini (2009), Gennaioli, Shleifer, and Vishny (2015), Calvet and Sodini (2014), and Calvet et al. (2020) find education, financial sophistication, financial advisory, human capital, wealth, and security design are factors encouraging financial risk-taking.

[9]Among others, Goldstein, Jiang, and Karolyi (2019), Philippon (2018) and Frost et al. (2019) discuss the FinTech opportunities and how their entrance might affect the household and financial institutions, Carlin, Olafsson, and Pagel (2017) show how FinTech adoption affect the use of consumer credit, and Reher and Sokolinski (2020) examines how reduction in minimum account size increases participation using data from a robo-advisor firm.

[10]There is an emerging literature on this topic. For example, Higgins (2019) finds that small retailers and customers can both benefit from FinTech adoption due to its network externalities. Chen et al. (2021) find that small entrepreneurs in China, with the availability of FinTech credit, are able to obtain more stable sales.

ies the individual-level preferences. One standard approach of eliciting risk aversion is through lottery-type questions. Conversely, the literature has approached the task by inferring individual-level risk aversion through their risk-taking behavior. For example, Calvet et al. (2021) estimate the cross-sectional distribution of preference parameters, including the relative risk-aversion coefficient, using a large administrative panel of Swedish households. Our paper adds to this literature by using consumption volatility to proxy for risk tolerance. By further establishing the positive link between consumption volatility (i.e., risk tolerance) and risk-taking, our paper also adds to the literature by providing empirical evidence on the connection between consumption and investment. As exemplified by the classic household-finance problem of Merton (1971), optimal decisions on risk-taking and consumption are central to the study of household finance, and, yet, it has not been fully studied empirically owing to the limitation of the data. One notable exception is 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]

The paper proceeds as follows. Section 2 describes our data and the institutional background. Section 3 provides a comprehensive exposition of our FinTech adoption measure. Section 4 documents the impact of FinTech adoption on individual risk-taking. Section 5 focuses on welfare implications of FinTech inclusion. 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. We provide detailed description of our Ant data and the development of FinTech platforms in this section.

2.1 Overview of the Ant Data

Our data is provided by Ant Group and it captures individuals' activities on its two mobile apps: Taobao for online consumption and Alipay for investments and digital payments. It allows us to track the monthly investment, payment, and consumption behavior for a sample of randomly selected 50,000 investors from January 2017 to March 2019. The sample is randomly selected from the entire population of the Ant platform, among investors who ever have at least one purchase or redemption of money market fund, or mutual fund, or

[11]By focusing on the link between consumption and investments, our paper is also related to recent studies on the impact of financial markets on individual consumption by Agarwal and Qian (2014), Di Maggio, Kermani, and Majlesi (2020), Agarwal, Charoenwong, and Ghosh (2020), and Loos, Meyer, and Pagel (2020).

short-term wealth management product on Ant platform.

In our data, individual's Taobao consumption is the total consumption on the Taobao (including Tmall) e-commerce platform. Taobao, the Amazon of China, is the online shopping platform operated by Alibaba. Individual's Alipay consumption refers to all the other consumption paid through the Alipay digital payment function, both online and offline, to third-party merchants (excluding the consumption on Taobao/Tmall).[12]

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 mutual fund investment data, we obtain the monthly purchase and redemption of each fund made by each investor. For a sub-sample period from August 2017 to December 2018, we also obtain the detailed fund holdings and portfolio monthly return information. Some users have very small amount of investment. Including them may add noise to measures of individual portfolio risk-taking. We thus further require a user to have at least 100 RMB total purchase amounts, and obtain 28,393 users for our "active user" sample.[13]

Panel A and B of Table 1 report the summary statistics for all the 50,000 users and the 28,393 active users, respectively. The distribution of Ant investors tilts toward female and young population: 61% of investors on the Ant platform are female and the average age is 30.4 years old. For reference, based on survey conducted by Asset Management Association of China in 2018, 47% of all mutual fund investors in the market are female and 36.5% of the investors are below 30 years old. An average investor on platform has a monthly Taobao consumption of 2,155 RMB and a monthly consumption growth volatility of 1.21 (or 121%). Our FinTech adoption measure, AliFrac, is calculated as the fraction of Alipay consumption out of total Alipay and Taobao consumption for each user. The average AliFrac is 0.54 in our sample, and investors on average make 20.3 times consumption payments using Alipay each month (Log(AliCnt), the logarithm of the monthly Alipay frequency, has a mean of 3.01). We also include change in AliFrac and change in Log(AliCnt) from year 2017 to 2018. Both variables suggest an increase in Alipay penetration during our sample period. Restricting the sample to the active users, we find a similar distribution in terms of personal characteristics. An average active user has an age of 31.1 years old, female probability of 61%, monthly Taobao consumption of 2,292 RMB, monthly consumption volatility of 1.21, and monthly Alipay payments of 21 times. We describe and examine these measures in detail in the following sub-sections.

[12]Payments that are not consumption items (for example, money transfer) are also excluded.

[13]Platform may offer free fund shares to some investors, or provide discount on first purchase under certain circumstances. Purchase of very small amount is most likely due to these promotion policies.

2.2 Mutual-Fund Investments and Risk-Taking Measures

The China Securities Regulatory Commission (CSRC) started allowing FinTech platforms to distribute mutual funds in 2012. By 2018, mutual fund distributions via FinTech platforms capture around 30% of the indirect fund sales. As a dominant player in this market, in 2017, Ant's sales and net income from mutual fund distribution are RMB 2.23 trillion and RMB 10.5 billion respectively.[14] Besides risk-free money market funds (MMF), there are six types of risky funds available on the Ant platform: bond, mixed, equity, index, QDII, and gold funds. Table 2 reports investors' detailed investment behaviors. Among the 28,393 active users with non-trivial total investment, the average total mutual fund purchase amount is 41,079 RMB, which is equivalent to about 18 months of their average Taobao consumption. On average, they have 8.9 transactions made in 3.1 months out of the 27 months in our sample period. Individuals on average invest in 3.7 different funds across 1.9 different asset classes, and the average trade size is 4,557 RMB per trade.

For each individual, we construct three measures to capture their risk taking via mutual fund investments: (a) Participation, a dummy variable that equals one for individuals who purchased at least 100 RMB in non-MMF mutual funds; (b) Risky Share, the fraction of holdings invested in risky mutual funds (= 1−MMF/Total); and (c) Portfolio Volatility (σ_{W}), the standard deviation of individual's portfolio monthly returns.

Table 1 provides the summary statistics for our three risk-taking measures. As shown in Panel A, around 37.5% of investors participate in non-MMF investments out of the 50,000 users. For the "active users" sample in Panel B, participation rate in risky mutual funds is much higher at 66%, as we already exclude the inactive users. Based on the holdings data from August 2017 to December 2018, active users on average put 45% of their portfolio holdings in risky mutual funds and their portfolio monthly return has a volatility of 1.77%.

Panel B of Table 2 further reports the correlation between the risk-taking measures and other investment variables. Consistent with our intuition, the three risk-taking measures are positively correlated with each other, with a pair-wise correlation varying from 0.39 to 0.62. Besides, the correlation analysis suggests that individuals with higher risk-taking trade more frequently but with smaller transaction size per trade. Meanwhile, their portfolio exhibits stronger diversification, in terms of both the number of funds and number of asset classes. Turning to the correlation between risk-taking and individual personal characteristics as shown in Panel C of Table 1, again we find the relationship is consistent with the prior literature (e.g., Sunden and Surette (1998), Jianakoplos and Bernasek (1998), Barber and

[14] The numbers come from Ant Group IPO prospectus. For a top bank like China Merchants Bank, the fund distribution sales and net income are only RMB 705.5 and 5.0 billion in 2017. More details can be found in Hong, Lu, and Pan (2019), which documents the economic impact of FinTech platforms on mutual-fund investors, fund managers and fund families in China.

Odean (2002), etc.) that male and younger users exhibit higher risk-taking. 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 our three risk-taking measures. Overall, these evidence gives us confidence that the three measures indeed capture individuals' risk-taking in mutual fund investment.

2.3 Consumption via Taobao E-Commerce Platform

Online consumption took off in China around 2003 and has since increased to account for about 25% of the economy-wide total consumption in 2020, as shown in the upper panel of Figure A1. In 2019, Taobao accounts for over 50% of the e-commerce sales in China.[15] As such, our Taobao consumption data comes from an online platform that is representative of online consumption in China. We also obtain information on detailed components of Taobao consumption. Out of the total Taobao consumption, basic goods consumption accounts for about 35%, followed by 20% on entertainment consumption (enjoy) and 10% on personal development (lower panel of Figure A1). There exists seasonality in the online consumption data, owing to the November 11 Online Shopping festival and the Chinese New Year holidays. In subsequent analyses, following the standard method, we combine consumption in January and February as one month in the calculation of consumption growth. We also conduct robustness tests to adjust the seasonality and durability of online purchases. For example, we exclude November purchases, calculate consumption growth by comparing same calendar month on a year-on-year basis, and our results remain robust.

Following the theoretical framework in Merton (1971), we infer individuals' risk tolerance from their consumption growth volatility. We compute each investor's consumption growth volatility (σ_{C}) using the monthly differences in log Taobao consumption.[16] As shown in Table 1, the average of σ_{C} is 1.21 per month, which is quite high. However, in our analyses, σ_{C} is used as a cross-individual characteristics, and our focus is mainly on the the cross-individual variation in σ_{C}. As such, the absolute level of σ_{C} is not as important for our purpose. For the cross-individual variation in σ_{C}, Panel B of Table A1 reports the summary statistics on σ_{C} by individual characteristics. Consistent with our intuition, male and young investors on average have higher σ_{C}. Also interesting is the fact that investors with higher FinTech adoption on average have more volatile consumption. Moreover, the high level of volatility is a general phenomenon of online consumption, not a unique feature of our data. As

[15]See, for example, https://www.emarketer.com/content/retail-and-ecommerce-sales-in-china-2018 for details of China e-commerce market.

[16]Section 5.1 provides detailed discussion on the theoretical motivation and validity of σ_{C} as a risk tolerance measure.

shown in Panel A of Table A1, the economy-wide online consumption exhibits a much higher level of volatility than that of total consumption and offline consumption. In particular, the monthly consumption growth volatility is 19.2% for economy-wide online, 21.1% for Taobao, 6.9% for economy-wide offline, and 5.3% for economy-wide total consumption.

2.4 Consumption via Alipay Digital Payment

Digital payments in China started in 2004, and it fosters China into a cashless society with over 852 million users using mobile digital payments for daily activities. Under the category of digital payment, the prevalence of QR-Scan payment is a recent phenomenon. It permeates the entire country with each street vendor at every corner in China eager to accept QR-Scan payment offered by Alipay or WeChat.[17]

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 of time, QR-Scan payment exploded from 0.6 trillion yuan in Q1 of 2017 to 7.2 trillion yuan in Q4 of 2018.[18] As shown in Graph A of Figure 1, the economy-wide offline QR-Scan pay to total offline consumption ratio (red line) increases from around 43% in Q1 of 2017 to 80% in Q4 of 2018. The same trend is captured in our data via the rapid increase in Alipay payment fraction: The fraction of consumption paid via Alipay out of total consumption (blue line) increased from 50% in January 2017 to 70% in March 2019. The alignment of the two lines suggests that Alipay consumption well captures the penetration of QR-Scan digital payment during our sample period.

Since the focus of the paper is on the relationship between FinTech adoption and individual risk-taking, one may wonder whether the development of Ant mutual fund investment platform coincides with the trend in the development of digital payment. This is not the case. During our sample period, the Alipay mutual-fund investment function has already been well developed. Moreover, Panel B of Figure 1 plots the total purchase of money market funds and risky mutual funds for the 50,000 individuals in our sample against their consumption via Taobao and Alipay. Over the same time span, online Taobao consumption was itself increasing, but it was "yesterday's technology", as reflected in the flattened slope of the purple line. Given this rapid penetration of Alipay digital payment during our sample period, we later use AliFrac as a measure of individual FinTech adoption, which we explain in more detail in Section 3.

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[17]Though Wechat accounts for 38% of the market share in digital payment in 2017, its mutual fund distribution service is not well developed. It was not until July 2018 that Wechat officially got the license to distribute risky mutual funds.

[18]See http://www.iresearchchina.com/content/details7_54532.html.

3 Measuring FinTech Adoption

An ideal test of FinTech's impact on risk-taking would involve tracking each individual's migration onto the FinTech platforms with records of his/her risk-taking behavior both on and off platforms. Absent of such an ideal data, we construct a FinTech adoption measure to mimic that migration. As explained in Section 2.4, China experiences a rapid increase in FinTech penetration in the form of QR-code scanning payment during our sample period. While online Taobao consumption also increases from 2017 to 2018, it has become "yesterdays technology" in the sense that most individuals in China have already adopted this technology. Amidst this fast-developing trend of QR-Scan payment in our sample, we capture each individual's FinTech adoption by their Alipay usage, AliFrac, calculated as the fraction of Alipay consumption amount out of the total consumption paid via Alipay and Taobao. As such, AliFrac measures an individual's usage of the new technology (Alipay) relative to the old technology (Taobao). Including Taobao consumption in the denominator also has the benefit that it helps control for individual wealth effect.[19]

Over the long run, as digital payments become the dominant payment method, AliFrac may reflect the individual's preference for offline versus online shopping. However, during our sample which covers the period of dramatic expansion in offline digital payment, the level of AliFrac and the change in AliFrac contain valuable information of the speed and intensity with which individuals adopt the new technology. According to Panel A of Table 1, both the level and the change of FinTech adoption vary substantially across individuals. An average user in our sample has an AliFrac of 54% with a standard deviation of 22%. The average level of AliFrac increases by 8% from year 2017 to year 2018 (ΔAliFrac), again with a large cross-sectional standard deviation of 22%. The large variation in FinTech adoption across different individuals could be driven by both nature and nurture. Some individuals are born to be tech-savvy, and are more willing to accept this new technology. In addition to natural inclination, environmental factors, such as how local governments and local vendors promote QR-Scan pay, could also affect individuals' FinTech adoption.

To understand the geographical distribution of FinTech adoption, we compute city-level AliFrac, calculated as the average AliFrac of all individuals in a city. Figure 2 shows that AliFrac varies substantially across geographical areas and over time from 2017 Q2 to 2018 Q4. Back in early 2017, Hangzhou, the headquarter of Ant Group, is the epicenter, leading the way in FinTech adoption. Among all cities, Hangzhou has the highest AliFrac of 0.58 (Graph A), suggesting that individuals in Hangzhou already have 58% of their consumption

[19] Individual's Taobao consumption may add noise to the FinTech adoption measure, diluting the effect of Alipay usage. Therefore, we also construct an alternative FinTech adoption measure, Log(AliCnt), using individuals' Alipay payments frequency.

paid through Alipay out of their total consumption. Other cities at that time only have an average AliFrac of 33.6%. With the passage of time, we observe a gradual penetration of FinTech from Hangzhou to cities in the inner region of China. Hangzhou still leads other cities in FinTech adoption with an AliFrac of 66.2% in 2018 Q4. In comparison, AliFrac for Shanghai, Beijing, Guangzhou, and Shenzhen, the tier-one cities, are 64%, 58.4%, 52.9%, and 54.6% respectively by the end of 2018.

The gradual penetration of Alipay during our sample period suggests that both the level and the change in AliFrac contain valuable information about FinTech penetration dynamics. Comparing Figure 2 with the upper graph in Figure A2, it is obvious that the distribution of city-level ΔAliFrac exhibits a rather different pattern from the level of AliFrac. Cities close to Hangzhou, equipped with high AliFrac level in early 2017, enjoyed less increase in FinTech penetration during 2018; while cities in the inner land of China witnessed a much larger increase in FinTech penetration during the same period.

Apart from environmental factors, the cross-sectional variation in AliFrac could also be explained by individuals' own willingness to adopt QR-Scan payment. Table 3 reports the determinants of AliFrac and ΔAliFrac on individual personal characteristics and city-level characteristics. We find that individual AliFrac is positively related with their consumption growth volatility, and negatively related with the female dummy, which suggests that male and those with higher risk tolerance are more open to the new technology of QR-Scan payment. When we include city-level economic variables, we find that cities with higher GDP and higher personal income have higher FinTech penetration. The coefficient on the tier-one city dummy is negative, due to the inclusion of Log(GDP) in the regression.[20]

Turning to change in AliFrac, we find that the increase in AliFrac from 2017 to 2018 is captured by a different group of individuals. In particular, the change in AliFrac is negatively related to consumption volatility, female dummy, and positively related to age. Back in 2017, younger individuals, and individuals with relatively high risk tolerance are the pioneers in adopting this new payment method. However, as the digital payment function became more widespread from 2017 to 2018, older individuals, and individuals with relatively low risk tolerance also started to use it. Moreover, the change measure is negatively related to Log(GDP) and Log(Income), which confirms our previous observation in Figure 2: From 2017 to 2018, the digital payment function of Alipay has penetrated into cities with relatively low level of economic development in the inner parts of China.

[20]The GDP levels are much higher for tier-one cities than those for other cities, whereas AliFrac measures for tier-one cities are only slightly higher than those for other cities.

4 FinTech Adoption and Individual Risk-Taking

4.1 FinTech Adoption and Level of Risk-Taking

Our hypothesis is that individuals of high AliFrac, either by their personal inclinations or the familiarity and trust built from repeated usages of the Alipay app, are more likely to use the existing FinTech platforms (e.g., Ant Groups mutual-fund platform) to fulfill their investment needs; while individuals of low AliFrac have not yet bought into the FinTech revolution. To explore the cross-individual difference in risk-taking along such dimensions of FinTech adoption, we first examine the cross-sectional relationship between our three risk-taking measures and the level of AliFrac.

As shown in Panel A of Table 4, all three risk-taking measures are positively and significantly related to AliFrac, consistent with the hypothesis that FinTech increases risk-taking. In particular, one unit increase in the level of AliFrac corresponds to an increase of 13.6% in risky participation. The economic significance of FinTech on risky participation is rather large, given that the average risky participation rate is 37.5% across the 50,000 individuals in our sample.[21]

Beyond the general decision to participate, we are also interested in whether with the repeated usages of the Alipay app, investors would increase their intensity of risk-taking on Ant Group's FinTech platform. Investors can put differential portfolio weights across a wide spectrum of funds with varying riskiness on the Ant platform, ranging from low risk bond funds to high risk equity and index funds. Therefore, risky share and portfolio volatility serve as better risk-taking measures capturing individuals' risk-taking intensity. Columns (4) to (9) in Panel A report the corresponding results for risky share and portfolio volatility. To focus on the investors with meaningful investment activity and alleviate the impact of noise, we restrict our analysis to the sample of active users with more than 100 RMB fund purchase ("active user" sample). Consistently, we find that one unit increase in the level of AliFrac corresponds to 14% in risky share and 0.52% in portfolio volatility, which are of big economic magnitude comparing to their respective sample averages of 45% for risky share and 1.77% for portfolio volatility.

As we have seen in Section 3, AliFrac correlates with some individual characteristics that are shown in the literature to reflect risk aversion. In particular, AliFrac is positively related to consumption growth volatility (σ_{C}), which, according to Merton (1969), is positively

[21]As an alternative way to express the economic magnitude, one standard deviation increase in AliFrac corresponds to a 2.99% (=13.6%×0.22) increase in risky asset participation rate, which is still a reasonably large magnitude, comparing to the average participation rate of 37.5%. Since our AliFrac measure ranges from 0 to 1, we still refer to the effect of one unit increase in AliFrac for the easiness of interpretation of regression coefficients in subsequent discussions.

related to investors' risk tolerance.[22] To disentangle potential confounding effects, we include σ_C in the second regression specification, and further include age, gender, consumption level to capture individual's risk attitude in the third regression specification. The empirical results on these control variables are consistent with our interpretation: First, we find a positive relation between σ_C and all three risk-taking measures. For example, one unit increase in σ_C corresponds to an increase of 3.7% in risky asset participation rate (Column (2) in Panel A). Second, further controlling for individual gender, age, and consumption level reduces the effect of σ_C on risky participation by half (from 3.7% to 1.9%), but the positive relation remains significant. The pattern is similar for the effect on risky share and portfolio volatility. These results indicate that σ_C indeed captures individuals' risk tolerance. While its effect is partially absorbed when we include other observable individual characteristics, it still contains additional information over these variables. Third, the effects of these additional controls are also consistent with the literature:[23] Investors who are male, young, have higher wealth level also tend to exhibit higher risk-taking, and the effects are mostly significant. Finally, in all regressions, we include city fixed effects to control for any difference in risk-taking behavioral due to unobserved local economic and social factors. Overall, the results suggest that the control variables we include indeed capture investors' risk tolerance level. Yet, controlling for the effect of risk tolerance, the results on AliFrac remain qualitatively the same, and the magnitudes of the AliFrac effect also remain economically significant.

After documenting a positive relationship between AliFrac and risk-taking, another important question is the channel behind this improved risk-taking. The positive impact of FinTech adoption on the intensity of risk-taking, beyond the simple participation decision, can help shed light on this issue. As documented in the prior literature (Campbell (2006), Hong, Kubik, and Stein (2004), Vissing-Jørgensen and Attanasio (2003)), despite the positive risk premium associated with financial investment, a substantial fraction of households do not invest in risky assets, possibly due to the existence of fixed physical costs and psychological costs (e.g., familiarity and trust). Our findings on the intensity of risk-taking point to the importance of building familiarity and trust as a potential solution to the low-participation puzzle. If the limited participation puzzle was only due to lack of access, then the FinTech convenience and efficiency can reduce the physical costs and increase participation, but not necessarily the level of risk-taking.[24] However, if the pre-FinTech friction also

[22]Section 5.1 discusses the theoretical motivation and provides validity of σ_C as a risk tolerance measure in more detail.

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

[24]With only the technological efficiency of FinTech platform, investors may put more investment capital onto the mutual fund platform. However, the weight they put into risky assets, i.e. risky share, should not be affected.

includes individuals' mistrust or psychological aversion of investing in risky assets, then advent of FinTech has implications for the level of risk-taking as well: with the repeated usage of one function of Alipay (e.g., digital payment), investors can build familiarity and trust with the investment vehicles offered on the FinTech platform, which further help reduce the psychological barriers against risky investment and lead to higher portfolio weight in risky mutual funds.

In addition to the regression setting, Figure 3 provides a more intuitive demonstration of our results. In particular, we sort the individuals in our sample into fifty groups according to their FinTech adoption level (AliFrac), and compute the average AliFrac and average risk-taking measures within each group. The upper two panels and the lower left panel of Figure 3 plot the average participation, risky share, and portfolio volatility of each group against their average AliFrac, respectively. One can observe a roughly monotonic and linear relation between AliFrac and all three measures of risk-taking. Consistent with the magnitude estimated from the cross-sectional individual regressions, a unit change of AliFrac from 0 to 1 corresponds to an increase of 15.3% in risky participation, 12.9% in risky share and 0.43% in portfolio volatility.

4.2 Panel Regression with Fixed Effects

Since both environmental factors and individual-specific factors could contribute to the effect of FinTech adoption on risk-taking, we further disentangle the relative importance of the two, utilizing a panel regression with different layers of fixed effects. We explore fixed effects in two dimensions: individual fixed effects that capture any time-invariant personal characteristics; city-times-month fixed effects that capture the gradual penetration of Alipay in each city in each month. It is worth emphasizing that the fixed effects themselves will capture part of the economic impact of FinTech adoption. Therefore, the coefficients on AliFrac in this regression setting can be interpreted as the lower bar of the effect of FinTech adoption on risk-taking. In particular, after controlling for individual fixed effects and the city-times-month fixed effects, the remaining effect of FinTech adoption on risk-taking only comes from the time-series variation in AliFrac at the individual level that is on top of the variation of FinTech adoption across cities over time.

Panel B of Table 4 reports the results for the effect of FinTech adoption on participation and risky share with various fixed effects. For participation, we have a panel of 50,000 investors for 27 months; For risky share measure, we only have 17 months of holdings data for these investors starting from August 2017. Portfolio volatility is excluded in this setting as the volatility measure has to be estimated using the monthly time series data. Starting with the effect on participation, as reported in columns (1) to (4), we find that both individual and city-times-month fixed effects explain an important proportion of the effect of FinTech adoption. Without any fixed effect, the coefficient on AliFrac is 0.126, which is comparable to the coefficient of 0.136 in column (1) of Panel A Table 4. With individual fixed effects only, the coefficient becomes 0.095 (t-stat= 5.47), representing a reduction of 24.6% (= $(0.126 - 0.095)/0.126$). The difference comes from the cross-individual dispersion in AliFrac. With city-times-month fixed effects only in column (3), the coefficient drops from 0.126 to 0.070, a reduction of 44.8% (= $(0.126 - 0.07)/0.126$). This pattern of reduction in coefficient estimates suggests that the change in FinTech adoption across different city over time largely explains individuals' decision on whether to participate or not, whereas the cross-individual dispersion explains a smaller part. Finally, with both individual fixed effects and city-times-month fixed effects, the coefficient drops to 0.006, although still significant with a t-stat of 3.01. Therefore, even if we only examine the time-series variation in FinTech adoption for each individual, excluding the effect of change in city-level FinTech adoption over time, we still find a positive relation between FinTech usage and investors' participation.

Moving to risky share, we also find a significant impact of FinTech adoption with and without fixed effects, although the pattern of the coefficient estimates is different from that for participation. In particular, without any fixed effects, the coefficient on AliFrac is 0.111 in column (5). With individual fixed effects only in column (6), the coefficient reduces to 0.039, representing a decrease of 64.9% (= $(0.111 - 0.039)/0.111$). With city-times-month fixed effects only in column (7), the coefficient drops to 0.092 (a reduction of 17.4%). In other word, individual fixed effects explain a larger proportion of the effect of FinTech adoption on risky share, whereas the gradual penetration of FinTech across different city over time explain a relatively smaller component. Finally, with both individual and city-times-month fixed effects, the coefficient drops to 0.020, although still significant with a t-stat of 4.89.

The comparison of the regression results between participation and risky share is consistent with the different economic interpretation of the two variables. The gradual penetration of FinTech in different cities reduces participation cost for individuals living in the city, which is likely to encourage participation. For example, with more merchants adopting the QR-Scan payment, individuals living in the city would find Alipay a more convenient app to use for every-day activities, which also helps lower the transaction costs and the searching costs of mutual fund investment. However, once the investors start to invest, how much of weight they put into risky assets is likely to be a reflection of their risk attitude, captured by individual fixed effects.

4.3 Change in FinTech Adoption and Change in Risk-Taking

Next, we move on to explore the cross-individual variations along the dimension of change in FinTech adoption and change in risk-taking. As discussed in Section 3, both the level of AliFrac and the change in AliFrac contain valuable information about the speed and intensity with which individuals adopt the new technology. Male and those with high risk tolerance are fast adopters. Equipped with high AliFrac level in early 2017, they enjoy less increase in FinTech penetration during 2018; while elder individuals and those with relatively lower risk tolerance living in the inner land of China witnessed a much larger increase in FinTech penetration during the same period.

Besides, focusing on individuals' change in FinTech adoption and change in risk-taking also helps alleviate the concern that some unobserved, hence uncontrolled, factors, may drive the previous cross-sectional results. For example, if individuals who are open-minded tend to use the newly-developed digital payment more often and are also more willing to invest in risky assets. We may attribute the effect of being open-minded to FinTech. However, ΔAliFrac is unique and it captures the speed of individual's FinTech adoption. It is unlikely that the aforementioned unobserved factors will drive both ΔAliFrac and changes in risk-taking at the same time. This is especially true given that Ant's mutual-fund platform has already been well established prior to 2017.

Specifically, we cut the sample into halves and use the year 2017 as the before sample and the year 2018 as the after sample. For each individual, change in FinTech adoption is calculated as the difference of average monthly AliFrac for year 2018 minus that of year 2017. Similarly, we measure the change in risky asset participation and the change in risky share at the individual level. A person is defined as participate for months on and after his/her first purchase of non-money market mutual funds.[25] Panel C of Table 4 reports the corresponding results for the effect of the change in FinTech adoption on the change in risk-taking. We follow a similar regression specification as in Panel A with all controls. Consistent with our prior, individuals with a larger increase in FinTech adoption participate more in risky asset investment. Meantime, they significantly increase their intensity of risk-taking, as reflected in higher portfolio risky share. In particular, as an individual's FinTech adoption increases from 0 to 1, his/her likelihood of risky fund participation increases by 1.4% from 2017 to 2018, which is smaller in magnitude than the cross-sectional estimate of 13.6%, but is still economically meaningful. The corresponding change in this individual's risky share increases by 8.7%, which is of the same order of magnitude as the cross-sectional result of 14.6%. The weaker effect of change in AliFrac on change in participation is to be expected, as it captures

[25] Since our data on investors' holding position is relatively short for 2017, the change in portfolio volatility cannot be measured.

only the variations from the late adopters restricted to their yes-or-no participation decision. By the end of 2018, when individuals already started to utilize Ant investment platform to fulfill their investment needs, individuals' change in risk-taking is better reflected by their portfolio risky share.

Finally, the relation between change in FinTech adoption and change in risk-taking is also evident from a graphical representation, as shown in the lower right panel of Figure 3. We sort the individuals in our sample into fifty groups according to their change in FinTech adoption (ΔAliFrac), and compute the average ΔAliFrac and average ΔRisky Share within each group. As average ΔAliFrac increases from 0 to 1, the corresponding change in these individuals' risky shares increases by 8.7%, which is consistent with the regression results in Panel C of Table 4.

4.4 Distance-to-Hangzhou as an Instrument

To further pin down the causal impact of FinTech adoption on household risk-taking, we employ an instrumental variable approach. As shown in Figure 2 and discussed in Section 2, the expansion footprint of the digital payment function of Alipay centers around Hangzhou and gradually penetrates into other cities. Ant Group initially cooperated with local government in Hangzhou to implement the QR code-based mobile payments in public transportation, hospitals and household utilities bills including electricity, water, communications. It then gradually expanded to other cities in Zhejiang province, the nearby cities in nearby provinces, and distant cities in distant provinces. Cities located closer to Hangzhou, the headquarter of Alibaba, are more likely being targeted the first. This is also because the penetration of the digital payment function of Alipay is associated with ground promotion, in which the marketing team of Ant Group has to communicate with local merchants in person and convince them to accept the QR-Scan pay function as a payment method. As a result, it naturally initiated from cities around Hangzhou. To the contrary, the marketing of the investment function of Alipay is not restricted from a geographical perspective and is mostly app based. Therefore, a city's physical distance to Hangzhou is less likely to directly affect individuals' risk-taking through the promotion of Alipay digital payment.

We use the natural logarithm of a city's distance to Hangzhou as an instrumental variable to predict the intensity of FinTech adoption across different cities. We then examine the effect of instrumented AliFrac on risk-taking in the second stage. Table 5 reports the IV test estimations. One may also worry that Hangzhou is geographically close to some metropolis or tier-one cities, especially Shanghai, and a city's distance to Hangzhou largely correlates with its distance to Shanghai. If being closer to metropolitan area encourages individual risk-taking, then our IV test may mistakenly attribute the effect of metropolitan to Hangzhou.

To distinguish the two effects, we compare the results for cities located within smaller radius around Hangzhou (HZ). The underlying assumption is that for cities located far from Hangzhou, distance to Hangzhou can be similar to distance to Shanghai. In contrast, for cities in a region close to Hangzhou and Shanghai, distance to Hangzhou and distance to Shanghai can be rather different. Panel A of Table 5 reports the results in the first stage regression in which FinTech adoption is regressed on Log(Distance) in a panel regression setting. In particular, columns (1), (2), (3) include a subsample of cities within 500km, 1000km, and 2000km radius from Hangzhou respectively, and column (4) include all cities. Columns (5) to (8) report the corresponding results using distance to Shanghai as the IV. These results confirm our observation that cities that are closer to Hangzhou have higher level of FinTech penetration due to the gradual spread of the promotion effort of Alipay as a new payment method.

In comparison, for the first-stage estimation using distance to Shanghai as the IV, the coefficients on Log(Distance) are only marginally significant. Moreover, within a small radium (500km) around Hangzhou, the coefficients on distance to Shanghai are statistically insignificant, and also have a much smaller magnitude. For example, focusing on the setting for cities within 500km radius, the coefficient on the log distance to Hangzhou in column (1) is -0.437 (t-stat=-3.99), whereas the coefficient on the log distance to Shanghai in column (5) is -0.129 (t-stat=-0.70). For the setting with all cities, the coefficient on the log distance to Hangzhou is -1.995 (t-stat=-2.16), which is similar to the corresponding coefficient on the log distance to Shanghai, -1.766 (t-stat=-1.77), in column (8). This contrast between Shanghai and Hangzhou is consistent with our intuition. For cities far from Hangzhou and Shanghai, their distance to these two cities are similar. Therefore, the coefficients on Log(Distance (to SH)) partially capture the effect of Log(Distance (to HZ)), and appear to be statistically significant. Within smaller circles, however, we find only distance to Hangzhou is related to FinTech adoption, whereas distance to Shanghai has no explanatory power.

In addition, cities near the eastern coast of China tend to have higher level of economic development than cites in the inner part of China. Therefore, we also include variables on city economic conditions and access to financial institutions, i.e. GDP, population, income and number of bank branches, as controls in the first stage regression. The coefficients on distance measures in Panel A of Table 5 capture the effect on top of these variables related to economic conditions.[26]

Moving to the second stage estimation in Panel B of Table 5, we examine the effect of

[26]In unreported analyses, we also conduct placebo tests using distance to the other three tier-one cities, Beijing, Shenzhen, and Guangzhou in the first stage regression. The regression coefficients on these distance measures are insignificant, confirming our observation of the geographical distribution pattern of FinTech penetration. The results are available upon request.

FinTech adoption on participation and risky share. For each risk-taking measure, we examine two regression settings: cities within a small circle around Hangzhou (500km) and all cites. Taking risky share as an example, one standard deviation increase in instrumented AliFrac for cities within 500 kilometers around Hangzhou predicts 4.1% increase in city-level risky share (= 3.94% × 1.04). For the setting with all cities as reported in column (4), one standard deviation increase in instrumented AliFrac predicts 1.16% increase in city-level risky share (= 4.6% × 0.25).[27] The IV estimation magnitude is comparable to that of city-level OLS estimations: Under OLS regressions, one standard deviation increase in city-level AliFrac is associated with 2.34% and 1.17% increase in city-level risky share for the 500km sample and the whole sample respectively. Using participation as the risk-taking measure, the results are consistent. In particular, one standard deviation increase in instrumented AliFrac leads to 2.55% (= 3.94% × 0.649) increase in participation rate for cities within the 500km circle around Hangzhou. The corresponding results for distance to Shanghai are reported in the right four columns for comparison. None of the coefficients on AliFrac are significant.

5 FinTech Inclusion and Welfare Implications

Our empirical results have so far shown that FinTech fosters financial inclusion – higher FinTech adoption is associated with higher risky participation and higher risk-taking. 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 evidences 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 live in cities under-served by the traditional financial infrastructure. Moving beyond the risk-taking measures, we also examine the efficiency of the investments on FinTech platforms, focusing on measures of Sharpe ratio and portfolio diversification.

5.1 Benefits of FinTech Inclusion for High Risk-Tolerant Investors

As FinTech expands its sphere of influence and includes more investors onto its platforms, who benefits more from this FinTech inclusion? Does the improvement in risk-taking align with the prediction of financial theory? In this section, we focus on the dimension of risk

[27]Instrumented city-level AliFrac has a standard deviation of 3.94% and 4.6% for the 500km sample and the whole sample respectively. For the uninstrumented city-level AliFrac, the corresponding standard deviation is 7.4 and 9.2 respectively.

aversion, which, according to financial theory, is the sole characteristics differentiating one investor's risk-taking from that of another. As a general result, more risk-tolerant individuals invest more in risky asset. 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 his 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. 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. Conversely, 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 the 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 for Risk Tolerance

Measuring individual-level risk aversion has always been an important and yet daunting task in the literature of household portfolio choice. One standard approach of eliciting risk aversion is through lottery-type questions. The reliability of the survey data and their connection to investors' risk-taking have yet to be established (e.g., Ameriks, Kézdi, Lee, and Shapiro (2020)). Conversely, the literature has approached the task by inferring individual-level risk aversion through their risk-taking behavior. In a recent paper, Calvet et al. (2021) estimate the cross-sectional distribution of preference parameters, including the relative risk-aversion coefficient, using a large administrative panel of Swedish households. Key to their estimation of the risk-aversion coefficient is the households' wealth and portfolio choice. The heterogeneity in portfolio choice has also been studied by Meeuwis, Parker, Schoar, and Simester (2018) and Giglio et al. (2021) via the connection between the observed risk-taking behavior and the cross-individual variation in preferences and beliefs.

One unique feature of our data is that it allows us to track both the consumption and investment behaviors of the same individual. Taking advantage of the consumption side of the data, we can use the individual-level consumption 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 to 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 validate the effectiveness of σ_{C} as a proxy for risk aversion in two dimensions. First, examining the cross-sectional determinants of σ_{C} in Table A1, we find that male and young investors on average have higher σ_{C}, consistent with the perception that such investors are relatively more risk tolerant. Second, we find that although consumption and risk-taking occur in two different platforms, one on Taobao and the other on the Ant platform, there is, however, a significant connection between the two. Consistent with our hypothesis that σ_{C} is a good proxy for risk tolerance, individuals with higher σ_{C} exhibit higher levels of financial risk-taking. As shown in Table 4, a one standard deviation increase in consumption growth volatility is associated with 1.48% ($= 0.4 \times 0.037\%$) increase in risky fund participation, 2.08% ($= 0.4 \times 0.0519\%$) increase in risky share, and 0.138% ($= 0.4 \times 0.345\%$) increase in portfolio monthly return volatility. Controlling for individual gender, age, and consumption level reduces the effect of consumption growth volatility on individual risk-taking by half approximately, but the positive relation remains significant.

The positive connection between σ_{C} and risk-taking can be further illustrated in the left panels of Figure 5. We sort individuals in our sample by their consumption volatility into 50 groups, and compute the average consumption volatility, risky participation rate, and portfolio volatility for each group. As shown in the left panels of Figure 5, there is a rather strong relation between consumption volatility and the two risk-taking measures. As indicated in the fitted lines, regressing the participation rate on the consumption volatility across the 50 groups, the coefficient is 4.64 (t-stat=7.07) and the R-squared is 51%; regressing portfolio volatility on consumption volatility, the coefficient is 0.39 (t-stat=9.02) and the R-squared is 62%. Overall, the empirical evidence is consistent with the interpretation that consumption growth volatility reveals the risk tolerance of investors, and this measure contains additional information above and beyond the other observable investor characteristics such as gender, age, and consumption level.

FinTech Adoption and Risk-Taking, Conditioning on Risk Tolerance

Who benefits more from FinTech inclusion? To answer this question, we examine the relation between FinTech adoption and risk-taking by conditioning on investor characteristics. As previously discussed, the characteristics of first-order importance in household portfolio choice is risk tolerance, which we proxy by individual-level consumption volatility. In addition to σ_{C}, other individual characteristics such as gender, age, and wealth are also used as conditioning variables in this section to proxy for risk aversion. The results are summarized in Table 6.

Focusing first on risky participation, we see that the coefficient for the interaction term between AliFrac and σ_{C} is positive and statistically significant, indicating that FinTech adoption indeed increases risky participation 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 the FinTech inclusion. In addition to consumption volatility, Table 6 further examines the relation between FinTech adoption and risky participation, conditioning on other investor characteristics. It shows that the effect of FinTech adoption on risky participation is significantly more pronounced for investors with higher consumption level (i.e., wealthier investors), as well as for young and male investors. Consistent with our intuition and the findings in the literature, such investors in general are less risk averse, and these additional results further confirm our hypothesis that investors with higher risk tolerance benefit more from the FinTech inclusion.

It is also interesting to see that the interaction term for AliFrac and σ_{C} reduces in magnitude and statistical significance after the interactions with the additional characteristics are included in the regression. This is consistent with the fact 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.

In addition to risky participation, Table 6 also reports the result for the other two risk-taking measures of risky share and portfolio volatility. The results for portfolio volatility are similar to those of risky participation, especially when σ_{C} is used as a proxy for risk tolerance. Among the other characteristics, age remains important while gender and consumption level become insignificant. The results for risky share are weaker. Given that both risky share and portfolio volatility measure the extent of risk-taking conditioning on participation, the relative weaker results for risky share can possibly be explained by investors with higher FinTech adoption moving within the risky funds, from those of lower risk to higher risk, while keeping risky share at the same level.

Welfare Gains for High Risk-Tolerant Investors

In addition to the regression setting, our findings can be summarized most concisely by the right panels of Figure 5. We double sort individuals in our sample by their AliFrac and σ_{C} into $25 \times 2 = 50$ groups. The top right panel of Figure 5 plots the relation between risky participation and FinTech adoption for each group. The blue dots are for those with high σ_{C} (i.e., high risk tolerance), while the green squares are for low σ_{C}. The bottom right panel repeat the same analysis for portfolio volatility.

In both cases, it is evident that the benefits of FinTech inclusion are stronger for the investors with higher risk tolerance. For two investors of the same level of FinTech adoption, the more risk-tolerant investor participates more in risky asset and, conditioning on participation, his/her risky exposure (i.e., portfolio volatility) is also higher. According to the financial theory summarized in Equation (1), this gap in risk-taking is exactly what we expect to see: higher risk-tolerant investors take on more risk to enhance their utility. But what is interesting is that, in both plots, the gap is relatively small when the investors' FinTech adoption level is low. In other words, when the FinTech adoption level is low, the high risk-tolerant investors behave not that differently than their low risk-tolerant counterparts. This, of course, is counter to financial theory and speaks to the fact that such high risk-tolerant investors are constrained and their utility not optimized. With the increase in FinTech adoption, however, this gap in risk-taking widens, indicating that, with the increase in FinTech adoption, such high risk-tolerant investors are less constrained and their welfare improved.

5.2 Benefits of FinTech Inclusion for Under-Banked Cities

The benefits of FinTech inclusion are without any doubt stronger for individuals underserved by the traditional financial infrastructures. As reviewed by Suri (2017), mobile money in developing economies has allowed individuals without bank accounts to digitally transact money. Households in Kenya, with the help of digital loans, are able to enhance their financial resiliency to shocks (Suri, Bharadwaj, and Jack (2021)). Motivated by this important trend, we examine the benefits of FinTech inclusion across Chinese cities with varying levels of financial services. Before the development of FinTech platforms, banks are the predominant distribution channel of mutual funds. As a result, investors living in areas with fewer bank branches have limited access as well as limited exposures to mutual fund investments. Based on these observations, our hypothesis is that investors living in such under-banked cities, who are otherwise more constrained prior to the arrival of FinTech platforms, would benefit more from FinTech inclusion.

Measuring City-Level Bank Coverage and FinTech Penetration

To capture city-level FinTech penetration, we start with the individual-level AliFrac and aggregate them to the city level, based on individuals' residency. As the local merchants across different cities in China gradually adopt the Alipay scan-to-pay QR code, the cross-city as well as time-series variation in AliFrac is thus developed, which can be viewed vividly in the penetration maps displayed in Figure 2. Figure A2 further plots the changes in city-level AliFrac between 2018 and 2017. Different from the level plot, which darkens along the coastal areas near Shanghai and Hangzhou, those cities experiencing the highest improvement in FinTech penetration from 2017 to 2018 are in fact away from the coastal areas. Overall, the richness of the cross-city variations in FinTech penetration and bank coverage provide a fertile ground for us to study the benefits of FinTech inclusion.

We measure the city-level bank coverage by the number of bank branches in each city. Figure A3 plots the geographic distribution of banking coverage in each city. Comparing the bank-coverage map against the FinTech penetration maps in Figure 2, we can see that the distribution of bank coverage is uniquely different from that of AliFrac. Moreover, as the number of bank branches in each city is itself an endogenous variable influenced by the economic and demographic conditions for each city, we use the city-level GDP, population, and income per capita as controls in our analysis. The first-tier cities of Beijing, Shanghai, Guangzhou, and Shenzhen have also been singled out as a unique group in our analysis given their mega-city status.

FinTech Penetration and Risk-Taking, Conditioning on Bank Coverage

Do individuals living in under-banked cities benefit more from FinTech inclusion? To answer this question, we examine the impact of FinTech penetration on risk-taking, conditioning on bank coverage, and the results are summarized in Table 7. As expected from our previous analyses, unconditionally, there is a positive and significant relation between risk-taking and AliFrac, controlling for city-level characteristics including number of bank branches, GDP, population, income, and tier-one city dummy. Overall, the unconditional results reported in Table 7 are comparable in magnitude and statistical significance to the results in Table 5 using the instrument-variable approach.

The more interesting results emerge as we examine the benefits of FinTech inclusion conditioning on bank coverage (i.e., Log(BB)). In particular, the coefficients on interaction term of AliFrac and Log(BB) are negative (although the coefficient for participation is not significant), indicating that the increase in risk-taking associated with FinTech penetration is stronger for cities with low-bank coverage. Taking the estimation for risky share as an example, when the AliFrac of an average city increases from 0 to 0.1, it drives up the local individual risky share by 2.54% (t-stat=1.89). For a city whose bank coverage log(BB) is one standard deviation below the mean, the same one unit increase in AliFrac would increase risky share by an extra 5.46% (t-stat=4.26).[28] Adding these two numbers together, an 10% increase in AliFrac increases risky share by 8.0% for such a one-std below average city. In other words, the benefits of FinTech inclusion is more significant, both statistically and economically, for individuals living in under-banked cities.

In addition to the regression setting, Figure 6 provides a more intuitive demonstration of our results. In the top panel, each city's risky share is plotted against its AliFrac. The 287 cities are further divided into two groups according to their bank coverage – the below-median cities plotted in red stars and above-median cities in orange circles. The solid fitted line indicates that among cities with low bank coverage, a 10% increase in city-level AliFrac increases risky share by 5.7% (t-stat=2.62). By contrast, the FinTech benefits among cities with high bank coverage are close to zero. In other words, the benefit of FinTech inclusion comes mostly from cities less served by banks.

Even more stark are the results demonstrated by the bottom panel of Figure 6, where changes in risk-taking are plotted against changes in FinTech penetration. As discussed earlier, the cross-city variation in FinTech penetration has a dynamic aspect. From 2017 to 2018, when the speed of FinTech penetration is the fastest, those cities experiencing the highest improvement in FinTech penetration are in fact away from the affluent coastal areas, where FinTech penetration is in general very high. As such, ΔAliFrac, which measures the changes in FinTech penetration, contains information that is different from the level of AliFrac. For under-banked cities, which are less affluent and located toward inner China, the information embedded in ΔAliFrac could be more valuable. This is indeed the case. Examining the relation between changes in risky share and ΔAliFrac, we see a positive and significant relation for cities with low bank coverage: a 1% increase in ΔAliFrac leads to a 2.33% (t-stat=2.82) increase in risky share.[29] For cities with above-median bank coverage, however, the relation has in fact turned negative, although the economic as well as statistical significance of the relation is weak. Again, at the city level, the benefits of FinTech inclusion are captured mostly by the under-banked cities.

Performing the same analysis using the regression setting, the right panel of Table 7 provides similar evidence. The interactions between ΔAliFrac and Log(BB) are significantly

[28]For ease of interpretation, the city-level control variables, with the exception of AliFrac, have all been normalized to have zero mean and standard deviation of one. The cross-city standard deviation of AliFrac is 0.092, close to the 0.1 number used in the above calculation.

[29]As shown in the bottom panel of Figure 6, large cross-city variations in ΔAliFrac exist for both the below-median cities (red stars) and the above-median cities (orange circles), with the cross-city standard deviation larger for the under-banked cities (1.66%) than the above-median cities (1.03%).

negative and they even subsume the effect of ΔAliFrac itself, indicating that individuals living in under-banked cities contribute in an important way to the positive findings between city-level FinTech penetration and risk-taking. Our approach of examining the relation using changes in addition to levels can help address the potential endogeneity concern over the city-level AliFrac, which could be influenced by the city-level economic and demographic conditions. By focusing on the changes in risk-taking over the 2017-2018 period, we dampen the influence of the low-frequency city-level characteristics on risk-taking and allow the information contained in ΔAliFrac to do the heavy lifting in explaining the changes in risk-taking.

5.3 FinTech Inclusion: Zero-Sum or Welfare Improving?

FinTech inclusion can take place through two channels. One is at the expense of the existing financial infrastructure. Because of the conveniences offered by the large FinTech platforms, individuals may reallocate their existing investment from the traditional channels onto FinTech platforms. In such a zero-sum scenario, the overall financial inclusion for the society remains unchanged. To the extent that investors can access a broader coverage of mutual funds on the same platform, paying lower transaction costs and enjoying technological convenience, there are some improvements in investor welfare, but the overall scope of welfare improvement is rather limited.

The second and truly welfare improving channel takes place when the penetration of technology opens the door for individuals who are unaware of financial investment opportunities and would otherwise remain unbanked. This is financial inclusion in the real sense of the word. For FinTech platforms to have a bright future in our society, it is imperative that FinTech platforms can help lower the physical as well as psychological costs of financial market participation. From this perspective, the empirical evidences so far summarized in this section on the heterogeneous benefits of FinTech inclusion are of great importance. The fact that the benefits of FinTech inclusion are stronger for individuals who are otherwise more constrained — individuals with more risk-taking capacity and individuals under-served by banks, provides a compelling evidence for the welfare-improving channel.

To enrich the finding that FinTech improves risk-taking for individuals who needs it the most and add more granular support for the welfare-improving channel, this section focuses directly on the population of individuals living in under-banked cities, and compare and contrast them against those living in cities with high bank coverage.

The Under-Banked Population

Out of the 28,393 active investors in our sample, there are 4,053 individuals living in cities 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 cities. We pair each of the 4,053 individuals with a counterpart living in cities with above-median bank coverage, requiring the pair to be of the same gender, born in the same year, and have the closest values in consumption level and consumption volatility. Panel A of Table 8 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 under high-bank coverage, the matching is quite effective and the distributions of these two samples are very close.[30]

Using these two matching samples, we compare and contrast the impact of AliFrac on risky share between the low- and high-bank groups. Focusing first on the level of risky share, the results in Panel B of Table 8 show that the impact of AliFrac is significant for both groups, indicating the importance of FinTech adoption on individuals' risk-taking behavior. The magnitude of AliFrac's importance, however, varies between the two groups – the regression coefficient is 0.183 (t-stat=4.87) for the low-bank sample and 0.148 (t-stat=2.91) for the high-bank group. Similar to the city-level results, the benefits of FinTech inclusion are stronger in magnitude as well as statistical significance for the under-banked individuals. Focusing on the change in risky share, the contrast is stronger and more apparent. As shown in Panel B of Table 8, the impact of ΔAliFrac on changes in risky share is positive and significant for the low-bank group, but not for the high-bank group. A formal test of the difference is positive and significant, indicating that the gradual penetration of FinTech from 2017 to 2018 of FinTech mainly improves the risk-taking for the under-banked individuals.

Segments of the Under-Banked Population

Taking advantage of the two matching samples, we can further investigate which under-banked populations benefit more from FinTech inclusion. For example, do matured individuals living in under-banked cities react to FinTech advancement differently from their high-bank counterpart? As shown in Panel C of Table 8, the answer is yes. Compared

[30] AliFrac is not used as a matching variable because the absolute level of AliFrac is not comparable between these two groups of individuals. As reported in Table 8, the low-bank coverage sample on average has lower AliFrac but higher ΔAliFrac than their high-bank matching sample. This is consistent with the fact that the low-bank coverage cities, located away from the coastal area and toward the inner China, tend to have lower levels of AliFrac but high levels of ΔAliFrac, as the QR-Scan payment spreads gradually from coastal to inner China from 2017 to 2018. Given the importance of cross-individual variation in our analysis, it should be mentioned that the standard deviations of AliFrac and ΔAliFrac are close between the two samples.

with young investors, mature investors, age 30 and above, have higher investment capacities and needs. Living in cities with high-bank coverage, such mature investors can invest in mutual funds via the traditional channels such as banks, but their counterparts living in cities 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 counterpart. This is indeed what we find. For mature individuals, the coefficient of risk-taking on AliFrac is 0.192 (t-stat=3.85) for the low-bank group, much larger in magnitude and statistical significance than the coefficient of 0.048 (t-stat=0.79) for the high-bank group, indicating stronger benefits of FinTech inclusion for under-banked individuals with stronger investment needs.

Another important dimension is via risk tolerance, proxied by σ_{C}. As shown in Section 5.1, the benefits of FinTech inclusion are higher for individuals with higher risk tolerance, as, prior to the arrival of FinTech platforms, the more risk-tolerant investors are more constrained. Compounding this effect with bank coverage, those high risk-tolerant investors living in cities with low-bank coverage are more constrained than their high-bank counterpart. The results in Panel C of Table 8 is strongly supportive of this hypothesis. For investors with high σ_{C}, the coefficient of risk-taking on AliFrac is 0.242 (t-stat=4.64) for the low-bank group, while that for the high-bank group is 0.058 (t-stat=0.80), indicating the benefits of FinTech inclusion to be strongest for those high risk-tolerant investors under-served by the traditional financial infrastructure.

5.4 Investment Efficiency and Portfolio Diversification

Given the positive risk premium offered by risky asset classes, non-participation is clearly sub-optimal for households of any levels of risk aversion. But in addition to non-participation, welfare costs could also incur due to the investment mistakes made by households. Investigating the investment efficiency of Swedish households, Calvet, Campbell, and Sodini (2007) show that the return cost of non-participation is smaller by almost one-half when taking account of the fact that non-participants would likely be inefficient investors. Motivated by this important observation, we study the investment efficiency for investors in our sample and examine its connection to individual-level FinTech adoption.

Investment Opportunity: Six Risky Asset Classes

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. Unlike the comprehensive data used by Calvet, Campbell, and Sodini (2007), we do not have the entire portfolio of our investors. To the extent that we can talk about investment efficiency, it is within the scope of their investments on the Ant investment platform. We evaluate the investment efficiency by taking into account of each individual's portfolio choice on the six risky assets. In terms of performance, we use the means and variances estimated at the level of the mutual-fund categories. Using data from January 2005 to May 2019, Panel A of Table 9 reports the monthly average means and standard deviations, using the aggregate performances of the six mutual-fund categories.

Effectively, investors in our sample have access to six risky asset classes, with equity offering high risk (7.32% monthly volatility) and high return (1.37% average mean); bond offering low risk (1.12% monthly volatility) and low return (0.54% average mean); and the mixed category in between equity and bond. Panel A of Table 9 further reports the correlations between these six risky asset classes. Not surprising, the equity, mixed, and index are highly correlated, but what's surprising is that even the bond category has a correlation of 61% with the equity. The most intriguing category for our analysis is gold, which correlates the least with the other asset classes, yields relatively low returns, and is of relatively high volatility. And yet, as shown in Panel A, investors on the Ant platform hold about 10% of their risky investments on gold, compared with 0.6% held by the market-wide retail investors during the same time period.

Participation by Asset Class

The propensity of risky participation in each asset class is analyzed in Panel B of Table 9. Similar to our main results, FinTech adoption has positive and significant impact on the participation of all six risky assets. But the magnitude of the impact varies across the asset classes. Participation in the mixed category is the most sensitive to FinTech adoption with a coefficient of 0.149 on AliFrac, indicating that an increase of AliFrac from 0 to 1 corresponds to an increase of 14.9% in the participation rate of the mixed category. This result is to be expected, given that mixed mutual funds are of the largest category, accounting for 65% of the total mutual fund holdings by retail investors. But what is unusual is the FinTech impact on gold participation, whose overall market share is a mere 0.6% for all retail investors. And yet an increase of AliFrac from 0 to 1 corresponds to an increase of 14% in gold participation.

The cross-individual relation between participation and σ_{C} exhibits a rather interesting pattern. For equity, mixed, index, and QDII, which are essentially equity investments, participation is positive related to σ_{C}, indicating that more risk tolerant investors indeed have a higher participation rate in such risky assets. For bond and gold, however, the relation between participation and σ_{C} is small in magnitude and statistically insignificant, and the point estimate for gold is negative. These results indicate that the participation motives could be different across the various asset classes, which in turn could affect how we interpret the investment efficiency results.

Portfolio Diversification

We start with measuring each individual i's portfolio variance, σ_i^2, calculated using the individual's portfolio weights w_i on the six risky asset classes and the variance-covariance matrix, Σ, estimated using monthly data from 2005 to 2019. Specifically,

$$\sigma_i^2 = w_i^{'}\,\Sigma\,w_i$$

We then compare σ_i^2 against a hypothetical variance $\sigma_{i,B}^2$, calculated with the assumption that there is no diversification benefit across the six asset classes (i.e., the cross-asset correlation is 1). The percentage difference between the two variance measures, $1 - \sigma_i^2/\sigma_{i,B}^2$, therefore captures the benefit of diversification across the multiple assets.

Overall, we find that investors with higher FinTech adoption tend to invest in more asset classes and more diversified. As reported in Panel B of Table 9, the individual-level variance reduction is positively related to AliFrac. For example, one unit increase in AliFrac leads to 3.8% (t-stat=9.77) in variance reduction. In terms of the effect of individual characteristics, we also find that individuals who are younger, male, with higher level of consumption are also more diversified. Dividing the sample by risky share and consumption volatility, respectively, into high and low, we find similar results. Within the samples of individuals with high risky share and high risk tolerance (i.e., high σ_{C}), the connection between FinTech adoption and portfolio diversification is slightly larger, although the difference is not very strong. Overall, we observe a uniformly positive effect of AliFrac on diversification benefit across different individuals, consistent with the possibility that individuals with more FinTech adoption, through their repeated usages on the FinTech platform, explore and invest in more asset classes on the FinTech platforms.

Portfolio Sharpe Ratio

To compute the Sharpe ratio of each individual's portfolio, we use the actual portfolio weights of the individual on the six asset classes. For performance, as reported in Panel A of Table 9, we use the longer time-series data from January 2005 to May 2019 to estimate the expected returns and variance-covariance matrix of the six risky asset classes and the one-year deposit rate is used as the risk-free rate.[31]

[31] 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

Overall, we find a positive and significant relation between AliFrac and Sharpe ratio, indicating that the investment efficiency is higher for investors with more FinTech adoption (Panel C of Table 9). This improvement in Sharpe ratio, however, comes mainly from the sample of low risky share individuals, which includes individuals with zero risky participation. Effectively, to participate or not is the main driver behind the improvement in Sharpe ratio – as individuals with more FinTech adoption choose to participate, their Sharpe ratios increase relative to the low AliFrac individuals who choose not to participate. This finding is consistent with the important observation in the household finance literature that, given the positive risk premium of risky assets, participation is welfare improving for investors of any levels of risk aversion.

As documented by Calvet, Campbell, and Sodini (2007), mistakes made by investors could dampen the welfare improvement associated with participation. For the population with high risky share, we find some evidence of this dampening effect. As shown in Panel C of Table 9, within the sample of high risky share investors, higher AliFrac does not result in higher Sharpe ratio, and the relation is in fact negative though with a small economic magnitude. As discussed earlier, investors on the Ant platform hold about 10% of their investment in gold, while the market-wide holding in gold mutual funds is a mere 0.6%, Moreover, as reported earlier, gold participation is highly sensitive to AliFrac, indicating that there is a population of investors with high FinTech adoption who like to invest in gold mutual funds. At the same time, compared with other assets, the risk-return tradeoff for gold mutual funds is relatively poor and the Sharpe ratio low. From the perspective of mean-variance optimization, this result speaks negatively to investment efficiency, indicating that investors on FinTech platforms have yet to reach their optimal portfolio choice.[32]

6 Conclusions

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. Using account-level data from Ant Group, our paper is among the first to offer empirical evidences

performance.

[32]The rationality behind the allocation to gold could be open for more discussion. For example, without any access to inflation-protected securities, such individuals might invest in gold mutual funds with the belief that gold is an effective inflation hedge. This hedging motive is also consistent with the early observation that, while more risk tolerant investors (i.e., σ_C), are found to have higher participation rates in equity and mixed mutual funds, they do not invest more in gold mutual funds. In fact, the relation between participation in gold and σ_C is negative, indicating that more risk-adverse investors tend to invest more in gold.

of how FinTech adoption can alleviate behavioral biases and improve household risk-taking.

As with any new technologies, a dark side always accompanies the bright side, and FinTech innovations are no exception. They have the potential to alleviate as well as exacerbate behavioral biases. 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 (2019) 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 investors heuristics to chase top-performing mutual funds.

Against this backdrop, the bright side of FinTech innovations documented in our paper pushes the literature toward a more comprehensive understanding of the FinTech revolution. Unlike the traditional financial institutions, one distinct feature of FinTech in China and other emerging markets is the integration of financial 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 against risky investment. Despite the extensive concerns over the monopoly power of big FinTech platforms, improving risky asset participation is one area where such an integrated model is indeed desirable. This is especially true for households under-served by the existing financial infrastructures, whose financial literacy could also be limited. For such individuals, the advent of FinTech remains the most efficient channel to optimal risk-taking.

The above discussions point to the multifaceted nature of the FinTech revolution. For FinTech regulations to be welfare-improving, 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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Table 1. Summary Statistics on Individual Characteristics

Panel A shows the characteristics for the randomly selected 50,000 individuals in our entire sample. Panel B and C show the distributions and correlations for the characteristic variables of 28,393 active users in our sample. Active users are investors who have ever made at least 100 RMB purchase of funds (including both money-market funds(MMF) and non-MMF) on the Ant platform. Age is the investor's age at 2019. Female is a dummy that equals one for female investors. Consumption (C) is the average monthly consumption in RMB via Taobao platform. Consumption growth volatility (σ_C) is the standard deviation of change in the natural logarithm of monthly Taobao consumption. Consumption in January and February are combined as one month following standard consumption calculation method for the Chinese data. Our FinTech adoption measure, AliFrac, is the fraction of consumption paid via Alipay out of total consumption paid via Alipay and Taobao. An alternative FinTech adoption measure, Log(AliCnt), is the natural logarithm of number of Alipay payments made in an average month. We also report information for ΔAliFrac and ΔLog(AliCnt), calculated as the average AliFrac and Log(AliCnt) in 2018 minus that of 2017 respectively. For individual risk-taking, we use three measures: Participate is a dummy variable that equals one for individuals who have ever made at least 100 RMB purchase of risky mutual funds (non-MMF) on Ant platform; Risky Share, is the average fraction of investment in non-MMF assets for an individual; Portfolio volatility (σ_W) is the standard deviation of individuals' portfolio monthly returns in percent.

Panel A. Summary Statistics for All Users (50,000 Users)

	Female	Age	Consumption	σ_C	AliFrac	Log(AliCnt)	ΔAliFrac	ΔLog(AliCnt)	Participate
Mean	0.61	30.4	2,155	1.21	0.54	3.01	0.08	0.59	0.375
Median	1.00	29.0	1,259	1.16	0.56	3.08	0.07	0.53	0.000
Std.	0.49	7.8	17,063	0.40	0.22	0.84	0.22	0.67	0.484

Panel B. Summary Statistics for Active Users (> 100 RMB Purchase, 28,393 Users)

	Female	Age	Consumption	σ_C	AliFrac	Log(AliCnt)	ΔAliFrac	ΔLog(AliCnt)	Participate	Risky Share	σ_W(%)
Mean	0.61	31.1	2,292	1.21	0.55	3.05	0.08	0.62	0.66	0.45	1.77
Median	1.00	30.0	1,396	1.16	0.57	3.12	0.07	0.54	1.00	0.15	0.18
Std	0.49	7.8	4,732	0.40	0.22	0.83	0.17	0.76	0.47	0.47	2.97
Q1	0.00	25.0	818	0.92	0.40	2.52	-0.03	0.16	0.00	0.00	0.00
Q3	1.00	35.0	2,480	1.44	0.72	3.65	0.18	1.01	1.00	1.00	2.69

Panel C. Correlations Among Key Variables (Active-User Sample)

	Female	Age	Log(C)	σ_{C}	AliFrac	Log(AliCnt)	ΔAliFrac	ΔLog(AliCnt)	Participate	Risky Share	σ_{W}(%)
Female	1.00	0.00	0.04	-0.28	-0.14	-0.10	-0.05	-0.01	-0.13	-0.12	-0.10
Log(Age)	0.00	1.00	0.13	-0.05	-0.08	-0.23	0.15	0.19	-0.13	-0.09	-0.07
Log(C)	0.04	0.13	1.00	-0.09	-0.41	0.12	-0.12	-0.11	0.00	0.01	0.01
σ_{C}	-0.28	-0.05	-0.09	1.00	0.13	0.05	0.00	-0.03	0.06	0.05	0.05
AliFrac	-0.14	-0.08	-0.41	0.13	1.00	0.52	0.13	-0.08	0.06	0.06	0.03
Log(AliCnt)	-0.10	-0.23	0.12	0.05	0.52	1.00	0.00	-0.08	0.13	0.13	0.09
ΔAliFrac	-0.05	0.15	-0.12	0.00	0.13	0.00	1.00	0.56	-0.02	-0.01	0.00
ΔLog(AliCnt)	-0.01	0.19	-0.11	-0.03	-0.08	-0.08	0.56	1.00	-0.04	-0.04	-0.01
Participate	0.13	-0.13	0.00	0.06	0.06	0.13	-0.02	-0.04	1.00	0.59	0.39
Risky Share	-0.12	-0.09	0.01	0.05	0.06	0.13	-0.01	-0.04	0.59	1.00	0.62
σ_{W}(%)	-0.10	-0.07	0.01	0.05	0.03	0.09	0.00	-0.01	0.39	0.62	1.00

Table 2. Summary Statistics on Investment

Panel A and B report the distribution and correlation statistics of detailed investment variables for the sample of active users. Active users are the 28,393 investors who have ever made at least 100 RMB purchase of funds (including both MMF and non-MMF) on Ant platform. Apart from the three risk-taking measures as defined in Table 1, we also include: investor's total purchase amount in RMB ($Invested); number of unique months in which the investor has trades for the total 27 months from 2017 January to 2019 March (#TradeMonth); number of unique asset classes (MMF, Bond, Mixed, Equity, Index, QDII, Gold) that the investor has invested in (#Assets); number of unique funds the investor invested in our sample period (#Funds), and the average trade size per purchase ($TradeSize).

Panel A. Summary Statistics

	Participate	Risky Share	σ_W(%)	$Invested	#TradeMonth	#Trades	#Assets	#Funds	$TradeSize
Mean	0.66	0.45	1.77	41,079	3.11	8.92	1.93	3.71	4,557
Median	1.00	0.15	0.18	3,010	2.00	3.00	1.00	2.00	696
Std.	0.47	0.47	2.97	415,030	3.20	44.50	1.30	5.85	13,797
Q1	0.00	0.00	0.00	460	1.00	1.00	1.00	1.00	99
Q3	1.00	1.00	2.69	20,000	4.00	7.00	3.00	4.00	4,533

Panel B. Correlation

	Participate	Risky Share	σ_W(%)	Log($Invested)	#TradeMonth	#Trades	#Assets	#Funds	Log($TradeSize)
Participate	1.00	0.59	0.39	-0.10	0.20	0.25	0.49	0.24	-0.21
Risky Share	0.59	1.00	0.62	-0.13	0.13	0.16	0.30	0.17	-0.18
σ_W	0.39	0.62	1.00	0.01	0.19	0.22	0.31	0.21	-0.11
Log($Invested)	-0.10	-0.13	0.01	1.00	0.49	0.54	0.26	0.32	0.42
#TradeMonth	0.20	0.13	0.19	0.49	1.00	0.86	0.60	0.60	0.01
Log(#Trades)	0.25	0.16	0.22	0.54	0.86	1.00	0.67	0.64	0.01
#Assets	0.49	0.30	0.31	0.26	0.60	0.67	1.00	0.63	-0.10
#Funds	0.24	0.17	0.21	0.32	0.60	0.64	0.63	1.00	-0.03
Log($TradeSize)	-0.21	-0.18	-0.11	0.42	0.01	0.01	-0.10	-0.03	1.00

Table 3. Determinants of FinTech Adoption

This table reports the determinants of FinTech adoption. Columns (1) to (4) report the results for the level of FinTech adoption (AliFrac) and columns (5) to (8) report the results for the change in FinTech adoption from year 2017 to 2018 (ΔAliFrac). AliFrac is defined as the fraction of consumption paid via Alipay out of total consumption paid via Alipay and Taobao. We regress the (change in) FinTech adoption measure on individual and city characteristics. Consumption growth volatility (σ_C) is calculated as the standard deviation of change in monthly Log(C). Log(C) is the natural logarithm of monthly online consumption on Taobao. Other individual characteristics include gender and age. For city-level characteristics, we include city GDP, income per person, population, and number of traditional banks. We also control for Citylevel=1, which is a dummy variable that equals one for Beijing, Shanghai, Guangzhou, Shenzhen, and zero otherwise. We include city fixed effects as indicated. Standard errors are clustered at the city level. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

	AliFrac				**ΔAliFrac**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All Users		Active Users		All Users		Active Users	
σ_C	0.032***	0.034***	0.033***	0.035***	-0.010***	-0.010***	-0.008***	-0.009***
	(11.13)	(12.31)	(9.47)	(10.52)	(-3.87)	(-3.77)	(-2.43)	(-2.55)
Log(C)	-0.104***	-0.107***	-0.107***	-0.109***	-0.026***	-0.026***	-0.023***	-0.022***
	(-81.59)	(-94.95)	(-72.19)	(-80.70)	(-18.29)	(-18.19)	(-12.74)	(-12.57)
Female	-0.054***	-0.050***	-0.055***	-0.051***	-0.016***	-0.016***	-0.017***	-0.017***
	(-16.95)	(-16.18)	(-16.00)	(-15.21)	(-6.79)	(-6.86)	(-5-41)	(-5.61)
Log(Age)	0.000	-0.002	-0.015	-0.017*	0.102***	0.101***	0.103***	0.102***
	(0.03)	(-0.27)	(-1.61)	(-1.86)	(16.32)	(16.26)	(14.90)	(14.78)
Log(GDP)	0.023**		0.022**		-0.004		-0.009**	
	(2.50)		(2.18)		(-1.61)		(-2.54)	
Log(Income)	0.029***		0.029***		-0.005***		-0.005**	
	(4.32)		(4.45)		(-3.24)		(-2.55)	
Log(Population)	0.006		0.005		0.002		0.001	
	(0.90)		(0.71)		(1.10)		(0.61)	
Log(#Branch)	-0.003		-0.004		-0.006**		0.002	
	(-0.35)		(-0.34)		(-2.10)		(0.45)	
Citylevel=1	-0.059**		-0.059**		0.005		0.003	
	(-2.50)		(-2.65)		(1.31)		(0.68)	
City FE	N	Y	N	Y	N	Y	N	Y
Adjusted R^2	0.210	0.208	0.230	0.230	0.021	0.021	0.019	0.019
N	49,087	50,000	27,886	28,393	49,087	50,000	27,886	28,393

Table 4. Individual FinTech Adoption and Risk-Taking

Panel A reports the cross-sectional regression estimates of individuals' risk taking on AliFrac and controls. Columns (1) to (3) report the results for risky fund participation, where participation is defined as having at least 100 RMB purchase of non-MMF mutual funds on platform. Columns (4) to (6) report the estimations for portfolio risky share, which is defined as the fraction of holdings invested in risky mutual funds ($= 1 - \text{MMF/Total}$). Columns (7) to (9) report the estimations for portfolio volatility (σ_{W}), calculated as the individual monthly portfolio return standard deviation in percent. AliFrac is defined as the fraction of consumption paid via Alipay out of total consumption paid via Alipay and Taobao. The control variables include individual personal characteristics: consumption growth volatility (σ_{C}), consumption level, female, and log(age). Log(C) is the natural logarithm of monthly online consumption on Taobao. Consumption growth volatility (σ_{C}) is calculated as the standard deviation of change in monthly Log(C). We include city fixed effects as indicated. Standard errors are clustered at the city level. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Panel A. FinTech Adoption and Risk-Taking

	Participate			Risky Share			σ_{W}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AliFrac	0.136***	0.127***	0.239***	0.140***	0.131***	0.146***	0.522***	0.431***	0.446***
	(11.50)	(10.47)	(17.94)	(8.64)	(7.65)	(7.80)	(5.79)	(4.76)	(4.59)
σ_{C}		0.037***	0.019***		0.0519***	0.018***		0.345***	0.163***
		(7.37)	(3.69)		(7.87)	(2.72)		(8.43)	(4.07)
Log(C)			0.076***			0.031***			0.128***
			(30.06)			(9.03)			(5.46)
Female			-0.067***			-0.102***			-0.542***
			(-12.24)			(-15.12)			(-15.52)
Log(Age)			0.007			-0.171***			-0.861***
			(0.57)			(-11.11)			(-10.50)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.004	0.004	0.024	0.004	0.006	0.025	0.001	0.004	0.016
N	50,000	50,000	50,000	28,393	28,393	28,393	28,393	28,393	28,393

Panel B reports the individual-month panel regression estimates with fixed effects as indicated. For each individual and for each month, we calculate their monthly AliFrac as their consumption paid via Alipay out of total consumption in that month. Risky share and participation are constructed based on the investment data of each specific month. We define the person-month as participate for the months on and after his/her first purchase of non-money market mutual funds. Standard errors are double clustered at the individual and month levels. Panel C shows the relation between change in individual FinTech adoption and change in risk taking. Change in FinTech adoption (ΔAliFrac) is calculated as the difference of Alipay consumption out of total consumption from year 2017 to year 2018. Change in participation (ΔParticipate) is calculated as the participation in risky mutual fund investment in 2018 minus that in 2017. Change in risky share (ΔRisky Share) is calculated as the individual's portfolio weight in risky mutual funds in December 2018 minus that of December 2017. The controls are the same as in Panel A. Standard errors are clustered at the city level. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Panel B. FinTech Adoption and Risk-Taking, Panel Regression

	Participate				Risky Share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AliFrac	0.1259***	0.0953***	0.0695***	0.0057***	0.1112***	0.0390***	0.0917***	0.0195***
	(12.65)	(5.47)	(16.55)	(3.01)	(8.99)	(3.27)	(10.09)	(4.89)
Individual FE	N	Y	N	Y	N	Y	N	Y
City*Month FE	N	N	Y	Y	N	N	Y	Y
Adjusted R^2	0.009	0.649	0.071	0.714	0.006	0.624	0.024	0.641
N	1,350,000	1,350,000	1,350,000	1,350,000	850,000	850,000	850,000	850,000

Panel C. Change in FinTech Adoption and Change in Risk-Taking

	ΔParticipate			ΔRisky Share		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔAliFrac	0.0013	0.0011	0.0136**	0.0896***	0.0896***	0.0870***
	(0.21)	(0.18)	(2.08)	(5.59)	(5.59)	(5.30)
σ_C		0.0163***	0.0093**		-0.0087	-0.0096
		(4.48)	(2.32)		(-1.24)	(-1.32)
Log(C)			0.0129***			0.0004
			(8.30)			(0.10)
Female			-0.0244***			-0.0036
			(-8.29)			(-0.68)
Log(Age)			-0.0406***			0.0122
			(-5.98)			(0.97)
City FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.0003	0.0005	0.0038	0.0011	0.0012	0.0012
N	50,000	50,000	50,000	28,393	28,393	28,393

Table 5. Distance to Hangzhou as IV for FinTech Adoption

This table reports the 2SLS estimation using the distance to Hangzhou as an instrument for FinTech adoption. Panel A reports the results for the first stage estimations. We include first-stage estimations for subsamples within the 500km, 1000km, and 2000km radius from Hangzhou. We control for the natural logarithm of GDP, population, income per person, and number of bank branches (denoted as Log(BB)). Time fixed effects are also included. Panel B reports the second stage IV estimates for the region within the 500km radius and for the whole sample. The dependent variables are participation and risky share. Risky mutual fund participation rate in each city is calculated as the proportion of investors who have ever purchased at least 100 RMB non-money market mutual funds. Risky share is the portfolio weight invested in risky mutual funds, equal weighted across all individuals in a city. Standard errors are double clustered at the city and time levels. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Panel A. First Stage: AliFrac on Log(Distance)

	Hangzhou				Shanghai			
	≤500km	≤1,000km	≤2,000km	All	≤500km	≤1,000km	≤2,000km	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Distance)	-0.437***	-1.096**	-1.955**	-1.995**	0.129	-0.936*	-1.731*	-1.766*
	(-3.99)	(-2.31)	(-2.14)	(-2.16)	(0.70)	(-1.84)	(-1.77)	(-1.77)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	799	2,278	4,624	4,879	799	2,278	4,624	4,879
R-squared	0.660	0.543	0.508	0.502	0.646	0.528	0.488	0.483
F-stat	15.93	5.32	4.59	4.65	0.49	3.39	3.14	3.13

Panel B. Second Stage: Using Log(Distance) as IV for AliFrac

	Hangzhou				Shanghai			
	Participate		Risky Share		Participate		Risky Share	
	≤500km	All	≤500km	All	≤500km	All	≤500km	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AliFrac	0.649***	0.179*	1.040***	0.253**	0.056	0.993	0.112	2.383
	(3.13)	(1.93)	(5.26)	(2.32)	(0.73)	(0.54)	(1.33)	(0.80)
Log(GDP)	-0.282	0.068	-3.123*	0.687	0.542	-1.252	1.233*	-6.909
	(-0.15)	(0.08)	(-1.69)	(0.84)	(0.70)	(-0.21)	(1.65)	(-0.75)
Log(Population)	0.504	0.189	2.252	0.261	0.168	0.883	0.237	3.733
	(0.33)	(0.39)	(1.53)	(0.54)	(0.35)	(0.27)	(0.51)	(0.73)
Log(Income)	-0.254	0.467	0.477	-0.132	0.489	-0.614	-0.106	-0.929
	(-0.19)	(1.14)	(0.49)	(-0.35)	(1.16)	(-0.48)	(-0.28)	(-0.38)
Log(BB)	-1.105	-0.373	-0.478	0.114	-0.341	-1.545	0.151	-2.196
	(-0.36)	(-0.60)	(-0.14)	(0.19)	(-0.54)	(-0.35)	(0.25)	(-0.32)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	799	4,879	799	4,879	799	4,879	799	4,879

Table 6. Individual FinTech Adoption and Risk-Taking, Conditioning on Risk Tolerance

This table shows the effect of FinTech adoption on risk taking, conditional on investor heterogeneity. In addition to the independent variables in Table 4, we also include the interaction between AliFrac and consumption growth volatility (σ_C) in columns (1), (3), and (5). We further include the interactions between AliFrac and all other investor characteristics in columns (2), (4), and (6). The dependent variables are risky fund participation, risky share, and portfolio volatility (σ_W) in percent. All variables are defined the same as in Table 4. We include city fixed effects in all specifications. Standard errors are clustered at the city level. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

	Participate		Risky Share		σ_W	
	(1)	(2)	(3)	(4)	(5)	(6)
AliFrac*σ_C	0.061**	0.047*	0.029	0.015	0.434**	0.381**
	(2.45)	(1.86)	(1.01)	(0.51)	(2.32)	(2.01)
AliFrac*Log(C)		0 037***		0.004		0.048
		(3.40)		(0.27)		(0.55)
AliFrac*Female		-0.063***		-0.036		-0.130
		(-2.84)		(-1.27)		(-0.69)
AliFrac*Log(Age)		-0.113**		-0.106**		-0.679**
		(-2.52)		(-1.91)		(-2.19)
AliFrac	0.165***	0.341**	0.111***	0.486**	-0.077	2.054
	(5.08)	(1.96)	(2.58)	(2.12)	(-0.30)	(1.55)
σ_C	-0.013	-0.005	0.002	0.010	-0.074	-0.043
	(-1.04)	(-0.41)	(0.13)	(0.55)	(-0.66)	(-0.38)
Log(C)	0 076***	0.058***	0.031***	0.030***	0.128***	0.107**
	(30.07)	(10.55)	(9.04)	(3.40)	(5.48)	(2.12)
Female	-0.067***	-0.032***	-0.102***	-0.081***	-0.541***	-0.464***
	(-12.11)	(-2.29)	(-15.10)	(-4.44)	(-15.50)	(-4.15)
Log(Age)	0.007	0 066***	-0.171***	-0.114***	-0.862***	-0.500***
	(0.56)	(3.09)	(-11.12)	(-3.77)	(-10.55)	(-2.75)
City FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.024	0.024	0.025	0.036	0.016	0.016
N	50,000	50,000	28,393	28,393	28,393	28,393

Table 7. City-Level FinTech Penetration and Risk-Taking, Conditioning on Bank Coverage

This table reports the effect of city-level FinTech penetration on local individuals' risk-taking. Columns (1) to (6) report the level of FinTech penetration on the level of risk taking, and columns (7) to (10) report the impact of change in FinTech penetration on the change in risk taking from 2017 to 2018. Risky fund participation is the fraction of individuals in the city who ever have at least 100 RMB purchase of non-MMF mutual funds on platform. Risky share is the portfolio weight in risky mutual funds (= 1−MMF/Total), equal weighted across all individuals in a given city. Portfolio volatility (σ_W) is calculated as the equal weighted average across all individuals' monthly portfolio return standard deviation in percent. Change in participation and FinTech penetration is calculated as the number in 2018 minus that in 2017. Change in risky share is calculated as the risky share in December 2018 minus that of December 2017. We control for the natural logarithm of GDP, population, income per person, and number of bank branches (denoted as Log(BB)). The control variables are normalized with mean zero and standard deviation of one. We also control for Citylevel= 1, which is a dummy variable that equals one for Beijing, Shanghai, Guangzhou, Shenzhen, and zero otherwise. Standard errors are clustered at the province level. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

	Participation		Risky Share		σ_W	
	(1)	(2)	(3)	(4)	(5)	(6)
AliFrac	0.212***	0.207***	0.310**	0.254*	0.676	0.594
	(2.92)	(2.84)	(2.25)	(1.89)	(1.60)	(1.41)
AliFrac*Log(BB)		-0.048		-0.546***		-0.803**
		(-0.69)		(-4.26)		(-2.00)
Log(BB)	-0.002	0.02	-0.018	0.229***	-0.033	0.331*
	(-0.26)	(0.62)	(-1.52)	(3.88)	(-0.89)	(1.78)
Log(GDP)	0.01	0.011	-0.018	-0.006	0.007	0.024
	(1.04)	(1.13)	(-0.99)	(-0.33)	(0.12)	(0.44)
Log(Population)	-0.009	-0.009	0.033***	0.034***	0.01	0.01
	(-1.36)	(-1.35)	(2.73)	(2.84)	(0.26)	(0.28)
Log(Income)	0.010*	0.011**	0.013	0.024**	0.047	0.063*
	(1.87)	(1.98)	(1.30)	(2.36)	(1.48)	(1.94)
CityLevel=1	0.037	0.042	-0.011	0.042	0.009	0.088
	(0.95)	(1.05)	(-0.15)	(0.58)	(0.04)	(0.38)
Constant	0.234***	0.238***	0.395***	0.437***	0.887***	0.948***
	(6.66)	(6.69)	(5.91)	(6.65)	(4.32)	(4.59)
Observations	287	287	287	287	287	287
R-squared	0.113	0.115	0.058	0.116	0.030	0.044

	ΔParticipate		ΔRisky Share	
	(7)	(8)	(9)	(10)
ΔAliFrac	0.149*	0.090	1.469**	0.400
	(1.76)	(1.07)	(2.44)	(0.99)
ΔAliFrac*Log(BB)		-0.150*		-2.714***
		(-1.81)		(-4.79)
Log(BB)	-0.002	0.005	-0.019	0.103***
	(-1.53)	(1.25)	(-1.19)	(3.63)
Log(GDP)	0.004	0.003	-0.018	-0.034*
	(1.66)	(1.39)	(-0.92)	(-1.78)
Log(Population)	-0.002	-0.002	0.019*	0.017*
	(-1.10)	(-1.13)	(1.77)	(1.67)
Log(Income)	0.001	0.001	0.022*	0.015
	(0.91)	(0.60)	(1.84)	(1.53)
CityLevel=1	0.004	0.001	-0.001	-0.053**
	(1.08)	(0.30)	(-0.04)	(-2.25)
Constant	0.052***	0.054***	-0.079***	-0.046***
	(15.04)	(16.00)	(-3.86)	(-3.16)
Observations	287	287	287	287
R-squared	0.034	0.042	0.105	0.207

Table 8. 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 cities, based on a matched sample of individuals. We match each individual in a low bank coverage city ("treated") with an individual in a high bank coverage city, by requiring the two to share the same gender, born in the same year, and have the closest value of consumption level and consumption growth volatility. Panel A reports the mean and standard deviation of the matching variables, (Δ)AliFrac, and (Δ)Risky Share for the low and high bank coverage individuals in the matched sample, as well as the difference between the "treated" and matched sample. Panel B reports the regression results for the low and high bank coverage sample respectively. The explanatory variables in the regressions are risky share and the change in risky share. The last two rows report the differences between the regression coefficients on AliFrac for the low and high bank coverage group, and the corresponding t-stat. In Panel C, we further cut the sample into four groups (2×2) based on investor characteristics (age, gender, consumption level, consumption growth volatility) and bank coverage, and report the regression coefficients on AliFrac as well as the differences in the coefficients between the high and low groups. Standard errors are clustered at the city level. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Panel A. Matched Sample Distribution

		Low Bank		High Bank		Low-High	
	N	Mean	Std.	Mean	Std.	Mean	t-stat
σ_{C}	4,053	1.208	0.381	1.208	0.371	0.000	0.00
Log(C)	4,053	7.248	0.822	7.249	0.814	-0.001	-0.65
Female	4,053	0.592	0.491	0.592	0.491	0.000	N.A.
Log(Age)	4,053	3.425	0.237	3.426	0.237	0.000	-1.20
AliFrac	4,053	0.478	0.234	0.566	0.211	-0.089	-20.13
ΔAliFrac	4,053	0.100	0.182	0.087	0.167	0.013	3.46
Risky Share	4,053	0.457	0.475	0.443	0.470	0.014	1.34
ΔRisky Share	4,053	0.067	0.456	0.055	0.445	0.011	1.14

Panel B. Risky Share Conditional on Bank Coverage

	Risky Share		
	Low Bank	High Bank	Low-High
AliFrac	0.183***	0.148***	0.035
	(4.87)	(2.91)	(0.55)
σ_C	0.037*	0.008	0.028
	(1.71)	(0.37)	(0.90)
Log(C)	0.039***	0.039***	0.000
	(3.75)	(4.20)	(0.01)
Female	-0.119***	-0.076***	-0.043*
	(-7.23)	(-3.92)	(-1.70)
Log(Age)	-0.114***	-0.216***	0.102*
	(-3.46)	(-5.22)	(1.93)
Constant	0.502***	0.849***	
	(3.20)	(4.52)	
City FE	Y	Y	
Observations	4,053	4,053	
R-squared	0.083	0.064	

	ΔRisky share		
	Low Bank	High Bank	Low-High
ΔAliFrac	0.086**	-0.034	0.121**
	(2.13)	(-0.79)	(2.03)
σ_C	-0.015	-0.022	0.007
	(-0.63)	(-1.04)	(0.23)
Log(C)	0.003	-0.021**	0.024*
	(0.28)	(-2.23)	(1.79)
Female	0.009	-0.016	0.026
	(0.48)	(-1.01)	(1.02)
Log(Age)	-0.002	0.017	-0.019
	(-0.07)	(0.48)	(-0.41)
Constant	0.06	0.19	
	(0.44)	(1.25)	
City FE	Y	Y	
Observations	4,053	4,053	
R-squared	0.05	0.036	

Panel C. Effect of AliFrac on Risk-Taking for Different Subsamples

Age	Low Bank	High Bank	Low-High
Young	0.132**	0.276***	-0.144
	(2.05)	(2.97)	(-1.28)
Mature	0.192***	0.048	0.144*
	(3.85)	(0.79)	(1.83)
Consumption	Low Bank	High Bank	Low-High
Low	0.194***	0.102	0.094
	(3.35)	(1.61)	(1.10)
High	0.186***	0.159**	0.025
	(3.07)	(2.07)	(0.26)

Gender	Low Bank	High Bank	Low-High
Female	0.171***	0.152**	0.019
	(3.36)	(2.17)	(0.21)
Male	0.175***	0.104	0.071
	(3.11)	(1.36)	(0.74)
$\boldsymbol{\sigma_C}$	Low Bank	High Bank	Low-High
Low σ_C	0.136**	0.202***	-0.066
	(2.47)	(3.27)	(0.80)
High σ_C	0.242***	0.058	0.184**
	(4.64)	(0.80)	(2.06)

Table 9. Investment Efficiency — Portfolio Diversification and Sharpe Ratio

Panel A reports the mean, t-stat, standard deviation, and Sharpe ratio of monthly returns for each fund asset class and the correlation matrix between them, estimated using data from Jan 2005 to May 2019. The last two columns of Panel A report the portfolio holdings in percent estimated using our sample period from August 2017 to December 2018 for "Ant investor" and "All Retail" investors in the entire economy. Portfolio weights are estimated month-by-month and the time-series averages are reported. Panel B exhibits the regression results of participation in each asset class on AliFrac, following the same model specification as in Panel A of Table 4. Participation is a dummy variable that equals one for individuals who purchased at least 100 RMB of funds in a particular asset class. Panel C reports the effect of FinTech adoption on individual portfolio diversification and Sharpe ratio. Portfolio diversification is captured by the variance improvement measure, defined as $1 - \frac{\sigma_i^2}{\sigma_{i,B}^2}$. Here, σ_i^2 is individuals' actual portfolio variance, computed using individuals' own portfolio weights and the actual variance-covariance matrix estimated using historical data from 2005 to 2019. $\sigma_i^2 = w_i' \sum w_i$, where w_i is individual i's vector of portfolio weights in each asset classes. $\sigma_{i,B}^2$ is the variance of a hypothetical benchmark portfolio, in which we assume all asset classes are perfectly correlated with each other. To compute the Sharpe ratio of each individuals portfolio, we use the actual portfolio weights of the individual on the six asset class. For performance, as reported in Panel A of this table, we use the longer time-series data from January 2005 to May 2019 to estimate the expected returns and variance-covariance matrix of the six risky asset classes. The one-year deposit rate is used as the risk-free rate.

Panel A. Summary Statistics on Asset Classes

Monthly Return Distribution						Correlation Matrix							Holdings (%)		
Style	N	Mean	t-stat of Mean	Std.	Sharpe Ratio		Bond	Mixed	Equity	Index	QDII	Gold		Ant Investor	All Retail
Bond	173	0.54%	6.31	1.12%	0.36	Bond	1.00	0.62	0.61	0.60	0.34	0.14	Bond	4.8	7.6
Mixed	173	1.18%	2.58	6.01%	0.17	Mixed	0.62	1.00	0.98	0.95	0.54	0.15	Mixed	42.7	65.0
Equity	173	1.37%	2.46	7.32%	0.17	Equity	0.61	0.98	1.00	0.94	0.53	0.13	Equity	15.1	10.1
Index	173	1.06%	1.84	7.55%	0.12	Index	0.60	0.95	0.94	1.00	0.58	0.14	Index	24.8	14.3
QDII	139	0.21%	0.57	4.33%	0.02	QDII	0.34	0.54	0.53	0.58	1.00	0.24	QDII	2.4	2.4
Gold	173	0.62%	1.63	4.99%	0.10	Gold	0.14	0.15	0.13	0.14	0.24	1.00	Gold	10.1	0.6

Panel B. Participation in Each Asset Class

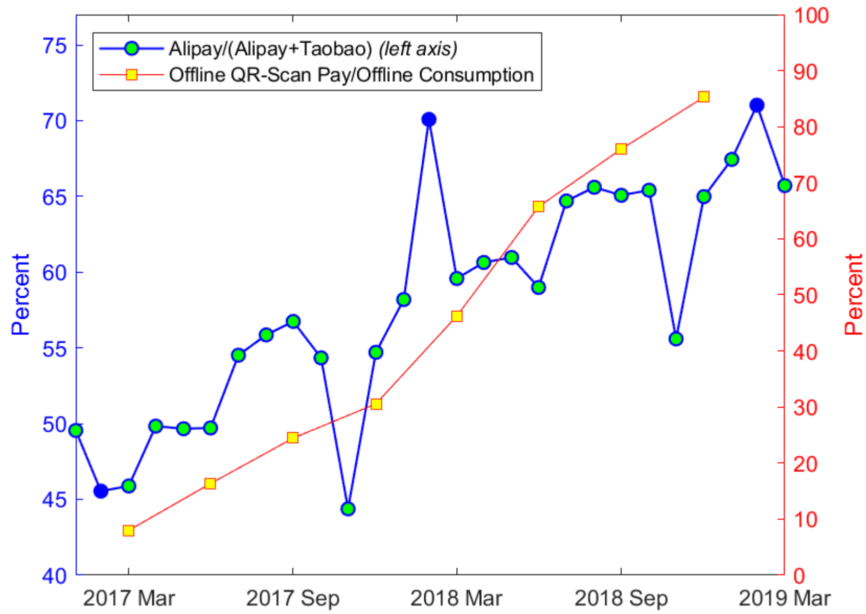
	Bond	Mixed	Equity	Index	QDII	Gold
	(1)	(2)	(3)	(4)	(5)	(6)
AliFrac	0.040***	0.149***	0.045***	0.072***	0.024***	0.140***
	(7.37)	(14.03)	(7.96)	(9.85)	(6.93)	(18.11)
σ_C	0.003	0.020***	0.011***	0.016***	0.004**	-0.004
	(0.95)	(4.60)	(3.68)	(4.75)	(2.15)	(-1.09)
Log(C)	0.016***	0.054***	0.017***	0.030***	0.010***	0.030***
	(12.66)	(25.71)	(13.18)	(13.66)	(11.16)	(15.32)
Female	-0.003	-0.048***	-0.020***	-0.039***	-0.012***	-0.045***
	(-1.12)	(-10.68)	(-8.14)	(-12.77)	(-6.81)	(-14.77)
Log(Age)	0.022***	0.039***	0.001	-0.013	0.001	-0.034***
	(4.98)	(3.65)	(0.22)	(-1.55)	(0.39)	(-5.08)
City FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.0036	0.0186	0.0058	0.0107	0.0048	0.0153
N	50,000	50,000	50,000	50,000	50,000	50,000

Panel C. Diversification Benefit and Sharpe Ratio

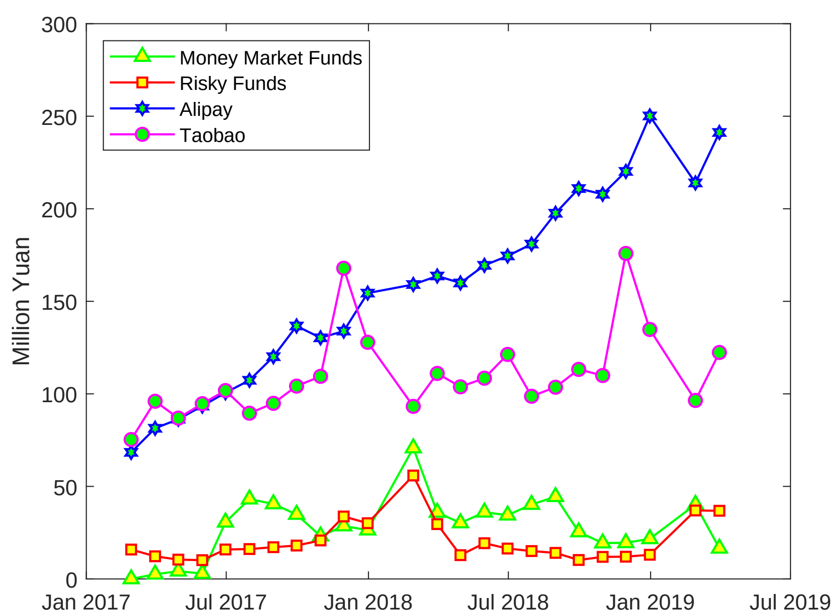
	Variance Improvement					Sharpe Ratio				
	All	By Risky Share		By σ_C		All	By Risky Share		By σ_C	
		Low	High	Low	High		Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AliFrac	0.038***	0.032***	0.037***	0.036***	0.040***	0.028***	0.040***	-0.007**	0.026***	0.030***
	(9.77)	(7.30)	(5.55)	(6.70)	(6.73)	(8.31)	(9.02)	(-2.33)	(4.75)	(7.49)
σ_C	-0.001	0.003	-0.003	0.003	0.001	0.003**	0.003	0.002	0.009*	0.002
	(-0.27)	(1.01)	(-0.87)	(0.40)	(0.30)	(2.30)	(1.58)	(1.00)	(1.78)	(0.51)
Log(C)	0.006***	0.006***	0.004***	0.006***	0.006***	0.006***	0.007***	0.000	0.008***	0.005***
	(6.42)	(4.61)	(3.19)	(4.33)	(4.10)	(9.52)	(6.81)	(-0.63)	(7.13)	(5.56)
Female	-0.014***	-0.012***	-0.006**	-0.018***	-0.010***	-0.013***	-0.009***	0.005***	-0.014***	-0.012***
	(-6.79)	(-5.51)	(-2.19)	(-6.97)	(-3.63)	(-9.75)	(-4.92)	(4.95)	(-7.31)	(-6.59)
Log(Age)	-0.048***	-0.035***	-0.048***	-0.042***	-0.056***	-0.036***	-0.036***	0.011***	-0.031***	-0.043***
	(-15.62)	(-9.01)	(-8.87)	(-10.06)	(-12.64)	(-15.51)	(-12.82)	(5.89)	(-9.92)	(-11.93)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	20,033	10,112	9,921	10,028	10,005	20,033	10,112	9,921	10,028	10,005
R-squared	0.038	0.053	0.043	0.056	0.052	0.045	0.058	0.043	0.058	0.062

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

Data is aggregated across 50,000 randomly sampled individuals from January 2017 through March 2019. In the upper graph, Alipay refers to third-party consumption paid via the digital payment function of Ant Groups Alipay app. Taobao refers to online consumption made via Alibaba's Taobao or Tmall ecommerce platform. Offline QR-Scan Pay/Offline Consumption is calculated based on statistics for the aggregate economy. The lower graph reports the time series variation of mutual-fund purchases on Ant Group's investment platform, together with the aggregate Alipay and Taobao consumption for the randomly selected 50,000 sample.



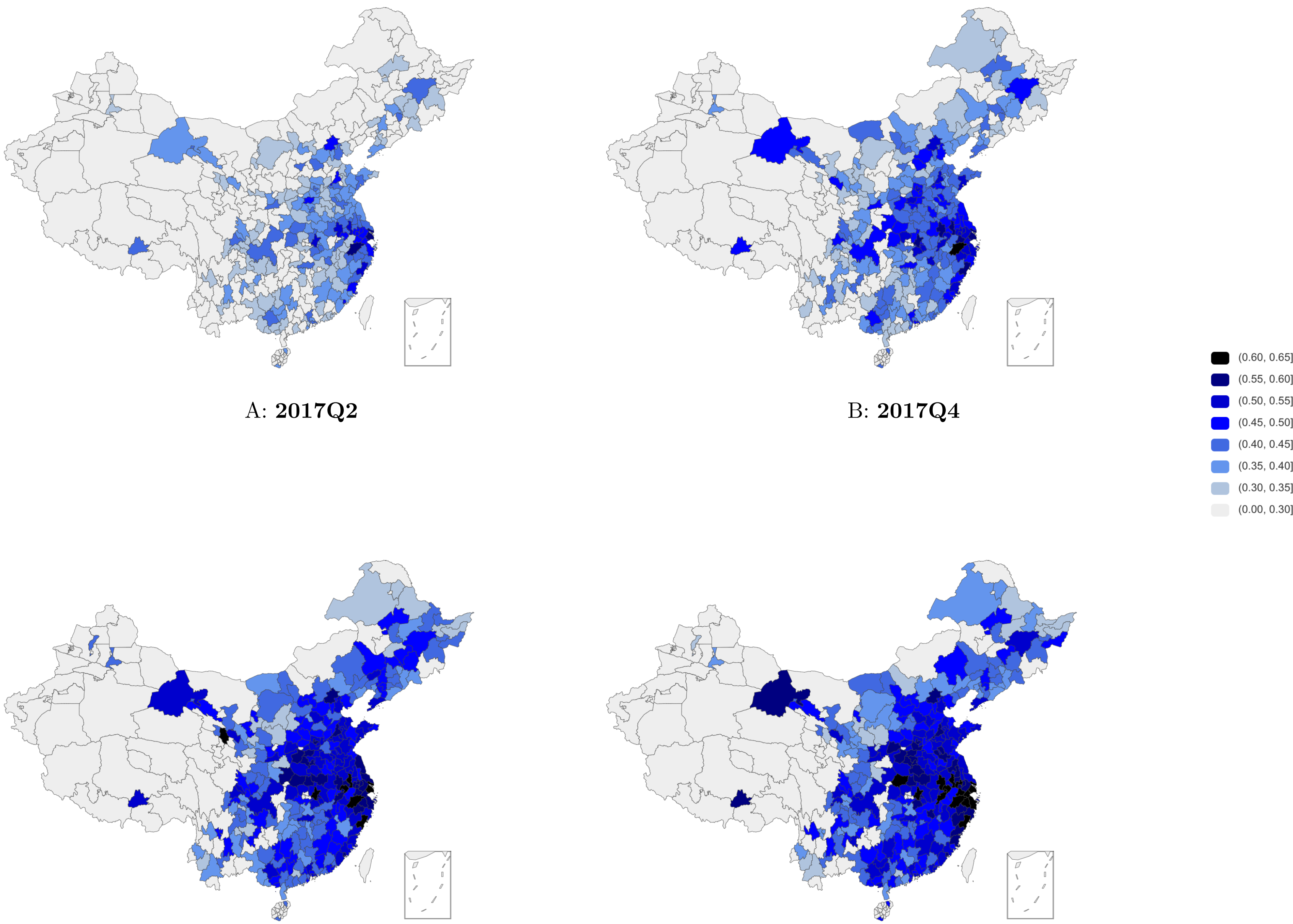
(A) Offline QR-Scan Payment vs. Alipay Consumption



(B) Mutual Fund Purchases and Consumption

Figure 2. Geographic Distribution of FinTech Adoption

Graphs A to D display the geographic distribution of city-level FinTech adoption from 2017Q2 to 2018Q4. City-level FinTech adoption is calculated as the average AliFrac for individuals in a given city. Individual AliFrac is computed as the fraction of consumption paid via Alipay digital payment out of total consumption: $\text{AliFrac}_t^i = \frac{\text{Alipay}_t^i}{\text{Alipay}_t^i + \text{Taobao}_t^i}$. The darker the color, the higher the FinTech adoption.



A: **2017Q2**

B: **2017Q4**

C: **2018Q2**

D: **2018Q4**

Figure 3. FinTech Adoption and Individual Risk Taking

We classify all individuals into 50 equal groups based on their AliFrac. We then calculate the average of risky fund participation rate, risky share, and portfolio volatility for each group of individuals. The upper two panels and the lower left panel plot the three risk-taking measures against the average AliFrac value of each group, respectively. The lower right panel further shows the relation between change in risky share and change in AliFrac from 2017 to 2018, for 50 groups of individuals classified based on change in AliFrac.

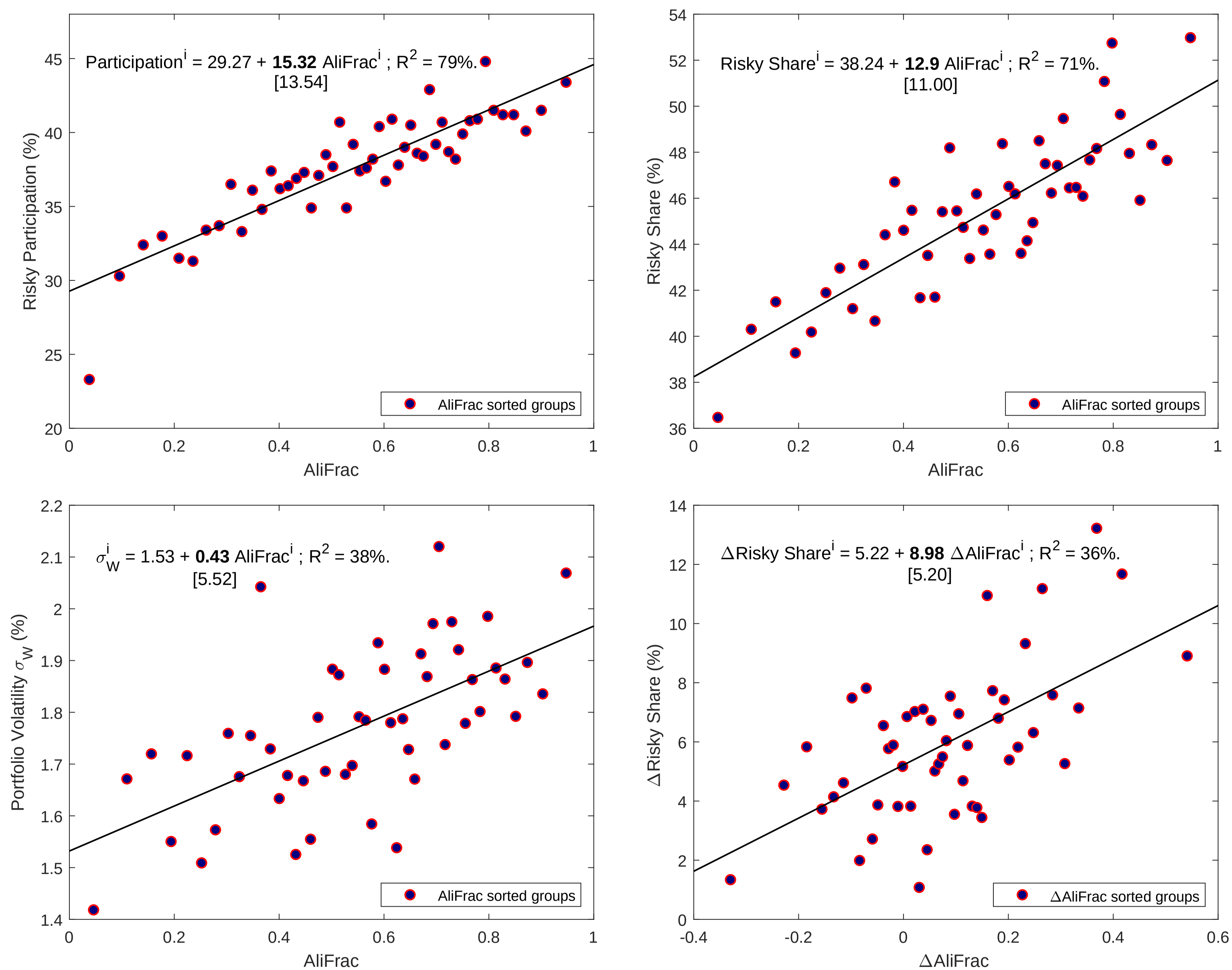


Figure 4. FinTech Adoption and Distance from Hangzhou

The figure shows the geographic distribution of city-level average FinTech adoption for the sample period from 2017Q1 to 2019Q1. City FinTech adoption is calculated as the average AliFrac for individuals in a given city during our sample. The headquarter of Ant group, Hangzhou, is highlighted in the graph. Centering Hangzhou, regions within the 500, 1000, and 2000 kilometers radius from Hangzhou are marked using red dotted circles.

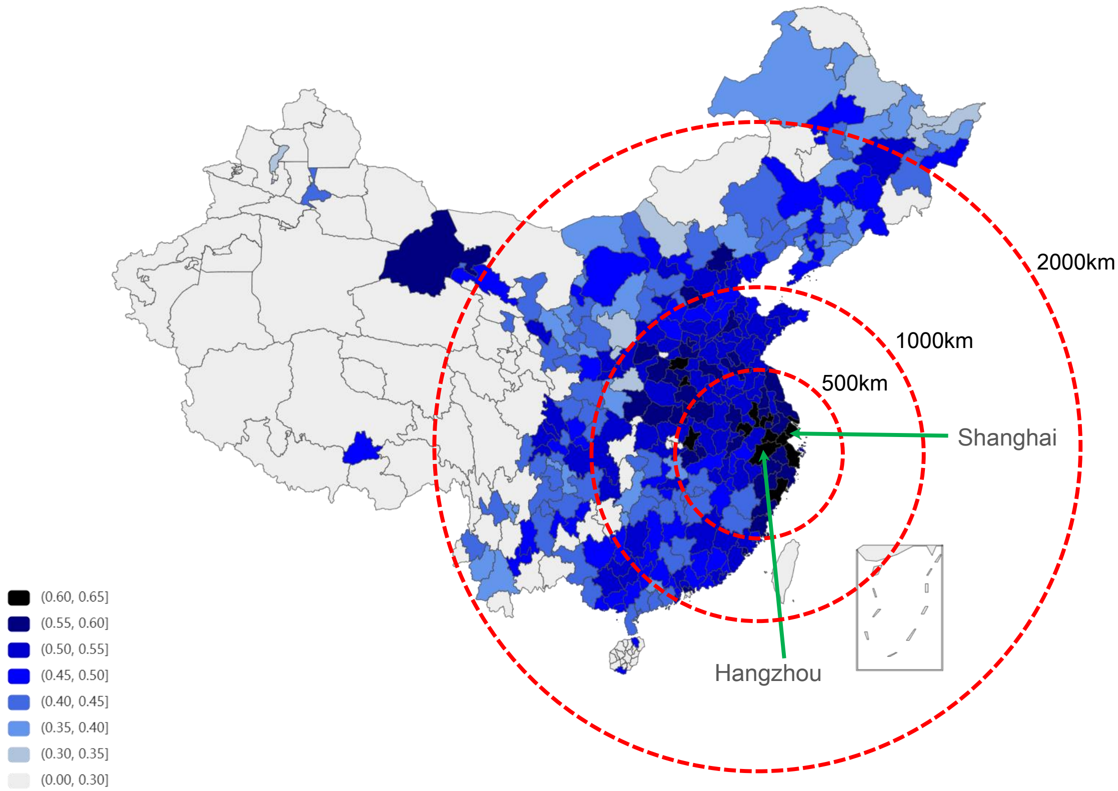


Figure 5. FinTech Adoption and Risk-Taking by Consumption Volatility Groups

In the left two panels, 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 risk-taking against their average monthly σ_C. In the right two panels, we dependently double sort all individuals into 2*25 groups first based on their σ_C and then AliFrac. We then report the relation between risk-taking measures and AliFrac for the high and low σ_C groups respectively.

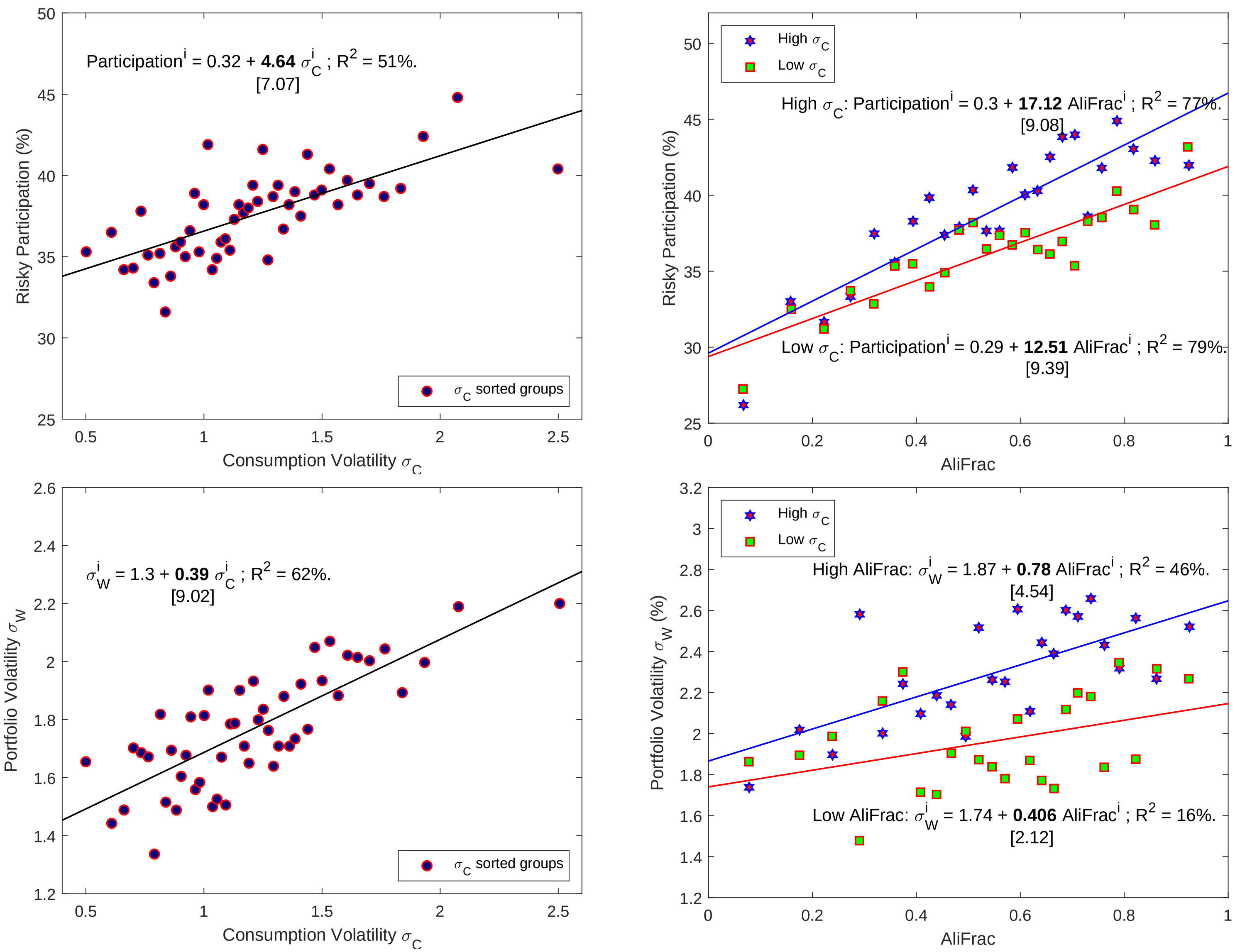
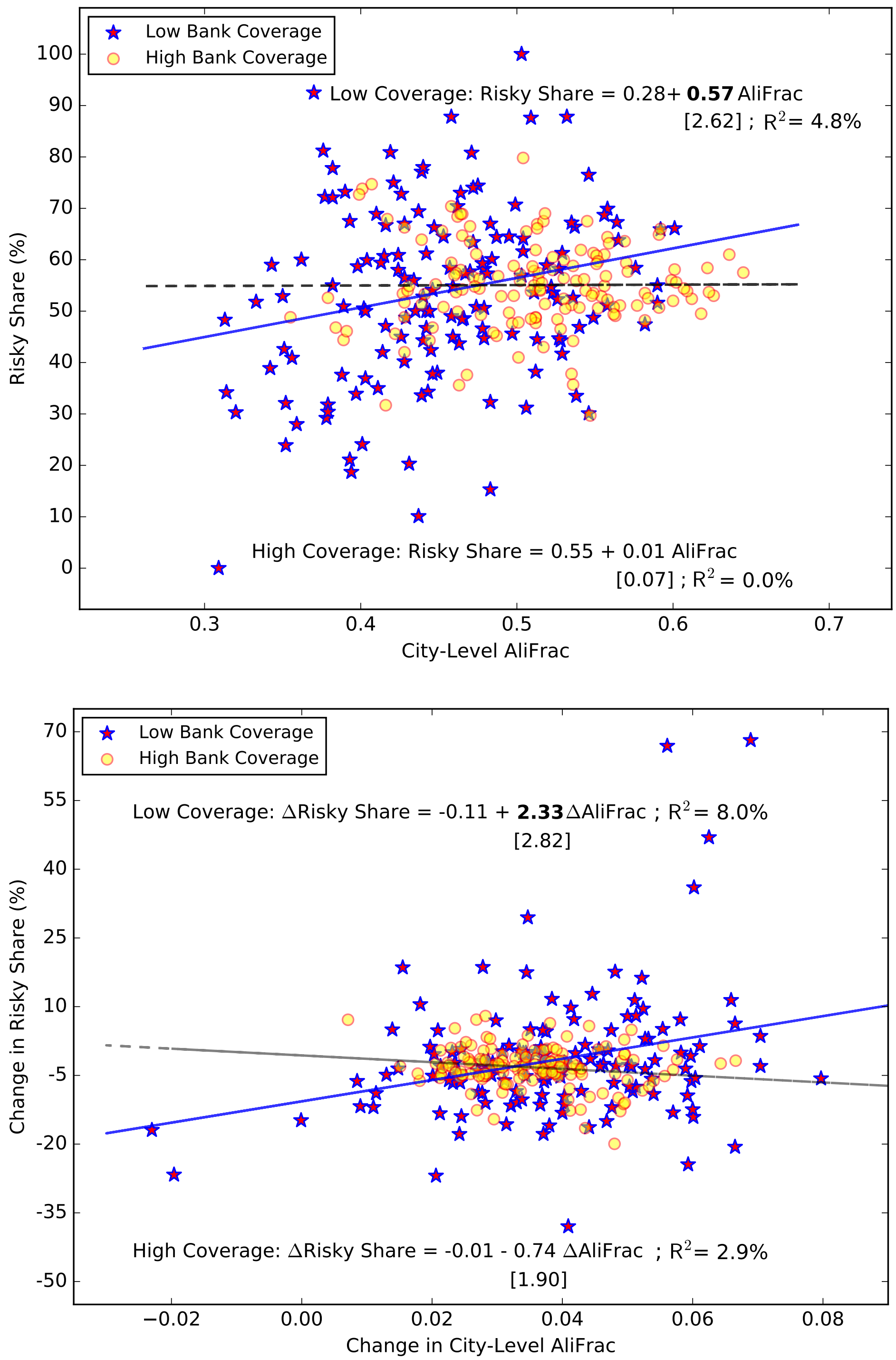


Figure 6. FinTech Adoption and Traditional Banking Coverage

We classify all cities into two groups based on the median cut-off of number of local bank branches. The upper graph plots the risky share of each city against the city-level AliFrac for cities with high and low bank coverage respectively. The lower graph plots the change in risky share from 2017 to 2018 against the change in city-level AliFrac from 2017 to 2018 for cities with high and low bank coverage respectively.



Appendix (For Online Publication) to "FinTech Adoption and Household Risk-Taking"

Claire Yurong Hong, Xiaomeng Lu, and Jun Pan

A Further Evidence and Robustness Tests

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

A1. Alternative Measures of FinTech Adoption

Our main measure of FinTech adoption scales Alipay consumption amount by total consumption amount to tease out the effect of difference in wealth level of each individual. However, one potential concern is that difference in AliFrac can be partially driven by the variation in individual's Taobao consumption, instead of by the variation in Alipay usage. An investor with a high level of Taobao consumption tends to have low level of Alipay fraction by construction. Despite the negative relationship between Taobao consumption and AliFrac, this issue is unlikely to lead to mechanical result, as we also control for the level of Taobao consumption in our regression estimations. To further alleviate this concern, we use the logarithm of Alipay payment frequency of each individual as an alternative measure of tech penetration. A higher frequency of Alipay usage reflects that the individual is more familiar with the Alipay app as a payment method. We also follow the same method to compute the change in the logarithm of Alipay payment counts from 2017 to 2018.

Appendix Table A2 reports the determinants of the logarithm of Alipay count (Log(AliCnt)). The results are qualitatively the same as those for the AliFrac measure. The only exception is that the logarithm of Alipay count is positively related to the logarithm of Taobao consumption. This is also consistent with our expectation: Rich individuals tend to consume more both online and offline. Thus, they also tend to use digital payment more frequently.

Using this alternative measure, we investigate its effect on investors' risk-taking behavior using the same regression settings. The results are reported in Appendix Table A3. Panel A reports the results at the individual investor level, similar to the setting in Table 4 and Table 6. The coefficients on FinTech adoption on risky fund participation, risky share, and portfolio volatility are qualitatively the same as those in the previous analyses. Panel B reports the corresponding results at the city level, similar to the setting in Table 7, a higher level of FinTech Adoption is associated with higher risk taking for all three measures of risk taking across all model specifications.

A2. Alternative Measures of Consumption Growth Volatility

According to Merton (1971), the consumption growth volatility reflects the risk tolerance level of each individual. Following this intuition, a higher necessity goods consumption growth volatility should translate into a larger variation in marginal utility, whereas the growth volatility of other consumption category may not have an equivalent impact. Therefore, we expect that FinTech adoption should increase risk taking for individuals with more volatile necessity consumption.

To capture this intuition in the data, we decompose individual consumption into narrowly defined consumption for basic, development, and enjoyable goods, and compute the consumption growth volatility within each category. Basic consumption is conceptually more related to the necessity goods consumption. We follow the same regression specification in Panel A of Table 4 and Table 6 to examine investors' portfolio volatility, and replace the consumption growth volatility variable with basic, development and enjoyable consumption growth volatility, respectively. The corresponding results are reported in Appendix Table A4. As reported in column (1), one unit increase in basic consumption growth volatility leads to a 0.05% increase in portfolio volatility (t-stat=2.50). In column (2), we further include the interaction between FinTech adoption and basic consumption growth volatility, we find the coefficient to be statistically significant on the interaction term. We find a similar effect for development consumption growth volatility in columns (3) and (4). However, for consumption growth volatility of enjoyable goods, we find no significant effect on the interaction term.

One potential concern on the measurement of consumption growth volatility is that monthly Taobao consumption exhibits strong seasonality, as shown in the lower panel of Figure 1. In addition, it also tends to increase substantially in Novembers due to the double 11 shopping festival. To rule out potential confounding effects related to these patterns (for example, individuals who tend to purchase more during shopping season, also somehow tend to invest on platforms), we compute two alternative measures of consumption growth volatility, and repeat the previous analyses. In particular, in columns (7) and (8), we replace the consumption growth volatility with the "YoY growth" volatility measure, which uses year on year consumption growth to compute consumption growth volatility, and will not be affected by the seasonality in Taobao consumption. In columns (9) and (10), we exclude monthly consumption data in Novembers and estimate consumption growth volatility using the remaining months in our sample. In both settings, the results are qualitatively the same as the corresponding regression results in Table 4 and Table 6.

Table A1. Summary Statistics on Consumption Growth

This table reports the summary statistics of monthly consumption growth. Panel A reports the mean and standard deviation of economy-wide monthly consumption growth during our sample period from 2017 January to 2019 March. The data for economy-wide consumptions are from National Bureau of Statistics. Offline consumption is calculated as “All minus “Online. For our Ant group sample, we report the consumption growth via Taobao and Alipay respectively. Consumption growth is calculated as change in natural logarithm of monthly consumption. Panel B reports the cross sectional mean and standard deviation of individual consumption growth volatility (σ_C) by personal characteristics. We group individuals based on their personal characteristics and report the σ_C for each group as the equal weighted average σ_C among all individuals in the group. σ_C is calculated as the standard deviation of change in natural logarithm of monthly Taobao consumption.

Panel A: Ant and Economy-wide Consumption Growth

	Economy-wide			Ant Sample	
	All	Online	Offline	Taobao	Alipay
Mean	0.39%	3.31%	-0.16%	2.11%	5.48%
Std.	5.26%	19.19%	6.91%	21.08%	6.97%

Panel B. σ_C by Personal Characteristics

		1	2	3	4	5
Gender (1=Male)	Mean	1.35				1.12
	Std.	0.43				0.36
Age (1=Young)	Mean	1.22	1.23	1.21	1.19	1.19
	Std.	0.40	0.41	0.41	0.40	0.39
Consumption level (1=Low)	Mean	1.25	1.23	1.22	1.19	1.16
	Std.	0.37	0.38	0.40	0.41	0.44
City level (1=Tier 1)	Mean	1.22	1.20	1.21	1.21	1.22
	Std.	0.40	0.40	0.40	0.39	0.43
AliFrac (1=Low)	Mean	1.15	1.18	1.20	1.24	1.28
	Std.	0.41	0.40	0.39	0.40	0.40

Table A2. Determinants of Alternative FinTech Adoption Measure

This table reports the determinants of FinTech adoption (Log(Alicnt)), which is defined as the natural logarithm of number of Alipay payments made in an average month. We regress the (change in) FinTech adoption measure on individual and city characteristics. Log(C) is the natural logarithm of monthly online consumption on Taobao. Consumption growth volatility (σ_C) is calculated as the standard deviation of change in monthly Log(C). Other individual characteristics include gender and age. For city-level characteristics, we include city GDP, income per person, population, and number of traditional banks. We also control for Citylevel= 1, which is a dummy variable that equals one for Beijing, Shanghai, Guangzhou, Shenzhen, and zero otherwise. Columns (1) to (4) report the results for Log(Alicnt) and columns (5) to (8) report the results for change in Log(Alicnt) from year 2017 to 2018. We include city fixed effects as indicated. Standard errors are clustered at the city level. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

	Log(AliCnt)				ΔLog(AliCnt)			
	All Users		Active Users		All Users		Active Users	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
σ_C	0.044***	0.054***	0.042***	0.052***	-0.054***	-0.053***	-0.056***	-0.054***
	(4.85)	(6.31)	(3.31)	(4.37)	(-6.78)	(-6.60)	(-5.13)	(-4.99)
Log(C)	0.133***	0.124***	0.130***	0.121***	-0.098***	-0.093***	-0.094***	-0.091***
	(19.60)	(25.10)	(17.15)	(20.31)	(-22.82)	(-21.56)	(-17.18)	(-16.45)
Female	-0.170***	-0.160***	-0.190***	-0.180***	-0.002	-0.002	-0.017**	-0.017**
	(-14.94)	(-13.70)	(-16.04)	(-14.74)	(-0.27)	(-0.35)	(-2.02)	(-2.01)
Log(Age)	-0.816***	-0.818***	-0.861***	-0.863***	0.500***	0.493***	0.532***	0.527***
	(-23.04)	(-28.26)	(-23.49)	(-26.97)	(20.46)	(20.16)	(17.50)	(17.28)
Log(GDP)	0.123**		0.1292**		-0.0302**		-0.0485***	
	(2-17)		(2.07)		(-2.44)		(-3.06)	
Log(Income)	0.1172***		0.1262***		-0.041***		-0.041***	
	(3.28)		(3.39)		(-5.37)		(-4.86)	
Log(Population)	0.0138		0.0233		0.0023		0.009	
	(0.35)		(0.59)		(0.33)		(1.11)	
Log(# Branch)	0.0194		-0.0077		0.0076		0.0221	
	(0.40)		(-0.13)		(0.49)		(1.15)	
Citylevel=1	-0.2612**		-0.267**		0.0789***		0.0802***	
	(-2.20)		(-2.22)		(3.01)		(2.89)	
City FE	N	Y	N	Y	N	Y	N	Y
R2	0.0857	0.086	0.096	0.095	0.0403	0.040	0.046	0.046
N	49,087	50,000	27,886	28,393	49,087	50,000	27,886	28,393

Table A3. Alternative Measures of FinTech Adoption

This table use the natural logarithm of Alipay payment counts as an alternative measure of FinTech adoption. In particular, panel A shows the corresponding results for panel A of Table 4, but we use Log(AliCnt) as proxy for FinTech adoption. Log(AliCnt) is the natural logarithm of the average individual monthly Alipay payment counts in our sample. Panel B shows the corresponding results for Table 7, where city-level FinTech adoption is measured as the average Log(AliCnt) for individuals in the city. City fixed effects are included and standard errors are clustered at the city level in all model specifications in Panel A. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Panel A. Individual Level Results

	Participate			Risky Share			σ_W		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log(AliCnt)	0.062***	0.056***	0.046***	0.090***	0.073***	0.066***	0.564***	0.301***	0.136***
	(16.80)	(14.89)	(4.99)	(23.69)	(17.80)	(6.08)	(8.80)	(14.24)	(2.54)
Log(AliCnt)*σ_C			0.008			0.006			0.138***
			(1.31)			(0.75)			(3.22)
σ_C		0.024***	-0.001		0.019***	0.000		0.163***	-0.260*
		(4.60)	(-0.04)		(2.89)	(0.02)		(4.09)	(-1.90)
Log(C)		0.043***	0.043***		0.006*	0.006*		0.043*	0.043*
		(16.41)	(16.40)		(1.76)	(1.76)		(1.90)	(1.89)
Female		-0.070***	-0.070***		-0.097***	-0.096***		-0.511***	-0.507***
		(-12.82)	(-12.81)		(-14.39)	(-14.28)		(-14.64)	(-14.48)
Log(Age)		0.053***	0.053***		-0.111***	-0.111***		-0.609***	-0.605***
		(4.02)	(4.07)		(-6.96)	(-6.98)		(-7.32)	(-7.29)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.009	0.022	0.02	0.02	0.03	0.03	0.01	0.02	0.01
N	50,000	50,000	50,000	28,393	28,393	28,393	28,393	28,393	28,393

Panel B. City Level Results

	Participate			Risky Share			σ_W		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log(AliCnt)	0.067***	0.061***	0.061***	0.074**	0.108**	0.094**	0.194**	0.230*	0.194*
	(4.38)	(3.43)	(3.47)	(2.40)	(2.69)	(2.48)	(2.69)	(2.01)	(1.73)
Log(AliCnt)*Log(#Branch)			0.00			-0.073***			-0.180***
			(-0.01)			(-5.08)			(-4.23)
Log(#Branch)		-0.006	-0.005		-0.025	0.395***		-0.048	0.984***
		(-0.95)	(-0.07)		(-1.32)	(4.94)		(-0.90)	(3.96)
Log(GDP)		0.007	0.007		-0.026	-0.004		-0.01	0.043
		(0.70)	(0.68)		(-1.09)	(-0.19)		(-0.15)	(0.75)
Log(Population)		-0.006	-0.006		0.037**	0.041***		0.018	0.028
		(-0.89)	(-0.88)		(2.45)	(2.97)		(0.56)	(0.92)
Log(Income)		0.011**	0.011**		0.014	0.025**		0.049	0.074**
		(2.60)	(2.33)		(1.49)	(2.56)		(1.37)	(2.13)
Citylevel=1		0.033**	0.033*		-0.018	0.034		-0.006	0.122
		(2.18)	(1.88)		(-0.38)	(1.08)		(-0.07)	(1.37)
Constant	-0.081	-0.042	-0.042	0.088	-0.126	-0.024	0.014	-0.21	0.04
	(-0.84)	(-0.37)	(-0.38)	(0.45)	(-0.50)	(-0.10)	(0.03)	(-0.29)	(0.06)
Observations	287	287	287	287	287	287	287	287	287
R-squared	0.088	0.129	0.129	0.031	0.08	0.131	0.023	0.041	0.074

Table A4. Alternative Measures of Consumption Growth Volatility

This table exhibits the regression results of portfolio volatility (σ_W) on consumption growth volatility (σ_C) for alternative specifications of consumption growth volatility. In particular, in columns (1) to (6), we construct the basic, development, and enjoyable goods consumption growth volatility, calculated as the standard deviation of change in monthly natural logarithm of the respective narrowly-defined consumption. Consumption in January and February are combined as one month following standard consumption calculation method for the Chinese data. In columns (7) and (8), we compute consumption growth as the year on year consumption growth. By comparing the consumption of a given month with same-calendar month consumption in the last year, it helps remove the seasonality. In columns (9) and (10), we exclude Novembers in the calculation of consumption growth to reduce the impact of Double 11 shopping holiday on consumption volatility. The dependent variables are the portfolio volatility (σ_W, in percent) for each investor. City fixed effects are included and standard errors are clustered at the city level in all model specifications. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

	Basic		Development		Enjoy		YoY Growth		Exclude Double 11	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AliFrac	0.438***	0.143	0.467***	-0.103	0.464***	0.151	0.452***	0.027	0.446***	-0.012
	(4.43)	(0.78)	(4.80)	(-0.31)	(4.76)	(0.45)	(4.67)	(0.12)	(4.58)	(-0.05)
σ_C	0.049**	-0.032	0.052**	-0.053	0.025	-0.034	0.163***	-0.029	0.183***	-0.031
	(2.50)	(-0.60)	(2.37)	(-0.87)	(1.25)	(-0.56)	(3.96)	(-0.28)	(4.69)	(-0.27)
AliFrac*σ_C		0.147*		0.193*		0.112		0.362**		0.393**
		(1.72)		(1.85)		(1.00)		(2.13)		(1.99)
Log(C)	0.127***	0.128***	0.110***	0.108***	0 125***	0 123***	0.123***	0.125***	0.128***	0.128***
	(5.46)	(5.46)	(4.63)	(4.52)	(5.32)	(5.30)	(5.22)	(5.33)	(5.45)	(5.48)
Female	-0.555***	-0.554***	-0.569***	-0.568***	-0.578***	-0.578***	-0.541***	-0.539***	-0.539***	-0.538***
	(-15.23)	(-15.24)	(-16.53)	(-16.54)	(-16.61)	(-16.62)	(-15.19)	(-15.21)	(-15.59)	(-15.58)
Log(Age)	-0.855***	-0.856***	-0.860***	-0.861***	-0.882***	-0.881***	-0.854***	-0.857***	-0.858***	-0.860***
	(-10.51)	(-10.54)	(-10.59)	(-10.60)	(-10.61)	(-10.59)	(-10.43)	(-10.47)	(-10.46)	(-10.51)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.0156	0.0157	0.0155	0.0157	0.0154	0.0155	0.0159	0.0160	0.0159	0.0161
N	28,393	28,393	28,393	28,393	28,393	28,393	28,393	28,393	28,393	28,393

Figure A1. Online and Offline Consumption in China

Economy-wide online and total monthly consumptions are from National Bureau of Statistics. Consumptions via Alibabas Taobao platform and consumptions paid via Alipay digital payment are aggregated across 50,000 randomly sampled individuals from January 2017 through March 2019.

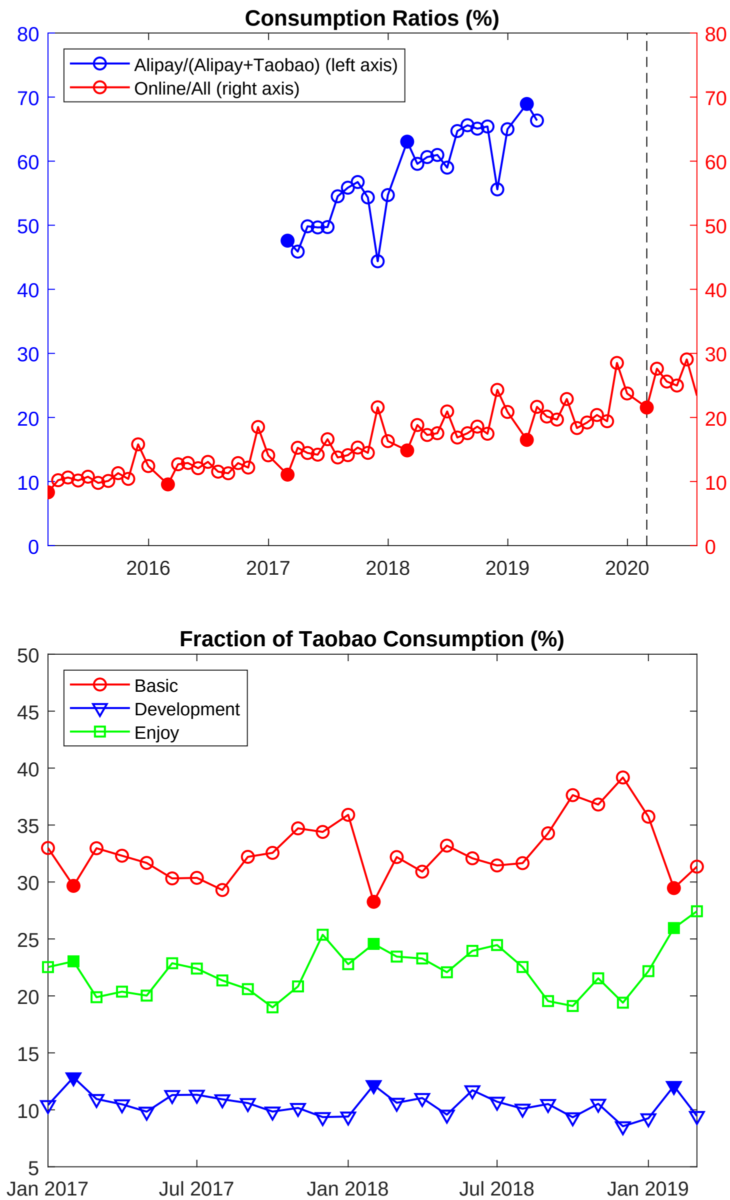
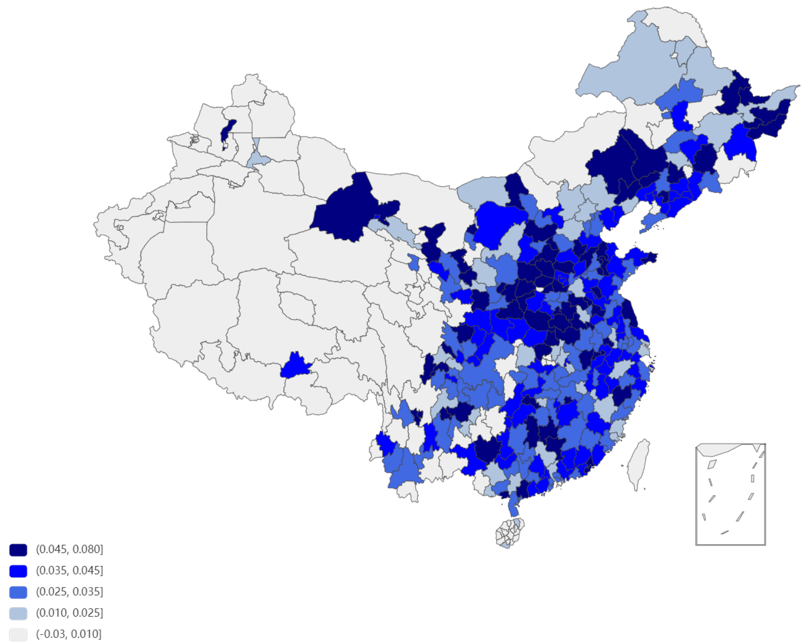
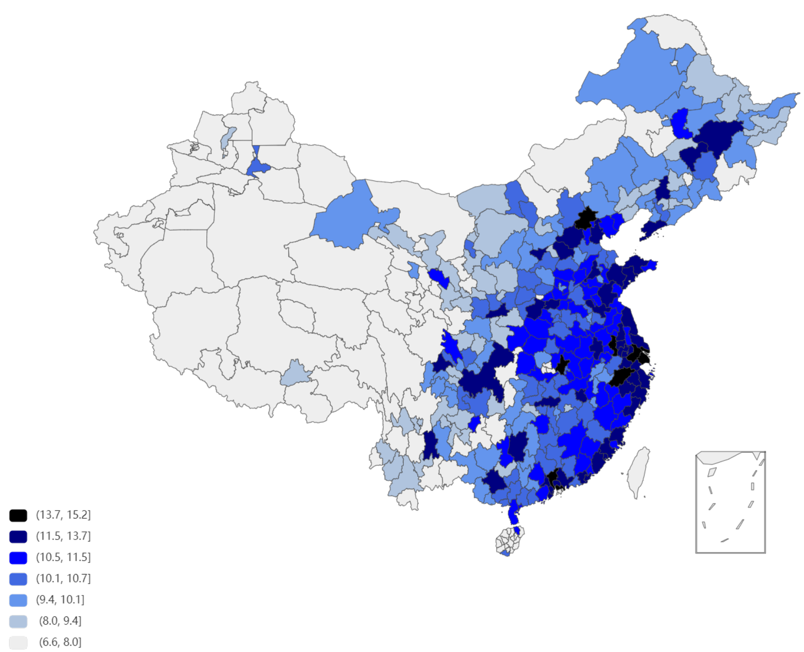


Figure A2. Geographic Distribution of Alternative FinTech Adoption Measures

Graph A shows the change in city-level FinTech penetration, calculated as the average AliFrac in 2018 minus that of year 2017. Panel B shows the geographic distribution of FinTech penetration measured using an alternative measure of Log(AliCnt). Log(AliCnt) is the natural logarithm of the average individual monthly alipay payment counts in our sample for a given city.



A: Change in AliFrac, from January 2017 to March 2019



B: FinTech Adoption Using Log(AliCnt)

Figure A3. Geographic Distribution of Banking Coverage

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