FinTech Adoption and Household Risk-Taking

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Abstract

This paper examines how FinTech can lower investment barriers and help households move toward optimal risk-taking, using a unique account-level data on consumption, investments, and FinTech usage from Ant Group. During our sample period, China experienced a rapid increase in FinTech penetration in the form of offline digital payment, and our measure of FinTech adoption is constructed relative to this fast-developing trend of new technology. Taking advantage of our consumption data, we further infer individuals' risk tolerance from their consumption volatility. We find that, while FinTech adoption improves risk-taking for all, the more risk-tolerant individuals benefit more from FinTech advancement. The magnitude of FinTech improvement is further quantified relative to the optimal alignment of risk-taking and consumption prescribed by Merton (1971). Aggregating to the city-level, we find significant variations in FinTech adoption across cities in China, owing to the gradual spread of the new technology from Hangzhou to inner China. Examining the enhancement in risk-taking across geographical locations, we find that cities with low financial-service coverage benefit the most from FinTech penetration. Overall, our results show that, by unshackling the traditional constraints, FinTech improves risk-taking for individuals who need it the most.

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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 – consumption, investments, and payments, are taking place on FinTech platforms, where, via mobile apps, individuals can fulfill their financial-service needs almost instantaneously regardless of the place or the time. 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, two years before Campbell's address, and are now literally permeating the entire country with each street vendor at every corner in China eager to accept Alipay or WeChat Pay.

The advent of FinTech is also revolutionizing the study of household finance. As more data from FinTech platforms are made available to researchers, the measurement difficulty so concerning Campbell (2006) is dissipating. Using account-level data from Ant Group that allows us to construct individual-level consumption, investments, and FinTech adoption, our paper is a study of household finance in the age of FinTech. Focusing on household risk-taking, a topic central to household finance, we study how FinTech adoption can lower investment barriers and help improve household risk-taking. An important puzzle in the study of household finance is the low participation in risky assets by households. Among others, explanations for under risk-taking include lack of financial education, fixed physical costs (money, time, and effort), and psychological factors such as familiarity and trust.[1] Compared with traditional venues, the technological efficiency of FinTech platforms can significantly reduce some of the physical costs. Their brand recognition and the repeated usage of FinTech apps by individuals (e.g., via digital payments) may very well help lower the psychological barriers by building familiarity and trust. Over the long run, FinTech apps can also serve as effective venues promoting financial literacy.

To study the impact of FinTech on household risk-taking, we take advantage of a unique measure of FinTech adoption, which we construct from the ground up for each individual

[1] 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. See, for example, Haliassos and Bertaut (1995) Campbell (2006), Vissing-Jørgensen and Attanasio (2003), Hong et al. (2004), and Guiso et al. (2008).

in our sample. 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, our paper uses the FinTech adoption measure to mimic that migration. Those with low FinTech adoption are at an early stage, while those with high FinTech-savvy adoption in our sample are taking full advantage of what FinTech has to offer. It is through exploring the difference in risk-taking behavior across this dimension of FinTech adoption, both at the individual level and across geographical locations in China, that we offer evidence on how FinTech can improve household risk-taking. Using the optimal risk-taking and consumption solutions of Merton (1971), we can further quantify the extent to which FinTech can help individuals move closer to their optimal alignment of risk-taking and consumption.

Central to our study is the measure of FinTech adoption, which we construct using the individual's third-party consumption paid via Alipay relative to his/her online consumption on Taobao.[2] In designing the measure of FinTech adoption, one important insight we have is that such measures need to be in sync with the technological development at the time. In other words, the propensity of an individual's FinTech adoption can be best measured amidst the fast-developing trend of a new technology. Over our sample period, from January 2017 to March 2019, China experienced a rapid increase in FinTech penetration in the form of offline QR-code scanning payment, of which Alipay was the pioneer adopter in China. Over the span of just two years, this form of payment exploded from 0.6 trillion yuan in Q1 of 2017 to 7.2 trillion yuan in Q4 of 2018. The same trend is captured in our data via the rapid increase in Alipay fraction: The ratio of Alipay to Taobao consumption increased from 90% in January 2017 to 197% in March 2019. Over the same time span, online Taobao consumption was itself increasing, but it was "yesterday's technology." Circa 2018 in China, the FinTech savviness of an individual is captured not by his/her online consumption, but by the FinTech penetration of his/her offline consumption.

Two aspects of the cross-sectional variation in FinTech adoption are important to our empirical tests on how FinTech adoption can improve risk-taking. First, at the individual-level, those with higher measures of FinTech adoption are more Tech-savvy, and are more likely to use the existing FinTech platforms (e.g., Ant Group's mutual-fund platform) to fulfill

[2]Specifically, each individual's FinTech adoption is Alipay/(Alipay+Taobao), a variable ranging from 0 to 1. We also construct an alternative measure of FinTech adoption, using the number of Alipay payments per individual. For the purpose of capturing FinTech adoption, the information contents of both measures are quite similar and our main results remain robust or become stronger with this alternative measure. Taobao, the Amazon of China, is the online shopping platform operated by Alibaba. Alipay is the first and also the largest digital payment system in China. It was originally created by Alibaba to overcome the lack of trust between buyers and sellers on Taobao, and has since been separated from Taobao and is now owned by Ant Group.

their investment needs. In addition to natural inclination, the repeated usage of Alipay app can also help individuals build trust and familiarity with the FinTech platforms, lowering the psychological barriers. Either by nature or nurture, the traditional barriers break down sooner for such individuals. As a result, this group of high FinTech adoption would be closer to the optimal risk-taking relative to their less FinTech-savvy counterparts of the same risk aversion. Indeed, this is the focal point of our empirical study.

Second, across geographical locations in China, FinTech penetration took place gradually during our sample period. Using individual-level location information and aggregating the FinTech adoption measures to the city-level, our map of city-level FinTech adoption reveals Hangzhou, the headquarter of Alibaba and Ant Group, as the epicenter, leading the way in FinTech penetration. But when it comes to changes in FinTech adoption, from January 2017 to March 2019, the center of the action moves away from the coastal areas surrounding Hangzhou and Shanghai, and into the inner China. Indeed, back in 2016, street vendors accepting QR-code scanning payments were a novelty sight spotted mostly near Hangzhou; by 2019, it has become part of the everyday life across 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.

To measure risk-taking, we use our mutual-fund data, which includes mutual-fund purchase and redemption taken place on Ant Group's platform by individuals in our sample. For a sub-period, from August 2017 through December 2018, we also have such individuals' mutual-fund holdings data. Third-party intermediation of mutual funds started in 2012 and have grown quickly in fund coverage and market share. Ant Group entered in 2014 and has since become a dominant player. Via the one-stop Alipay app, investors can purchase and redeem nearly the entire universe of mutual funds in China with a few taps on their mobile phone.[3] We measure individuals risk-taking from three aspects. For all individuals in our sample, "risky participation" is a zero-one variable measuring their participation in non money-market funds, which include bond funds, mixed funds, equity funds, index funds, QDII funds, and gold funds. For active investors in our sample, we further construct their "risky shares," which are the portfolio weights on the non money-market funds, and their "portfolio volatility" from monthly returns to their mutual-fund holdings.

[3]Hong et al. (2019) study the third-party mutual-fund platforms and document their economic impact on mutual-fund investors, fund managers and fund families.

Our empirical results at the individual-level can be summarized as follows. Using FinTech adoption to explain the cross-individual variation in risk-taking, we find that all three risk-taking measures are positive and significantly related to FinTech adoption. Quantitatively, moving the FinTech adoption measure from zero to one corresponds to an increase of 13.6% in risky participation, where the average risky participation rate is 37.5% across the 50,000 individuals in our sample. Likewise, moving the FinTech adoption measure from zero to one corresponds to increases of 14% in risky share and 0.52% in portfolio volatility, where, across the 28,393 active users in our sample, the average risky portfolio weight is 45% and the average monthly portfolio volatility is 1.77%.

In additional to exploring this cross-individual variation in FinTech adoption, we also follow the same individual and measure his/her change in FinTech adoption from 2017 to 2018. We find a significant relation between changes in FinTech adoption and changes in risk taking. As an individual increases his/her FinTech savviness from 0 to 1, his/her likelihood of risky participation increases by 1.4%, which is smaller in magnitude than the cross-sectional result of 13.6%, but is still economically meaningful. The corresponding change in this individual's risky shares increases by 8.7%, which is of the same order of magnitude as the cross-sectional result of 14%. It should be emphasize that this positive relation between risk-taking and FinTech adoption is not driven by new technologies being available at the same time. During our sample period, the third-party mutual-fund platforms have already been well developed and, unlike the increasing trend in Alipay, the aggregate mutual-fund purchases in our data do not exhibit a time trend and are driven mostly by the performance of the capital markets.

So far, our empirical results indicate that FinTech adoption fosters risk-taking. But to what extent is our result driven by risk aversion, given that FinTech-savvy investors tend to be more risk tolerant? For this, we follow Merton (1971), where the optimal consumption volatility is linear in risk tolerance, and infer individuals' risk tolerance from their consumption growth volatility. We obtain our consumption data from Ant Group, but the actual consumption takes place on Alibaba's Taobao platform.[4] It includes monthly Taobao consumption of each individual in our sample, from which we construct individual-level consumption volatility. Consistent with Merton (1971), we find that individuals with more volatile consumption, hence higher risk tolerance, do invest more in risky assets. All three risk-taking measures are positive and significantly related to consumption volatility.[5]

[4]Most users in China have two mobile apps: Taobao for online consumption and Alipay for investments and digital payments. Our data is unique in that it allows us to track the investments and consumption behavior of the same individual.

[5]These results exploring the link between risk-taking and consumption are interesting and important in their own right, as the measurement difficulty emphasized by Campbell (2006) hinders comprehensive studies

Moreover, both FinTech adoption and consumption volatility are important in explaining risk-taking. In particular, after controlling for risk aversion, our earlier results of FinTech adoption fostering risk-taking remain strong.

More interestingly, including the interaction of FinTech adoption and consumption volatility in explaining individual risk-taking, we find that the enhancement of FinTech adoption on risk-taking increases with risk tolerance. In other words, while FinTech adoption fosters risk-taking for all individuals, it is the more risk-tolerant investors who benefit more from the FinTech advancement. If the advent of FinTech can indeed break down barrier and unshackle the constraints, both physical and psychological, then it is the more risk-tolerant investors who stand to benefit the most, as they were otherwise more constrained in the absence of FinTech.

With respect to the low participation puzzle, our finding of increased risk-taking is an improvement. But to what extent is the risk-taking optimal? Could FinTech induce over risk-taking? To answer this question, we quantify the risk-taking improvement relative to the optimal solutions of Merton (1971), where the optimal consumption volatility equals the optimal portfolio volatility and both are linear in risk tolerance.[6] Consider investors with varying risk aversion in this hypothetical world of Merton (1971) and plot their portfolio volatilities against their consumption volatilities. Investors with the same risk-aversion will be a dot on the plot, and the dots will line up along the 45-degree line. Applying this thought experiment to our data, we double sort individuals in our sample by their FinTech adoption and consumption volatility into $2 \times 25 = 50$ groups. For each group, we calculate the average portfolio volatility and consumption volatility and, to focus on the cross-group variation, we normalize the portfolio and consumption volatilities by their respective cross-group standard deviations. Regressing portfolio volatilities on consumption volatilities, we find the alignment of portfolio and consumption volatilities to be substantially closer to the optimal for the groups with high FinTech adoption. Relative to Merton (1971), where the slope coefficient is 1 and the R-squared is 100%, the slope coefficient is 0.91 (t-stat=8.86)

in household finance that incorporates both investments and consumption. It should also be emphasized that this positive connection between risk-taking and online Taobao consumption is not driven by two increasing time trends. Unlike the significant growth in Alipay, online shopping on Taobao and online mutual-fund transactions on Ant's platform are well established during our sample period.

[6] As solved by Merton (1971), the optimal portfolio weight is $w^* = (\mu - r) / \left(\gamma \sigma_R^2\right)$, 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 $\sigma_c = \sigma_w = w^* \sigma_R$. Using online Taobao consumption, our measures of consumption volatility are much higher than the volatility of individuals' total consumption. Nevertheless, we expect the cross-individual variation in σ_c to capture the cross-individual variation in risk tolerance, $1/\gamma$. For this reason, we compare the normalized versions of portfolio and consumption volatility, after scaling both volatilities using their respective cross-sectional standard deviations.

for the high groups and 0.58 (t-stat=4.42) for the low groups, and the R-squared's are 77% and 45% respectively.

We further explore a second and equally interesting cross-sectional variation – the FinTech penetration across geographical locations in China. As discussed early, during our sample period, there was a gradual penetration of Alipay into different cities in China, with coastal areas surrounding Hangzhou and Shanghai leading the way. This serves as a natural experiment for us to examine the extent to which FinTech can help lower the investment barriers and foster risk-taking. Of particular interest to us are those cities in China underserved by banks, as individuals living in such cities stand to benefit the most from FinTech adoption. Indeed, this is what we find. Our results show a positive and significant relation between city-level FinTech penetration and risk-taking, and the results are robust to further controls of city GDP, population, income, and bank accessibility. Using the number of local bank branches as a measure of the city-level coverage of financial services, we find that the effect of FinTech penetration on risk-taking is stronger for cities with low financial-service coverage. This finding indicates that FinTech could provide a complementary role to traditional financial institutions in the provision of financial services.

Compared with that at the individual-level, the city-level variation in FinTech adoption is more exogenous owing to the gradual spread of Alipay penetration across China. To further exogenize this cross-city variation, we design two more empirical tests. First, taking advantage of the gradual spread of FinTech penetration, we track the FinTech penetration of the same city from 2017 to 2018, and examine the relation between changes in FinTech penetration and changes in local risk-taking. By focusing on the changes instead of the levels, the impact of any city-level characteristics that do not comove with the city-level penetration shocks is taken out. Our results remain robust. Second, we employ an instrumental variable approach, using the distance to Hangzhou to instrument city-level FinTech penetration. 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. From this perspective, cities closer to Hangzhou, with cooperation from local merchants, are more likely to be selected by Ant Group to implement this new technology. In other words, distance-to-Hangzhou, our instrumental variable, contains valuable information with respect to FinTech penetration, but is not driven by individual risk-taking. Our results show that a 10% increase in FinTech penetration, instrumented by distance-to-Hangzhou, predicts a 3.05% ($t = 2.33$) increase in risky fund participation for individuals in the city. Using the distances to the four tier-one cities (Shanghai, Beijing, Guangzhou, Shenzhen) as placebo tests, we find no such result.

Our paper contributes, first and foremost, to the extensive literature on household finance.[7] 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. Against this backdrop, our paper is the first comprehensive study on the link between optimal risk-taking and consumption.[8] Compared with the prior literature, which relies on low-frequency observations from survey or census data, our paper is unique in that, taking advantage of the individual-level high-frequency data, we are able to construct consumption and investments volatilities for each individual in our sample. Along with Mankiw and Zeldes (1991), we are among the very few in the literature to document empirically the theory's prediction on the positive relation between risk-taking and consumption volatility. We further offer the first quantitative evaluation of the optimality predicted by Merton (1971) by taking advantage of the richness of our data across a large cross-section of individuals.

Another important contribution of our paper is to document the positive relation between FinTech adoption and risk-taking, which can help shed light on the long standing puzzle of low-participation and under risk-taking in household finance. If the pre-FinTech inefficiency 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. But if the pre-FinTech friction also includes individuals' mistrust of the traditional distribution channels, then the cost of information asymmetry can be more severe for risky securities. Consequently, the advent of FinTech has implications for the level of risk-taking as well, as repeated usages of Alipay can build familiarity and trust and help reduce the psychological barriers and the information-asymmetry costs. Our findings of increased risk-taking, after controlling for risk tolerance, therefore are in support of Hong et al. (2004) and Guiso et al. (2008), who document that familiarity and trust are important drivers for the low-participation puzzle.[9] Interestingly, our result indicates that the pre-FinTech barrier was actually more binding for the more risk-tolerant investors, as they are found in our paper to enjoy stronger improvement in risk-taking with FinTech adoption. Overall, our evidences

[7]Campbell (2006) provides the first comprehensive review of the academic literature on household finance, and is followed by review articles by Guiso and Sodini (2013) and Beshears et al. (2018).

[8]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 et al. (2020), Agarwal et al. (2020), and Loos et al. (2020).

[9]Among others, Christiansen et al. (2008), Calvet et al. (2009), Gennaioli et al. (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.

point to FinTech advancement as a potential solution to household under risk-taking.

Finally, our paper contributes to the growing literature on the impact of technology on household finance. This includes Barber and Odean (2002), Choi et al. (2002), and Bogan (2008), who examine how the introduction of Internet in the early 2000s can help improve stock participation. Tracing further back in history, the emergence of technologies such as steamships and telegraph in finance can be viewed as early prototypes of FinTech. While technologies were used by financial institutions as tools and facilitators during the earlier waves of technology developments, the current wave of FinTech is disrupting and even threatening to replace the existing financial institutions. Leveraging on their huge client bases, low operational costs, and super-convenient user interfaces such as the Alipay mobile app, the FinTech platforms are delivering financial products and services directly to individual investors. In other words, the current wave of FinTech is unique in that it has the potential to reshape the practice of household finance from the group up.[10] Focusing on this exciting development, our paper is in essence a study of household finance in the age of FinTech and our results point to the risk-taking improvement of FinTech. Our finding on how FinTech can benefit individuals less served by traditional banks has profound implications for the future of FinTech. For emerging-market countries with less developed financial infrastructures (e.g., Badarinza et al. (2019)), FinTech platforms can help fill the vacuum left open by the traditional financial services.

The paper proceeds as follows. Section 2 describes and summarizes our data. Section 3 provides a comprehensive exposition of our FinTech adoption measure. Section 4 studies the risk-taking improvement of FinTech at the individual level, and Section 5 focuses on the FinTech penetration across geographical locations in China. Further analyses and robustness tests are provided in Section 6, and Section 7 concludes.

2 Data

The main dataset used in this study is an individual account level data from the Ant Group. Most users in China have two mobile apps: Taobao for online consumption and Alipay for investments and digital payments. Taobao, the Amazon of China, is the online shopping platform operated by Alibaba. Alipay is the first and also the largest digital payment system in China. It was originally created by Alibaba to overcome the lack of trust between buyers and sellers on Taobao, and has since been separated from Taobao and is now owned by Ant

[10] Among others, Goldstein et al. (2019), Philippon (2018) and Frost et al. (2019) discuss the FinTech opportunities and how their entrance might affect the household and financial institutions, Carlin et al. (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.

Group. Starting from 2014, via the one-stop Alipay app, investors can also access and invest in almost the entire universe of mutual funds in China.

Our data is unique in that it allows us to track the investments and consumption behavior of the same individual. The dataset contains detailed monthly consumption and mutual fund transactions for randomly selected 50,000 investors in the period from January 2017 to March 2019. For consumption variables, we have two broad categories: Taobao consumption and Alipay consumption. Taobao consumption is the total consumption expense that occurs on the Taobao online shopping platform, whereas Alipay consumption contains all other consumption expense paid through the Alipay app. For investment data, we obtain 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 obtain the detailed fund holdings and portfolio monthly return information for each investor. The data also include individual personal characteristics such as age, gender, residential province, and residential city. Investors are required to have at least one purchase or redemption of money market fund, or mutual fund, or short-term wealth management product on Alipay app to be included. Below we describe our data in detail along the dimensions of our sample distribution, individual investment and consumption behaviors.

2.1 Sample of Individuals

Table 1 provides a summary on the distribution of our sample investors. We provide summary statistics for both the whole sample (50,000 users) and a subsample of active users (28,393 users). Some users in our sample have very small amount of investment at the magnitude of around 10 RMB. It is possible that these users are still in the process of the adoption of platform. Including them in the sample may add additional noise to measures of individual 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.[11]

Panel A of Table 1 shows the distribution for all 50,000 users in our sample. The distribution of Ant platform investors tilts toward female and young population. In particular, 61% of investors on the Ant platform are female with an average age of 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. A typical investor on platform has a monthly Taobao consumption of

[11]One major reason for investor to invest a small amount is due to the promotion of the Ant investment platform. In particular, the platform may offer free fund shares to some investors, or provide discount on first purchase under certain circumstances. Purchase of very small amount is more likely to due to these promotion policies.

2,155 RMB and a monthly consumption growth volatility of 1.21 (or 121%).[12] Alipay fraction (AliFrac) is calculated as the fraction of Alipay consumption out of total Alipay and Taobao consumption for each user. Investors with a higher fraction of Alipay consumption are more familiar with the usage of the Alipay App as they frequently use it for payments. Therefore, we later use this measure as a proxy for investors' tech savviness.[13] The average Alipay fraction is 0.54 in our sample, suggesting that investors on average have 54% of their consumption paid through Alipay out of total Alipay and Taobao Consumption. The average of the logarithm of the monthly Alipay frequency (Log(AliCnt)) is 3.01, suggesting that investors on average make 20.3 times Alipay payments a month in our sample period. 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. Among those 50,000 users, many investors only participate in money market fund but not risky mutual funds due to the popularity of Yu'ebao in China. Hence, we construct our first risk taking measure using risky mutual fund participation dummy that equals one for individuals who ever purchase at least 100 RMB in non-MMF mutual funds. We find only 37.5% of investors participate in non-money market fund investments out of the 50,000 users.

Panel B shows the summary statistics for the 28,393 users in our "active user" sample. Restricting the sample to users with at least 100 purchase enables us to further examine risk taking measures of portfolio risky share and portfolio volatility. With respect to personal characteristics, active users exhibit similar patterns as those of the whole sample users. 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 payment of 21 times. Among the active users, participation rate in risky mutual funds is much higher at 66%, as we already exclude the inactive users with less than 100 RMB purchase. Based on the holding data from August 2017 to December 2018, active users on average put 45% of their portfolio holdings in risky mutual funds (Non-MMF) and their portfolio monthly return has a volatility of 1.77%.

Panel C further reports the correlation for the variables in Panel B. 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. More interestingly, AliFrac and Log(AliCnt) are positively correlated with risk taking measures, suggesting that tech-savvy individuals exhibit stronger risk taking. Consistent with the theoretical prediction that consumption growth volatility captures individual risk tolerance, we find consumption growth volatility is

[12]See detailed discussions on individual consumption and economy-wide consumption pattern in Section 2.3 and Section 2.4.

[13]We devote special effort in explaining our FinTech adoption measures in Section 3.

positively correlated with our three risk taking measures.

2.2 Mutual-Fund Investments

Along with the development of Alipay, mutual-fund distributions via FinTech platforms grew from non-existence in 2012 and now captures an estimated 30% of the total market share.[14] In February 2012, China Securities Regulatory Commission (CSRC) issued four licenses allowing platforms to distribute mutual funds. Ant initially missed the first batch of license issuance, but quickly entered the platform business in 2014 and became one of the two dominant players in this market shortly.

Table 2 details the mutual fund investment behaviors for our 28,393 active users on the Ant investment platform. We see that, within these investors with a non-trivial total investment, the average total mutual fund purchase amount is 41,079 RMB throughout our sample period, 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 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. Panel B further reports the correlations between our risk taking measures and those fund investment statistics. We find that all of our three risk taking measures are positively correlated with trading activeness, as captured by number of trading months, number of unique funds, and number of asset classes an investor invest in. This further confirms that our risk taking measures well capture individual investors' risk preference in their mutual fund investment. Risk taking is negatively correlated with total purchasing amount and trade size per trade, which suggests that individuals with high risk taking are not necessarily accompanied with large investment wealth.

Turning to individual investors' asset class allocation decisions, Appendix Table A1 reports the portfolio asset allocations for investors on- and off-platforms. There are six types of risky mutual funds available on the Ant investment platform: bond mutual funds, mixed mutual funds, equity mutual funds, index mutual funds, QDII mutual funds, and gold mutual funds.[15] Panel A of Appendix Table A1 reports the value-weighted monthly returns of the six fund types in our sample period from 2017 January to 2019 March. The overall pattern is consistent with our prior: The returns are highest for equity funds, followed by mixed fund, and then followed by QDII, index and bond funds. Gold funds have lower returns, consistent with investors' hedging demand.

To better understand individual investors' asset allocations on platforms, Panel B of

[14]See Hong et al. (2019) for details on FinTech platforms in the intermediation of mutual funds.

[15]We obtain the fund information, including fund size, flow, and return, for all the mutual funds from CSMAR (China Stock Market &Accounting Research) and Wind.

Appendix Table A1 compares Ant investors' risky fund asset allocations with that of an average retail investor in the market as a benchmark. We find that Ant investors invest less in funds with lower risk, i.e., bond and mixed funds, invest more in equity, index, QDII, and gold funds. The on- and off-platform difference is statistically significant for almost all asset classes.[16]

2.3 Online Taobao Consumption

In China, online consumption took off around 2003 and has since increased to account for about 25% of the total consumption in 2020 (the upper left panel of Figure 1). Taobao, the Amazon of China, is the online shopping platform operated by Alibaba, the undisputed leader in the online shopping market. In 2015, Taobao (including Tmall) accounts for around 80% of the e-commerce shares in China. In recent years, Alibaba's e-commerce sales are growing slower than the overall e-commerce growth, as new entrants like JingDong and Pingduoduo keep entering the market.[17] Panel A of Table 3 shows that during our sample period from January 2017 to March 2019, online consumption grows at a monthly rate of 3.31% (annualized 39.7%) and Taobao consumption grows at a monthly rate of 2.11% (annualized 25.3%).

Due to Alibaba's dominating role in the e-commerce market, our data on Ant investors' consumption via Taobao (including Tmall) is pretty representative of the entire economy. The upper right panel of Figure 1 plots the correlation between economy-wide total consumption and online consumptions. Consistent with online shopping seizing the market share of offline shopping, we see an increase in the correlation of "All and Online" from around 20% in 2015 to around 50% in 2020. Meantime, the correlation between offline and online consumption growth is negative at around -35%, suggesting that online consumption largely substitutes for offline consumption.[18] The green line plots the correlation between total economy-wide consumption and Tabao consumption calculated using our data, which closely tracks the red line of the economy-wide online consumption. Besides, the unique dataset from Ant group also allows us to zoom into the detailed consumption categories of Taobao consumption. The non-mutually exclusive consumption categories include basic, enjoy, development, durable, and non-durable. Lower right panel of Figure 1 shows that on average, around 30% to 40% of Taobao consumption are basic consumption or non-durable

[16] In Appendix Table A2, we further report the asset class choices by investors with difference characteristics.

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

[18] We observe strong seasonality in online and offline consumption, due to the November 11 Online Shopping festival and the Chinese New Year holidays.

consumption, 20% to 30% of consumption goes to the enjoy category, and 10% goes to the development category.

Turning to consumption growth volatilities, Panel A of Table 3 shows that online and Taobao consumptions are much more volatile than the economy-wide total consumption and offline consumptions. During our sample period, the monthly standard deviation of consumption growth is 19.2% for economy-wide online consumption, 21.1% for Taobao consumption, 6.9% for economy-wide offline consumptions, and 5.3% for economy-wide total consumption. The large standard deviation of online consumption is not driven by our specific sample period, as the magnitude remains similar when we extend the sample to early years starting from 2015. The lower left panel of Figure 1 shows the monthly EWMA volatility for economy-wide total consumption, online, and offline consumptions over time. It is apparent from the figure that online consumption (Green line) exhibits higher volatility than total consumption (Black line) and offline consumption (Red line). It terms of representativeness, our Taobao consumption (Blue line) closely tracks the online consumption (Green line). In other words, despite a relatively small sample with 50,000 Ant investors, our online Taobao consumption data is quite representative of the general online consumption pattern in the economy.

The representativeness of Taobao consumption in our data is crucial for the construction of individual consumption growth volatility. According to the classic model in Merton (1971) a higher consumption growth volatility of an agent reflects that the agent can tolerate higher risk. Motivated by this intuition, we later use consumption growth volatility as our proxy for individual risk appetite. For each user, we compute the consumption growth volatility (σ_{C}) as the standard deviation of consecutive month log differences in Taobao consumption. We use only Taobao consumption in the calculation of consumption volatility as investors shopping via Taobao platform has already reached its steady growth stage in our sample period. Besides, Taobao consumption is very representative of the entire economy's online consumption pattern. As we will show later in Section 2.4, consumption via Alipay digital payment is still at its fast growing stage. Including Alipay consumption into the calculation of consumption volatility will largely capture the differential adoption of Alipay by each investor.

Panel B of Table 3 further reports the summary statistics on consumption growth volatility, by different individual characteristics. The average individual consumption growth volatility is much higher than aggregate online or Taobao consumption, as the aggregation from individual to the economy smooths out most of the variation in consumption. In our paper, we are less worry about the level of consumption growth volatility from online to offline, as we rely on the cross-individual variation in σ_{C} to capture the cross-individual variation in risk tolerance. Investors that are male, young, with low consumption level and high

FinTech savviness, residing in tier-one cities on average have higher consumption growth volatility than other investors.

2.4 Alipay Digital Payment

Digital payments in China started in 2004, and are now literally permeating the entire country with each street vendor at every corner in China eager to accept Alipay or WeChat Pay. Alipay is the first and also the largest digital payment system in China. It was originally created by Alibaba to overcome the lack of trust between buyers and sellers on Taobao, and has since been separated from Taobao and is now owned by Ant Group.

There is a rapid increase in the penetration of digital payment in the form of offline QR-code scan during our sample period from January 2017 to March 2019. In just two years of time, this form of payment exploded from 0.6 trillion yuan in Q1 of 2017 to 7.2 trillion yuan in Q4 of 2018.[19] As shown in Graph A of Figure 2, the same trend is captured in our data via the rapid increase in Alipay-to-Taobao ratio: The ratio of Alipay to Taobao consumption (Blue line) increased from 90% in January 2017 to 197% in March 2019, which coincides well with the economy-wide offline QR-Scan pay to total offline consumption ratio (Red line).

Over the same time span, online Taobao consumption was itself increasing, but it was "yesterday's technology". The upper left panel of Figure 1 plots total Alipay consumption to Taobao consumption together with economy-wide online consumption out of total consumption. We see the former have much sharper increase in the past five years. The same evidence is there from Panel A of Table 3. During our sample period from January 2017 to March 2019, consumption via Alipay exhibits a monthly growth rate of 5.48% (annualized 65.8%), substantially larger than the 2.11% of Taobao and 3.31% of online consumption. This rapid penetration of Alipay digital payment during our sample period then motivate us to use Alipay for construction of individual tech-savviness, which we explain in more detail in Section 3.

Finally, one may wonder whether the development of Ant investment platform coincides with the trend in the development of digital payment function. As described in Section 2.2, the Ant Group enters the mutual fund distribution market in 2014. Moreover, Panel B of Figure 2 plots 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. We see individuals' investment coincides with capital market movements, but not with the growth of Alipay. Overall, the graph suggests that Ant investment platform have already been well

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

developed. The aggregate mutual-fund purchases in our data do not exhibit a growing time trend, unlike the increasing trend in digital payment through Alipay.

3 Measures of FinTech Adoption

Central to our study is the measure of FinTech adoption. Over our sample period, from January 2017 to March 2019, China experienced a rapid increase in FinTech penetration in the form of offline QR-code scanning payment. Over the same time span, online Taobao consumption was itself increasing, but the magnitude of the increase is relatively steady compared to the trend of Alipay usage. In this section, we explain in detail how we take advantage of the differing growing trend of Alipay digital payment and Taobao consumption to construct individual tech adoption measures.

3.1 Main Measure: Alipay Fraction

Amidst the fast-developing trend of digital payment, the propensity to quickly adopt such new invention may vary across different individuals. Some individuals are more Tech-savvy, and are more likely to adopt this new technology. In addition to natural inclination, the repeated usage of Alipay app can also help individuals build trust and familiarity with the FinTech platforms. To capture this cross-individual variation in FinTech adoption and familiarity, our main measure of Tech savviness is calculated as the fraction of Alipay payment amount in the sum of Alipay payment amount and Taobao consumption for each individual. Individuals with a higher fraction of Alipay payment are more willing to use the new payment method, and are also more familiar with the Alipay app as they frequently use it as a payment method. The average Alipay fraction (AliFrac) is 0.54 in our sample, suggesting that investors on average have 54% of their consumption paid through the Alipay payment function out of their total consumption.

Alipay adoption varies across geographical areas. Figure 3 shows the geographic distribution of Alipay fraction (AliFrac) at the city level, which is calculated as the average AliFrac of all investors in a city. The darker the color in the map, the higher level is the AliFrac. City tech-penetration varies across different cities with a range between 0 to 0.7. The city with highest tech penetration in our sample is Hangzhou, the headquarter of Alibaba. Hangzhou has a tech penetration score of 0.645, suggesting that individuals in Hangzhou on average have 64.5% of their consumption paid through Alipay out of total Alipay and Taobao Consumption. Centering at Hangzhou, we observe a gradual decline of tech penetration as the city move further away from Hangzhou, which is consistent with the Ant Group's expansion footprints. Top tier cities on average enjoy high tech-penetration, though with an intensity lower than Hangzhou: Shanghai, the closest metropolis to Hangzhou, has a tech-penetration score of 0.623, Beijing 0.577, Guangzhou 0.53, and Shenzhen 0.55.

In addition, over our sample period, the digital payment function of Alipay gradually increases their market share in the offline payment market. In this process, there is also cross-sectional variation in the change in Alipay adoption both at the individual level and at the city level. To capture this dynamic change in FinTech adoption for each individual, we compute the change in Alipay fraction from 2017 to 2018 for each individual. By construction, the change measure reflects the gradual adoption of the new payment technology by the same individual, which is arguably less related to the variation in FinTech adoption driven by the nature of each individual. We average the change in individual Alipay fraction in each city and show the distribution of the change in Alipay fraction across all the cities in Panel B of Figure 3. The distribution of this change measure exhibits a rather different pattern from the level measure. During our sample period, the cities in the inner land of China experienced a larger change in Alipay fraction than the cities in the coastal area near Hangzhou. This pattern suggests that the digital payment function of Alipay has already played an important role in more developed cities along the coast line, and started to spread to cities with lower level of economic development in the inner parts of China.

3.2 Alternative Measure: Alipay Count

Our main measure scales the Alipay payment amount by total consumption level to tease out the effect of difference in wealth level of each individual. However, one potential concern is that different levels of Alipay fraction variable 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 tend to have low level of Alipay fraction by construction. [20] To 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 count from 2017 to 2018.

3.3 Determinants of FinTech Adoption

Table 4 reports the determinants of Tech savviness for both the main measure and the alternative measure. In particular, Panel A reports the determinants of the levels of the main

[20]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.

measure in columns (1) to (4), and the alternative measures in columns (5) to (8). We report the results for both the sample of all users (50,000 users) and the sample of active users (28,393 users). As shown in columns (1) to (2), the AliFrac measure is positively related to the consumption growth volatility, and negatively related to the female dummy. Consistent with our expectation, AliFrac is negatively related to the logarithm of Taobao consumption by construction. Therefore, we control for Taobao consumption in our subsequent analyses. When we include city-level economic variables in columns (1), we find that AliFrac is positively related to the logarithm of GDP and Income.[21] Column (2) includes city fixed effect, and the result remains similar to the result in column (1). Moreover, when we restrict our analysis to the active users sample in columns (3) and (4), the overall patterns remain roughly the same.

Columns (4) to (8) report the results using 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.

Panel B reports the determinants of the change in FinTech Adoption. The pattern is slightly different from the results on the levels of the measure. In particular, we find that both the change in Alipay fraction and the change in the logarithm of Alipay count are negatively related to consumption volatility, and positively related to age. As indicated in the results in Panel A, young individuals, and individuals with relatively high risk tolerance are the pioneers in adopting this new payment method. However, as the digital payment function of Alipay became more widespread from 2017 to 2018, older individuals, and individuals with relatively low risk tolerance also started to use it as an important method of payment. The changes in these two measures are also negatively related to logarithm of Taobao consumption. This is potentially due to the reason that individuals who consume more on Taobao tend to adopt the digital payment of Alipay early on. Therefore, they experience less change in payment behavior in our sample period. Moreover, as shown in columns (1), (3), (5), (7), both change measures are negatively related to Log(GDP) and Log(Income). This result confirms our previous observation from the geographical distribution of the change in FinTech adoption: during our sample period, the digital payment function of Alipay has spread to the cities with relatively low level of economic development in the inner parts of China.

[21] The coefficient on the Tier one city dummy is negative, due to the inclusion of Log(GDP) in the regression. The GDP levels are much higher for tier 1 cities than those for other cities, whereas the Alipay fractions of tier 1 cities are only slightly higher than those for tier 2 cities.

4 Empirical Results: Individual FinTech Adoption

In this section, we examine how FinTech adoption affects risk taking at the individual level. Utilizing our rich micro-account data on both consumption and investment, we also examine the effect of FinTech adoption on risk-taking conditional on heterogeneous individual risk tolerance as suggested in Merton (1971).

4.1 FinTech Adoption and Risk Taking

At the individual level, those with higher measures of FinTech adoption are more Tech-savvy, and are more likely to use the existing FinTech platforms to fulfill their investment needs. In addition to this natural inclination, the repeated usage of Alipay app can also help individuals build trust and familiarity with the FinTech platforms, lowering the psychological barriers. As a result, we expect FinTech adoption to improve risk taking at the individual level.

We examine the relation between the three risk taking measures and tech savviness in a regression setting, and report the corresponding results in Panel A of Table 5. Columns (1) to (4) report the results for participation. In column (1), we only include tech savviness in the regression. In this setting, we obtain a coefficient of 0.154 with a t-stat of 13.06. In other words, moving the tech savviness measure from zero to one corresponds to an increase of 15.4% in risky participation, where the average risky participation rate is 37.5% across the 50,000 individuals in our sample. Column (2) includes city fixed effect, which will absorb the variation of FinTech adoption across cities. The magnitude of the coefficient is reduced slightly to 0.136 (t-stat = 11.50), which suggests that the city-level variation in Fintech adoption also has some effect on investor participation. To further capture investors' risk preferences, column (3) includes consumption growth volatility, and column (4) further control for investor personal characteristics. The results for tech savviness are qualitatively the same across all specifications.

The above pattern is similar for risky share and for portfolio volatility, as reported in Columns (5) to (8) and Columns (9) to (12), respectively. For example, in the setting with all controls, moving the FinTech adoption measure from zero to one corresponds to increases of 14.6% in risky share and 0.45% in portfolio volatility, where, across the 28,393 active users in our sample, the average risky portfolio weight is 45% and the average monthly return portfolio volatility is 1.8%. Moreover, the coefficients on tech savviness in other specification have a comparable magnitude and statistical significance. Overall, we find that individuals with higher tech savviness are associated with a higher risk taking level after controlling for various investor personal and consumption characteristics, and the results are both economic and statistically significant.

One may argue that some unobserved investor personal characteristic which correlates with tech savviness may drive the previous results. To rule out this possibility, we examine the effect of the change in tech savviness on the change in investors risk taking behavior at the individual level. In particular, for each individual, we compute the change in tech savviness from year 2017 to year 2018. Correspondingly, we measure the change in risky asset participation and the change in risky share at the individual level.[22] We also include the change in average monthly trading propensity from 2017 to 2018 as an additional measure of active investment participation in risky assets.

Panel B of Table 5 reports the corresponding results for the effect of the change in FinTech adoption. We follow a similar regression specification in Panel A with all controls. Consistent with our prior, individuals with a larger increase in tech savviness also participate more in risky asset investment, and increase the risky share in their portfolio. In particular, as an individual's tech savviness increases from 0 to 1, his/her likelihood of risky fund participation increases by 1.4%, which is smaller in magnitude than the cross-sectional result of 13.6%, but is still economically meaningful. The corresponding change in this individual's risky shares increases by 8.7%, which is of the same order of magnitude as the cross-sectional result of 14.6%. Moreover, according to column (3), as an individual's tech savviness increases from 0 to 1, his/her average trade probability in each month increases by 2.5%.

The aforementioned patterns are also evident from a graphical representation. In particular, we sort all individuals into fifty groups according to tech savviness, and compute the average tech savviness and average risk taking measures within each group. The upper two panel and the lower left panel of Figure 4 plot the average participation, risky share, and portfolio volatility of each group against their average tech savviness, respectively. One can observe a roughly monotone and linear relation between tech savviness and all three measures of risk taking, as indicated by the dots on the graphs. When we regress the risk taking measures on the average tech savviness at the group level, the R-squared measures of the regressions are 79%, 71%, and 38%, respectively. Moreover, the lower right panel of Figure 4 repeats the analysis using the change in risky share and the change in tech savviness. The overall pattern is quite similar to the pattern for the tech savviness level.

Finally, it should be emphasized that this positive relation between risk-taking and FinTech adoption is not driven by new technologies being available at the same time. As discussed in Section 2.2, mutual fund distribution through the Alipay App have already been well developed during our sample period, and, unlike the increasing trend in the usage

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

of digital payment through Alipay, the aggregate mutual-fund purchases in our data do not exhibit a time trend and are driven mostly by the performance of the capital markets.

4.2 Consumption Volatility, Risk Tolerance, and Risk Taking

The previous subsection discusses the relation between FinTech adoption and risk taking. One important questions is to what extent is this result driven by risk aversion, given that tech-savvy investors tend to be more risk tolerant. Motivated by the portfolio choice problem in Merton (1971), we use the realized consumption growth volatility of each individual as a proxy for their revealed risk tolerance level. In the basic Merton framework, an investor must choose how much to consume and must allocate his wealth between a risky asset and a risk-free asset so as to maximize expected utility. A high risk averter prefers a steadier flow of consumption at a lower level of expected return.

Consistent with the theoretical prediction in Merton (1971),[23] we find that individuals with higher consumption growth volatility indeed exhibit higher levels of financial risk taking. For example, as shown in columns (3), (7), (11) in Panel A of Table 5, a one standard deviation increase in consumption growth volatility is associated with 1.48 ($= 0.4 * 3.7$)% increase in risky fund participation, 2.08% increase in risky share, and 0.138% increase in portfolio monthly return volatility. Further controlling for individual gender, age, and consumption level reduces the effect of consumption growth volatility on individual risk taking by half, but the positive relation remains significant, according to columns (4), (8), and (12) in Panel A of Table 5.[24] The empirical evidence is consistent with the interpretation that consumption growth volatility reveals the risk tolerance of investors, and the measure contains additional information over the other observable characteristics, like gender, age, and consumption level.

4.3 FinTech Adoption and Risk Tolerance

Next, we examine the heterogeneous effect of FinTech adoption conditional on investors' risk preferences. In particular, since consumption growth volatility well captures individual risk-taking preference, it is important to understand whether tech savviness helps increase

[23]Merton (1971)'s model is derived in a frictionless setting and abstracts from the issue of participation. However, one can imagine a similar intuition to be at work when investors face a fixed participation cost in risky assets. Investors with higher consumption volatility should have higher incentive to participate in risky asset investment.

[24]Since individual risk preference is hard to observe in the data, the literature often use individual portfolio holding or survey questions to infer their revealed risk preference (Friend and Blume (1975)). Consistent with these literature (for example, Fagereng et al. (2017)), we find that individuals with high consumption growth volatility are more likely to be males at their younger age.

financial risk taking for individuals with high risk appetite. To capture this intuition, we include the interaction of FinTech adoption with consumption volatility, as well as with other investor personal characteristics, in explaining individual risk taking.

First, columns (1), (3), (5) in Table 6 report the regression specification with the interaction between tech savviness and consumption growth volatility. The coefficients on the interaction terms are significantly positive in the regression of participation and portfolio volatility, suggesting that tech savviness indeed increases the risk taking behavior of the individuals with higher risk tolerance level. This is consistent with the interpretation that the increase in risk taking is beneficial for investors. For risky share, although the coefficient on the cross term is insignificant, we still observe a positive and significant effect on tech savviness. Moreover, columns (2), (4), (6) further include the interactions between tech savviness and other investor characteristics. The coefficients on the interaction between tech savviness and consumption growth volatility remains similar after including other interaction terms. We also find that the effect of tech savviness on participation is significantly more pronounced for investors with higher consumption level, male investors, young investors, and investors in tier one cities. According to findings in the previous literature, investors with these characteristics should have higher risk tolerance. The coefficients on the interactions between tech savviness and additional investor characteristics are less significant in the regression for risky share.

This interaction effect can also be observed from a graphical representation. We first exhibit the relationship between consumption volatility and participation as a benchmark. We sort the individuals into 50 groups according to their consumption volatility, and compute the average consumption volatility and the participation rate for each group. The upper left panel in Figure 5 reports the relationship between normalized consumption volatility and participation rate, in which we normalize consumption volatilities by the cross-group standard deviations. As indicated in the regression line in the upper left panel, when we regress the participation rate on the normalized consumption volatility across the 50 groups, the coefficient is 1.86, confirming an overall positive relationship between consumption volatility and participation rate.

To further show the effect of FinTech adoption on this relationship, we double sort individuals in our sample by their tech-savviness and consumption growth volatility into $2 \times 25 = 50$ groups, and repeat the analyses for the high and low tech savviness group respectively. In the upper right panel of Figure 5, the stars indicate the 25 high tech-savvy groups, whereas the squares denote the 25 low tech-savvy groups. When we fit a regression line for each of the two categories, the slope is higher for the high tech-savviness group (2.33, with a t-stat of 6.98) than the low tech-savviness group (1.09, with a t-stat of 3.37). In other words, within the high tech-savviness group, individuals with high risk appetite are much more likely to participate and invest in riskier funds to satisfy their investment needs than individuals with low risk appetite. To the contrary, within the low tech-savviness group, individuals with high risk appetite and individuals with low risk appetite do not differ in participation rate in a similar magnitude.

In summary, while FinTech adoption fosters risk-taking for all individuals, it is the more risk-tolerance investors who benefit more from the FinTech advancement. If the advent of FinTech can indeed break down barrier and unshackle the constraints, both physical and psychological, then it is the more risk-tolerant investors who stand to benefit the most, as they were otherwise more constrained in the absence of FinTech.

4.4 Optimal Alignment of Risk-Taking and Consumption

Given that we find FinTech adoption fosters individual risk taking, a more important question is whether this is optimal for individuals to move in this direction. To answer this question, we follow the framework in Merton (1971) to quantify more precisely the risk-taking improvement of FinTech adoption.

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

$$\sigma_c = \sigma_w = w^*\, \sigma_R\,.$$

Effectively, according to Merton (1971), the optimal consumption volatility equals the optimal portfolio volatility and both are linear in risk tolerance.

It should be noted that, using online Taobao consumption at monthly frequency, our measures of consumption volatility are much higher than the volatility of individuals' total consumption. Nevertheless, we expect the cross-individual variation in σ_c to capture the cross-individual variation in risk tolerance, $1/\gamma$. Therefore, we compare the normalized versions of portfolio and consumption volatility, after scaling both volatilities using their respective cross-sectional standard deviations. Suppose there are investors with varying risk aversion living in this hypothetical world of Merton (1971). Plotting their portfolio volatilities against their consumption volatilities, investors with the same level of risk-aversion will be a dot on the plot, and the dots will line up along the 45-degree line.

Applying this thought experiment to our data, we present the relation between normalized portfolio volatility and normalized consumption volatility in the lower two panels in Figure 5. In particular, in the lower left panel, we sort investors into 50 groups according to their consumption growth volatility, and compute the average portfolio volatility and average consumption volatility within each group. We normalize the portfolio and consumption volatilities by their cross-group standard deviations. As indicated in the regression line in the figure, when we regress the normalized portfolio volatility on the normalized consumption volatility, the coefficient is 0.79, which is below the 45-degree line predicted by theory. This is also consistent with the consensus in the household finance literature that an average household in the economy takes too little risk relative to the theoretical benchmark.

Next, we examine the effect of FinTech adoption on this predicted relationship between the revealed risk tolerance and portfolio volatility. We double sort individuals in our sample by their tech savviness and consumption volatility into $2 \times 25 = 50$ groups, and repeat the analyses for the high and low tech savviness group respectively. The lower right panel of Figure 5 exhibits the results. The stars indicate the 25 high FinTech-savvy groups, whereas the squares denote the 25 low FinTech-savvy groups. We also fit a regression line for these two categories, respectively. Regressing portfolio volatilities on consumption volatilities, we find a slope coefficient of 0.91 (t-stat=8.86) for the high FinTech-savvy groups, and 0.58 (t-stat=4.42) for the low FinTech-savvy groups. The R-squared of the regression is 77% and 45%, respectively, for the high and low groups. Relative to optimal risk-taking and consumption alignment in the Merton (1971), where the slope coefficient is 1 and the R-squared is 100%, the risk-taking and consumption alignment is 0.91 for the high FinTech-savvy investors, a significant improvement when compared against the alignment of 0.58 for the low FinTech-savvy investors. In other words, FinTech adoption improves the relationship between risk taking and risk tolerance by pushing investors toward their optimal risk-taking level.

5 Empirical Results: City-Level FinTech Penetration

In this section, we examine how tech penetration at city level affect individual financial risk taking. By aggregating individuals to city levels, we utilize the gradual penetration of Alipay payment into different cities to examine whether technology lowers the barriers to provision of financial services and promotes financial inclusion especially for cities with low bank accessibility.

5.1 FinTech Penetration and Traditional Banking Coverage

Panel A of Table 7 reports the OLS estimation for the impact of city tech penetration on individual risk taking. We use the average consumption paid through Alipay out of total consumption in the city as a measure of tech penetration. With local merchants gradually adopting the Alipay scan-to-pay QR code across different cities, the cross-sectional variation in Alipay consumption fraction captures the intensity of tech penetration in different cities. As shown in Figure 3, city tech-penetration varies across different cities with a range between 0 to 0.7.

To capture financial risk taking of individuals in a city, we use the same three proxies in the previous section, and take a simple average. Risk taking for a city is the equally-weighted average of all individuals' risk taking in the city. Columns (1), (4), and (7) in Panel A of Table 7 show that individuals in cities with higher tech-penetration are associated with higher risk taking. When tech penetration of a city increases from zero to one, individuals in the city on average have 27.2% higher risky fund participation rate, 30.4% portfolio weight invested more in risky funds, and 0.76% higher portfolio monthly return volatility. We further include city level controls of number of bank branches in the city, city GDP, population, average income, and tier-one city dummy in columns (2), (5), and (8), the results remain with similar magnitude.[25] The results remain robust when we use the number of Alipay transaction made per month for an average individual in a city as alternative tech-penetration measures, as reported in Panel B in Table 11. Hence, the city level estimation suggests that individuals in cities with high tech penetration are more willing to participate in mutual fund investment, they put more weight in risky fund investment, and their portfolio volatility is higher.

Investment in mutual funds through Ant investment platform may capture only part of individual's financial investment. Outside the Ant platform, individuals can also purchase mutual funds through banks, brokers, and fund families. Hence, there are at least two channels that can explain why tech penetration increases risk taking on FinTech platforms. First, with the penetration of technology, individuals may reallocate their existing investment from traditional channels onto FinTech platform. Due to well-established brand-recognition of Alibaba, secure transaction system, broader coverage of mutual funds, and lower transaction cost, investors may find Ant platform a much more convenient investment venue, compared with purchasing funds through bank counter, family website, or financial advisors. Hence, they move the existing investments from traditional channels to platforms, with the total financial risk-taking unchanged. Second, the penetration of technology opens the door for individuals who are unaware of financial investment opportunities and would otherwise re-

[25] All the city controls are normalized with mean zero and standard deviation of one for easiness of interpretation.

main unbanked. It offers financial services to individuals and areas less served by banks and brokers. Building on its secured payment system and simple user interface, investing in risky financial products also become complicated and require a lower threshold. Hence, technology lowers the barriers for financial investment and encourages risk taking.

The two hypotheses are not mutually exclusive but the economic and welfare improvement channels are different. To offer insight on what better explains our city findings, we examine the impact of tech on risk taking conditional on local bank-accessibility. If the investment on Ant platform mainly comes from a reallocation of capital from traditional channels, we expect the positive relation between tech-penetration and individual risk taking to be stronger among areas well-served by banks. On the other hand, if tech increases risk taking for individuals unbanked, we expect the results to be stronger for low bank-accessibility cites. In columns (3), (6), and (9) of Table 7, we further include the interaction term of Tech-Penetration and Log(#Branch). The coefficient on the interaction terms are mostly negative, indicating that tech increases risk-taking for cities with low bank accessibility. Take the estimation for risky share in column (6) as an example, for an average city, when technology penetration score increases from zero to one, it drives up local individual risky share by 25.4% ($t = 1.89$). If the city bank accessibility decreases by one standard deviation, the same one unit increase in tech-penetration increases risky share by extra 54.6% ($t = 4.26$). Altogether, an increase in tech-penetration from zero to one increases risky share by 80.0% for cities one standard deviation below average city bank accessibility level.

Consistently, Panel A of Figure 6 shows the relation between individual risky share and city-level tech penetration, conditional on local bank accessibility. We divide all cities into half based on the median cut-off of Log(#Branch). Stars represent cities with low bank coverage and circles refer to cities with high bank coverage. The solid fitted line indicates that among cities with low bank coverage, one unit increase in tech-penetration increases risky share by 57%. While among cities with high bank coverage, the same unit increase in tech-penetration increases individual risk taking by only 1%. Hence, overall our results suggest that effect of city tech-penetration on individual risk taking mainly comes from cities less served by banks.

5.2 Change in FinTech Penetration

One may worry that the penetration of technology into cities are endogenous and correlated with certain city level characteristics, which simultaneously affect the local individual risk taking and tech-penetration. Despite that we have controlled for city GDP, income, population, and financial development in the regression estimation in Table 7, there may still exist omitted variables driving the positive relation between tech-penetration and local risk taking. For example, if cities with high tech-penetration happen to have individuals who are more socially connected. Socially connected individuals earn positive utility by talking with friends about participating in the mutual fund market (Hong, Kubik, and Stein, 2004). Then, our finding that tech increases risk taking may capture the effect of this social connectedness which is not well controlled for in our regression specification.[26] To address this type of concerns, we examine the change in city tech-penetration on change in local risk taking. Using change in the variables is equivalent to including city fixed effects, which absorbs any city invariant characteristics.

Panel B of Table 7 reports the results. To measure the change in tech-penetration and change in risk taking, we cut the sample into half and use the year 2017 as before sample and the year 2018 as after sample. Change in tech-penetration is calculated as the difference of average monthly Alipay consumption out of total consumption for year 2018 minus that of 2017. For an average city in our sample, tech-penetration increases from an average of 42% in 2017 to 46% in 2018. There exists large cross sectional variation in change of tech-penetration, with the smallest value around -2% and highest value at 7.9%. Only two cities have a negative change in tech-penetration in our sample. For change in financial risk taking, we follow similar methodology. Change in participation is calculated as the average fraction of investors participated in risky mutual fund in 2018 minus that of 2017. A person is defined as participate for months on and after his/her first purchase of non-money market mutual funds.[27] For an individual that purchase a non-MMF at the beginning of 2017 but subsequently passively hold the fund without any trading, the individual will still be counted as participation thereafter. Hence, to better capture the active trading (participation) behavior of individuals, we also include individuals' trade probability. Change in trade probability is calculated as the fraction of investors who trade in an average month in 2018 minus that of 2017. Finally, change in risky share is defined as the average individual portfolio weight in risky mutual funds in December 2018 minus that of December 2017.

Columns (1), (3), and (5) of Panel B show that when tech penetration of a city increases by 10% from 2017 to 2018, individual participation in risky mutual funds increases by 1.49%, trading probability in an average month increases by 0.84%, and portfolio weight in risky funds increases by 14.7%. In Columns (2), (4), and (6), we further add the interactions between change in tech penetration and Log(#Branch). Consistent with Panel A, the interactions are significantly negative and they even subsume the effect of change in tech penetration itself. This indicates that increase in tech penetration promotes financial

[26]If the penetration of technology increases social connectedness, which subsequently increases local risk taking. It is actually consistent with our story.

[27]We require the purchase to be larger than 10 RMB so as to exclude trivial or non-real purchase.

inclusion, encourages financial risking, especially for cities less served by banks.

Panel B of Figure 6 further confirms the finding by plotting change in risky share from 2017 to 2018 against change in city tech-penetration, conditional on local bank coverage. Consistent with our regression estimation, 10% increase in FinTech penetration leads to 23.3% increase in risky share for cities with low bank coverage. In cities with above-median bank coverage, increase in FinTech penetration does not lead to increase in risky share.

5.3 Distance-to-Hangzhou as an Instrument

The observed positive effect of tech-penetration on individual financial risk taking may not be causal, as the intensity of city tech-penetration and individual risk taking may be subject to other unobserved factors. To identify the causality, we further employ an instrumental variable approach. The instrumental variable is used to predict the intensity of tech penetration across different cities but has no direct effect on individual risk-taking. The instrumental variable for tech-penetration is the distance to Hangzhou. As shown in Figure 3 and discussed in Section 3, the expansion footprint of Alipay centers around Hangzhou and gradually penetrates into other cities in Zhejiang province, the nearby cities, and then distant cities, with cities geographically closer to Hangzhou (the headquarter of Alibaba) more likely being targeted the first. On the other hand, the distance to Hangzhou is arguably orthogonal to individual risk taking. One may worry that Hangzhou is geographically close to some metropolis or tier one cities (especially Shanghai) and the distance to Hangzhou largely overlaps with the distance to Shanghai. If being closer to metropolitan area encourages individual risk taking, then our IV test may mistakenly contribute the effect of metropolitan to Hangzhou. Hence, we further conduct several placebo tests using distance to tier one cities and find no results.

Table 8 report the IV test estimations. In Panel A of Table 8, we report the first stage regression results using distance to Hangzhou as an instrument. We also include first stage placebo regression estimates by replacing distance to Hangzhou with distance to the four tier-one cities (Shanghai, Beijing, Guangzhou, and Shenzhen). Columns (1) and (2) indicate that being closer to Hangzhou significantly predicts higher tech-penetration. Apart from distance to Hangzhou, local GDP also positively predicts tech penetration. For the four placebo cities, we find distance to Shanghai significantly predicts tech penetration, as Shanghai and Hangzhou are geographically very close (two hours by drive). However, the R-square and t-stat both suggests that distance to Hangzhou is a stronger predictor than distance to Shanghai. Moving to the second stage estimation, the IV estimation suggests that a 10% increase in tech-penetration, instrumented by distance to Hangzhou, predicts a 3.05% (t = 2.33) increase in risky fund participation for individuals in the city, 0.86%

($t = 0.67$) increase in risky share, and 0.092% ($t = 3.08$) increase in portfolio volatility. The magnitude estimated using IV test is similar to that of Table 7. Interestingly, when we use distance to Shanghai to instrument, the coefficient estimate is smaller at 0.26 ($t = 2.04$) for participation rate, 0.74 ($t = 2.05$) for portfolio volatility, and insignificant for risky share.[28]

6 Further Evidence and Robustness

In this section, we provide further evidence on the effect of tech savviness on the risk-taking behavior of individual investors from three angles. First, we zoom in on the detailed consumption category and examine the channel through which FinTech adoption affects risk taking. Second, we examine the participation in each particular asset class as alternative risk taking measures. Finally, we provide robustness tests using alternative measures of FinTech penetration.

6.1 Which Component of Consumption?

According to Merton (1971), the consumption growth volatility reflects the risk tolerance level of each individual. Following this intuition, a higher necessity 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 tech savviness 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, enjoyable, durable, and non-durable goods, and compute the consumption growth volatility within each category. These categories are not mutually exclusive. For example, a consumption item can belong to both the basic consumption category and the non-durable consumption category. Basic consumption and non-durable goods consumption are conceptually more related to the necessity goods consumption. We follow the same regression specification in Panel A of Table 5 and Table 6 to examine investors' portfolio volatility, and replace the consumption growth volatility variable with basic, enjoyable, development, durable, and non-durable goods consumption growth volatility, respectively. The corresponding results are reported in Table 9. As reported in column (1), one unit increase in basic consumption growth volatility leads to a

[28]The second stage IV tests with controls are qualitatively similar but much weaker. This is because the nearby cities around Shanghai and Hangzhou (Yangtze River Delta region) are often associated with high GDPs. Hence, controlling for GDPs absorbs a large fraction of the effect of distance. Still, the relative difference between Hangzhou and Shanghai remains.

0.05% increase in portfolio volatility ($t = 2.50$). In column (2), we further include the interaction between tech savviness and basic consumption growth volatility, we find the coefficient to be statistically significant on the interaction term. We find a similar effect for non-durable consumption growth volatility in column (8).[29] However, for enjoyable and durable consumption, we find no significant effect on the interaction term.

Overall, consistent with necessity consumption being more binding for individual investors, we find that tech savviness increases risk taking for individuals with more volatile basic and non-durable consumption.

6.2 Which Asset Class?

Another dimension of risk-taking behavior is the participation in each asset class. In Table 10, we examine participation in each asset class separately. For example, participation in bond fund is set at one if the individual invest a positive amount in bond funds, and zero otherwise. As indicated in columns (1), (3), (5), (7), (9), and (11) of Table 10, tech savviness affects the participation in all asset classes, whereas consumption growth volatility is only significantly related to participation in high risk asset class, i.e., mixed, equity, index, QDII funds. These results are consistent with our prior: Tech-savvy investors are more likely invest in risky asset classes. However, as a measure for risk preference, consumption growth volatility is more relevant to participation in funds with higher risk. When we further examine the interaction between tech savviness and consumption growth volatility, we find that the effect is significant for several risky asset classes.

6.3 Alternative Measure of Tech Savviness

In our main setting, tech savviness is calculated as the fraction of Alipay consumption in the sum of Alipay consumption and Taobao consumption for each investor. One potential concern is that this variable can be partially driven by the variation in individual's Taobao consumption, instead of by the variation in Alipay usage. To 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 to pay for consumption reflects that the individual is more familiar with the App as a payment method. Using this alternative measure, we investigate its effect on investors' risk-taking behavior in the same regression settings. The results are reported in Table 11. Panel A reports the corresponding results at the city level, similar to the setting in Panel A of Table 7, a higher tech-penetration is associated with higher risk taking for all three measures of risk taking across all model

[29] The t-statistic is smaller at 1.63.

specifications. Panel B reports the results at the individual investor level, similar to the setting in Table 5. The coefficients on tech penetration on risky fund participation, risky share and portfolio volatility are qualitatively the same as the results Table 5.

7 Conclusions

The inroads of tech firms into the financial industry substantially break down the barrier and unshackle the constraints for individual investors participating in the financial market. Compared with traditional venues, the technological efficiency of FinTech platforms can significantly reduce both the physical costs and the psychological costs of financial market participation. With FinTech platforms rapidly dominating and even replacing conventional financial institutions, it raises critical need for researchers and policy makers to understand who are those quick adopters of FinTech platforms and how does the penetration of FinTech affect individual financial risk-taking.

Using account-level data from Ant Group that allows us to track each individual's consumption, investment, as well as tech adoption, we provide, for the first time in the existing literature, micro-level evidence on how FinTech adoption affects individual risk taking, and its heterogeneous impact on individuals with varying level of risk tolerance.

At the individual level, individuals that quickly adopt the Alipay digital payment technology exhibit higher risky fund participation rate, their portfolio risky share and portfolio volatility are also higher. We further use the framework in Merton (1971) to quantify the extent to which FinTech can help individuals move closer to their optimal risk taking level. At the city level, we find FinTech fosters local individual financial risk taking, especially for cities less covered by traditional banks. The empirical findings suggest FinTech largely broadens financial inclusion for individuals most in need of it.

Our findings shed light on the potential benefit of tech firms in the provision of financial services. Leveraging on their huge client bases, low operational costs, and super-convenient user interfaces (e.g., mobile apps), the FinTech platforms are reshaping the household finance at a fundamental level. The advent of FinTech could be especially helpful for investors in emerging markets who are in urgent need of financial services due to their rapid growth of household income. Given the lack of existing financial infrastructure in these markets, tech-based options, both less expensive and scalable, are the most promising business model to fill in the current vacuum. Our empirical evidence thus offers reference not only for Chinese investors but also the tech infrastructure development worldwide.

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Figure 1. Online and Offline Consumption in China

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

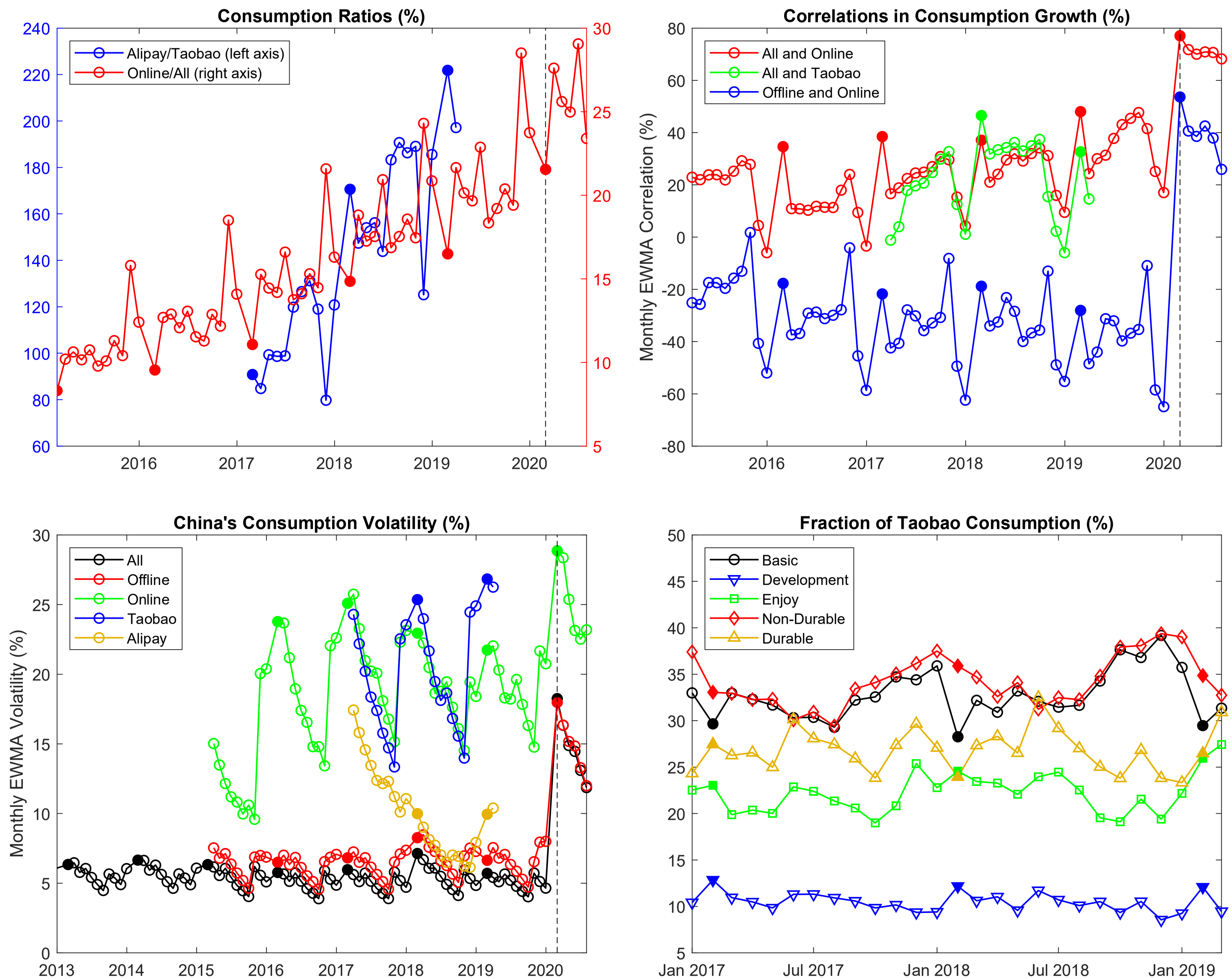
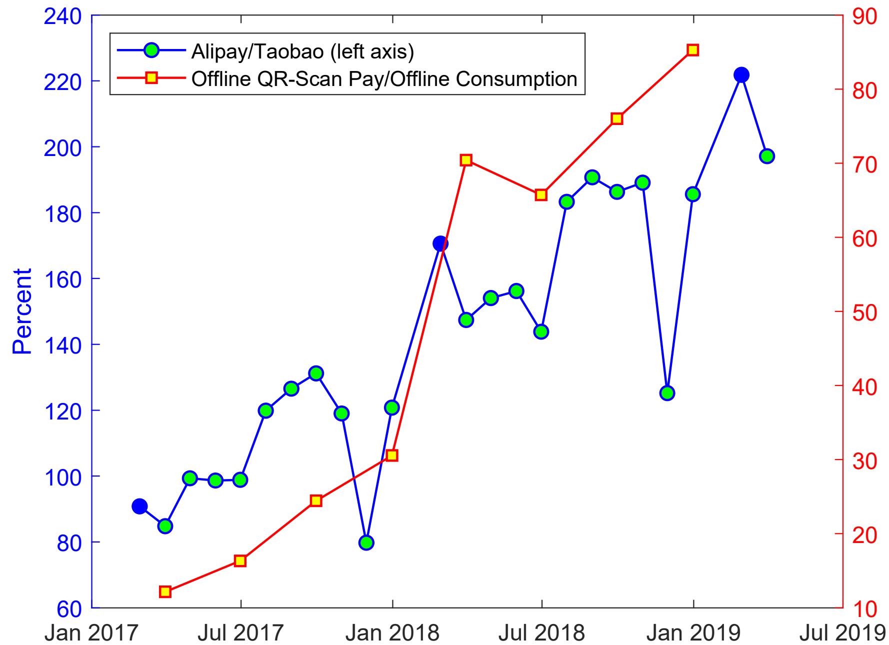
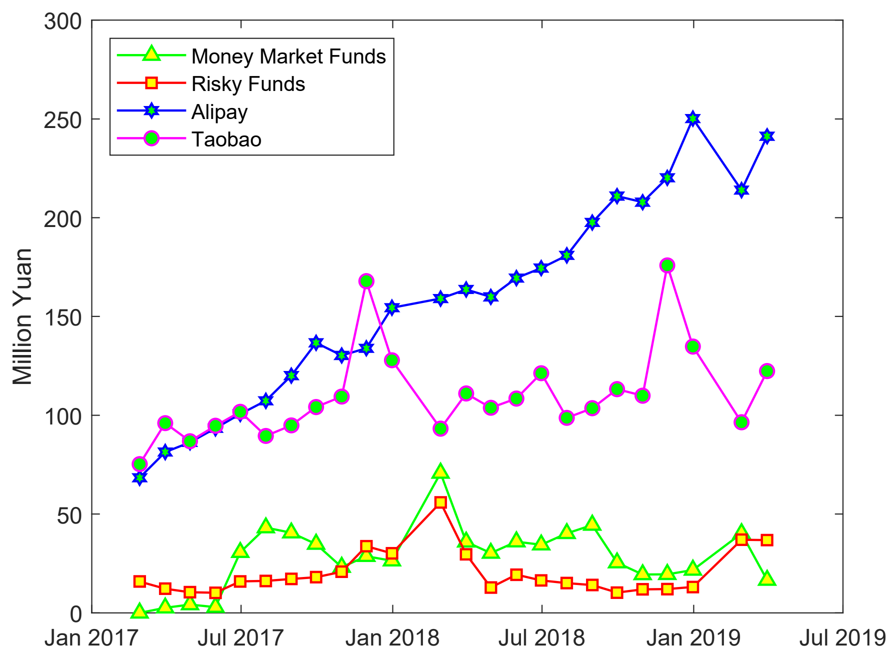


Figure 2. FinTech in China

Data aggregated across 50,000 randomly sampled individuals from January 2017 through March 2019. Consumption data includes online consumption on Alibaba's Taobao platform, and third-party consumption paid via digital payment on Ant Group's Alipay. Monthly mutual-fund purchases are from Ant Group's investment platform.



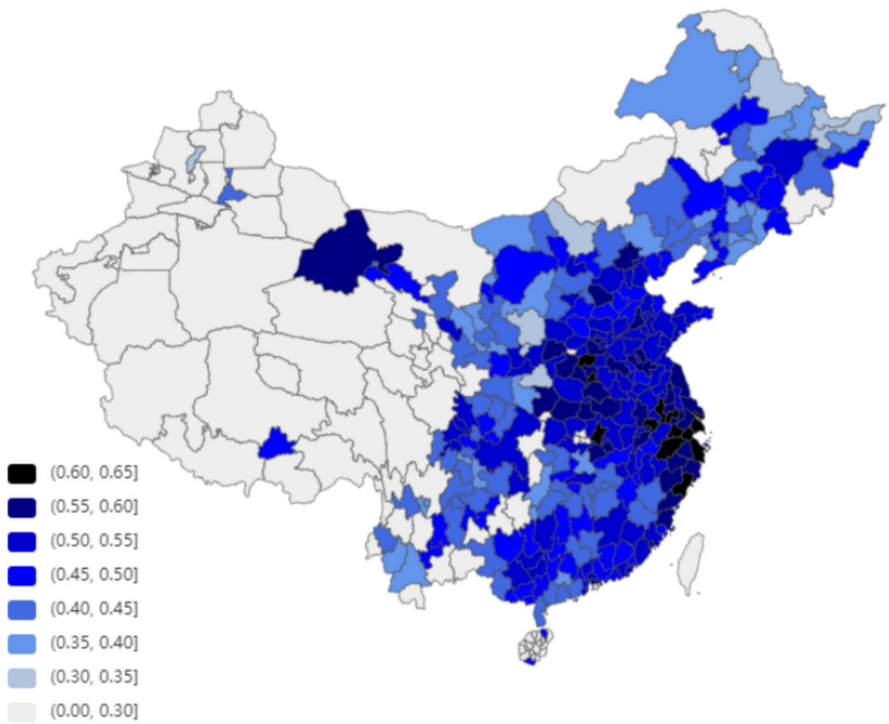
(A) Offline QR-Scan Payment and Alipay Consumption



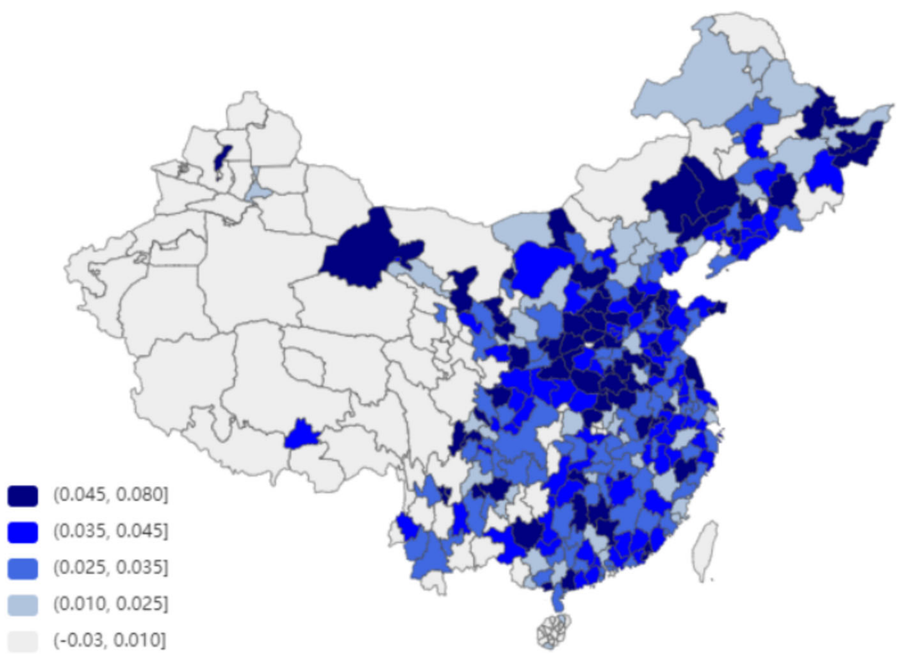
(B) Mutual Fund Purchases and Alipay and Taobao Consumption

Figure 3. Geographic Distribution of FinTech Adoption

Graph A shows the geographic distribution of city-level FinTech penetration. City FinTech adoption is the average fraction of consumption paid via Alipay digital payment out of total consumption for individuals in a city. Change in city FinTech penetration is the average FinTech penetration in 2018 minus that of year 2017.



(A) FinTech Adoption



(B) Change in FinTech Adoption, from January 2017 to March 2019

Figure 4. FinTech Adoption and Risk Taking

We classify all individuals into 50 equal groups based on their tech savviness. We then calculate the risky fund participation rate, risky share, and portfolio volatility for each group of individuals. The lower right panel further shows the relation between change in tech-savviness and change in risky share from 2017 to 2018, for 50 groups of individuals classified based on change in tech-savvniness.

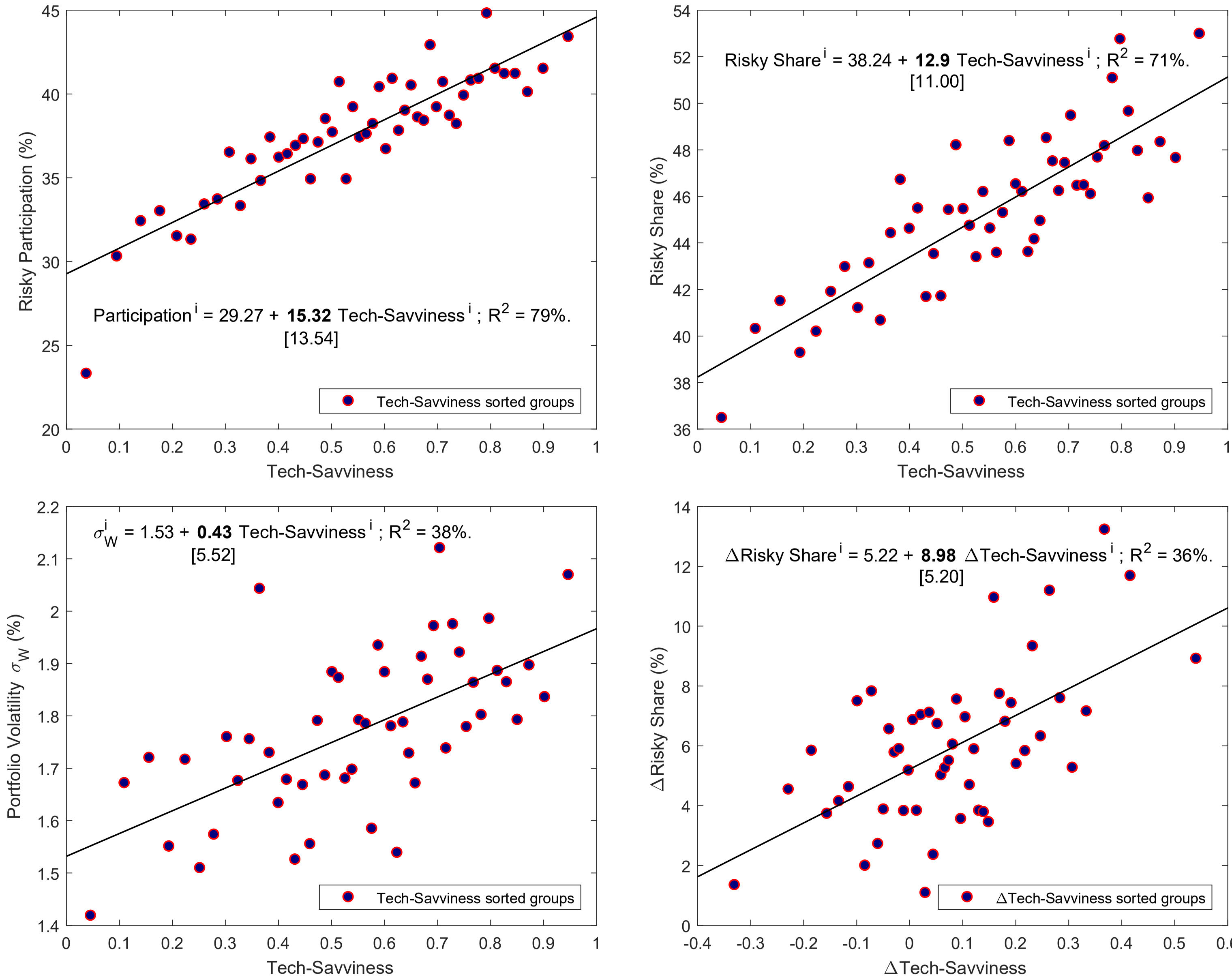


Figure 5. FinTech Adoption on the Alignment of Risk-Taking and Consumption Volatility

We classify all individuals into 50 equal groups based on their consumption growth volatility. We then plot the equal-weighted average of individual portfolio risk-taking against their average monthly consumption growth volatility in the left two panels. In the right two panels, we double sort all individuals into 2*25 groups based on their tech-savviness and consumption growth volatility and report the relation between risk taking and consumption growth volatility for the high and low tech-savviness groups respectively.

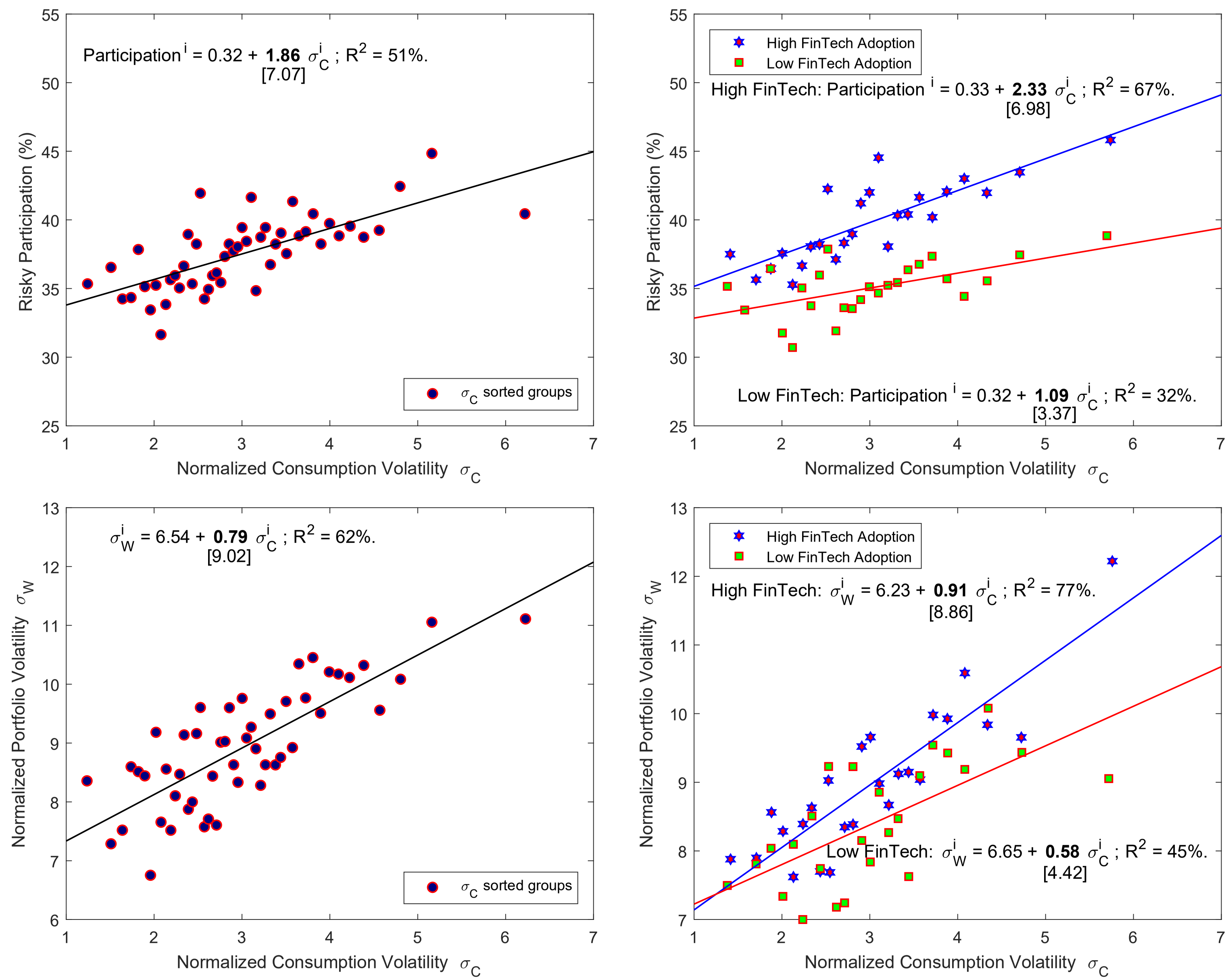


Figure 6. FinTech Penetration and Traditional Banking Coverage

We classify all cities into two groups based on the median cut-off of traditional bank coverage. The upper graph plots the risky share of each city against the city tech-penetration. The lower graph plots the change in risky share from 2017 to 2018 against the change in tech penetration from 2017 to 2018.

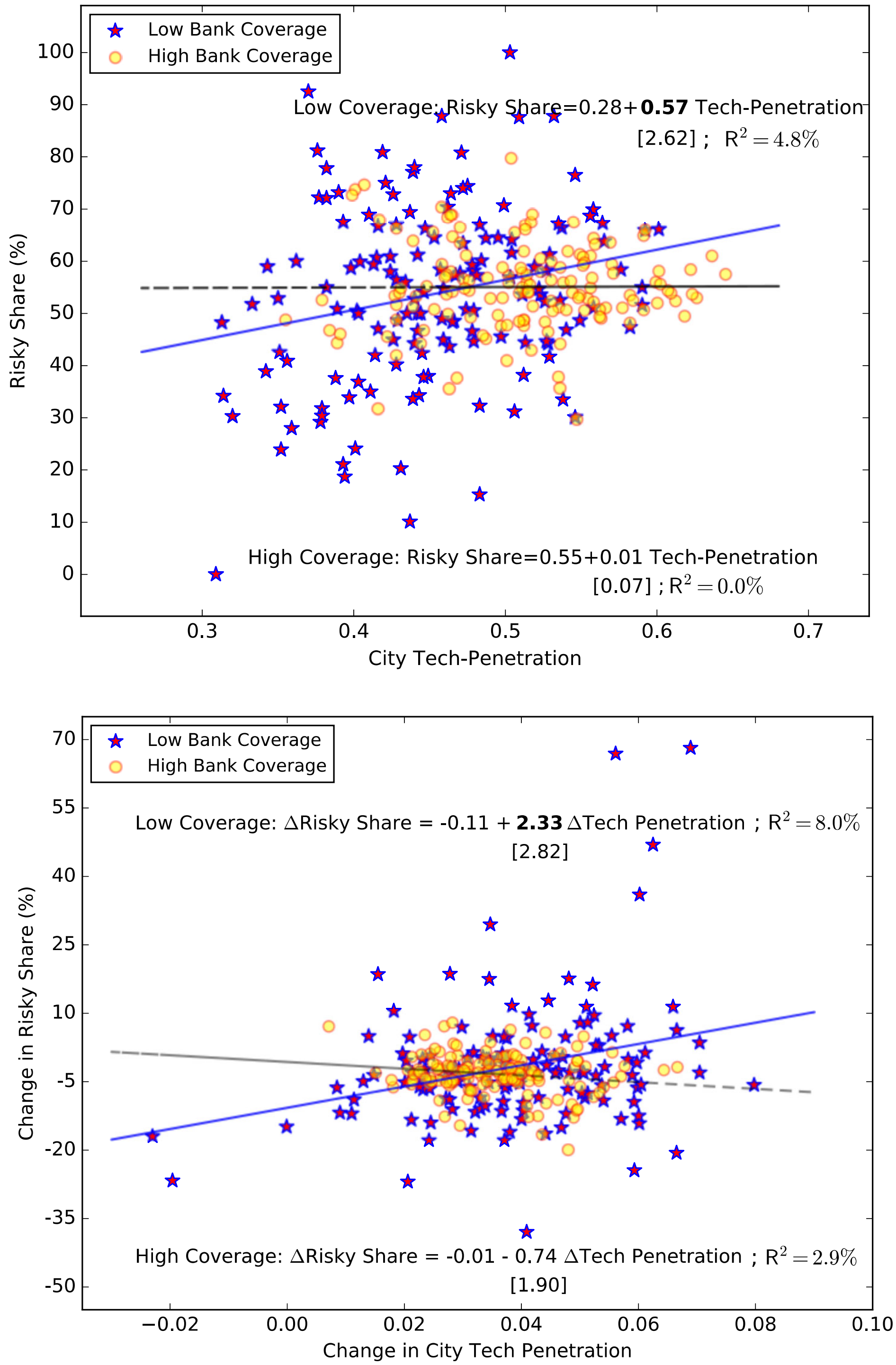


Table 1. Summary Statistics on Individual Characteristics and Investment

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 MMF and non-MMF) on the Ant platform. Age is the investors 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. We use two tech-savviness measures. Alipay fraction (Alifrac) is the fraction of consumption paid via Alipay out of total consumption paid via Alipay and Taobao. Log(AliCnt) is the natural logarithm of number of Alipay payment made in an average month. We also include 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 investments in non-money market fund (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	0.00
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. Pair-Wise 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: investors' total purchase amount in RMB ($Invested); number of unique months in which the investors have trades in for the total 27 months from 2017 January to 2019 March (#Trademonths); number of unique asset classes (MMF, Bond, Mixed, Equity, Index, QDII, Gold) that the investor has invested in (#Assets); number of unique funds the investor invested in our sample period (#Funds) and the average trade size per purchase ($Trade size).

Panel A. Summary Statistics

	Participate	Risky Share	σ_W	$Invested	#Trade months	#Trades	#Asset classes	#Funds	$Trade size
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	$Invested	#Trade months	#Trades	#Asset classes	#Funds	$Trade size
Participate	1.00	0.59	0.39	-0.10	0.20	0.25	0.49	0.24	-0.21
Risky Share	0.59	1.00	0.62	-0.13	0.13	0.16	0.30	0.17	-0.18
σ_W	0.39	0.62	1.00	0.01	0.19	0.22	0.31	0.21	-0.11
Log($Invested)	-0.10	-0.13	0.01	1.00	0.49	0.54	0.26	0.32	0.42
#Trade months	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
#Asset classes	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
$Trade size	-0.21	-0.18	-0.11	0.42	0.01	0.01	-0.10	-0.03	1.00

Table 3. 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. The data for economy-wide all consumptions and online consumptions are from National Bureau of Statistics. Offline consumption is calculated as "All'' minus "Online". Since the data for online consumption is only available starting from year 2015, we include the statistics for the two subsamples: sample from 2015 January to 2019 December, as well as our data sample period from 2017 January to 2019 March. For our sample, we also 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

	Sample 2015–2019			Sample Jan.2017–Mar.2019				
	All	Online	Offline	All	Online	Offline	Taobao	Alipay
Mean	0.74%	2.83%	0.55%	0.39%	3.31%	-0.16%	2.11%	5.48%
Std.	5.14%	19.02%	6.61%	5.26%	19.19%	6.91%	21.08%	6.97%

Panel B. Consumption growth volatilities (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
Tech-Savviness (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 4. Determinants of Tech-Savviness

This table reports the determinants of tech-savviness. We use two measures of tech-savviness. AliFrac is the fraction of consumption paid via Alipay out of total consumption paid via Alipay and Taobao. Log(AliCnt) is the natural logarithm of number of Alipay payment made in an average month. We regress the tech-savviness measures 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. Panel A reports the results for tech-savviness and Panel B report the results for change in tech-savviness 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.

Panel A. Tech-Savviness

	AliFrac				Log(AliCnt)			
	All Users		Active Users		All Users		Active Users	
σ_C	0.032***	0.034***	0.033***	0.035***	0.044***	0.054***	0.042***	0.052***
	(11.13)	(12.31)	(9.47)	(10.52)	(4.85)	(6.31)	(3.31)	(4.37)
Log(C)	-0.104***	-0.107***	-0.107***	-0.109***	0.133***	0.124***	0.130***	0.121***
	(-81.59)	(-94.95)	(-72.19)	(-80.70)	(19.60)	(25.10)	(17.15)	(20.31)
Female	-0.054***	-0.050***	-0.055***	-0.051***	-0.170***	-0.160***	-0.190***	-0.180***
	(-16.95)	(-16.18)	(-16.00)	(-15.21)	(-14.94)	(-13.70)	(-16.04)	(-14.74)
Log(Age)	0.000	-0.002	-0.015	-0.017	-0.816	-0.818	-0.861	-0.863
	(0.03)	(-0.27)	(-1.61)	(-1.86)	(-23.04)	(-28.26)	(-23.49)	(-26.97)
Log(GDP)	0.023**		0.022**		0.123**		0.1292**	
	(2.50)		(2.18)		(2.17)		(2.07)	
Log(Income)	0.029***		0.029***		0.1172***		0.1262***	
	(4.32)		(4.45)		(3.28)		(3.39)	
Log(Population)	0.006		0.005		0.0138		0.0233	
	(0.90)		(0.71)		(0.35)		(0.59)	
Log(#Branch)	-0.003		-0.004		0.0194		-0.0077	
	(-0.35)		(-0.34)		(0.40)		(-0.13)	
Citylevel=1	-0.059**		-0.059**		-0.2612**		-0.267**	
	(-2.50)		(-2.65)		(-2.20)		(-2.22)	
City FE	N	Y	N	Y	N	Y	N	Y
R2	0.210	0.208	0.230	0.230	0.0857	0.086	0.096	0.095
N	49,087	50,000	27,886	28,393	49,087	50,000	27,886	28,393

Panel B. Change in Tech-Savviness

	ΔAliFrac				ΔLog(AliCnt)			
	All Users		Active Users		All Users		Active Users	
σ_C	-0.010***	-0.010***	-0.008***	-0.009***	-0.054***	-0.053***	-0.056***	-0.054***
	(-3.87)	(-3.77)	(-2.43)	(-2.55)	(-6.78)	(-6.60)	(-5.13)	(-4.99)
Log(C)	-0.026***	-0.026***	-0.023***	-0.022***	-0.098***	-0.093***	-0.094***	-0.091***
	(-18.29)	(-18.19)	(-12.74)	(-12.57)	(-22.82)	(-21.56)	(-17.18)	(-16.45)
Female	-0.016***	-0.016***	-0.017***	-0.017***	-0.002	-0.002	-0.017	-0.017
	(-6.79)	(-6.86)	(-5.41)	(-5.61)	(-0.27)	(-0.35)	(-2.02)	(-2.01)
Log(Age)	0.102***	0.101***	0.103***	0.102***	0.500***	0.493***	0.532***	0.527***
	(16.32)	(16.26)	(14.90)	(14.78)	(20.46)	(20.16)	(17.50)	(17.28)
Log(GDP)	-0.004		-0.009**		-0.0302**		-0.0485***	
	(-1.61)		(-2.54)		(-2.44)		(-3.06)	
Log(Income)	-0.005***		-0.005**		-0.041***		-0.041***	
	(-3.24)		(-2.55)		(-5.37)		(-4.86)	
Log(Population)	0.002		0.001		0.0023		0.009	
	(1.10)		(0.61)		(0.33)		(1.11)	
Log(#Branch)	-0.006		0.002		0.0076		0.0221	
	(-2.10)		(0.45)		(0.49)		(1.15)	
Citylevel=1	0.005		0.003		0.0789***		0.0802***	
	(1.31)		(0.68)		(3.01)		(2.89)	
City FE	N	Y	N	Y	N	Y	N	Y
R2	0.021	0.021	0.019	0.019	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 5. Individual Tech-Savviness and Investment Participation

Panel A shows the determinants of individuals' risk taking. Columns (1) to (4) report the results for risky fund participation, where participation is defined as having at least 100 RMB purchase of non-money market mutual funds on platform. Columns (5) to (8) report the estimations for portfolio risky share, which is defined as the fraction of holdings invested in risky mutual funds (= 1−MMF/Total) for each individual. Columns (9) to (12) report the estimations for portfolio volatility (σ_{W}) in percent, calculated as the individual monthly portfolio return standard deviation in percent. The independent variables include individual personal characteristics: tech-savviness, consumption growth volatility (σ_{C}), consumption level, female, and log(age). Tech-savviness is calculated as the fraction of consumption paid through Alipay (AliFrac). 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. Tech-Savviness and Risk Taking

	Participate				Risky Share				σ_{W}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Tech-Savviness	0.154***	0.136***	0.127***	0.239***	0.130***	0.140***	0.131***	0.146***	0.438***	0.522***	0.431***	0.446***
	(13.06)	(11.50)	(10.47)	(17.94)	(7.68)	(8.64)	(7.65)	(7.80)	(4.85)	(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	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Adjusted R2	0.005	0.004	0.004	0.024	0.004	0.004	0.006	0.025	0.001	0.001	0.004	0.016
N	50,000	50,000	50,000	50,000	28,393	28,393	28,393	28,393	28,393	28,393	28,393	28,393

Panel B shows the relation between change in individual tech-savviness and change in individual risk taking. Change in tech-savviness (ΔAliFrac) is calculated as the difference of Alipay consumption out of total consumption from year 2017 to year 2018. We use three risk taking measures. In column (1), the dependent variable is change in participation, calculated as the participation in risky mutual fund investment in 2018 minus that in 2017. We define the person-month as participate for the months on and after his/her first purchase of non-money market mutual funds. In column (2), change in risky share is calculated as the individual's portfolio weight in risky mutual funds in December 2018 minus that of December 2017. In column (3), trade propensity is defined as the average number of months with trading in 2018 minus that of 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. Change in Tech-Savviness and Risk Taking

	ΔParticipate	ΔRisky Share	ΔTrade Propensity
	(1)	(2)	(3)
ΔTech-Savviness	0.014**	0.087***	0.025***
	(2.08)	(5.30)	(6.60)
σ_{C}	0.009**	-0.010	0.000
	(2.23)	(-1.32)	(0.09)
Log(C)	0.013***	0.000	-0.002**
	(8.25)	(0.10)	(-2.13)
Female	-0.025***	-0.004	0.000
	(-8.31)	(-0.68)	(-0.076)
Log(Age)	-0.041***	0.012	-0.005**
	(-5.98)	(0.98)	(-2.05)
City FE	Y	Y	Y
R-squared	0.004	0.154	0.001
N	50.000	28,393	50,000

Table 6. Investor Heterogeneity and the Effect of Individual Tech-Savviness on Risk Taking

This table shows the determinants of individuals' risk taking. In addition to the independent variables in Table 5, we also include the interaction between tech-savviness and consumption growth volatility (σ_C) in columns (1), (3) and (5). We further include the interactions between tech-savviness and all other investor characteristics in columns (2), (4) and (6). Columns (1) to (3) report the results for risky fund participation. Columns (4) to (6) report the estimations for risky share. Columns (7) to (9) report the estimations for portfolio volatility (σ_W) in percent. All variables are the same as in Table 5. 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)
Tech-Savviness*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)
Tech-Savviness*Log(C)		0.037***		0.004		0.048
		(3.40)		(0.27)		(0.55)
Tech-Savviness*Female		-0.063***		-0.036		-0.130
		(-2.84)		(-1.27)		(-0.69)
Tech-Savviness*Log(Age)		-0.113**		-0.106		-0.679
		(-2.52)		(-1.91)		(-2.19)
Tech-Savviness	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 R2	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 Tech-Penetration and Individual Risk Taking

Panel A shows the effect of city tech-penetration on local individuals' risk-taking. We use three proxies of risk-taking. Columns (1) to (3) show the results for risky mutual fund participation. Risky fund participation is the fraction of individuals in the city who ever have at least 100 RMB purchase of non-money market mutual funds on platform. Columns (4) to (6) show the results for risky share, defined as the equal weighted individual portfolio weight in risky mutual funds (= 1−MMF/Total) in the city. Columns (7) to (9) show the results for portfolio volatility (σ_{W}), calculated as the monthly portfolio return standard deviation in percent, equal weighted across all individuals in a city. City tech-penetration is defined as the average individual AliFrac, i.e., the consumption paid through Alipay out of total consumption in the city. We control for the natural logarithm of GDP, population, income per person, and number of bank branches. 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.

Panel A. Tech-Penetration and Risk Taking

	Participate			Risky Share			σ_{W}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Tech-Penetration	0.272***	0.212***	0.207***	0.304***	0.310**	0.254*	0.759**	0.676	0.594
	(3.51)	(2.92)	(2.84)	(2.64)	(2.25)	(1.89)	(2.17)	(1.60)	(1.41)
Tech-Penetration*Log(#Branch)			-0.048			-0.546***			-0.803**
			(-0.69)			(-4.26)			(-2.00)
Log(#Branch)		-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	0.206***	0.234***	0.238***	0.398***	0.395***	0.437***	0.847***	0.887***	0.948***
	(5.21)	(6.66)	(6.69)	(7.10)	(5.91)	(6.65)	(4.98)	(4.32)	(4.59)
Observations	287	287	287	287	287	287	287	287	287
R-squared	0.065	0.113	0.115	0.024	0.058	0.116	0.016	0.03	0.044

Panel B shows the results for change in city tech-penetration and change in individual risk taking. Change in tech-penetration is calculated as the average tech-penetration in year 2018 minus that of the 2017 (ΔAliFrac). In columns (1) and (2) of Panel B, the dependent variable is change in participation from 2017 to 2018. We define the person-month as participate for the months on and after his/her first purchase of non-money market mutual funds. In columns (3) and (4), the dependent variable is change in risky share, calculated as the individual portfolio weight in risky mutual fund (= 1−MMF/Total) in December 2018 minus that of December 2017. Columns (5) and (6) report the results for change in trade propensity, defined as the average number of months with trading in 2018 minus that of 2017. The controls are the same as in Panel A. Standard errors are clustered at the province level. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Panel B. Change in Tech-Penetration and Risk Taking

	ΔParticipate		ΔRisky Share		ΔTrade Propensity	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTech-Penetration	0.149*	0.090	1.469**	0.400	0.084**	0.056
	(1.76)	(1.07)	(2.44)	(0.99)	(2.03)	(1.40)
Log(#Branch)	-0.002	0.005	-0.019	0.103***	0.000	0.003
	(-1.53)	(1.25)	(-1.19)	(3.63)	(-0.40)	(1.27)
ΔTech-Penetration*Log(#Branch)		-0.150*		-2.714***		-0.071*
		(-1.81)		(-4.79)		(-1.68)
Log(GDP)	0.004	0.003	-0.018	-0.034*	-0.001	-0.001
	(1.66)	(1.39)	(-0.92)	(-1.78)	(-0.69)	(-1.02)
Log(Population)	-0.002	-0.002	0.019*	0.017*	0.000	0.000
	(-1.10)	(-1.13)	(1.77)	(1.67)	(0.14)	(0.08)
Log(Income)	0.001	0.001	0.022*	0.015	0.000	0.000
	(0.91)	(0.60)	(1.84)	(1.53)	(0.15)	(-0.06)
CityLevel=1	0.004	0.001	-0.001	-0.053**	0.004**	0.002
	(1.08)	(0.30)	(-0.04)	(-2.25)	(1.97)	(1.32)
Constant	0.052***	0.054***	-0.079***	-0.046***	-0.002	-0.001
	(15.04)	(16.00)	(-3.86)	(-3.16)	(-0.94)	(-0.42)
Observations	287	287	287	287	287	287
R-squared	0.034	0.042	0.105	0.207	0.036	0.045

Table 8. City Tech-Penetration and Distance-to-Hangzhou as an Instrument

This table reports the 2SLS estimation using the distance to Hangzhou as an instrument for tech-penetration. Panel A reports the results for the first stage estimations. Columns (1) and (2) report the first stage estimation using the natural logarithm of distance to Hangzhou as an instrument. Columns (3) to (10) show the first stage placebo tests when we use the distance to Shanghai, Beijing, Guangzhou, or Shenzhen to replace the distance to Hangzhou. We control for city bank accessibility, city population, GDP, income, and city level when indicated. Citylevel= 1 is a dummy variable that equals one for Beijing, Shanghai, Guangzhou, Shenzhen, and zero otherwise. Panel B reports the results for the second stage. In particular, the dependent variables are the three risky taking measures as defined in Table 7. 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 average portfolio weight invested in risky mutual funds. Portfolio volatility (σ_W) is calculated as the monthly portfolio return standard deviation in percent, equal weighted across all individuals in a city. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Panel A. First Stage Regression for Tech-Penetration

	Hangzhou		Shanghai		Beijing		Guangzhou		Shenzhen	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log(Distance to City X)	-0.028**	-0.020**	-0.027*	-0.020**	-0.007**	0.000	-0.007	0.000	-0.009	-0.003
	(-2.67)	(-2.34)	(-1.98)	(-2.06)	(-2.27)	(-0.08)	(-1.09)	(-0.08)	(-1.28)	(-0.41)
Log(#Branch)		-0.003		-0.002		-0.001		-0.001		0.000
		(-0.57)		(-0.50)		(-0.14)		(-0.12)		(-0.05)
Log(GDP)		0.033***		0.036***		0.039***		0.039***		0.038***
		(3.45)		(3.54)		(3.46)		(3.41)		(3.26)
Log(Population)		0.003		0.001		0.002		0.002		0.003
		(0.44)		(0.19)		(0.32)		(0.33)		(0.36)
Log(Income)		-0.004		-0.003		-0.001		-0.001		0.000
		(-0.36)		(-0.25)		(-0.05)		(-0.05)		(-0.03)
CityLevel=1		0.005		-0.078		-0.022		-0.023		-0.031
		(0.23)		(-1.33)		(-0.64)		(-0.57)		(-0.76)
Constant	0.670***	0.617***	0.666***	0.618***	0.533***	0.484***	0.530***	0.485***	0.544***	0.500***
	(9.52)	(10.63)	(6.98)	(9.04)	(20.54)	(17.46)	(11.86)	(10.93)	(11.10)	(10.95)
Observations	287	287	287	287	287	287	287	287	287	287
R-squared	0.23	0.42	0.20	0.40	0.02	0.31	0.02	0.31	0.02	0.32
F-statistics	7.12	5.47	3.91	4.24	5.14	0.01	1.18	0.94	1.65	0.17

Panel B. Second Stage Regression

	Hangzhou			Shanghai		
	(1) Participate	(2) Risky Share	(3) σ_{W}	(4) Participate	(5) Risky Share	(6) σ_{W}
Tech-Penetration	0.305**	0.086	0.919***	0.263**	-0.043	0.742**
	(2.33)	(0.67)	(3.08)	(2.04)	(-0.33)	(2.05)
Constant	0.190***	0.503***	0.770***	0.210***	0.565***	0.856***
	(2.93)	(7.48)	(4.90)	(3.24)	(8.17)	(4.61)
Controls	N	N	N	N	N	N
Observations	287	287	287	287	287	287
R-squared	0.064	0.012	0.016	0.065	0.000	0.016

Table 9. Which Component of Consumption?

This table exhibits the regression results of portfolio volatility (σ_{W}) on consumption growth volatility (σ_{C}) for each consumption category. In particular, we compute the basic, development, enjoy, non-durable, and durable consumption growth volatility as the standard deviation of change in monthly natrual logarithm of the respective consumption. Consumption in January and February are combined as one month following standard consumption calculation method for the Chinese data. The dependent variables are the portfolio volatility (σ_{W}) for each investor. Columns (1) (3) (5) (7) and (9) report the regression results with Tech-savviness and σ_{C} in each narrowly defined consumption categories. Columns (2) (4) (6) (8) and (10) further include the interaction between Tech-savviness and σ_{C} for each consumption category. Tech-Savviness is computed as the fraction of Alipay consumption out of the sum of Alipay and Taobao consumption (AliFrac) for each investor. We include the natural logarithm of Taobao consumption, the female dummy, the natural logarithm of age as controls. 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.

Dependent Variable: Portfolio Volatility σ_{W}

	Basic		Development		Enjoy		Non-Durable		Durable	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tech-Savviness	0.438***	0.143	0.467***	-0.103	0.464***	0.151	0.454***	0.171	0.459***	0.309
	(4.43)	(0.78)	(4.80)	(-0.31)	(4.76)	(0.45)	(4.65)	(0.90)	(4.71)	(1.00)
σ_{C}	0.049**	-0.032	0.052**	-0.053	0.025	-0.034	0.031*	-0.060	0.087***	0.061
	(2.50)	(-0.60)	(2.37)	(-0.87)	(1.25)	(-0.56)	(1.67)	(0.99)	(4.13)	(1.08)
Tech-Savviness*σ_{C}		0.147*		0.193*		0.112		0.162		0.051
		(1.72)		(1.85)		(1.00)		(1.63)		(0.54)
Log(C)	-0.555***	-0.554***	-0.569***	-0.568***	-0.578***	-0.578***	-0.563***	-0.563***	-0.588***	-0.587***
	(-15.23)	(-15.24)	(-16.53)	(-16.54)	(-16.61)	(-16.62)	(-15.73)	(-15.74)	(-16.86)	(-16.81)
Female	-0.855***	-0.856***	-0.860***	-0.861***	-0.882***	-0.881***	-0.870***	-0.870***	-0.863***	-0.863***
	(-10.51)	(-10.54)	(-10.59)	(-10.60)	(-10.61)	(-10.59)	(-10.60)	(-10.60)	(-10.57)	(-10.56)
Log(Age)	0.127***	0.128***	0.110***	0.108***	0.125***	0.123***	0.126***	0.127***	0.115***	0.114***
	(5.46)	(5.46)	(4.63)	(4.52)	(5.32)	(5.30)	(5.40)	(5.40)	(4.91)	(4.93)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R2	0.0156	0.0157	0.0155	0.0157	0.0154	0.0155	0.0159	0.0159	0.0154	0.0155
N	28,393	28,393	28,393	28,393	28,393	28,393	28,393	28,393	28,393	28,393

Table 10. Which Asset Class?

This table exhibits the regression results of participation in each individual asset class on tech-savviness and consumption growth volatility (σ_C). In particular, we consider an investor to participate in a particular asset class if the investor purchases more than 100 RMB of funds in the asset class. We examine participation in bond, mixed, equity, index, QDII, and gold mutual funds. The independent variables include individual personal characteristics: tech-savviness, consumption growth volatility, consumption level, female, and log(age). Tech-savviness is proxied by AliFrac, the fraction of consumption paid through Alipay out of total consumption via Alipay and Taobao. Log(C) is the natural logarithm of monthly online consumption on Taobao. σ_C is calculated as the standard deviation of change in monthly Log(C). 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.

Dependent Variable: Participation in Each Asset Class

	Bond		Mixed		Equity		Index		QDII		Gold	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Tech-Savviness	0.040***	0.015	0.149***	0.115***	0.045***	0.021	0.072***	0.046***	0.024***	0.002	0.140***	0.115***
	(7.37)	(0.96)	(14.03)	(4.67)	(7.96)	(1.56)	(9.85)	(2.75)	(6.93)	(0.17)	(18.11)	(6.23)
Tech-Savviness*σ_C		0.021*		0.028		0.019**		0.021		0.019		0.021
		(1.79)		(1.38)		(1.89)		(1.57)		(2.21)		(1.43)
σ_C	0.003	-0.008	0.020***	0.006	0.011***	0.001	0.016***	0.004	0.004**	-0.006	-0.004	-0.016*
	(0.95)	(1.24)	(4.60)	(0.53)	(3.68)	(0.11)	(4.75)	(0.57)	(2.15)	(-1.34)	(-1.09)	(-1.75)
Log(C)	0.016***	0.016***	0.054***	0.054***	0.017***	0.017***	0.030***	0.030***	0.010***	0.010***	0.030***	0.030***
	(12.66)	(12.65)	(25.71)	(25.72)	(13.18)	(13.21)	(13.66)	(13.64)	(11.16)	(11.16)	(15.32)	(15.33)
Female	-0.003	-0.003	-0.048***	-0.048***	-0.020***	-0.020***	-0.039***	-0.039***	-0.012***	-0.012***	-0.045***	-0.045***
	(-1.12)	(-1.08)	(-10.68)	(-10.58)	(-8.14)	(-8.11)	(-12.77)	(-12.76)	(-6.81)	(-6.74)	(-14.77)	(-14.76)
Log(Age)	0.022***	0.022***	0.039***	0.039 ***	0.001	0.001	-0.013	-0.013	0.001	0.001	-0.034***	-0.034***
	(4.98)	(4.97)	(3.65)	(3.65)	(0.22)	(0.21)	(-1.55)	(-1.56)	(0.39)	(0.37)	(-5.08)	(-5.10)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.0036	0.0037	0.0186	0.0187	0.0058	0.0059	0.0107	0.0107	0.0048	0.0049	0.0153	0.0154
N	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000

Table 11. Robustness: Alternative Measure of Tech-Penetration/Savviness

This table use the natural logarithm of Alipay payment counts as an alternative measure of tech-penetration/savviness. In particular, panel A shows the corresponding results for panel A of Table 5, but we use Log(AliCnt) as proxy for tech-penetration, where Alipay payment counts is the average individual monthly alipay payment counts in our sample for a given city. Panel B shows the corresponding results for Table 7, where tech-savviness of each individual is measured as Log(AliCnt). 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)
Tech-Savviness	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)
Tech-Savviness*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 R2	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)
Tech-Penetration	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)
Tech-Penetration*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

Appendix A

Table A1. Asset Allocation On- and Off-Platform

Panel A reports the value-weighted average monthly return, monthly return standard deviation, and annualized Sharpe ratio for funds in each asset class. The sample period is from January 2017 to March 2019. The value weight is given by last quarter end fund TNA. Panel B shows the portfolio weights in percent for "Ant investor" and "Total Retailer" in the entire economy. We calculate the portfolio weights month-by-month and report the time series monthly average. Panel C shows the portfolio weights allocated to quintile groups of funds sorted based on fund volatility. We calculate funds' volatility as the standard deviation of monthly returns for the sample from January 2017 to March 2019. We sort funds into quintile groups based on their return volatility and report the time-series average portfolio weights for Ant investor and total retailer. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Panel A. Asset Monthly Return in %, 2017 January-2019 March

	Bond	Mixed	Equity	Index	QDII	Gold
Mean	0.30	0.53	0.63	0.43	0.50	0.15
Median	0.23	0.61	0.89	0.50	0.38	-0.10
Std.	0.39	3.40	4.96	4.88	2.45	1.78

Panel B. Asset Allocation by Asset Class

	Bond	Mixed	Equity	Index	QDII	Gold
Ant Investor (%)	4.8	42.7	15.1	24.8	2.4	10.1
All Retail (%)	7.6	65.0	10.1	14.3	2.4	0.6
Ant Investor - All Retail	-2.8***	-22.3***	5.0***	10.5***	0.0	9.6***
t-stat	(-5.89)	(-42.20)	(9.34)	(18.91)	(0.11)	(15.20)

Panel C. Asset Allocation by Fund Return Volatility

	1 (Low)	2	3	4	5 (High)
Fund Monthly Volatility(%)	0.3	0.8	2.5	4.8	7.4
Ant Investor (%)	2.5	2.3	17.7	32.5	45.0
All Retailer (%)	6.2	6.5	12.0	43.5	31.8
Ant Investor - All Retail	-3.7***	-4.3***	5.7***	-10.9***	13.2***
t-stat	(-9.26)	(-13.78)	(9.60)	(-30.47)	(20.93)

Table A2. Platform Investors Characteristics and Asset Allocations

Panel A, B, C, and D report the portfolio weight (%) in bond, mixed, equity, index, QDII, and gold funds for investors in each characteristics group. We classify individuals into two or five equal groups based on their gender, age, consumption level, and city respectively. We calculate the asset class holdings weight for each group of investors at each month. The asset class weight reported is the time-series average of monthly holdings weight in percent. Our data on individual holdings is from August 2017 to December 2018. The differences between top and bottom quintile groups are reported. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Panel A. By Gender

Groups	Bond	Mix	Equity	Index	QDII	Gold
Male	3.5	41.1	15.7	25	3.6	11
Female	5.1	45.3	15	22.2	1.7	10.7
Female-Male	1.6***	4.2***	-0.7**	-2.9***	-2.0***	-0.3
t-stat	(4.56)	(9.37)	(-2.54)	(-8.45)	(-7.82)	(-0.62)

Panel B. By Age

Groups	Age	Bond	Mix	Equity	Index	QDII	Gold
1 (Young)	18–24	2.8	36.4	12.2	23.8	2.8	22
2	25–27	4.2	35.4	18	26.1	2.3	14
3	28–31	3.9	39.3	14	27.7	2.9	12.2
4	32–36	4.9	43	16.2	24	2.8	9.1
5 (Old)	37–79	4.2	48.9	15.1	20.4	2.7	8.7
Old-Young		1.3***	12.5***	2.9***	-3.4***	-0.1	-13.3***
t-stat		(2.66)	(23.56)	(4.14)	(-3.42)	(-0.23)	(-8.23)

Panel C. By Consumption Level

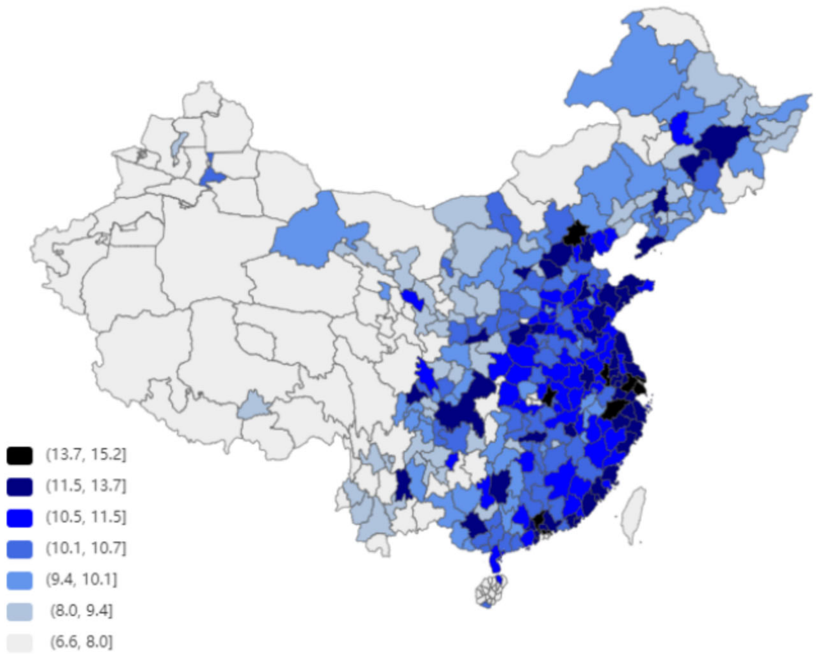
Groups	Consumption	Bond	Mix	Equity	Index	QDII	Gold
1 (Low)	<724	4.5	46	14	24.3	1.5	9.7
2	724-1,140	5.2	40.6	19.1	19.4	2.6	13.2
3	1,140-1,724	4.1	45.5	12.3	23.9	2.7	11.6
4	1,724-2,860	4.7	40.9	17.1	27.6	2.8	6.9
5 (High)	>2,860	3.5	43.3	14.8	22.5	3.3	12.5
High-Low		-1.0	-2.7***	0.8	-1.7*	1.8*	2.8***
t-stat		(-1.00)	(-2.84)	(1.17)	(-1.78)	(9.23)	(2.28)

Panel D. By City Level

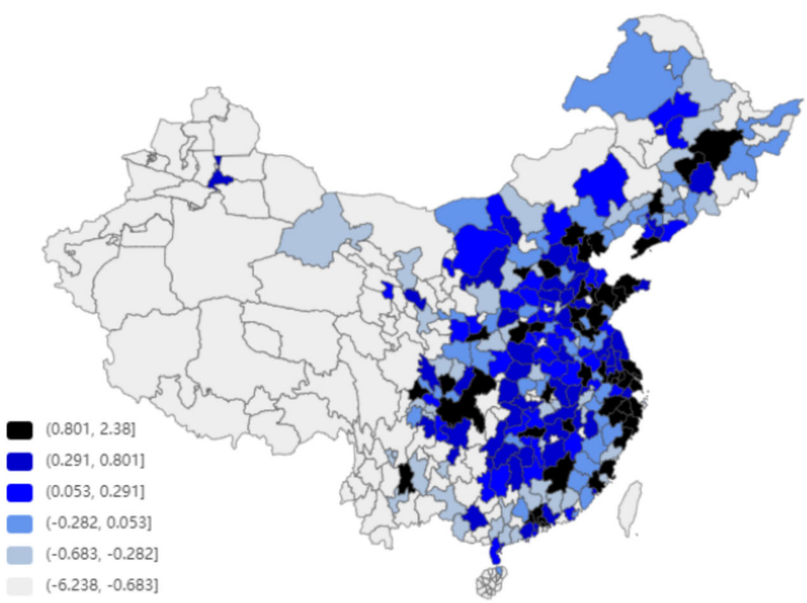
City level	Bond	Mix	Equity	Index	QDII	Gold
Tier 1	4.6	42.2	12.4	25.8	3.2	11.7
Tier 2	3.6	42.6	17.6	24	2.9	9.3
Tier 3	3.9	45.1	16.1	22.7	1.9	10.4
Tier 4	5.8	42.8	14.3	20.4	2.2	14.4
Tier 5	3.9	48.3	17.1	10.8	2.4	17.5
Tier 5-Tier 1	-0.7*	6.1***	4.7***	-15.0***	-0.8	5.8***
t-stat	(-1.73)	(3.70)	(3.41)	(-17.53)	(-1.47)	(4.34)

Figure A1. Geographic Distribution

Graph A shows the geographic distribution of the alternative tech penetration measure, calculated as the natural logarithm of number of Alipay payments. Graph B shows the geographic distribution of city-level traditional bank coverage.



(A) Log(Ali Count)



(B) Bank Branch Distribution, 2017