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FinTech adoption and the effects of economic uncertainty on household consumption[☆]

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ABSTRACT

This paper examines how the adoption of FinTech affects household consumption in the presence of economic uncertainty. We use regional-level FinTech adoption and economic uncertainty measurement, along with representative household-level consumption data, to investigate this issue. Our empirical analysis shows that while high levels of economic uncertainty lead to a shift in household consumption from services to non-durable goods, widespread adoption of FinTech overcomes this negative effect and prevents the reduction in service spending. We use the distance of a household from Hangzhou and the economic uncertainty in the United States as proxies for exogenous variation in FinTech adoption and economic uncertainty in China, respectively, and find similar results. Focusing on the transmission channel, we find that FinTech helps alleviate credit constraints, contributes to entrepreneurship and employment opportunities, and thus mitigates the negative impact of economic uncertainty on household consumption.

1. Introduction

The consumer market has experienced a significant transformation in recent years as a result of the widespread adoption of financial technology (FinTech) by consumers. This has greatly improved the accessibility and affordability of financial services (Philippon, 2016), leading to a reshaping of domestic economic activity. Increasingly, households are managing their finances on FinTech platforms, which have removed many of the financial barriers that they previously faced. Firstly, FinTech platforms mainly rely on soft information for their lending decisions, which allows them to provide credit to consumers who were previously financially excluded. This has helped to alleviate consumers' credit constraints when making purchasing decisions. Secondly, the convenience of FinTech platforms' applications (apps) has enabled customers to access a much wider range of goods from around the country and the world through online department stores, thus greatly enlarging potential markets. This has resulted in increased entrepreneurship and employment opportunities.

In this paper, we investigate the impact of economic uncertainty on household economic activity in the age of FinTech. Previous research has shown that economic and political shocks can lead to a significant change in household economic activity, which can have

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numerous real economic consequences (Baker et al., 2016; Bloom, 2009; Bloom et al., 2018; Julio & Yook, 2012; Jurado et al., 2015). Particularly, in situations where households face economic uncertainty, they may reduce their consumption or downgrade their purchasing choices, potentially leading to a slowdown in economic growth. To address this issue, we explore whether and how FinTech can mitigate the negative impact of economic uncertainty on household consumption. Firstly, FinTech credit can alleviate households' concerns about their ability to make future purchases, which can help boost their confidence and willingness to spend. Secondly, FinTech can expand merchants' market potential and create new entrepreneurial and employment opportunities, which can further stimulate household consumption. Overall, FinTech is expected to play an important role in alleviating the negative impact of economic uncertainty on household consumption, especially for those who have been excluded from traditional economic and financial systems.

To investigate, we combine regional indicators of FinTech adoption and economic uncertainty with household-level data. To achieve this, we use data from the China Family Panel Studies (CFPS), a nationally representative biannual longitudinal survey of Chinese communities, families, and individuals, conducted by the Institute of Social Science Survey of Peking University, China, since 2010. Our analysis focuses on the transitional period of 2012–2018, during which FinTech emerged and rapidly developed in China, leading to significant impacts on household consumption. Using the CFPS data, we can track not only household consumption, but also individual characteristics, such as age, sex, health, and education.

To measure economic uncertainty in China, we adopt the methodology developed by Jurado et al. (2015) and calculate provincial-quarter level economic uncertainty spanning from Q1 2006 to Q4 2019, based on the unpredictable conditional volatility of various economic indicators, including national accounts, financial, household survey, goods and services, inflation, investment, agriculture, manufacturing, energy, construction, insurance, and real estate data. To track the development of FinTech adoption, we employ the digital financial inclusion index system developed by Guo et al. (2020), which utilizes account-level data from the Ant Group. This index provides information on regional FinTech adoption, such as Alipay account coverage, online and offline third-party digital payments via Alipay, as well as online investment, credit, and insurance activity on the Ant Group's FinTech platform. We collected annual data on regional FinTech adoption spanning from 2011 to 2020, a period of significant FinTech expansion in China. Based on these measures, our analysis investigates how the level of FinTech adoption impacts the relationship between economic uncertainty and consumption across households. We find that FinTech adoption mitigates the negative impact of economic uncertainty on households, thus improving their welfare.

First, to examine the impact of economic uncertainty on household consumption, we conduct household-level panel regressions with fixed effects. Our findings reveal that economic uncertainty has a mixed effect on consumption patterns. Specifically, we observed a slight increase in spending on non-durable goods, while expenditure on services declined. These results suggest that economic uncertainty tends to downgrade household consumption by reducing service spending. We further investigate the robustness of our results by controlling for various factors, including the characteristics of the household head, domestic variables, and regional development indicators, and the results remain statistically and economically significant. A 1% increase in economic uncertainty corresponds to a 0.5% rise in non-durable goods spending, but a 1.9% and 1.1% decline in durable goods and services spending, respectively.

Second, we investigate how FinTech impacts household consumption during times of economic uncertainty. We introduce FinTech adoption as a variable and examine its interaction with economic uncertainty in a household-level panel model. Our results indicate that FinTech not only supports current levels of household consumption, but also mitigates the negative impact of economic uncertainty, especially on service spending. This finding is robust even after accounting for alternative measures of spending and economic uncertainty. Furthermore, our study reveals that FinTech adoption in nearly 40% of Chinese cities has fully offset the negative impact of economic uncertainty on service spending by 2018. This implies that FinTech is beneficial for overall welfare, as it contributes to China's sustainable economic development by helping households overcome economic uncertainty, stabilize their consumption levels, and alleviate the welfare losses caused by economic uncertainty as documented in the literature (Busch et al., 2022; Di Maggio et al., 2022; McKay, 2017).

Third, to establish the causal impact of FinTech and economic uncertainty on consumption, we employ two instrumental variables: distance to Hangzhou and an interactive term between a measure of economic uncertainty in the United States and provincial trade with the US. Hangzhou is widely recognized as the center of FinTech innovation in China, so proximity to this city could increase the likelihood of FinTech adoption. Additionally, we expected that economic uncertainty in China and the US would be highly correlated due to their strong economic ties, and that provinces with higher levels of trade with the US would be more closely connected to the US economy, resulting in a stronger relationship between their economic uncertainty and that in the US. Using these measures, we were able to confirm that the adoption of FinTech mitigates the negative impact of economic uncertainty on household consumption.

Finally, we investigate the channels through which FinTech can help mitigate the impact of economic uncertainty on household consumption. We propose two hypotheses. Firstly, we suggest that FinTech can provide additional credit to households that are credit-constrained due to inadequate future incomes, thereby enabling them to consume more. Empirical evidence confirms that the availability of FinTech credit helps prevent a downgrade in household consumption from service to non-durable goods. This effect is particularly pronounced for households with credit constraints. Secondly, we hypothesize that FinTech can counter economic uncertainty by expanding market potential, incentivizing entrepreneurial activities, and increasing demand for labor, which in turn can boost household income and consumption. Our empirical findings demonstrate that FinTech adoption not only increases entrepreneurial and employment opportunities but also mitigates the negative effect of economic uncertainty on such opportunities. We also find that FinTech has a greater effect on the employment of rural residents or those with limited education, highlighting its potential for inclusive growth.

Our paper is related to the literature on household consumption. According to the standard incomplete markets model, permanent

shocks to incomes have nearly one-for-one effects on consumption, whereas transitory shocks to incomes have minor effects. However, recent reviews by Jappelli and Pistaferri (2010) and Meghir and Pistaferri (2011) suggest that consumers tend to overreact to transitory shocks and underreact to permanent shocks. Various barriers to consumption exist, such as the time required to travel to a store or bank (Ljungqvist & Sargent, 2004), credit constraints, particularly among the young (Blundell et al., 2008; Jappelli, 1990; Zeldes, 1989), and uncertainty about the future (Busch et al., 2022; Di Maggio et al., 2022; McKay, 2017).

Our paper also contributes to the literature on the effects of economic uncertainty. Similar to Jurado et al. (2015), we use the unpredictable conditional volatility of numerous economic variables as the basis for our measure of uncertainty, but we follow Qiu (2021) and extend the measure to the provincial-quarter level within China. In terms of economic impact, previous studies suggest that during periods of increased economic uncertainty, the real-option value of waiting to enter into difficult-to-abrogate contracts is higher than in other periods (Abel & Eberly, 1994; Bernanke, 1983; Titman, 1985). Recent research has further examined the role of uncertainty in economic fluctuations and the decisions made by firms. For instance, Guiso and Parigi (1999) and Bloom et al. (2007) demonstrate that high levels of uncertainty cause firms to become more cautious and reduce their investments compared to low levels of uncertainty. Additionally, Bloom (2009) finds that high levels of uncertainty cause firms to temporarily pause investments and hiring, which can lead to lower productivity. Christiano, Motto, & Rostagno (2014) show that uncertainty or risk can lower the value of collateral and increase credit spreads due to the presence of financial friction, thus limiting the supply of credit to entrepreneurs and slowing economic activity. Leduc and Liu (2016) provide evidence that increased uncertainty leads to increased unemployment but decreased inflation. Finally, Basu and Bundick (2017) show that uncertainty about the future causes a contraction in output, which Bloom et al. (2018) estimate to be approximately 2.5%.

However, few previous studies examine household's responses to economic uncertainty. Previous research by Ben-David et al. (2018), Christelis et al. (2020), and Dietrich et al. (2022) has shown that households that are uncertain about future economic outcomes tend to be more cautious in their consumption and investment decisions, resulting in stronger precautionary savings behavior. Additionally, Di Maggio et al. (2022) have found that increased firm-level uncertainty can lead to greater financial fragility among lower-income earners, causing them to reduce their consumption.

Importantly, our study contributes to a growing body of literature on the impact of technology on economic development, such as the research of Kolko (2012), Akerman et al. (2015), Hjort and Poulsen (2019), and Zuo (2021), who examine how access to the Internet improves economic growth. FinTech is a unique phenomenon, as FinTech platforms are run by leading technology firms who take advantage of high-speed broadband to deliver financial products and services, such as payment and credit services, directly to agents. Jack and Suri (2014), Suri (2017), and Lee et al. (2021) document that mobile money in developing economies enables individuals without bank accounts to digitally transact money, which both directly reduces poverty and mitigates the negative impact of economic shocks. Yi and Zhou (2018) and Yang and Zhang (2022) have demonstrated that FinTech adoption contributes to household consumption. Suri et al. (2021) find that households in Kenya become more financially resilient to shocks when they receive digital loans than when they do not receive such loans. Chen et al. (2022) document that the availability of FinTech credit enables SMEs in China to obtain more stable sales than they would obtain without FinTech credit.

This paper makes three significant contributions. Firstly, we contribute to the literature on economic uncertainty and household consumption by presenting empirical evidence from China, the largest developing country in the world. Our findings could have broader implications for assessing the impact of economic uncertainty in other developing countries. Secondly, we identify FinTech as a novel tool that households use to mitigate the adverse effects of economic uncertainty on their consumption. Finally, we contribute to the literature by identifying a new channel, besides FinTech credit, through which FinTech can mitigate the negative impact of economic uncertainty on economic activity: by enhancing entrepreneurial and employment opportunities.

This paper proceeds as follows. Section 2 provides a comprehensive explanation of our specification, measurements, and data. Section 3 documents the impact of economic uncertainty on household consumption and the moderating effect of FinTech adoption. Sections 4 and 5 focus on heterogeneity and channel analysis, respectively. Section 6 concludes.

2. Specification, measurement, and data

2.1. Specification

We first establish the following empirical model to investigate the impact of economic uncertainty on household consumption:

$$\ln(\text{Con}_{ijpt}) = \gamma_0 + \gamma_1 \ln(\text{EU}_{pt}) + X'_{ijpt} \gamma + \phi_i + \varphi_t + u_{ijpt} \quad (2.1)$$

In model (2.1), i represents households, j cities, p provinces, and t quarter-by-year. Con_{ijpt} denotes the level of (categorized) consumption of household i in city j of province p of quarter t . In the empirical analysis, we further decompose household consumption into three categories: non-durable goods, durable goods, and services. EU_{pt} denotes the degree of economic uncertainty in the province where a household is located. X_{ijpt} are control variables at the household and regional levels, ϕ_i and φ_t represent household fixed effects and quarter-by-year fixed effects, respectively, and u_{ijpt} is a random error term. To alleviate any reverse causality that may be present, we lag the measurement of economic uncertainty by 1 year. We also cluster the standard errors at the provincial level. Thus, γ_1 measures the overall impact of economic uncertainty on consumption and is expected to be negative.

To establish the role of FinTech adoption on the relationship between economic uncertainty on household consumption, we consider the following model:

$$\ln(\text{Con}_{ijt}) = \beta_0 + \beta_1 \ln(\text{EU}_{jt}) \times \text{FinTech}_{jt} + X'_{ijt} \beta + \phi_i + \varphi_t + \varepsilon_{ijt} \quad (2.2)$$

Model (2.2) is very similar to model (2.1), except that we introduce the variable FinTech_{jt} , which denotes the degree of FinTech adoption in the city where a household is located. We further interact this variable with economic uncertainty, in addition to controlling for both these variables. We also lag the measurement of FinTech adoption by 1 year to avoid reverse causality. As the interaction term varies across cities, we cluster standard errors at the city level. Thus, the sign of β_1 determines whether FinTech adoption aggravates or alleviates the negative relationship between economic uncertainty and household consumption.

Control variables include the household head's characteristics (age, years in education, marriage status, health status, and living condition), and household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). These are all important determinants of household consumption.

2.2. Measurement of FinTech adoption

We apply the digital financial inclusion index system of Guo et al. (2020) to characterize FinTech adoption in China. This draws on account-level data from Ant Group and is measured by (1) Alipay account coverage; (2) third-party digital payments via Alipay, both online and offline; and (3) online investment, credit, and insurance via the FinTech platform of Ant Group. Thus, the index system provides information on regional FinTech adoption at the household level, as summarized in Table 1.

A general index in this system measures overall FinTech development at the regional level, which comprises three level I indices consisting of several level II indicators. These are calculated based on a set of specific indicators that measure FinTech adoption by households. The level I indices are breadth of coverage, depth of usage, and level of digitalization. Breadth of coverage measures regional FinTech penetration, based on Alipay account coverage-rate information and the number of credit cards per account. Depth of usage represents the actual use of financial services via FinTech platforms, classified as payment, monetary fund, credit, insurance, investment, and credit investigation services. Depth of usage also represents to the number of actual users, the number of transactions per capita, and the average transaction amount per capita. Level of digitalization measures the accessibility of digital financial services. As digital financial services become more convenient (e.g., more mobile) and cheaper (i.e., as their loan interest rates decrease), the

Table 1
Index system of digital financial inclusion.

Level I	Level II	Specific Indicators
Breadth of Coverage	Account Coverage Rate	Number of Alipay accounts per 10,000 people
		Proportion of Alipay users who have bank cards bound to their Alipay accounts
Depth of Usage	Payment	Average number of bank cards bound to each Alipay account
		Number of payments per capita
	Money Funds	Amount of payments per capita
		Proportion of high-frequency active users (50 times or more per year) in the total number of users with a frequency of at least once per year
	Individual User	Number of Yu'eobao purchases per capita
		Amount of Yu'eobao purchases per capita
	Credit	Number of people who have purchased Yu'eobao per 10,000 Alipay users
		Number of users with an Internet loan for consumption per 10,000 adult Alipay users
	Small & Micro Businesses	Number of loans per capita
		Total amount of loans per capita
	Insurance	Number of users with an Internet loan for small or micro businesses per 10,000 adult Alipay users
		Number of loans per small or micro business
	Investment	Average amount of loans for small and micro businesses
		Number of insured users per 10,000 Alipay users
Credit Investigation	Number of insurance policies per capita	
	Average insurance amount per capita	
Mobility	Number of people engaged in Internet investment and money management per 10,000 Alipay users	
	Number of investments per capita	
Affordability	Average investment amount per capita	
	Number of credit investigations by natural persons per capita	
Level of Digitalization	Credit	Number of users with access to credit-based livelihood services (such as finance, accommodations, mobility, and social contacts) per 10,000 Alipay users
		Proportion of total number of mobile payments
	Convenience	Proportion of total amount of mobile payments
		Average loan interest rate for small and micro businesses
		Average loan interest rate for individuals
		Number of Ant Check Later payments
		Total amount of Ant Check Later payments
		Proportion of "Zhima Credit as deposit" cases (of the number of full deposit cases)
		Proportion of "Zhima Credit as deposit" (of the total deposits)
		Number of QR code payments by users
		Proportion of "average amount" or "total amount" of QR code payments by users

Note: See Guo et al. (2020).

demand for these services increases, and vice versa.

The index system is constructed in two steps. In the first step, a logarithmic efficacy function is applied for nondimensionalization and then specific indicators are used to construct the level II indices, with weights assigned according to the coefficient of variation. In the second step, the analytic hierarchy process (AHP) is employed to assign the weights of level II indices to level I indices and those from level I indices to the general index of digital financial inclusion.

Annual data are obtained for 2011–2020, when FinTech adoption in China was at its peak. We illustrate the rapid growth of FinTech in Table 2, which reports the constructed indices across provinces in 2011 and in 2020. The national average index increased from 40.00 in 2011 to 341.22 in 2020, and the indices of all provinces increased significantly. Fig. 1 provides city-level data: Panel A displays the values across cities in 2011, and Panel B illustrates the growth from 2011 to 2020. Although the rate of FinTech adoption is highest in eastern China in this period, the rate of FinTech adoption in middle and western China steadily increases. Thus, FinTech is being adopted nationwide by all consumers, including those previously excluded from financial services, and is therefore leading to comprehensive financial inclusion.

2.3. Measurement of economic uncertainty

Jurado et al. (2015) develop an index of economic uncertainty based on numerous economic variables, but it only includes time series data at the national level and cannot account for the variation in economic uncertainty across regions. Thus, we follow Qiu (2021), utilize conditional volatility model, and calculate the index of economic uncertainty based on numerous economic variables at the provincial-quarter level in China. The main steps are as follows:

Firstly, we define the uncertainty of a single economic variable as the conditional volatility of its unpredicted component. Specifically, we use $u_{p,st}^y(h)$ to denote the economic uncertainty expected in the future h periods at time t in province p , where $y_{st} \in Y_t = (y_{1t}, \dots, y_{N_t})'$ represents a series of economic variables. We could thus denote the uncertainty of variable y_{st} as $u_{p,st}^y(h)$ as the conditional volatility of the unpredicted component after exclusion of the predictable component of provincial economic variables, as follow:

$$u_{p,st}^y(h) = \sqrt{E\left[\left(y_{p,s,t+h} - E[y_{p,s,t+h}|I_t]\right)^2 | I_t\right]} \tag{2.3}$$

where $E[\bullet | I_t]$ denotes the expectation under the information set I_t available at time t . It is thus obvious that, the uncertainty of variable y_{st} is not equal to the conditional volatility but the remainder of the conditional volatility after removal of the predictable volatility (as the latter would be mistaken as a component of economic uncertainty). If the mean squared error of $y_{p,s,t+h}$ conditioned on all available information increases, the economic uncertainty of variable y_{st} for province p also increases.

Secondly, based on the calculated conditional volatility of the unpredicted component of variable y_{st} , we compute the index of economic uncertainty, as follow:

$$EU_{p,t}(h) \equiv \text{plim}_{N_y \rightarrow \infty} \sum_{s=1}^{N_y} w_s u_{p,st}^y(h) \equiv E_w \left[u_{p,st}^y(h) \right] \tag{2.4}$$

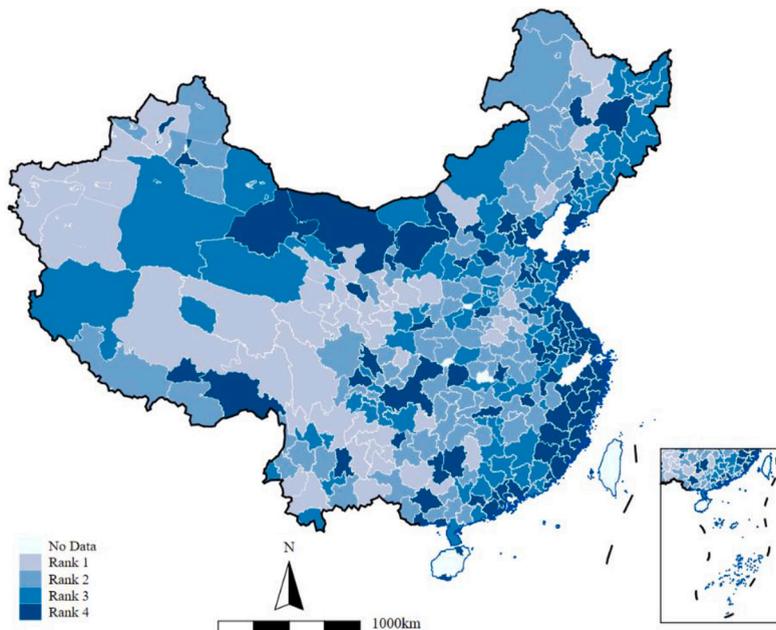
where w_s denotes the weight of economic variable s . In fact, business cycle theory suggests that common changes occur in the level of uncertainty across many series, indicating that economic uncertainty is not equal to the uncertainty of any single economic variable

Table 2
FinTech adoption in China.

Province	General Index of Digital Financial Inclusion		Province	General Index of Digital Financial Inclusion	
	2011	2020		2011	2020
China (average)	40.00	341.22	Henan	28.4	340.81
Beijing	79.41	417.88	Hubei	39.82	358.64
Tianjin	60.58	361.46	Hunan	32.68	332.03
Hebei	32.42	322.70	Guangdong	69.48	379.53
Shanxi	33.41	325.73	Guangxi	33.89	325.17
Inner Mongolia	28.89	309.39	Hainan	45.56	344.05
Liaoning	43.29	326.29	Chongqing	41.89	344.76
Jilin	24.51	308.26	Sichuan	40.16	334.82
Heilongjiang	33.58	306.08	Guizhou	18.47	307.94
Shanghai	80.19	431.93	Yunnan	24.91	318.48
Jiangsu	62.08	381.61	Tibet	16.22	310.53
Zhejiang	77.39	406.88	Shaanxi	40.96	342.04
Anhui	33.07	350.16	Gansu	18.84	305.50
Fujian	61.76	380.13	Qinghai	18.33	298.23
Jiangxi	29.74	340.61	Ningxia	31.31	310.02
Shandong	38.55	347.81	Xinjiang	20.34	308.35

Note: Data are from Guo et al. (2020).

Panel A. Index of Digital Financial Inclusion in China (2011)



Panel B. Growth of Index of Digital Financial Inclusion in China (2011-2020)

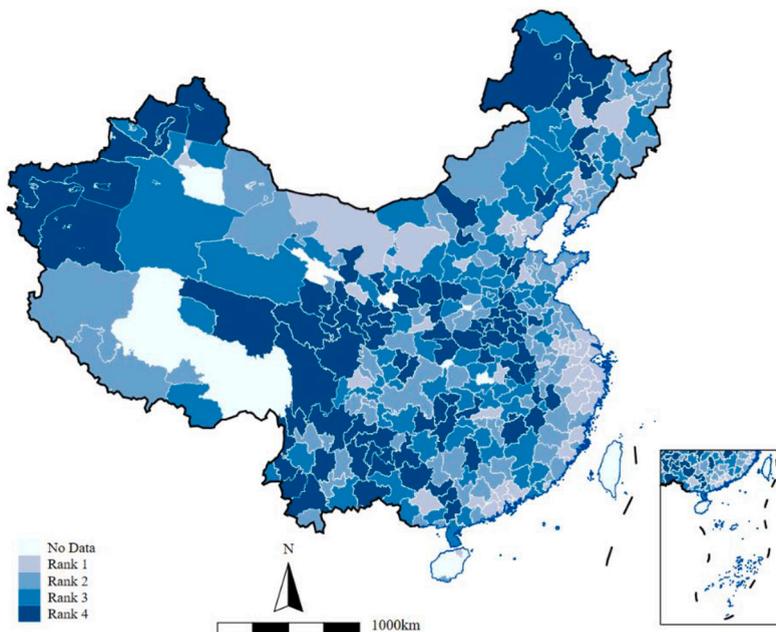


Fig. 1. FinTech adoption and financial inclusion in China.

Note: Data are from Guo et al. (2020).

but measures the common change in uncertainty of all economic variables.

Finally, we approximate the information set using a variety of economic variables. To this end, we utilize 61-dimensional provincial quarterly economic data spanning from the first quarter of 2006 to the fourth quarter of 2019. This dataset includes national account, financial, household survey, goods and services, inflation, investment, agriculture, manufacturing, energy, construction, insurance,

and real estate data. To extract potential common factors, we employ principal component analysis, and use the resulting factors to construct an economic uncertainty index for each province using a stochastic volatility model. The evolution of economic uncertainty is depicted in Fig. 2, which shows that our constructed index captures the variation of real economic uncertainty over time. For instance, the index reached its highest level in 2008, likely due to the subprime financial crisis, and rose again after 2017 as a result of the Sino-US trade war. Fig. 2 also displays the economic uncertainty index across provinces in 2008 (Panel A) and in 2019 (Panel B), highlighting regional disparities that vary over time. This variation allows us to investigate the impact of economic uncertainty on consumption across households and over time. (See Fig. 3.)

2.4. Data

We employ two datasets to estimate models (2.1) and (2.2). The first is obtained from the CFPS, a nationally representative survey of China's communities, families, and individuals conducted biennially from 2010 to 2018. The CFPS covers a wide range of domains for families and individuals from 162 counties in 25 Chinese provinces, including their economic activities, education outcomes, family dynamics and relationships, and health status.

The CFPS collects data on household consumption expenditures over the past year through a questionnaire. Expenditures on daily food, clothing, and other necessities are classified as nondurable goods, which include perishable items and those with a short lifespan, and are essential for meeting household needs. Expenditures on housing, medical care, transportation, communication, entertainment, and education are classified as services. Durable goods, such as household appliances with an expected lifespan of more than three years, are also tracked separately.

To analyze the impact of economic uncertainty on household consumption, we use a representative household approach, focusing on the head of the household. Fig. 4 displays the distribution of household consumption across three categories in 2012 and 2018. Overall, household consumption increased during this period and the distribution became more concentrated, indicating a reduction in consumption inequality. Notably, non-durable goods had the highest level and most concentrated distribution of household spending, which aligns with the fact that daily necessities comprise a significant portion of household expenditures. Conversely, households spent the least on durable goods, whose distribution was also the most dispersed due to their longer lifetimes.

The second dataset consists of regional variables. We measure FinTech adoption using a city-level index of digital financial inclusion in China, as introduced in section 2.2. We also follow the method introduced in section 2.3 to calculate economic uncertainty. We control for indicators that reflect regional economic development. By combining the two datasets in models (2.1) and (2.2), we estimate the relationship between economic uncertainty and household consumption, as well as the impact of FinTech adoption on the relationship. Table 3 tabulates the summary statistics.

3. Baseline results

3.1. Economic uncertainty and household consumption

We begin our empirical work by investigating the effect of economic uncertainty on household consumption. We hypothesize that due to precautionary saving, compared with households that experience lower economic uncertainty, households that experience higher economic uncertainty are more likely to spend less, particularly on items with higher elasticity such as services.

In Table 4, we estimate the relationship between the level of categorized household consumption and economic uncertainty using the full CFPS sample from 2012 to 2018. Columns (1) and (2) show the household expenditure on non-durable goods, columns (3) and (4) show the household expenditure on durable goods, and columns (5) and (6) show the household expenditure on services. In all regressions, we control for household fixed effects and quarter-by-year fixed effects. In addition, we cluster standard errors at the provincial level to prevent the serially correlation of error terms across households within a province. As Table 4 shows, there is heterogeneity across the three categories of consumption. In times of economic uncertainty, there is significantly decreased household expenditure on durable goods and services but significantly increased household expenditure on non-durable goods that fulfill the basic needs of households. This indicates that economic uncertainty is associated with the downgrading of household consumption from services to non-durable goods. This is intuitive, as households tend to become more conservative when faced with economic uncertainty and therefore reduce their higher elasticity expenditure. In terms of economic significance, a 1% increase in economic uncertainty is associated with a 0.5% increase in spending on non-durable goods but 1.9% and 1.1% decreases in spending on durable goods and services, respectively.

3.2. FinTech adoption and economic uncertainty

The results above indicate that economic uncertainty is associated with a reduction in household consumption, especially in service spending, possibly due to an increase in conservative perceptions among households regarding sustainable economic growth and future income. As a result, households tend to reduce their consumption, particularly of goods with higher elasticity such as services.

However, FinTech has a significant impact on decisions related to household consumption. One example is the provision of FinTech credit, which is particularly beneficial to those who were previously unable to obtain bank loan. This alleviates concerns about future income volatility and enables households to make purchases they might not have been able to make otherwise. Furthermore, the growth of FinTech has increased the market potential for sellers, creating additional entrepreneurial and employment opportunities. Therefore, we expect that the adoption of FinTech can help reduce the negative relationship between economic uncertainty and

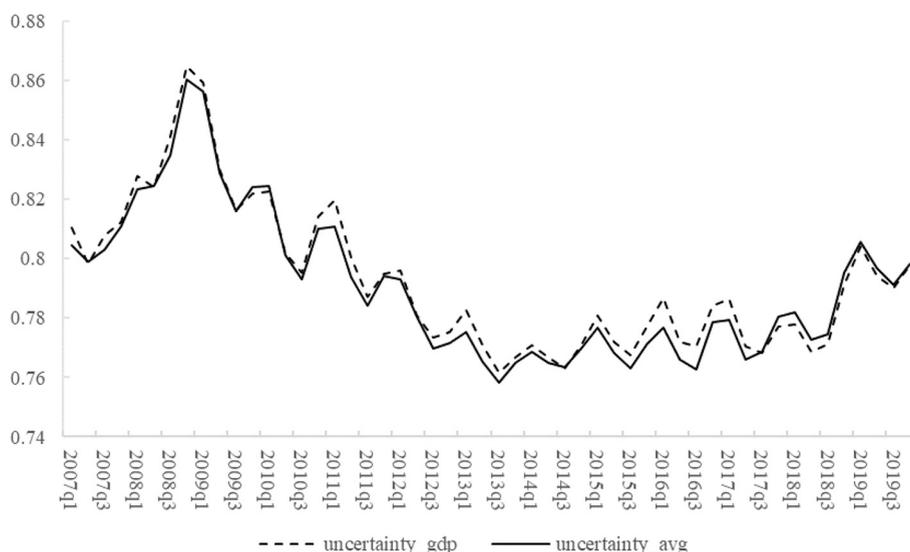


Fig. 2. Evolution of economic uncertainty in China.

Note: Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. The “uncertainty_gdp” refers to the national average economic uncertainty treating regional GDP as weight, while the “uncertainty_avg” refers to the national arithmetic average economic uncertainty.

household consumption.

Based on model (2.2), we estimated the combined relationship between FinTech adoption, economic uncertainty, and household consumption, and present our findings in Table 5. As with Table 4, we report the results for non-durable goods, durable goods, and services expenditure categories separately. The results in Table 5 corroborate those of Table 4, with the coefficients of economic uncertainty for non-durable goods being significantly positive, and those for services being significantly negative. These results further support our finding that economic uncertainty is linked to a downgrade in household consumption. Importantly, the interaction term between FinTech adoption and economic uncertainty is significant and positive for service estimates, suggesting that FinTech mitigates the relationship between economic uncertainty and consumption downgrading from service to non-durable goods. As stated, daily necessities comprise a significant portion of household expenditures and therefore, FinTech could hardly affect the expenditure on non-durable goods significantly. The finding that FinTech mitigates the relationship between economic uncertainty and service spending also aligns with literature arguing that households become more financially resilient to shocks with the help of FinTech (Suri et al., 2021).

In terms of economic significance, the digital financial inclusion index must be at least 223.50 to fully offset the negative correlation between economic uncertainty and service spending. In 2016, only Hangzhou had a digital financial inclusion index above 223.50, but by 2018, nearly 40% of Chinese cities had values above this threshold. This implies that FinTech adoption not only boosts household consumption, as most studies suggest, but also contributes to China’s sustainable economic development by helping households overcome economic uncertainty and stabilize their consumption levels.

3.3. Eight types of consumption expenditure

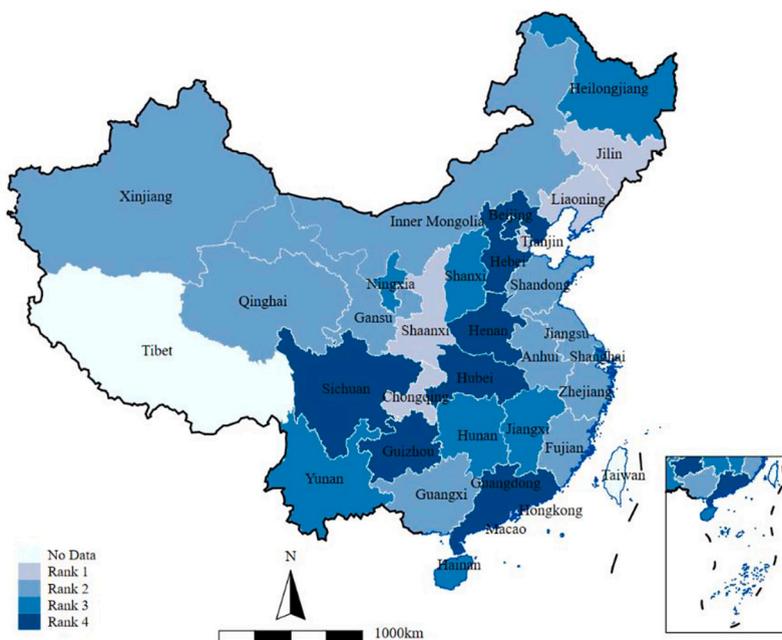
We now categorize household consumption into eight types following the criteria established by the National Bureau of Statistics in China: (1) food consumed daily; (2) clothing; (3) housing; (4) household appliances, daily commodities, and necessities; (5) transportation and communication; (6) entertainment and education; (7) medical care; and (8) other expenses. We then examined FinTech’s impact on the relationship between economic uncertainty and these eight categories of consumption (See Table 6.). Our analysis reveals that FinTech helps to alleviate the decrease in consumption, particularly in clothing, transportation and communication, and other expenses. These findings confirm that FinTech plays a crucial role in mitigating the negative effects of economic uncertainty on household consumption.

4. Robustness check

4.1. Alternative spending measurement

In our baseline regressions, we use the logarithms of household consumption categories as dependent variables, as discussed in Section 3. To test the robustness of our results, we also consider the proportion of each type of consumption relative to total household-level consumption. Specifically, Table 7 presents the results for the proportion of household expenditure on non-durable goods,

Panel A. Economic Uncertainty in China (2008)



Panel B. Economic Uncertainty in China (2019)

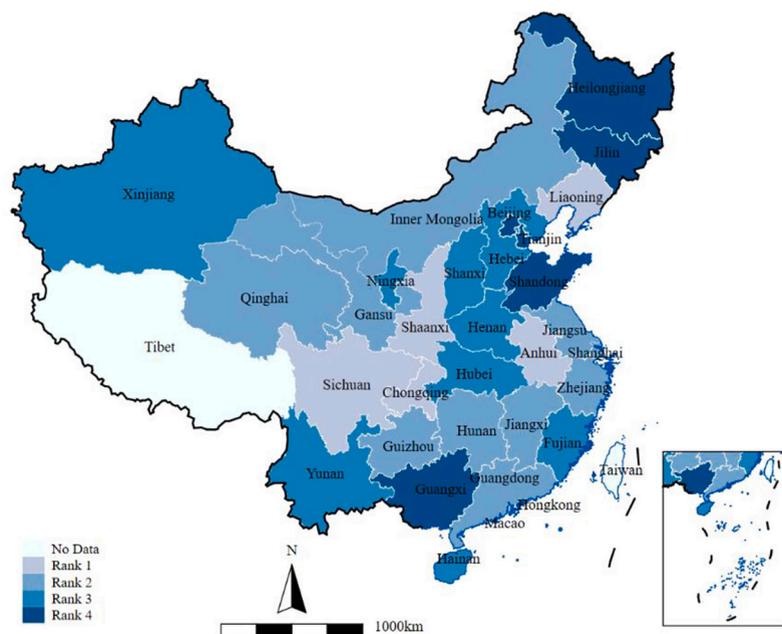
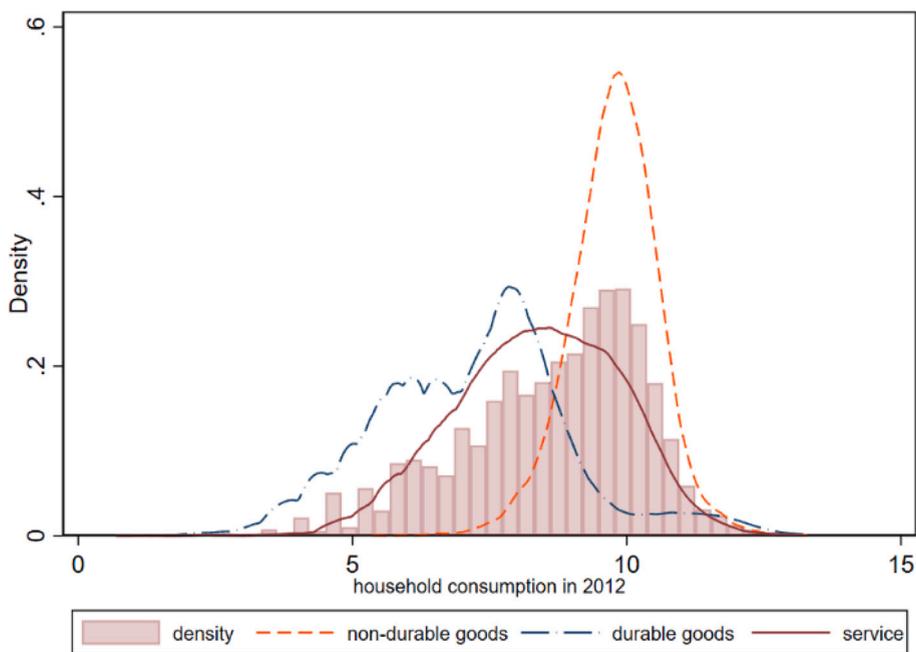


Fig. 3. Regional disparity of economic uncertainty in China.
 Note: Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables.

Panel A. Distribution of Household Consumption (2012)



Panel B. Distribution of Household Consumption (2018)

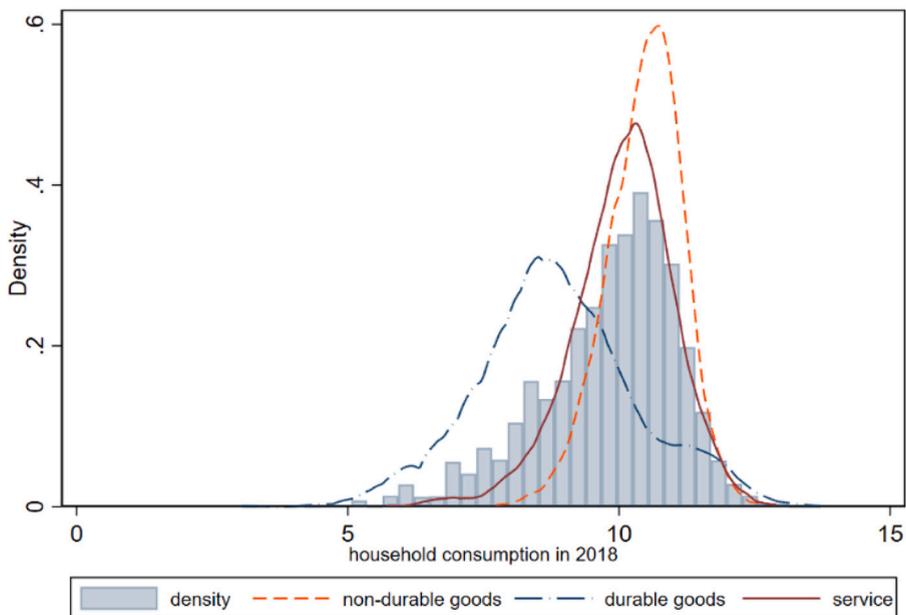


Fig. 4. Distribution of household consumption.
 Note: Authors' calculation based on data from China Family Panel Studies (CFPS).

durable goods, and services. We control for the characteristics of the household head, household, and region, as well as for household and quarter-by-year fixed effects. Our findings indicate that economic uncertainty leads to a downgrade in household consumption, with a reduction in expenditure on services and an increase in expenditure on non-durable goods, consistent with our baseline results.

Table 3
Summary statistics.

Variables	Obs	Mean	Std. Dev.	Min	Max
Non-Durable Goods	24,374	27,391.018	27,373.13	212	855,400
Durable Goods	24,374	7074.533	40,775.134	0	4,500,200
Services	24,374	14,104.686	22,543.804	0	613,400
Age	24,374	53.196	12.327	17	94
Schooling Years	24,374	6.655	4.749	0	19
Marriage Status	24,374	0.891	0.312	0	1
Health Status	24,374	0.812	0.391	0	1
Living Condition	24,374	0.456	0.498	0	1
Family Income Per Capita	24,374	17,375.4	49,437.196	0	4,168,000
Family Wealth	24,374	48,606.548	196,103.08	0	10,500,000
Family Size	24,374	3.921	1.806	1	19
Young Dependency Ratio	24,374	0.144	0.166	0	0.857
Old Dependency Ratio	24,374	0.212	0.313	0	1
Social Security Participation	24,374	0.233	0.423	0	1
Population	24,374	4241.873	5257.237	128	86,000
Economic condition	24,374	4.598	1.318	1	7

Note: This table gives the characteristics of households in our sample. (Categorized) Consumption is yearly household consumption. Health status is a dummy that equals one if the household is in good health. Living condition is approximated using a dummy variable that equals one if the household is in an urban area. Family wealth is the total value of household-level financial assets. The dependency ratio is calculated as the proportion of young/elderly members in a family. Social security participation is a dummy variable that equals one if the household has been enrolled in any insurance. Population and economic condition are defined at the village level. Economic condition is measured by the subjective judgment of interviewers.

Table 4
Economic uncertainty and household consumption.

Household Consumption	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Durable Goods		Durable Goods		Services	
Economic Uncertainty	0.517 (0.359)	0.509 ^S (0.298)	-1.976** (0.947)	-1.759** (0.792)	-1.147*** (0.326)	-1.069*** (0.325)
Head Controls	N	Y	N	Y	N	Y
Household Controls	N	Y	N	Y	N	Y
County Controls	N	Y	N	Y	N	Y
Household Fixed Effect	Y	Y	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y	Y	Y
N	24,374	24,374	24,374	24,374	24,374	24,374
R ²	0.703	0.714	0.563	0.576	0.788	0.802

Note: The dependent variable is the logarithm of (categorized) household consumption and is estimated using a fixed-effects model at the household level. Economic uncertainty is measured at provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. The control variables are the characteristics of the head of a household (age, years in education, marriage status, health status, and living condition), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the provincial level. ^S, *, **, and *** denote significance at the 12%, 10%, 5%, and 1% levels, respectively.

Notably, we find that FinTech adoption increases expenditure on services, which helps mitigate the negative impact of economic uncertainty on household consumption.

4.2. Alternative economic uncertainty measurement

In our baseline results, we measured FinTech adoption and household consumption indicators annually, while economic uncertainty was measured quarterly. This difference in the time dimension of measurement could introduce additional estimation bias. To address this, in Table 8, we average the economic uncertainty indicator into an annual measure using simple arithmetic and re-estimated the model with this new measure. We again control for household head, household, and regional characteristics, as well as household and year fixed effects. We find that the estimated results remained unchanged and robust, demonstrating the validity of our methodology.

4.3. Additional lags on economic uncertainty

In accordance with Bloom (2014), a major challenge in the economic uncertainty literature is how to distinguish between the effects of first and second moments since most significant events that generate uncertainty are associated with a significant deterioration in the economic outlook. To address this endogeneity issue, we opt to replace the 1-year lag measurement of economic uncertainty with a 2-year lag measurement, with corresponding controls as presented in Table 9. This approach accounts for the fact that

Table 5
FinTech adoption, economic uncertainty, and household consumption.

Household Consumption	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Durable Goods		Durable Goods		Services	
Economic Uncertainty	0.772 (0.517)	0.856* (0.496)	-1.545 (2.285)	-0.961 (2.163)	-2.400*** (0.665)	-2.083*** (0.675)
Economic Uncertainty × FinTech Adoption	-0.00337 (0.00299)	-0.00403 (0.00291)	-0.00544 (0.0161)	-0.00760 (0.0145)	0.0111** (0.00431)	0.00932** (0.00424)
FinTech Adoption	0.00458** (0.00222)	0.00354 (0.00216)	0.00645 (0.00885)	-0.000712 (0.00811)	0.00576** (0.00284)	0.00270 (0.00270)
Head Controls	N	Y	N	Y	N	Y
Household Controls	N	Y	N	Y	N	Y
County Controls	N	Y	N	Y	N	Y
Household Fixed Effect	Y	Y	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y	Y	Y
N	24,374	24,374	24,374	24,374	24,374	24,374
R ²	0.704	0.715	0.563	0.576	0.789	0.802

Note: The dependent variable is the logarithm of (categorized) household consumption and is estimated using a fixed-effects model at the household level. Economic uncertainty is measured at provincial- quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption is measured using the index of digital financial inclusion. The control variables are the characteristics of the head of a household (age, years in education, marriage status, health status, and living condition), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6
FinTech adoption, economic uncertainty, and eight types of consumption expenditure.

Household Consumption	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Food	Clothing	Housing	Household Appliances	Health Care	Transportation & Communication	Education & Recreation	Other
Economic Uncertainty	1.416 (1.020)	-2.154*** (0.777)	0.194 (0.902)	-1.468* (0.881)	-1.602 (1.197)	-2.401*** (0.629)	-2.374 (1.450)	-10.08*** (2.851)
Economic Uncertainty × FinTech Adoption	-0.00542 (0.00577)	0.0139** (0.00533)	-0.000359 (0.00611)	0.00254 (0.00638)	0.0105 (0.00809)	0.0107*** (0.00407)	0.0111 (0.0106)	0.0618*** (0.0196)
FinTech Adoption	0.00537 (0.00371)	0.00368 (0.00291)	-0.00199 (0.00440)	0.00410 (0.00393)	0.00166 (0.00525)	0.00124 (0.00295)	0.00772 (0.00613)	0.0465*** (0.0105)
Head Controls	Y	Y	Y	Y	Y	Y	Y	Y
Household Controls	Y	Y	Y	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y	Y	Y	Y
Household Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
N	24,374	24,374	24,374	24,374	24,374	24,374	24,374	24,374
R ²	0.642	0.687	0.639	0.619	0.551	0.768	0.749	0.596

Note: The dependent variables are the logarithm of eight types of consumption expenditure and are estimated using a fixed-effects model at the household level. Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption is measured using the index of digital financial inclusion. The control variables are the characteristics of the head of a household (age, years in education, marriage status, health status, and living condition), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

households typically perceive economic conditions as worse in the first moment, experience economic uncertainty in the second moment, and then adjust their consumption decisions. The findings in Table 9 are consistent with those in Table 4, demonstrating that it is economic uncertainty, rather than a deteriorating economy, that results in decreased consumption, and that FinTech adoption can mitigate this negative impact.

4.4. Instrumental variable approach

There are several other endogeneity issues related to the variables of economic uncertainty and FinTech adoption that should be considered. For instance, one potential problem is that an improvement in household consumption and thus domestic demand may lead to a reduction in economic uncertainty, resulting in reverse causality bias. Additionally, any measurement error in the index of FinTech adoption could also introduce bias into the empirical results. Furthermore, it is impossible to control for all the variables that

Table 7
Robustness: Alternative Spending Measurement.

Household Consumption	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Durable Goods		Durable Goods		Services	
Economic Uncertainty	0.316*** (0.102)	0.618** (0.236)	-0.0123 (0.0298)	-0.0327 (0.0584)	-0.203*** (0.0773)	-0.507*** (0.168)
Economic Uncertainty × FinTech Adoption		-0.00256 (0.00156)		0.000193 (0.000491)		0.00310*** (0.00105)
FinTech Adoption		-0.00198* (0.00115)		0.0000274 (0.000244)		-0.000819 (0.000540)
Head Controls	N	Y	N	Y	N	Y
Household Controls	N	Y	N	Y	N	Y
County Controls	N	Y	N	Y	N	Y
Household Fixed Effect	Y	Y	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y	Y	Y
N	24,374	24,374	24,374	24,374	24,374	24,374
R ²	0.424	0.424	0.405	0.405	0.451	0.452

Note: The dependent variable is the proportion of (categorized) household consumption over total household consumption and is estimated using a fixed-effects model at the household level. Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption is measured using the index of digital financial inclusion. The control variables are the characteristics of the head of a household (age, years in education, marriage status, health status, and living condition), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 8
Robustness: alternative economic uncertainty measurement.

Household Consumption	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Durable Goods		Durable Goods		Services	
Economic Uncertainty	0.372* (0.220)	0.154 (0.473)	-0.475 (1.232)	-0.0179 (2.137)	-0.999*** (0.302)	-2.404*** (0.638)
Economic Uncertainty × FinTech Adoption		0.00143 (0.00312)		-0.00387 (0.0144)		0.0119*** (0.00436)
FinTech Adoption		0.00530** (0.00205)		-0.00107 (0.00829)		0.00309 (0.00275)
Head Controls	Y	Y	Y	Y	Y	Y
Household Controls	Y	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y	Y
Household Fixed Effect	Y	Y	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y	Y	Y
N	24,374	24,374	24,374	24,374	24,374	24,374
R ²	0.714	0.714	0.576	0.576	0.802	0.802

Note: The dependent variable is the logarithm of (categorized) household consumption and is estimated using a fixed-effects model at the household level. Economic uncertainty is measured with 2-year lags at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption is measured using the index of digital financial inclusion. The control variables are the characteristics of the head of a household (age, years in education, marriage status, health status, and living condition), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

affect household consumption and that are correlated with economic uncertainty and FinTech adoption. These endogeneity issues cannot be effectively addressed by including household and time-fixed effects, as changes in consumption that are specific to each household and vary over time may also affect economic uncertainty and FinTech adoption.

In light of this, we employ an instrument variable approach. For the indicator of FinTech adoption, following [Hong et al. \(2021\)](#) and [Yang and Zhang \(2022\)](#), we use the logarithm of a city's distance to Hangzhou, the headquarters of Ant Group, as an instrument variable to predict the intensity of FinTech adoption across different cities. As [Hong et al. \(2021\)](#) state, this distance could predict FinTech adoption due to the marketing activities of Ant Group, which initially worked with the local government of Hangzhou to implement QR code-based digital payments. It then expanded this service through local promotional activities, such that local merchants gradually implemented the QR-scan payment method. FinTech was thus first adopted in cities around Hangzhou, which therefore have higher levels of FinTech penetration than other cities. Note that the distance variable is time-invariant, and we therefore interact this IV with national FinTech adoption in counterpart cities.

For the variable of economic uncertainty, we instrument it based on the interaction between the time-series economic uncertainty in the US and the trade value between the US and each province in China in 2011. Given the close economic ties between China and the

Table 9
Robustness: additional lags on economic uncertainty.

Household Consumption	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Durable Goods		Durable Goods		Services	
Economic Uncertainty	0.462** (0.207)	0.724 (0.448)	-1.337 (1.102)	-0.819 (1.902)	-1.071*** (0.293)	-2.357*** (0.613)
Economic Uncertainty × FinTech Adoption		-0.00256 (0.00263)		-0.00447 (0.0123)		0.0110*** (0.00375)
FinTech Adoption		0.00402* (0.00208)		-0.000902 (0.00816)		0.00315 (0.00266)
Head Controls	Y	Y	Y	Y	Y	Y
Household Controls	Y	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y	Y
Household Fixed Effect	Y	Y	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y	Y	Y
N	24,374	24,374	24,374	24,374	24,374	24,374
R ²	0.714	0.715	0.576	0.576	0.802	0.803

Note: The dependent variable is the logarithm of (categorized) household consumption and is estimated using a fixed-effects model at the household level. Economic uncertainty is measured with 2-year lags at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption is measured using the index of digital financial inclusion. The control variables are the characteristics of the head of a household (age, years in education, marriage status, health status, and living condition), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

US, we expect that economic uncertainty in the two countries will be highly correlated. Moreover, we anticipate that provinces with higher levels of trade with the US will be more closely connected to the US economy, leading to a stronger relationship between their economic uncertainty and that in the US.

The exclusion restriction conditions are also met. Firstly, the existence of multiple economic centers throughout China means that cities in proximity to Hangzhou do not inherently exhibit higher levels of consumption. Secondly, household consumption in China is not directly influenced by economic uncertainty in the US, except insofar as it correlates with China's own economic uncertainty.

In Table 10, columns (1)–(3) present the results of our first-stage estimations. Column (1) shows a negative correlation between a city's FinTech adoption and its distance to Hangzhou, indicating that cities closer to Hangzhou tend to have higher rates of FinTech adoption. In columns (2) and (3), we introduce two measures of economic uncertainty in the US: News-Based Economic Policy Uncertainty (EPU) developed by Baker et al. (2016), and EPU based on three components: newspaper coverage, the number of federal tax code provisions set to expire, and disagreement among economic forecasters.¹ Our estimated results confirm that economic uncertainty in China is highly correlated with that in the US, as expected.

Columns (4)–(5) present the results of our second-stage estimation, in which we mainly focus on service spending. In column (4), we use the News-based EPU as an IV for economic uncertainty in China, while in column (5) we instrument economic uncertainty with the three-component EPU. The results confirm that economic uncertainty has a negative causal effect on service spending. Importantly, our findings also reveal that FinTech adoption helps mitigate this negative impact by preventing households from downgrading their consumption from services to non-durable goods, which aligns with our baseline results. The IV estimate is larger in magnitude, compared with the estimated coefficient in the baseline result, confirming the existence of endogeneity problem. Economically, the development of FinTech could fully offset the negative impact of economic uncertainty in China, suggesting the important role FinTech plays in economic development.

5. Heterogeneity analysis

The above results suggest that FinTech adoption serves to mitigate the negative impact of economic uncertainty on household consumption, particularly on service spending. We now conduct heterogeneity analyses across regions and households.

5.1. Urban–rural heterogeneity

We first examine the impact of the *hukou* system on urban-rural segregation and urban bias in China. To investigate the possible heterogeneity between urban and rural areas, we separate our sample to explore how the adoption of FinTech mitigates the negative effects of economic uncertainty.

Our analysis reveals that the effects of FinTech adoption on consumption decisions differ significantly between urban and rural areas. Specifically, our results (reported in Table 11) indicate that FinTech adoption mainly affects service spending in urban areas, while its impact on consumption in rural areas is not significant. One explanation for this difference may be the relatively low Internet

¹ Methodology and Data are from <http://www.policyuncertainty.com/index.html>.

Table 10
IV regression.

	(1)	(2)	(3)	(4)	(5)
	FinTech Adoption	Economic Uncertainty		Services	
Ln (Distance to Hangzhou) × Average FinTech adoption of counterpart cities	−0.0346*** (0.00371)				
News-Based EPU in the US		0.0268*** (0.00880)			
Three Components EPU in the US			0.0191** (0.00761)		
Economic Uncertainty				−1.462 (5.697)	−2.275 (7.193)
Economic Uncertainty × FinTech Adoption				0.0427** (0.0166)	0.0603** (0.0233)
Head Controls	N	N	N	Y	Y
Household Controls	N	N	N	Y	Y
County Controls	N	N	N	Y	Y
Household Fixed Effect	N	N	N	Y	Y
Year Fixed Effect	Y	Y	Y	Y	Y
City/Province Fixed Effect	Y	Y	Y	N	N
N	3016	308	308	24,374	24,374
R ²	0.993	0.408	0.398	0.802	0.802

Note: Column (1) reports the first-stage estimation using the interactive term of the distance to Hangzhou with national FinTech adoption of counterpart cities as an instrument for FinTech adoption. Columns (2)–(3) report the first-stage estimation using the interactive term of economic uncertainty in the US (News-Based EPU in column 2 and three-component EPU in column 3) and provincial trade value with the US in 2011 as an instrument for provincial economic uncertainty in China. Columns (4)–(5) report the second-stage estimation (News-Based EPU as an IV of economic uncertainty in column 4 and three-component EPU as an IV of economic uncertainty in column 5). FinTech adoption is measured by the index of digital financial inclusion. Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. The control variables are the characteristics of the head of a household (age, years in education, marriage status, and health status), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 11
Urban–rural heterogeneity.

Services	(1)	(2)	(3)	(4)
	Urban		Rural	
Economic Uncertainty	−1.048*** (0.356)	−2.224*** (0.665)	−1.132** (0.456)	−1.975** (0.978)
Economic Uncertainty × FinTech Adoption		0.00993** (0.00407)		0.00836 (0.00688)
FinTech Adoption		0.00469** (0.00235)		0.00125 (0.00473)
Head Controls	Y	Y	Y	Y
Household Controls	Y	Y	Y	Y
County Controls	Y	Y	Y	Y
Household Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
N	10,850	10,850	12,980	12,980
R ²	0.821	0.822	0.779	0.779

Note: The dependent variable is the logarithm of service spending and is estimated using a fixed-effects model at the household level. Columns (1) and (2) report the results for the urban sample, and columns (3) and (4) report the results for the rural sample. Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption is measured using the index of digital financial inclusion. The control variables are the characteristics of the head of a household (age, years in education, marriage status, and health status), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The results of Fisher's permutation test indicate a significant difference between the two samples in terms of the estimated coefficient of the interactive term (p -value = 0.000).

Table 12
Heterogeneity in human capital.

Services	(1)	(2)	(3)	(4)
	High Human Capital		Low Human Capital	
Economic Uncertainty	0.157 (0.462)	0.739 (0.823)	-1.331*** (0.369)	-2.540*** (0.747)
Economic Uncertainty × FinTech Adoption		-0.00604 (0.00569)		0.0114** (0.00476)
FinTech Adoption		0.00205 (0.00264)		0.00344 (0.00317)
Head Controls	Y	Y	Y	Y
Household Controls	Y	Y	Y	Y
County Controls	Y	Y	Y	Y
Household Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
N	3823	3823	19,727	19,727
R ²	0.796	0.797	0.789	0.789

Note: The dependent variable is the logarithm of service spending and is estimated using a fixed-effects model at the household level. Columns (1) and (2) report the results with more than 12 years of education, and columns (3) and (4) report those with a below-high school level of education. Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption is measured using the index of digital financial inclusion. The control variables are the characteristics of the head of a household (age, marriage status, health status, and living condition), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The results of Fisher's permutation test indicate a significant difference between the two samples in terms of the estimated coefficient of the interactive term (p -value = 0.000).

coverage rate in rural areas compared to urban areas,² which limits the effect of FinTech. Furthermore, the underdeveloped infrastructure of rural areas may also constrain consumer choice. Moreover, we find that FinTech adoption is unlikely to significantly reduce the precautionary savings behavior of rural residents due to the additional uncertainties and risks they face when making consumption decisions.

5.2. Heterogeneity in human capital

We next consider whether the impact of FinTech adoption on consumption during economic uncertainty varies by household. [Ben-David et al. \(2018\)](#) document that individuals with lower skills are more vulnerable to economic uncertainty, as they have less bargaining power than those with higher skills. As a result, economic uncertainty may have a more significant impact on the consumption of households with lower levels of human capital than those with higher levels. However, FinTech adoption could potentially provide these households with tools to better navigate the negative effects of economic uncertainty.

In [Table 12](#), we investigate the relationship between FinTech adoption, economic uncertainty, and service spending, with a focus on heterogeneity in human capital. Specifically, we analyze the impact of these factors on household heads with varying levels of education. Columns (1) and (2) present the results for those with more than 12 years of education (i.e., high school degrees and above), while columns (3) and (4) report the findings for those with a below-high school level of education. Our results indicate that the effects of FinTech adoption and economic uncertainty are significant only in the subsample with lower human capital, which is in line with our expectations. This implies that FinTech adoption has the potential to enhance social welfare, particularly among those with less education, by enabling them to manage economic uncertainty more effectively. As a result, this can contribute to financial inclusion and promote inclusive growth.

5.3. Heterogeneity in risk attitude

Finally, we examine how economic uncertainty and FinTech adoption affect households with varying levels of risk attitude. Since households may have different attitudes towards economic risk, this heterogeneity can influence their consumption choices. To explore this, we classify households as risk-averse if they hold low-risk assets, and risk-preference if they hold high-risk assets such as stocks, funds, or options. [Table 13](#) reports our empirical findings. Specifically, columns (1) and (2) show the results for risk-averse households, while columns (3) and (4) present the results for risk-preference ones. The results reveal that the impact of economic uncertainty and FinTech adoption is more pronounced among risk-averse households. This aligns with our expectations that risk-averse households are more likely to adjust their consumption decisions in response to economic uncertainty, and that FinTech adoption can mitigate such adjustments by reducing household welfare.

² In 2020, 44.1% of rural Chinese households did not have Internet access.

Table 13
Heterogeneity in risk attitude.

Services	(1)	(2)	(3)	(4)
	Risk Aversion		Risk Preference	
Economic Uncertainty	-1.072*** (0.355)	-2.223*** (0.726)	-0.543 (0.443)	-0.624 (0.917)
Economic Uncertainty × FinTech Adoption		0.0106** (0.00474)		0.000407 (0.00533)
FinTech Adoption		0.00451 (0.00337)		0.000797 (0.00267)
Head Controls	Y	Y	Y	Y
Household Controls	Y	Y	Y	Y
County Controls	Y	Y	Y	Y
Household Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
N	21,653	21,653	2699	2699
R2	0.789	0.790	0.789	0.789

Note: The dependent variable is the logarithm of service spending and is estimated using a fixed-effects model at the household level. Columns (1) and (2) report the results for risk-averse households, and columns (3) and (4) report the results for risk-preference ones. Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption is measured using the index of digital financial inclusion. The control variables are the characteristics of the head of a household (age, marriage status, health status, and living condition), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The results of Fisher's permutation test indicate a significant difference between the two samples in terms of the estimated coefficient of the interactive term (p-value = 0.000).

6. Channel analysis

In this section, we investigate the channels through which FinTech adoption mitigates the negative impact of economic uncertainty on household consumption, particularly on service spending. We mainly consider two channels. The first channel is the alleviation of credit constraints, and the second channel considers FinTech's effect on entrepreneurship and employment.

6.1. Alleviation of credit constraints

As mentioned, households tend to become more cautious about sustainable economic growth and future income as economic uncertainty increases. However, FinTech can play a crucial role in guaranteeing optimal household consumption levels by providing additional credit, even in times of volatility (Christelis et al., 2020). In this way, FinTech adoption can help alleviate credit constraints caused by economic uncertainty and overcome its negative effects.

To examine this effect, we first explore the sub-indices of digital financial inclusion in Table 14. Column (1) replicates the results of

Table 14
Alleviation of credit constraints: index of digital financial inclusion.

Services	(1)	(2)	(3)
	FinTech Adoption	Depth of Usage	Credit
Economic Uncertainty	-2.083*** (0.675)	-1.889*** (0.634)	-2.276*** (0.779)
Economic Uncertainty × FinTech Adoption	0.00932** (0.00424)	0.00935** (0.00397)	0.0161** (0.00681)
FinTech Adoption	0.00270 (0.00270)	0.000514 (0.00165)	0.00104 (0.00234)
Head Controls	Y	Y	Y
Household Controls	Y	Y	Y
County Controls	Y	Y	Y
Household Fixed Effect	Y	Y	Y
Year Fixed Effect	Y	Y	Y
N	24,374	24,374	24,374
R ²	0.802	0.802	0.802

Note: The dependent variable is the logarithm of service spending and is estimated using a fixed-effects model at the household level. Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption, depth of usage, and credit-based FinTech adoption are measured using the index of digital financial inclusion. The control variables are the characteristics of the head of a household (age, years in education, marriage status, health status, and living condition), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

column (6) in Table 5, with the general index of digital financial inclusion as a baseline comparison. In column (2), we use the level I depth of usage index, which includes payment, monetary funds, credit, insurance, investment, and credit investigation. In column (3), we apply the specific index of credit sectoral development. The estimated results suggest that it is the depth of usage, particularly the development of FinTech credit, rather than just account coverage, that helps mitigate the negative impacts of economic uncertainty on service spending.

Secondly, since FinTech adoption has been found to mitigate credit constraints, it is expected that the impact of FinTech adoption is more pronounced among households facing credit constraints than those who are not. To identify such households, we follow the criteria proposed by Zeldes (1989) and Gan et al. (2018), where households with total financial assets less than their permanent income³ for two months in the initial sample period are considered to be credit constrained. The estimation results for this subsample are presented in Table 15. We observe that economic uncertainty and FinTech adoption have significant effects on service spending only among credit-constrained households. This finding is unsurprising as these households tend to curtail their expenditure, especially on goods with higher elasticity, when faced with economic uncertainty due to their constraints. Notably, the interaction effect between FinTech adoption and economic uncertainty is positive and significant, suggesting that credit-constrained households benefit more from FinTech adoption during times of economic uncertainty.

Finally, we verify the channel of credit constraint alleviation in terms of cash holdings. Household cash reserves may decrease due to credit constraints, resulting in a lack of liquidity, or because households have adopted FinTech and no longer require as much cash as before. In either scenario, the moderating impact of FinTech on economic uncertainty is more significant for households with lower cash holdings than those with higher cash reserves. Therefore, we divide the household sample based on the median value of total cash holdings. According to Table 16, economic uncertainty leads to less spending on services by households with lower cash holdings, indicating that cash reserves are a measure of credit constraints. Moreover, FinTech mitigates the adverse consequences of economic uncertainty for households with lower cash holdings, consistent with our hypothesis regarding credit constraint alleviation.

6.2. Contributing to entrepreneurship and employment

Macroeconomic fluctuations can have negative effects on household consumption, leading to a decrease in employment and entrepreneurial opportunities. However, the adoption of FinTech can mitigate economic uncertainty by expanding market potential, providing greater incentives for entrepreneurial activities, and ultimately increasing the demand for labor. This, in turn, can contribute to higher household income and consumption.

The reason why FinTech adoption can increase market potential is due to its convenience and efficiency. Prior to the emergence of FinTech, shopping could be very time-consuming as it required physical visits to stores and banks to withdraw cash. This limited shopping behavior and the market potential for most sellers to local areas. However, the online and offline mobile payment options enabled by FinTech have made shopping much more convenient. FinTech platforms enable safe and quick payments to be made via mobile phones using a balance or linked bank card, significantly reducing the time required to complete a purchase. These payment methods have also removed geographic barriers between customers and merchants, allowing customers to access a much wider range of goods from around the country and the world through online department stores. This, in turn, has greatly enlarged potential markets, increasing entrepreneurship and employment opportunities.

6.2.1. FinTech adoption, economic uncertainty, and entrepreneurship

We begin by examining the impact of economic uncertainty and FinTech adoption on entrepreneurship. Specifically, we analyze household-level entrepreneurial activities using a binary variable indicating whether any family member is self-employed or owns his/her own businesses (Table 17). Columns (1) and (2) present our findings on the relationship between entrepreneurship and economic uncertainty. Our results show that higher levels of economic uncertainty are associated with a lower likelihood of household members engaging in entrepreneurial activities, as anticipated. In columns (3) and (4), we introduce an interaction term of FinTech adoption and economic uncertainty, and find that FinTech adoption has a marginally positive effect on mitigating the negative impact of economic uncertainty on entrepreneurship. We attribute this effect to the increased market potential resulting from the wider adoption of FinTech. Overall, our results suggest that economic uncertainty can act as a deterrent for entrepreneurial activities, but the use of FinTech may help alleviate some of these negative effects.

According to Table 11, the adoption of FinTech can help to reduce the adverse effects of economic uncertainty on service spending, particularly in urban areas. This leads us to believe that FinTech primarily moderates entrepreneurial activities in urban areas. To investigate this further, we conduct a subsample analysis that examines the relationship between FinTech adoption, economic uncertainty, and entrepreneurial activities while focusing on urban-rural differences. The results presented in Table 18 confirm our hypothesis that the impact of FinTech on entrepreneurship is significant only in urban areas. As a result, it prevents any decline in household consumption from services to non-durable goods.

6.2.2. FinTech adoption, economic uncertainty, and employment

We next investigate how FinTech impacts the relationship between economic uncertainty and employment. To measure

³ We follow Shen and Xie (2012) and estimate household permanent income by regressing total household income on a set of control variables, including characteristics of household head, household, and region. The predicted values from this regression were used as estimates of household permanent income.

Table 15
Heterogeneity of credit constraints.

Services	(1)	(2)	(3)	(4)
	Credit Constrained		No Credit Constrained	
Economic Uncertainty	-1.540*** (0.517)	-2.627** (1.021)	-0.891** (0.366)	-1.410** (0.627)
Economic Uncertainty × FinTech Adoption		0.0112* (0.00668)		0.00483 (0.00446)
FinTech Adoption		0.00479 (0.00463)		0.00180 (0.00242)
Head Controls	Y	Y	Y	Y
Household Controls	Y	Y	Y	Y
County Controls	Y	Y	Y	Y
Household Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
N	9061	9061	10,660	10,660
R ²	0.727	0.728	0.826	0.826

Note: The dependent variable is the logarithm of service spending and is estimated using a fixed-effects model at the household level. Columns (1) and (2) give the results for households with credit constraints, and columns (3) and (4) give the results for households with no credit constraints. Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption is measured using the index of digital financial inclusion. The control variables are the characteristics of the head of a household (age, years in education, marriage status, health status, and living condition), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The results of Fisher's permutation test indicate a significant difference between the two samples in terms of the estimated coefficient of the interactive term (p -value = 0.000).

Table 16
Heterogeneity of cash holdings.

Services	(1)	(2)	(3)	(4)
	Low Cash Holdings		High Cash Holdings	
Economic Uncertainty	-1.387*** (0.386)	-2.462*** (0.817)	0.0292 (0.412)	-0.170 (0.737)
Economic Uncertainty × FinTech Adoption		0.00998* (0.00527)		0.00204 (0.00493)
FinTech Adoption		0.00465 (0.00365)		-0.000450 (0.00234)
Head Controls	Y	Y	Y	Y
Household Controls	Y	Y	Y	Y
County Controls	Y	Y	Y	Y
Household Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
N	18,161	18,161	5389	5389
R ²	0.793	0.793	0.792	0.792

Note: The dependent variable is the logarithm of service spending and is estimated using a fixed-effects model at the household level. Columns (1) and (2) give the results for households with low levels of cash holdings, and columns (3) and (4) give the results for those with high levels of cash holdings. Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption is measured using the index of digital financial inclusion. The control variables are the characteristics of the head of a household (age, years in education, marriage status, health status, and living condition), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The results of Fisher's permutation test indicate a significant difference between the two samples in terms of the estimated coefficient of the interactive term (p -value = 0.000).

employment, we calculate the proportion of employed household members. In Table 19, we present our estimates of the relationship between employment and economic uncertainty in columns (1) and (2). Our findings suggest that higher levels of economic uncertainty correspond with a lower proportion of household members who are employed. This negative impact on entrepreneurial activities can be passed onto labor demand, resulting in a reduced employment rate. Importantly, when we add the interaction term of FinTech adoption and economic uncertainty in columns (3) and (4), we find that FinTech helps to alleviate the negative effects of uncertainty on employment. This confirms that the beneficial impact of FinTech on entrepreneurial activities contributes to increased employment.

Table 20 examines the urban-rural divide in the effects of FinTech adoption on employment. While FinTech has a bias towards urban areas in terms of its impact on service spending and entrepreneurship, it has a stronger positive effect on employment in rural

Table 17
FinTech adoption, economic uncertainty, and entrepreneurship.

Entrepreneurship	(1)	(2)	(3)	(4)
Economic Uncertainty	-1.160*** (0.365)	-1.150*** (0.359)	-1.234** (0.557)	-1.266** (0.539)
Economic Uncertainty × FinTech Adoption			0.00261 (0.00316)	0.00315 (0.00306)
FinTech Adoption			-0.00864*** (0.00270)	-0.00830*** (0.00263)
Head Controls	N	Y	N	Y
Household Controls	N	Y	N	Y
County Controls	N	Y	N	Y
Household Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
N	21,629	21,629	21,629	21,629
R ²	0.705	0.708	0.712	0.715

Note: The dependent variable is a dummy indicating whether any family member engages in self-employment or a private enterprise and is estimated using a fixed-effects model at the household level. Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption is measured using the index of digital financial inclusion. The control variables are characteristics of the head of a household (age, years in education, marriage status, health status, and living condition), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 18
Entrepreneurship: urban-rural heterogeneity.

Entrepreneurship	(1)	(2)	(3)	(4)
	Urban		Rural	
Economic Uncertainty	-1.014*** (0.268)	-1.519*** (0.512)	-0.624*** (0.231)	-0.524 (0.383)
Economic Uncertainty × FinTech Adoption		0.00559* (0.00319)		-0.00009 (0.00242)
FinTech Adoption		-0.00262 (0.00172)		-0.00576** (0.00248)
Head Controls	Y	Y	Y	Y
Household Controls	Y	Y	Y	Y
County Controls	Y	Y	Y	Y
Household Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
N	10,070	10,070	11,084	11,084
R ²	0.653	0.657	0.767	0.768

Note: The dependent variable is a dummy indicating whether any family member engages in self-employment or a private enterprise and is estimated using a fixed-effects model at the household level. Columns (1) and (2) give the results for the urban sample, and columns (3) and (4) those for the rural sample. Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption is measured using the index of digital financial inclusion. The control variables are the characteristics of the head of a household (age, years in education, marriage status, and health status), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The results of Fisher's permutation test indicate a significant difference between the two samples in terms of the estimated coefficient of the interactive term (p-value = 0.000).

households than in urban households by mitigating the negative impact of economic uncertainty. This is likely because rural workers can benefit from increased demand for labor resulting from FinTech-induced entrepreneurial activities, which tend to generate low-skilled jobs such as courier and delivery services and taxis. To explore the relationship between economic uncertainty, FinTech adoption, and employment further, we also analyze the heterogeneity in human capital. Table 21 indicates that FinTech's positive impact on employment is more pronounced in the lower human capital group, where the negative impact of economic uncertainty is more severe, again confirming FinTech's role in financial inclusion and inclusive growth.

7. Concluding remarks

FinTech removes barriers that prevent households from participating in economic activity, especially in the presence of economic uncertainty. In this paper, we use regional-level FinTech adoption and economic uncertainty measurement data, along with representative household-level consumption data, to investigate this issue. Our empirical analysis shows that while high levels of economic

Table 19
FinTech adoption, economic uncertainty, and employment.

Employment	(1)	(2)	(3)	(4)
Economic Uncertainty	-0.325** (0.156)	-0.349** (0.151)	-0.921*** (0.347)	-0.964*** (0.337)
Economic Uncertainty × FinTech Adoption			0.00565** (0.00220)	0.00587*** (0.00218)
FinTech Adoption			0.000140 (0.00131)	-0.000113 (0.00128)
Head Controls	N	Y	N	Y
Household Controls	N	Y	N	Y
County Controls	N	Y	N	Y
Household Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
N	21,752	21,752	21,752	21,752
R ²	0.605	0.614	0.607	0.617

Note: The dependent variable is the proportion of household members employed and is estimated using a fixed-effects model at the household level. Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption is measured using the index of digital financial inclusion. The control variables are the characteristics of the head of a household (age, years in education, marriage status, health status, and living condition), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 20
Employment: urban-rural heterogeneity.

Employment	(1)	(2)	(3)	(4)
	Urban		Rural	
Economic Uncertainty	-0.321** (0.158)	-0.640** (0.275)	-0.426** (0.190)	-1.301*** (0.455)
Economic Uncertainty × FinTech Adoption		0.00294* (0.00169)		0.00849*** (0.00312)
FinTech Adoption		-0.00141 (0.000956)		0.00117 (0.00198)
Head Controls	Y	Y	Y	Y
Household Controls	Y	Y	Y	Y
County Controls	Y	Y	Y	Y
Household Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
N	9197	9197	12,069	12,069
R ²	0.666	0.669	0.581	0.585
Fisher's Permutation Test p-value	0.183	0.000	0.183	0.000

Note: The dependent variable is the proportion of household members employed and is estimated using a fixed-effects model at the household level. Columns (1) and (2) give the results for the urban sample, and columns (3) and (4) give those for the rural sample. Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption is measured using the index of digital financial inclusion. The control variables are the characteristics of the head of a household head (age, years in education, marriage status, and health status), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The results of Fisher's permutation test indicate a significant difference between the two samples in terms of the estimated coefficient of the interactive term (p-value = 0.000).

uncertainty lead to a shift in household consumption from services to non-durable goods, widespread adoption of FinTech overcomes this negative effect and prevents the reduction in service spending. We use the distance of a household from Hangzhou and the economic uncertainty in the United States as proxies for exogenous variation in FinTech adoption and economic uncertainty in China, respectively, and find similar results. Focusing on the transmission channel, we find that FinTech helps alleviate credit constraints, contributes to entrepreneurship and employment opportunities, and thus mitigates the negative impact of economic uncertainty on household consumption.

Our research reveals the potential benefits of tech firms providing financial services. FinTech can be particularly helpful for consumers in emerging markets, as they often face economic uncertainty more frequently than consumers in established markets. Inexpensive and highly scalable FinTech options can address the limitations of traditional financial institutions and mitigate the negative effects of economic uncertainty, given the lack of financial infrastructure in these regions.

However, the rapid growth of FinTech platforms from 2011 to 2020, as shown in the index of digital financial inclusion, has raised some challenges. One direct consequence is the overreliance on credit and excessive consumption, particularly among younger people who may be too optimistic about their future incomes. The overprovision of credit, while temporarily bringing higher profits to

Table 21
Employment: heterogeneity in human capital.

Employment	(1)	(2)	(3)	(4)
	High Human Capital		Low Human Capital	
Economic Uncertainty	-0.250*	-0.364	-0.351**	-1.061***
	(0.145)	(0.291)	(0.171)	(0.380)
Economic Uncertainty × FinTech Adoption		0.00127		0.00683***
		(0.00167)		(0.00249)
FinTech Adoption		-0.000760		0.000441
		(0.00103)		(0.00144)
Head Controls	Y	Y	Y	Y
Household Controls	Y	Y	Y	Y
County Controls	Y	Y	Y	Y
Household Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
N	3531	3531	17,484	17,484
R ²	0.637	0.638	0.617	0.620

Note: The dependent variable is the proportion of household members employed and is estimated using a fixed-effect model at the household level. Columns (1) and (2) give the results for high levels of human capital, and columns (3) and (4) those for low levels. Economic uncertainty is measured at the provincial-quarter level based on the unpredictable conditional volatility of numerous economic variables. FinTech adoption is measured using the index of digital financial inclusion. The control variables are the characteristics of the head of a household (age, marriage status, health status, and living condition), household factors (logarithm of family income per capita, logarithm of family wealth, family size, dependency ratio, and social security participation), and indicators of regional development (economic condition and logarithm of population). Standard errors are clustered at the city level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The results of Fisher's permutation test indicate a significant difference between the two samples in terms of the estimated coefficient of the interactive term (p-value = 0.000).

FinTech firms, ultimately results in systemic credit risk. Therefore, there is a pressing need to establish regulations on FinTech firms.

Our findings also show that FinTech in China prevents a downgrade in household consumption in urban areas more than in underdeveloped rural areas. This has major policy implications, suggesting that urbanization should be actively promoted and rural-urban segregation discouraged. This can promote fairer income distribution over the long term and contribute to the effective functioning of the market, allowing FinTech to play a positive role. It is important to note that the proactive promotion of urbanization requires careful planning and implementation of specific strategies and policies to ensure any problems are alleviated or avoided.

Data availability

Data will be made available on request.

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