The Australian Journal of
Agricultural and Resource Economics

AARES
AUSTRALASIAN AGRICULTURAL & RESOURCE ECONOMICS SOCIETY



*Australian Journal of Agricultural and Resource Economics*, 66, pp. 93–117

# The Great Chinese Famine (1959–1961) and farm households' adoption of technology: evidence from China*

Xinyan Hu, Xiangpo Chen, Siqi Yao and Gaiqing Zhang†

The diffusion of new technology is an important driver of agricultural development, especially in the developing world. In this research, we follow the persistence of major historical events, employing a difference-in-differences method to carefully examine the long-term effect of China's 1959–1961 famine on farm households' current decisions to adopt technology. Further, we combine a mediating regression procedure with a bootstrap method to explore the mechanism of impact in this relationship. Overall, this study provides strong empirical evidence that the Great Famine attenuated technology adoption; moreover, a 1% increase in exposure to famine in childhood and adolescence resulted in a 0.137% decrease in the probability of technology adoption when controlling for village dummies. An analysis of mediating effects reveals that risk preferences account for the channel of famine persistence.

**Key words:** difference in differences, famine, mediating effect analysis, risk preferences, technology adoption.

## 1. Introduction

New technology is regarded as a critical pathway to promote agricultural transformation in developing countries and exerts an important role in boosting agricultural productivity and farmers' income (Abay *et al.*, 2018; Gollin, 2010). The Green Revolution, which began in the mid-1960s, made a historic contribution to eliminating poverty and providing greater food security in the developing world (Evenson & Gollin, 2003; Ofreneo, 2004; Quibod *et al.*, 2020). However, the diffusion of new technology has revealed considerable regional and individual disparities. Ample empirical evidence

* We would like to thank the financial support from the Education Innovation Team Project of Guangdong (2017WCXTD001) the National Social Science Fund of China (19ZDA115) and the 'Climbing' Program of Guangdong (PDJH2020B0101).

† Xinyan Hu (email: huxyan@scau.edu.cn) is a Professor and Executive Dean at the National School of Agricultural Institution and Development, South China Agricultural University, Guangzhou, Guangdong 510642, China. Xiangpo Chen is a Doctoral Student at the National School of Agricultural Institution and Development, South China Agricultural University, Guangzhou, Guangdong 510642, China. Siqi Yao is a Graduate Student at the National School of Agricultural Institution and Development, South China Agricultural University, Guangzhou, Guangdong 510642, China. Gaiqing Zhang is a professor at the Henan University of Economics and Law, Zhengzhou, Henan 450000, China.


doi: 10.1111/1467-8489.12444

demonstrates low mobility in the diffusion of technology among agricultural sectors and the impoverished farmers in developing countries (Abay *et al.*, 2018; Liu & Huang, 2013). Despite the benefits of improved agricultural technology, the low level of adoption has long been an empirical conundrum. Clearly, farmers are the ultimate recipients and users of agricultural technologies and are vitally important to technology diffusion. Therefore, the study of how to transform farmers into active adopters of improved technology has significant value in policy decision-making for promoting agricultural modernisation.

Why is the level of technology adoption often characterised as low in the developing world? Assuming that farmers are rational economic agents (Duflo, 2006; Schultz, 1964), technology adoption behaviour depends on whether they can benefit from innovation and maximise expected profits (Adnan *et al.*, 2018). However, the uncertainty of technology, cognitive or credit constraints, and other market defects may invalidate this rational response (Duflo *et al.*, 2011; Giné & Yang, 2009; Minten *et al.*, 2013; Moser & Barrett, 2006), resulting in the slow adoption of agricultural technologies, especially among poor farmers in lesser developed regions worldwide.

Unlike the rational–economic assumption, Chayanov (1974) and Scott (1977) argued that subsistence-oriented farmers typically prefer to avoid economic disasters – such as crop failure – rather than take risks to maximise their profits. Further, Huang's (1990) work highlighted the survival rationality and vulnerability of the 'small-peasant' in rural China and revealed that poor farmers are always subsistence-oriented and marketing more for survival needs, which depend largely on expectations of a stable crop yield to meet their requirements for subsistence. Such results provide significant implications for our topic; that is, in the behaviour of farmers' technology adoption, risk preferences do matters (Spiegel *et al.*, 2018).

Impoverished farm households in developing countries are often characterised by a high degree of risk aversion (Franken *et al.*, 2014; Harrison *et al.*, 2010; Humphrey & Verschoor, 2004). Their allocation decisions do not typically involve choosing the opportunities anticipated to maximise profit, but rather those resulting from algorithms that minimise risk exposure, as the concern for potential losses tends to outweigh any potential gains. Further, risk-averse farmers are reluctant to adopt such innovations as improved agricultural technologies (Alem *et al.*, 2010; Fafchamps, 2010; Lamb, 2003; Mao *et al.*, 2019). Traditionally, empirical studies categorise risk preferences as exogenous explanatory factors and rarely analyse how risk preferences are shaped by exploring their antecedent influencing factors (Bhattamishra & Barrett, 2010; Dercon, 2008).

In fact, Freud (1915) proposed that one's behavioural decision-making is based on both life experience and accumulated knowledge, and traumatic experiences profoundly shape one's psychological characteristics. Hess (1959) later argued that individuals' early experiences profoundly affect their adult behaviour; in this process, painful stimulation increases the effectiveness of the ‘imprinting’ experience. Such results have been supported by Weber *et al.*, (1993) and Hertwig *et al.*, (2004). Recent insights from behavioural economics, however, suggest that early-life experiences can lead to important changes in individuals’ behaviour (Cassar *et al.*, 2017; Malmendier & Nagel, 2011).

The nationwide famine of 1959-1961 is listed as one of the ten most important national events since the People’s Republic of China was founded (Weigelin-Schwiedrzik, 2003), and its survivors maintain profound memories of this severe historical tragedy (Cao, 2005). Moreover, growing evidence suggests that major historical events can generate long-term effects on modern society (Ager *et al.*, 2019; Ambrus *et al.*, 2020; Jedwab *et al.*, 2019; Whatley, 2018). Thus, we consider the famine’s cross-century history and examine its impact on technology adoption decisions, which persist to this day through a process that involves weighing risk preferences long after the famine itself ended. This article focuses not only on the famine’s long-term effects, but also on the formation of farmers’ risk preferences. Figure 1 graphically represents our empirical strategy in the form of a path diagram. We discuss famine’s persistent effect on technology adoption through a difference-in-differences (DID) estimator in our baseline estimation. We then perform a mechanism analysis to determine the channel through which such persistence occurs.

Our research contributes to existing literature in several ways. Foremost, we improve the accuracy of the measurement of China’s famine intensity. Typically, previous empirical studies adopted the back-calculation method developed by Huang and Martorell (2009), which utilises a one per cent sample of China’s 1990 population census and demographic information to derive a measure of famine severity. This approach excludes people who died before our investigation, and creates a biased estimation. Instead, we visited local statistical bureaus to obtain official data on recorded deaths between 1956 and 1964, which allows us to more precisely measure the famine’s intensity and derive an unbiased estimation.

Second, we emphasise historical events’ long-term effects by shifting the spotlight from external factors to the internal psychological feature of risk tolerance. This provides an internal explanation for farmers’ technology adoption based on their early-life trauma, as it is vital to understand farmers’ adoption behaviours in the process of agricultural technological advancement from a disaster management perspective.

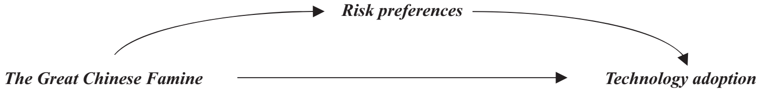


**Figure 1** Path diagram of the empirical strategy.

Finally, this study not only reveals the origin of farmers' risk aversion and the channel between famine and farmers' technology adoption, but also contributes to a growing body of literature examining how historical events can persist in the development process. We also present empirical evidence on real-life risk behaviour, highlighting the importance of our results.

The remainder of this paper proceeds as follows: The next section provides a historical background on Great Chinese Famine and briefly discusses its feasibility. Section 3 introduces our data and identification strategy. Then, we discuss and interpret our results in Section 4. Section 5 subjects our estimates to several sensitivity checks to probe its robustness. In Section 6, we briefly present our concluding remarks.

## 2. The Great Chinese Famine

Following the launch of its nationwide 'Great Leap Forward' campaign in 1958, China went through a widespread famine between 1959 and 1961, known as the 'Great Chinese Famine'. The outbreak of such a famine was attributed to natural causes, including extreme droughts; and radical policies, such as communal dining (Feng & Johansson, 2018) and the 1959 elimination of the right to leave a collective (Lin, 1990). The sharp declines in agricultural production and excess deaths were the two most important aspects of China's economic crisis during the famine period. After years of steady growth, China's grain output suddenly dropped by 15% in 1959, and output continued to decline in the subsequent two years, with food supplies dropping to only 70% of the 1958 level.

The Great Famine has been declared one of the worst catastrophes in human history. During this particular period, massive starvation prevailed in China. A careful study of demographic data concludes that this crisis resulted in excess deaths of 30 million (Ashton *et al.*, 1984), a death toll far exceeding the deaths of nine million combatants and seven million civilians in World War I. Although the famine reached almost every region in China, the severity of the shock demonstrated considerable regional disparities because of the variances in natural resource conditions, population density and exposure to natural disasters.

The geographic spread of the Great Famine and the way it occurred provides us with a unique opportunity to explore the long-term effects of early-life trauma on the decision to adopt technology. First, the majority did not anticipate such an outbreak of tragedy, and it was unlikely that individuals could have predicted or controlled the famine itself. Therefore, it is logical to assume that the Great Famine was an exogenous shock. Second, China experienced low internal mobility for decades due to the enforcement of the *hukou* registration system in 1951, which placed strict limitations on internal migration and relocation; thus, the majority of people had no choice but to remain in their hometowns. However, this allowed us to identify the severity of famine in certain regions. Low mobility also alleviates the potential selection bias triggered by migration and relocation. Finally, the famine's severity ultimately varied across regions. In this case, we can use a difference-in-differences (DID) estimator to capture the famine's long-term effects by adding the interaction between birth cohorts and the excess death rate.

## 3. Data and empirical strategy

### 3.1 Data sources

Henan Province was one of the most severely affected by the famine tragedy from 1959 to 1961 (Li, 2016), as demonstrated by the 1960 'Xinyang event', in which nine Xinyang counties had a mortality rate of more than 10%. In comparison, the Tangshan earthquake of 1976 killed over 240,000 people, making it the deadliest earthquake of the 20th century, but its mortality rate was only approximately 4.5%. Further, county and prefecture gazetteers reveal a more detailed view of the Great Famine itself. Huaibin County in Xinyang City had the most severe mortality rate recorded in prefecture gazetteers; its population sharply decreased from 378,140 in 1959 to 266,170 in 1960. Of this decline of 111,970, 102,010 were recorded deaths, with an incredibly high mortality rate of 38.3% (Huaibin Government, 1987). Other examples of high mortality rates from Henan Province include Guangshan's rate of 27.7%, Xi's rate of 27.5% and Zhengyang's rate of 13.8%. Consequently, people in Henan suffered an unimaginable negative shock during the famine. The same conclusions can be drawn from Cao's (2005) findings, in that the abnormal deaths in the most affected provinces – Sichuan, Anhui, Henan, Hunan and Shandong – account for 71% of all excess deaths in China during the famine period.

As a major food province in China, the people living in Henan highly value the land and have become deeply connected to it. Meng and Qian (2009) illustrate that famine is more likely to occur in traditional grain-producing counties, as these have a higher proportion of grains requisitioned by the higher echelons of government and a lower proportion of grain retained for themselves. When the harvest is poor, it leads to a more serious shortage in local grain reserves to uphold the amount purchased by the government. Therefore, Henan's data may be more representative.

Our original data were collected from two sources. First, we obtained data on deaths and the total population from 1956 to 1964 and the number of local technicians who provided farmers with technology services from 2014 to 2016 by visiting the local bureaus of statistics, including those in Shangcai, Zhengyang, Wuyang, Qi, Xin'an and Anyang counties. Regarding the second part of the data, we adopted a multiple random-sampling method and conducted one-to-one questionnaire surveys with farm households in the main wheat-producing areas of Henan in 2016. We first selected six sample counties based on geographic location, the rural residents' per capita disposable income and sown areas of wheat: Shangcai, Zhengyang, Wuyang, Qi, Xin'an and Anyang. We then selected the sample towns and villages. All counties and towns were divided into five equal groups according to their levels of economic development, and one sample was randomly selected from each division. Five sample towns were obtained from each county, or 30 sample towns. Similarly, each sample town was divided into two groups of villages according to their levels of economic development. A village was randomly selected from each group, or 60 sample villages from the 30 sample towns. Finally, 40 farm households were randomly selected from each village, or 2,400 sample farm households. After making appointments with the sample farm households and sample village cadres, trained investigators conducted one-to-one interviews with the farm householders to obtain 2,400 valid questionnaires. The questionnaire includes detailed information about the villages, farm households, individuals and plots. Based on our research needs, we adopted the information on farm households and the relevant information on the villages where the farmers are located.

## 3.2 Quantifying the Great Famine

We use the interaction between birth cohorts and the average excess death rate (EDR) from 1959 to 1961 as a proxy for the Great Famine.

### *3.2.1 Excess death rate*

The accurate measurement of regional famine severity is a crucial issue in related research. A commonly used measurement involves recent census data combined with a back-calculation method (Huang & Martorell, 2009). However, a certain gap exists between each region's calculated number and real population during the famine period. Fortunately, the access to confidential death and total population records as preserved by the local Bureaus of Statistics allows us to more accurately measure the famine's intensity. Specifically, we draw on Chen and Zhou's (2007) proposed method to characterise the famine's severity by the excess death rate (EDR). This is based on an analysis of the death population in the sample counties over the years, and calculated as follows.

First, we calculate the normal average death ratio ($Die_{normal}$), with time span restricted to the three years before (1956 to 1958) and three years after (1962 to 1964) the famine period (1959 to 1961). Second, we calculate the average death ratio within the famine period ($Die_{fan\min e}$); each sample county's degree of famine is then given by Equation (1):

$$EDR = \frac{Die_{fa\min e} - Die_{normal}}{Die_{normal}} \tag{1}$$

Table 1 presents the EDR index's distribution and reveals that Shangcai and Zhengyang counties have the most severe degrees of famine, with EDR indices of 349.59% and 334.60%, respectively. The remaining four sample counties – Wuyang, Qi, Xin'an and Anyang – have EDR indexes of 48.83%, 47.49%, 11.99% and 9.46%, respectively.

### *3.2.2 Birth cohorts*

Following Cheng and Zhang (2011), we take the householder's famine experience as a proxy for the farm household's famine experience. An individual's life cycle can be divided into five stages: infancy (life before age 3), early childhood (age 3 to 6), childhood (age 7 to 11), adolescence (age 12 to 18) and adulthood (after age 18). In particular, the life span from childhood through adolescence has been identified as a key phase for children's understanding of the world, during which individuals create permanent memories and develop their character (Shaffer & Kipp, 2013). Moreover, few facts about infancy are as obvious as the apparent inaccessibility of memories from the months and years just after birth (Josselyn & Frankland, 2012; Nadel & Zola-Morgan, 1984); the purported 'infantile amnesia' (Freud, 1905) is described as the phenomenon in which people are unable to recall events from early childhood. Dudycha and Dudycha (1941) observed that infantile amnesia spans the first 3.5 years of life, an average age further confirmed by Kihlstrom and Harackiewicz (1982). Given this, we placed householders who were in their childhood and adolescence during the famine period (1959–1961) into one birth cohort. We then assigned birth cohorts by setting year dummies as follows: cohort1 (unborn and infancy), cohort2 (early childhood), cohort3 (childhood and adolescence) and cohort4 (adulthood) (Table 2).

Table 3 describes the data's basic characteristics. Compared with farm households with householders younger than 55, farm households with householders aged 55 or older received more job training and had a shorter distance to markets. Meanwhile, their families included more party members and village cadres. In this sense, these farm households are more likely to adopt new technologies. However, the means of the two groups' improved seed adoption rates are 3.315 and 2.972, respectively, and the means of risk preferences are 1.668 and 1.562, respectively; this demonstrates that in terms of technology adoption and risk preferences, farm households with householders aged 55 years or older are relatively more passive and conservative. Considering that these householders survived the famine, we argue that the slow technology adoption and high-risk aversion could relate to their early-life trauma.

**Table 1** Overview of EDR index

| | Shangcai | Zhengyang | Wuyang | Qi | Xin'an | Anyang | Total |
|---|---|---|---|---|---|---|---|
| EDR (%) | 349.59 | 334.60 | 48.84 | 47.50 | 11.99 | 9.46 | 121.35 |

**Table 2** Definition of birth cohorts

| Age (at time of survey) | Birth year | Age (during famine period) | Life stage (during famine period) | Birth cohorts |
|---|---|---|---|---|
| < 58 | after 1958 | < 3 | Unborn and infancy | Cohort1 |
| [58, 62) | (1954–1958] | [3, 7) | Early childhood | Cohort2 |
| [62, 75) | (1941–1954] | [7, 18) | Childhood and adolescence | Cohort3 |
| ≥ 75 | before 1941 | ≥ 18 | Adulthood | Cohort4 |

### 3.3 Other variables

#### *3.3.1 Technology adoption*

Agricultural technologies are divided into two categories according to their developmental targets: mechanical technology and biotechnology. The former aims to increase labour productivity, while the latter increases production; however, biotechnology includes improved seeds, chemical fertilisers and pesticides. Among these, seeds are a basic driver of agricultural development and a fundamental input for improving crop production and productivity (Abebe & Alemu, 2017; Yapa, 1993). Given their various functions in agriculture, they remain a strategic influence in a range of debates, but particularly those concerned with food security (McGuire & Sperling, 2011) and the adoption of corresponding agricultural technologies. Moreover, the size of farmers' harvests and their living standards largely depend on the choice of seeds in less-developed regions (Cameron, 1999). Therefore, we adopt a question to analyse the use of improved seeds or: 'How is your family using improved seeds in agricultural production?' The five corresponding responses include the following: 1, or 'very late'; 2, or 'late'; 3, or 'general'; 4, or 'early'; 5, or 'earliest'.

#### *3.3.2 Risk preferences*

We conduct context-free experimental measures of risk preferences using a behavioural game designed to elicit risk attitudes due to the overweighing of potential losses over potential gains (Gneezy & Potters, 1997). In practice, the respondents are expected to choose from one of five separate scenarios, and their answers are converted into risk tolerance indexes, with the following options: (1) 'Earn 1,000 yuan with certainty', coded as one; (2) 'Half chance of earning 900, half chance of earning 1,600', coded as two; (3) 'Half chance of earning 800, half chance of earning 2,000', coded as three; (4) 'Half chance of earning 400, half chance of earning 3,000', coded as four; and (5) 'Half chance of earning nothing, but half chance of earning 4,000', coded as five. We ensured quality data by fully informing respondents of the positive and negative probabilities and the corresponding gains and losses.

**Table 3** Summary statistics

| Age ($n$ = sample size) | Definition and description | <55 ($n$ = 1,086) | ≥ 55 ($n$ = 1,356) | Total ($n$ = 2,400) |
|---|---|---|---|---|
| Variables | | Mean (standard error) | | |
| Using improved seeds | Latest = 1; Late = 2; General = 3; Early = 4; Earliest = 5 | 3.315 (1.060) | 2.972 (1.220) | 3.125 (1.164) |
| Risk preferences | Highly aversive = 1; Aversive = 2; Neutral = 3; Preferred = 4; Highly preferred = 5 | 1.668 (1.116) | 1.562 (1.114) | 1.610 (1.116) |
| Householder level | | | | |
| Age | / | 46.568 (6.378) | 64.971 (6.784) | 56.755 (11.285) |
| Age squared | / | 2,209(552) | 4,267(917) | 3,348 (1,284) |
| Gender | Male = 1; Female = 0 | 0.950 (0.217) | 0.880 (0.325) | 0.911 (0.284) |
| Education | Years | 7.446 (2.782) | 6.240 (3.633) | 6.777 (3.335) |
| Work outside | Years | 6.295 (8.265) | 2.045 (6.252) | 4.015 (7.556) |
| Household level | | | | |
| Technician density | Local technicians/Mha | 446(205) | 441(240) | 443(225) |
| Job training | Number of people | 0.088 (0.365) | 0.105 (0.424) | 0.097 (0.399) |
| Ln (Family income) | Yuan | 10.106 (0.955) | 9.833 (1.070) | 9.955 (1.029) |
| Family size | Number of people | 4.576 (1.451) | 4.261 (2.026) | 4.401 (1.800) |
| Party member | Yes = 1; No = 0 | 0.120 (0.325) | 0.162 (0.369) | 0.143 (0.351) |
| Village cadre | Yes = 1; No = 0 | 0.075 (0.263) | 0.077 (0.267) | 0.076 (0.265) |
| Land size | Mu | 6.176 (4.553) | 6.273 (4.772) | 6.230 (4.675) |
| Distance to markets | Km | 18.306 (11.051) | 18.048 (10.998) | 18.163 (11.020) |

Note: Mha = million hectare; 1 mu = 0.0666667 ha.

### *3.3.3 Control variables*

We follow Liu and Huang (2013) and Adnan *et al.*, (2018) and set the core control variable as the number of family members who received agricultural training. Job training is generally considered important because it mitigates information constraints. Further, rural populations live with limited modern communication technologies. Agricultural training provides farmers with rare learning opportunities and is likely to mitigate their risk aversion. Moreover, as local technicians may also directly affect farm households' technology adoption behaviour, we include technician density in the empirical model as a proxy for sample counties' capacities to provide agricultural technology and services to farmers. We also include other control variables for householder characteristics (e.g. age, age-squared, gender, education and years of working outside the household) and family characteristics (e.g. family income, family size, land size, presence of party members in family, presence of a village cadre member in family and the distance to markets – the straight-line distance between the county's centre and each farm household's address).

## 3.4 Empirical strategy

### *3.4.1 Difference in differences*

The Great Famine was an unprecedented major historical event since the founding of the People's Republic of China. Thus, this disaster can be interpreted as an exogenous shock to individuals, and the way it occurred allows us to treat it as a randomised controlled trial. Following Chen and Zhou (2007), Cheng and Zhang (2011), and Meng and Qian (2009), we establish a difference-in-differences model (DID) with EDR and birth cohort variations (cohort1 to cohort4) to estimate the famine's long-term effects. As the dependent variable is both limited and ordered, an ordinary least-squares (OLS) estimation would be biased; therefore, we use an ordered probit model (Oprobit), which is a typical limited dependent variable model. We set $TA_i^*$ to denote potential technology adoption, and its true value is an unobserved latent variable. The Oprobit model can be estimated from the observable ordered data, allowing us to analyse the changes in the latent variable. The linear equation for $TA_i^*$ is

$$TA_{icj}^* = \alpha_1 EDR_{ij} + \sum_{c=2}^{4} \beta_c cohort_{ic} \times EDR_{ij} + \sum_{c=2}^{4} \alpha_{2c} cohort_{ic} + \theta Controls_{icj} + \varepsilon_{icj} \quad (2)$$

where $TA_{icj}^*$ is the potential for technology adoption of farm household $i$ born in county $j$, and belonging to a cohort; $EDR_{ij}$ is the famine intensity in county $j$ in which farm household $i$ is located; $cohort_{ic}$ is a dummy variable representing whether farm householder $i$ lived through the famine; $Controls_{icj}$ denotes the series of control variables; $\beta_c$ are the coefficients of interactions between the EDR and birth cohorts, which are assigned to measure the long-term impact of surviving the famine on farm household $i$'s adoption of new technologies; and $\varepsilon_{icj}$ is the error term. Further, $TA_{icj}^*$ can be expressed as

$$TA_{icj} = F(TA_{icj}^*) = \begin{cases} 1 \quad TA_{icj}^* \le \delta_1 \\ 2\delta_2 \le TA_{icj}^* \le \delta_2 \\ 3\delta_2 \le TA_{icj}^* \le \delta_3 \end{cases} \quad (3)$$

where $TA_{icj}^*$ denotes farm household $i$'s technology adoption behaviour, and $\delta_1 < \delta_2 < \delta_3 \cdots < \delta_N$ are point parameters to be estimated. We divide $TA_{icj}^*$ into $N$ intervals to express the probability of observing the value $n$ for farm household $i$ as

$$P(TA_{icj}=n)=f(x)=$$
$$\begin{cases} F(\delta_1-\alpha_1 EDR_{ij}-\sum_{c=2}^{4}\beta_c cohort_{ic}\times EDR_{ij}-\sum_{c=2}^{4}\alpha_{2c}cohort_{ic}-\theta Controls_{icj}) & n=1 \\ F(\delta_n-\alpha_1 EDR_{ij}-\sum_{c=2}^{4}\beta_c cohort_{ic}\times EDR_{ij}-\sum_{c=2}^{4}\alpha_{2c}cohort_{ic}-\theta Controls_{icj})-F(\delta_{n-1}-\alpha_1 EDR_{ij} & \\ \quad -\sum_{c=2}^{4}\beta_c cohort_{ic}\times EDR_{ij}-\sum_{c=2}^{4}\alpha_{2c}cohort_{ic}-\theta Controls_{icj}) & 2\leq n\leq N-1 \\ 1-F(\delta_{n-1}-\alpha_1 EDR_{ij}-\sum_{c=2}^{4}\beta_c cohort_{ic}\times EDR_{ij}-\sum_{c=2}^{4}\alpha_{2c}cohort_{ic}-\theta Controls_{icj}) & n=N \end{cases} \tag{4}$$

Replacing the interpreted variable with $TA^*_{icj}$ leads to the Oprobit model

$$TA_{icj}=F(\alpha_1 EDR_{ij}+\sum_{c=2}^{4}\beta_c cohort_{ic}\times EDR_{ij}+\sum_{c=2}^{4}\alpha_{2c}cohort_{ic}+\theta Controls_{icj}+\varepsilon_{icj}) \tag{5}$$

Using Equation (4), the likelihood function for farm household $i$ can be written as.

$$\ln L=\sum_{i=1}^{M}\sum_{n=1}^{N}\ln\Big[F(\delta_n-\alpha_1 EDR_{ij}-\sum_{c=2}^{4}\beta_c cohort_{ic}\times EDR_{ij}-\sum_{c=2}^{4}\alpha_{2c}cohort_{ic}-\theta Controls_{icj})-F(\delta_{n-1}-\alpha_1 EDR_{ij} -\sum_{c=2}^{4}\beta_c cohort_{ic}\times EDR_{ij}-\sum_{c=2}^{4}\alpha_{2c}cohort_{ic}-\theta Controls_{icj})\Big]. \tag{6}$$

where the unbiased estimates of $\beta_c$, $\alpha_1$, $\alpha_{2c}$ and $\theta$ can be obtained through a maximum-likelihood estimation.

### *3.4.2 Mediated effect*

We then analyse the impact and mechanism of famine exposure on farm households' technology adoption behaviour through the mediation effect model, with two empirical methods to consolidate our estimation. The first is Baron and Kenny's (1986) proposed step-by-step method. This is followed by the bootstrap method, which is generally considered to be better for directly testing the mediating effect's significance. Compared with a single mediating effect analysis, such a mixed process brings higher efficacy (Wen & Ye, 2014).

### *3.4.3 Conditional mixed processing*

While we primarily focus on the adoption of improved seed technology, potentially strong complementarities exist in farm households' decisions over agricultural technologies. As a robustness check, we consider the joint effect from seed and fertiliser, with a conditional mixed processing (CMP) model to jointly estimate endogeneity (Roodman, 2011).

## 4. Results

### 4.1 The Great Famine's long-term effect on technology adoption

Table 4 reports the famine's impact on farm households' technology adoption. Column (1) displays the regression results when controlling for the series of control variables; Columns (2), (3) and (4) control for the county-, town- and village-level dummies, respectively. The coefficient of the EDR*Cohort3 interaction remains significant at the same level for all these estimates, while the EDR*Cohort2 and EDR*Cohort4 coefficients are statistically insignificant.

Literature has focused ample attention on childhood and adolescent development (Damon & Hart, 1991; Giedd *et al.*, 1999; Jacobs & Klaczynski, 2002), such as the brain, reasoning and judgement – both in biology and psychology. Major experiences across this life span vary, but are vital for humankind's psychological development (Shaffer & Kipp, 2013). In theory, early experiences before childhood and after adulthood may lose their effectiveness on subsequent behaviours in the long run, due to infantile amnesia and generally maturing development into adulthood.

As anticipated, we discovered that childhood and adolescent exposure to the Great Famine significantly correlated with the slow adoption of technology. Column (1) in Table 4 displays a coefficient of the interaction between EDR and cohort3 of −0.147; this is significant at the 1% level, indicating that early-life famine experience attenuated their technology adoption. Columns (2), (3) and (4) present corresponding coefficients of −0.159, −0.159 and −0.153, respectively, at a 1% significance level; the negative sign and significance are essentially consistent with our estimate in column (1). This evidence further increases our confidence in identifying famine's causal effects on technology adoption.

Additionally, column (5) and the bottom panel in Table 4 report the OLS results and marginal results, respectively. This approach follows Angrist and Pischke (2008), who argue that the differences in conclusion between the linear and nonlinear models are incredibly small when considering marginal effects. The average derivative, known as the marginal effect as constructed from a nonlinear regression, differs only slightly from the linear regression's results, verifying the estimates' robustness. In line with Occam's razor principle, an explanation will be given relative to the OLS model. Moreover, we determine the changes in probability between the farm households' different levels of technology adoption through a marginal effect estimation method as developed by Borooah (2002). The results demonstrate that when including village dummies, increasing the intensity of famine by 1% decreases the probability of farm households' technology adoption by 0.137%, with the farm households' probabilities of falling in the 'very late', 'later' and 'general' categories increasing by 0.018%, 0.030% and 0.007%, respectively; the farm household's likelihood of being in the 'early' and 'earliest' categories

**Table 4** Famine's long-term effect on farm households' technology adoption

| Explained Variable: Technology Adoption | | | | | |
|---|---|---|---|---|---|
| | Oprobit | | | | OLS |
| | (1) | (2) | (3) | (4) | (5) |
| Cohort2 | −0.095 | −0.080 | −0.082 | −0.092 | −0.074 |
| | (0.103) | (0.106) | (0.108) | (0.110) | (0.103) |
| Cohort3 | −0.550*** | −0.497*** | −0.462*** | −0.501*** | −0.450*** |
| | (0.128) | (0.134) | (0.134) | (0.137) | (0.124) |
| Cohort4 | −0.860 | −1.249** | −1.192** | −1.193** | −0.914* |
| | (0.633) | (0.589) | (0.571) | (0.550) | (0.515) |
| EDR | −0.005 | 0.000 | −0.001 | 0.001 | 0.001 |
| | (0.021) | (0.022) | (0.022) | (0.023) | (0.021) |
| EDR*Cohort2 | −0.220 | −0.142 | −0.163 | −0.169 | −0.168 |
| | (0.181) | (0.156) | (0.185) | (0.193) | (0.192) |
| EDR*Cohort3 | −0.147*** | −0.159*** | −0.159*** | −0.153*** | −0.137*** |
| | (0.050) | (0.053) | (0.053) | (0.053) | (0.047) |
| EDR*Cohort4 | 0.061 | 0.200 | 0.189 | 0.185 | 0.117 |
| | (0.145) | (0.132) | (0.126) | (0.116) | (0.096) |
| Age | −0.043 | −0.030 | −0.030 | −0.019 | −0.017 |
| | (0.027) | (0.028) | (0.028) | (0.029) | (0.025) |
| Age squared | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Gender | −0.067 | −0.087 | −0.070 | −0.092 | −0.082 |
| | (0.089) | (0.091) | (0.093) | (0.094) | (0.087) |
| Education level | 0.008 | 0.014* | 0.017* | 0.015* | 0.014* |
| | (0.008) | (0.009) | (0.009) | (0.009) | (0.008) |
| Work outside | −0.000 | −0.004 | −0.003 | −0.003 | −0.003 |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Technician density | 0.001*** | 0.009*** | 0.009*** | 0.006*** | 0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) |
| Job training | 0.096 | 0.192*** | 0.214*** | 0.224*** | 0.179*** |
| | (0.066) | (0.065) | (0.067) | (0.069) | (0.058) |
| Ln (Family income) | 0.031 | 0.062** | 0.050* | 0.049 | 0.041 |
| | (0.027) | (0.028) | (0.029) | (0.030) | (0.028) |
| Family size | −0.000 | 0.012 | 0.013 | 0.003 | 0.003 |
| | (0.014) | (0.015) | (0.015) | (0.016) | (0.015) |
| Party member | 0.075 | 0.076 | 0.066 | 0.049 | 0.066 |
| | (0.076) | (0.079) | (0.081) | (0.083) | (0.077) |
| Village cadre | 0.280** | 0.172 | 0.149 | 0.152 | 0.140 |
| | (0.110) | (0.113) | (0.115) | (0.116) | (0.104) |
| Land size | 0.010* | −0.002 | 0.000 | 0.004 | 0.003 |
| | (0.006) | (0.007) | (0.008) | (0.008) | (0.007) |
| Distance to markets | 0.002 | −0.005* | 0.005 | 0.004 | 0.002 |
| | (0.002) | (0.003) | (0.004) | (0.004) | (0.004) |
| County level | | Fixed | | | |
| Town level | | | Fixed | | |
| Village level | | | | Fixed | Fixed |
| $R^2$ | 0.049 | 0.109 | 0.119 | 0.137 | 0.302 |
| Obs. | 1,990 | 1,990 | 1,990 | 1,990 | 1,990 |

**Table 4** *(Continued)*

| Marginal Effect | | | | | |
|---|---|---|---|---|---|
| | Very late (value = 1) | Late (value = 2) | General (value = 3) | Early (value = 4) | Earliest (value = 5) |
| EDR*Cohort3 | 0.018*** (0.006) | 0.030*** (0.011) | 0.007** (0.003) | -0.030*** (0.010) | -0.026*** (0.009) |

Note: Robust standard errors are presented in parentheses; $^{*}P < 0.10$, $^{**}P < 0.05$ and $^{***}P < 0.01$.

decreases by 0.030% and 0.026%, respectively. Additionally, columns (2) to (4) indicate that the coefficients of technician density and job training are significant at the 1% level. Therefore, the more family members who have participated in agricultural technology training, the more this promotes the farm household's adoption of new technologies. A similar positive impact is found for technician density, as expected. Adnan *et al.*, (2018) argue that farm households' new technology adoption decisions depend on whether they believe that they benefit from innovation; this belief can result from relaxing farmers' information constraints. Thus, we incorporate job training and technician density into the baseline model to provide a more reliable estimation.

### 4.2 Mediating effect analysis

How has the Great Famine affected current farm households' technology adoption? This section identifies the possible channel through which the famine affected farm households' technology adoption. To do so, we use the step-by-step method to test our assumption: that the profound exposure to famine fundamentally changed householders' risk tolerance, which affects farm households' adoption of technology. According to the step-by-step approach, the estimation model is established as:

$$TA_{icj} = F(\alpha_1 EDR_{ij} + \sum_{c=2}^{4} \beta_c cohort_{ic} \times EDR_{ij} + \sum_{c=2}^{4} \alpha_{2c} cohort_{ic} + \theta Controls_{icj} + \varepsilon_{icj}) \quad (7)$$

$$RP_{icj} = F(\alpha_3 EDR_{ij} + \sum_{c=2}^{4} \beta_{1c} cohort_{ic} \times EDR_{ij} + \sum_{c=2}^{4} \alpha_{4c} cohort_{ic} + \theta_1 Controls_{icj} + \mu_{icj}) \quad (8)$$

$$TA_{icj} = F(\alpha_5 EDR_{ij} + \sum_{c=2}^{4} \beta_{2c} cohort_{ic} \times EDR_{ij} + \sum_{c=2}^{4} \alpha_{6c} cohort_{ic} + \delta_c RP_{icj} + \theta_2 Controls_{icj} + \xi_{icj}) \quad (9)$$

where $RP_{icj}$ represents farm householder $i$'s degree of risk tolerance;$\alpha_1$, $\alpha_3$, $\alpha_5$, $\alpha_{2c}$, $\alpha_{4c}$, $\alpha_{6c}$, $\beta_{1c}$ and $\beta_{2c}$ represent the coefficients; and $\mu_{icj}$ and $\xi_{icj}$ represent residual errors.

Table 5 reports the mediating effects. Column (1) presents the total effects, in that famine attenuates farm households' adoption of technology, with its coefficients significant at the 1% level. Column (2) includes risk preferences, with a strong, negative correlation between childhood and adolescent famine and farm households' risk aversion. On this basis, we add both the interaction terms and risk preferences in column (3), and the results indicate that a higher level of risk tolerance leads to more positive technology adoption, an effect that is significant at the 1% level. More importantly, including the risk preferences in column (3) weakens both the magnitude and statistical significance of EDR*Cohort3 in our column (1) baseline results, suggesting that risk preferences mediated the famine's effect on technology adoption. To ensure robustness, the bottom panel in Table 5 presents the estimated results from a bootstrapping procedure (1,000 times). The estimated coefficient is found to be –0.015 and significant at the 1% level, and the degree of the mediating effect accounts for 14.4%; again, the mediating effect is verified.

## 5. Sensitivity analysis

There are five main potential concerns with our identification strategy. First, the restriction on the internal migration as a result of the strict *hukou* policy enforced in 1949 has its limit. As we cannot observe internal, cross-regional population movements after the Great Famine, we cannot relate the extent to which observations are hit during the famine to later outcomes. Since China implemented its reform and opening-up policy in 1978, the entire nation has experienced the largest migration in human history. Initially, one to two million farmers left their *hukou* residences; this figure reached 147 million in 2005 (National Bureau of Statistics of China, 2006). Second, we rely on a difference-in-differences method to identify the famine's causal effect on the survivors' technology adoption behaviour. For the DID estimator to remain free from bias, the variation in the excess death rate should not systematically relate to other omitted factors that also affect technology adoption. Third, risk preferences as subjective perceptions are difficult to measure, and a proxy may lead to measurement error; technology adoption as a self-reported variable may also trigger the same concern. Fourth, we observed a complementarity between seeds and fertiliser, with a potential concern that solely considering seed adoption and ignoring fertiliser may lead to estimation biases. Finally, previous criteria in dividing birth cohorts may also lead to a potential estimation bias, and its validity needs further discussion. We empirically address each of these concerns in the following subsections.

### 5.1 Cross-regional movement

Internal mobility may lead to a biased estimation. We check this by including a question in our survey ('How many generations of your family have lived in

**Table 5** Mediating effect of risk preferences

| | Technology Adoption (1) | Risk Preferences (2) | Technology Adoption (3) |
|---|---|---|---|
| Risk preferences | | | 0.067*** |
| | | | (0.024) |
| Cohort2 | −0.092 | −0.024 | −0.119 |
| | (0.110) | (0.138) | (0.112) |
| Cohort3 | −0.501*** | 0.541*** | −0.535*** |
| | (0.137) | (0.158) | (0.137) |
| Cohort4 | −1.193** | −0.027 | −1.141** |
| | (0.550) | (0.622) | (0.550) |
| EDR | 0.001 | 0.019 | −0.002 |
| | (0.023) | (0.026) | (0.023) |
| EDR*Cohort2 | −0.169 | −0.300 | −0.144 |
| | (0.193) | (0.202) | (0.193) |
| EDR*Cohort3 | −0.153*** | −0.251*** | −0.134** |
| | (0.053) | (0.062) | (0.054) |
| EDR*Cohort4 | 0.185 | −0.117 | 0.195 |
| | (0.116) | (0.128) | (0.127) |
| Control variables | Included | Included | Included |
| Village level | Fixed | Fixed | Fixed |
| $R^2$ | 0.137 | 0.054 | 0.138 |
| Obs. | 1,990 | 1,976 | 1,961 |
| Bootstrap result | −0.015***(0.005) | | |

Note: Robust standard errors are presented in parentheses; $^{*}P < 0.10$, $^{**}P < 0.05$ and $^{***}P < 0.01$.

this village?') to acquire essential information about population movements, including three dividing options: 'one generation', 'two generations' and 'three generations or more'.

According to Li (1988), China's mean childbearing age increased from 22.0 in 1960 to 24.2 in 1981. Song and Zhang (2017) also found an increasing trend in China's mean childbearing age based on national censuses from China, Japan and South Korea conducted between 1990 and 2015. Thus, we take the least stringent standard of the mean childbearing age in 1960 of 22 to divide ages into generations, suggesting that three generations are roughly equivalent to 66 years. Specifically, if the sample farmers live in their villages for three or more generations, then they are unlikely to have migrated from 1950 to 2016. In practice, we omitted sample farmers whose families have lived in the same village for less than three generations; Table 6 reports the regression results. The subsample regression provides a fairly close, consistent estimation with the baseline results, both in magnitude and in statistical significance.

## 5.2 Test of the assumption of the difference-in-differences estimation

The DID estimation is based on a parallel trend assumption prior to the implementation of the intervention. Therefore, we conduct a pre-trend test for technology adoption to examine the null hypothesis, which states that no significant difference exists in the linear trends between the non-famine age groups or those born after 1961. We check this with a subsample of individuals who were born between 1962 and 1981, then divided them into four birth cohorts by setting year dummies: cohort5 (age 50 to 55), cohort6 (age 45 to 50), cohort7 (age 40 to 45) and cohort8 (age 35 to 40). As none of these birth cohorts were ever directly exposed to the famine, we anticipate that the Great Famine would not produce any negative effects on these groups. Table 7 reports the regression results, with cohort5 as the control group; clearly, the famine's effects for the EDR*Cohort6, EDR*Cohort7 and EDR*Cohort8 interactions either have no statistical significance or have the incorrect sign to be considered as such. This experiment strongly suggests that our DID estimator works well in this case.

## 5.3 Measurement error

In this section, we reconsider whether the prior indicators are appropriate measures of risk preferences and technology adoption. First, we employ an alternative measurement of risk tolerance to determine our results' robustness; this can be measured in many different ways. Farmers' risk attitudes often relate to their attitudes towards accepting new things (Binswanger & Sillers, 1983; Liu & Huang, 2013). For example, individuals who prefer to

**Table 6** Test for cross-regional movement

| | Technology Adoption (1) | Risk Preferences (2) | Technology Adoption (3) |
|---|---|---|---|
| Risk preferences | | | $0.074^{***}$ |
| | | | (0.025) |
| Cohort2 | −0.072 | −0.007 | −0.100 |
| | (0.113) | (0.142) | (0.115) |
| Cohort3 | $-0.519^{***}$ | $0.619^{***}$ | $-0.558^{***}$ |
| | (0.139) | (0.165) | (0.140) |
| Cohort4 | $-1.287^{**}$ | 0.197 | $-1.232^{**}$ |
| | (0.544) | (0.740) | (0.543) |
| EDR | 0.003 | 0.033 | −0.001 |
| | (0.023) | (0.027) | (0.024) |
| EDR*Cohort2 | −0.180 | −0.274 | −0.154 |
| | (0.195) | (0.192) | (0.196) |
| EDR*Cohort3 | $-0.158^{***}$ | $-0.261^{***}$ | $-0.136^{**}$ |
| | (0.054) | (0.065) | (0.055) |
| EDR*Cohort4 | 0.180 | −0.113 | 0.191 |
| | (0.115) | (0.155) | (0.116) |
| Control variables | Included | Included | Included |
| Village level | Fixed | Fixed | Fixed |
| $R^2$ | 0.139 | 0.058 | 0.140 |
| Obs. | 1,889 | 1,876 | 1,862 |
| Bootstrap result | $-0.018^{***}$(0.006) | | |

Note: Robust standard errors are presented in parentheses; $^{*}P < 0.10$, $^{**}P < 0.05$ and $^{***}P < 0.01$.

avoid risks are more reluctant to accept something new. Therefore, we adopt farm households' acceptance of new things as an alternative measure of their risk tolerance by employing a close-ended question to elicit risk attitudes, including three dividing options: 'less active', coded as one; 'general', coded as two; and 'more positive', coded as three. Additionally, when acquiring information about technology adoption behaviour in our field survey, we tried to clarify about the distinction between different options to the respondents and made a double check before processing. Even by doing so, the respondents may still find it hard to distinguish and lead to the problem of misreport. Given that the adoption behaviour is measured by a categorical variable, we reduce the five categories (1, or 'very late'; 2, or 'late'; 3, or 'general'; 4, or 'early'; 5, or 'earliest') to three categories (1, or 'very late', or 'late'; 2, or 'general'; 3, or 'early', or 'earliest') to make the answers more comparable. Table 8 summarises the results.

In Panel A, the coefficients of the interaction term in columns (1) and (3) are −0.158 (significant at the 1% level) and −0.087. A comparison of the coefficients in columns (1) and (3) reveals that the famine's direct effect on farm households' technology adoption is weakened by risk preferences. Therefore, we argue that risk preferences act as mediators. The estimated results of the bootstrap procedure (1,000 times) as displayed in Panel A also verify the mediating role of risk preferences, demonstrating the mediated mechanism's robustness. Similarly, the robust check addressing technology adoption in Panel B works quite well.

**Table 7** Pre−trend test for DID estimation

| | Technology adoption (1) |
|---|---|
| Cohort6 (45–50 years old) | 0.393* |
| | (0.222) |
| Cohort7 (40–45 years old) | 0.834 |
| | (0.513) |
| Cohort8 (35–40 years old) | −0.481 |
| | (0.889) |
| EDR | 0.027 |
| | (0.145) |
| EDR*Cohort6 | −0.214 |
| | (0.159) |
| EDR*Cohort7 | −0.159 |
| | (0.183) |
| EDR*Cohort8 | 0.424 |
| | (0.268) |
| Control variables | Included |
| Village level | Fixed |
| $R^2$ | 0.189 |
| Obs. | 769 |

Note: Robust standard errors are presented in parentheses; $^{*}P < 0.10$, $^{**}P < 0.05$ and $^{***}P < 0.01$.

### 5.4 Mixed process involving seeds and fertiliser

Considering the complementarities among a series of agricultural inputs, seeds and fertilisers are one of the most closely related pairs (Abay *et al.*, 2018), which could be a potential concern in the baseline regression. Therefore, we link the adoption of improved seeds with that of improved fertiliser, and apply a CMP approach to identify whether the possible connection interferes with our basic results. Table 9 presents the estimation results.

The 'Atanhrho_12' indicator represents the residual correlation of the two-stage regression model. Its coefficient is significant at the 1% level, indicating that a mixed process is necessary. Therefore, the hypothesis that a complementarity exists between seeds and fertiliser reflects both intuition and empirical evidence. After including all control variables and village dummies, the coefficient of the interaction between EDR and cohort3 is negative, but insignificant in the chemical fertiliser model, and negatively significant at the 1% level in the improved seed model. Specifically, considering only the single variable of improved seeds may not result in a biased estimation. Both coefficients reveal that adopting a chemical fertiliser does not affect the causal inference between famine and technology adoption, or its interference statistically equals zero.

Further, agricultural inputs involve joint decisions regarding a series of technologies; seed technology adoption as a starting point for agricultural input makes it a pre-condition for farmers to consider other matching agricultural technologies. In practice, compared with the flexibility of adjustment in chemical fertiliser applications, using improved seeds is more like a lockdown deal with higher opportunity cost. Typically, farmers do not switch to another crop until the previous crop is harvested due to the relatively extensive costs involved. Therefore, the potential risk is higher when adopting a new seed variety. These findings also provide us with possible extensions to the baseline results, as famine affects the adoption of critical and risk-sensitive technologies with high uncertainty, rather than the adoption of supporting technologies with relatively lower risk, such as chemical fertilisers.

### 5.5 Test for birth cohorts

It is well documented that childhood events related to nutrition intake produce long-lasting effects on one's physical health, even during infancy, or from birth to age three (Barker, 1990, 2004; Victora *et al.*, 2008). Further, little evidence indicates that infant malnutrition or hunger impact adult psychological characteristics and behaviour. However, we still cannot theoretically eliminate the possible connection between infants' exposure to famine and technology adoption. In this sense, previous birth cohorts' standards of division may have created an estimation bias, as our cohort1

**Table 8** Alternative measures for risk preferences and technology adoption

| | Technology adoption (1) | Risk preferences (2) | Technology adoption (3) |
|---|---|---|---|
| Panel A: Risk preferences | | | |
| Risk preferences | | | 0.515*** |
| | | | (0.045) |
| Cohort2 | −0.072 | 0.009 | −0.121 |
| | (0.113) | (0.131) | (0.116) |
| Cohort3 | −0.519*** | 0.402** | −0.733*** |
| | (0.139) | (0.164) | (0.147) |
| Cohort4 | −1.287** | 0.520 | −1.491*** |
| | (0.544) | (0.789) | (0.574) |
| EDR | 0.003 | −0.019 | 0.013 |
| | (0.023) | (0.026) | (0.024) |
| EDR*Cohort2 | −0.180 | −0.155 | −0.149 |
| | (0.195) | (0.209) | (0.159) |
| EDR*Cohort3 | −0.158*** | −0.251*** | −0.087 |
| | (0.054) | (0.057) | (0.057) |
| EDR*Cohort4 | 0.180 | −0.194 | 0.215 |
| | (0.115) | (0.186) | (0.144) |
| Control variables | Included | Included | Included |
| Village level | Fixed | Fixed | Fixed |
| $R^2$ | 0.139 | 0.112 | 0.169 |
| Obs. | 1,889 | 1,817 | 1,802 |
| Bootstrap result | −0.063***(0.014) | | |
| Panel B: Technology adoption | | | |
| Risk preferences | | | 0.073*** |
| | | | (0.028) |
| Cohort2 | −0.016 | −0.007 | −0.026 |
| | (0.125) | (0.142) | (0.128) |
| Cohort3 | −0.423*** | 0.619*** | −0.448*** |
| | (0.151) | (0.165) | (0.152) |
| Cohort4 | −0.888 | 0.197 | −0.793 |
| | (0.573) | (0.740) | (0.573) |
| EDR | 0.003 | 0.033 | −0.002 |
| | (0.026) | (0.027) | (0.026) |
| EDR*Cohort2 | −0.274 | −0.274 | −0.248 |
| | (0.337) | (0.192) | (0.335) |
| EDR*Cohort3 | −0.163*** | −0.261*** | −0.137** |
| | (0.059) | (0.065) | (0.060) |
| EDR*Cohort4 | 0.177 | −0.113 | 0.193 |
| | (0.145) | (0.155) | (0.146) |
| Control variables | Included | Included | Included |
| Village level | Fixed | Fixed | Fixed |
| $R^2$ | 0.140 | 0.058 | 0.142 |
| Obs. | 1,889 | 1,876 | 1,862 |
| Bootstrap result | −0.011***(0.004) | | |

Note: Robust standard errors are presented in parentheses; $^{*}P < 0.10$, $^{**}P < 0.05$ and $^{***}P < 0.01$.

combines observations of those who have experienced the Great Famine during infancy with those who have not.

We address this concern by categorising a new set of birth cohorts that place infancy into a separate group: cohort9 (unborn), cohort10 (infancy),

**Table 9** Mixed process – seeds and fertiliser with CMP

| | Chemical fertiliser (1) | Improved seeds (2) |
|---|---|---|
| Cohort2 | 0.078 | −0.055 |
| | (0.118) | (0.116) |
| Cohort3 | 0.102 | −0.498*** |
| | (0.137) | (0.137) |
| Cohort4 | −0.470 | −1.294* |
| | (0.656) | (0.663) |
| EDR | 0.001 | −0.002 |
| | (0.024) | (0.024) |
| EDR*Cohort2 | 0.117 | −0.164 |
| | (0.191) | (0.181) |
| EDR*Cohort3 | −0.013 | −0.146*** |
| | (0.050) | (0.050) |
| EDR*Cohort4 | 0.150 | 0.196 |
| | (0.148) | (0.157) |
| Control variables | Included | Included |
| Village level | Fixed | Fixed |
| Obs. | 1,892 | 1,892 |
| Atanhrho_12 | 0.811*** (0.030) | |

Note: Robust standard errors are presented in parentheses; $^{*}P < 0.10$, $^{**}P < 0.05$, $^{***}P < 0.01$.

cohort11 (early childhood), cohort12 (childhood and adolescence) and cohort13 (adulthood). The estimates, reported in Table 10, are empirically consistent with the baseline results.

## 6. Conclusion

This paper addresses the long-standing question regarding the slow diffusion of improved agricultural technology in developing countries. We find evidence that the Great Famine, an extremely traumatic experience in China, accounts for farmers' conservative behaviour, and it persists through the channel of risk preferences. Specifically, we demonstrate that famine exposure during childhood and adolescence attenuates technology adoption, and farmers with higher degrees of famine exposure tend to be more risk-averse. Our results are robust to controls for the village level, various observable attributes among the sample householders and farm households, and different sensitivity checks and specifications. We also comprehensively address the concern with selective migration to discover this does not appear to drive our estimation.

Overall, our results indicate that risk preferences evolve in response to extreme famine exposure and suggest that farmers are not inherently reluctant to accept improved technology. Rather, slow technology adoption can be modified by decreasing the exposure to famine or severe crop failure. And policies can exert some role in improving farm households' adoption of technology by ensuring food security and further protecting them from future famine.

**Table 10** Test for birth cohorts

| | Technology adoption (1) | Risk preferences (2) | Technology adoption (3) |
|---|---|---|---|
| Risk preferences | | | 0.075*** |
| | | | (0.025) |
| Cohort10 | 0.180 | −0.222 | 0.213 |
| | (0.126) | (0.168) | (0.161) |
| Cohort11 | 0.039 | −0.103 | 0.024 |
| | (0.127) | (0.161) | (0.129) |
| Cohort12 | −0.383** | 0.501*** | −0.406** |
| | (0.159) | (0.189) | (0.159) |
| Cohort13 | −1.018* | −0.072 | −0.929 |
| | (0.566) | (0.778) | (0.565) |
| EDR | 0.016 | 0.021 | 0.013 |
| | (0.025) | (0.029) | (0.025) |
| EDR*Cohort10 | 0.089 | 0.124 | 0.054 |
| | (0.185) | (0.317) | (0.205) |
| EDR*Cohort11 | −0.193 | −0.260 | −0.171 |
| | (0.196) | (0.191) | (0.197) |
| EDR*Cohort12 | −0.158*** | −0.260*** | −0.136** |
| | (0.054) | (0.065) | (0.055) |
| EDR*Cohort13 | 0.158 | −0.083 | 0.166 |
| | (0.117) | (0.157) | (0.118) |
| Control variables | Included | Included | Included |
| Village level | Fixed | Fixed | Fixed |
| $R^2$ | 0.139 | 0.059 | 0.141 |
| Obs. | 1,889 | 1,876 | 1,862 |
| Bootstrap result | −0.015***(0.005) | | |

Note: Robust standard errors are presented in parentheses; $^{*}P < 0.10$, $^{**}P < 0.05$ and $^{***}P < 0.01$.

Our findings also suggest that farmers with more extreme famine experiences are less risk-tolerant. In contrast to conventional thinking in existing literature, we envisage farmers as not inherently risk-averse, assuming risk preferences as a given prior condition must be re-examined. It is not yet clear how to intervene from the perspective of post-traumatic stress disorder, which may be vital for helping farm households with their irrational technology adoption decisions. Therefore, specific psychological interventions may alleviate the risk aversion of target farmers who were exposed to famine in their childhood and adolescence, as the limits of economic interventions addressing farmers' conservative behaviour – such as agricultural insurance or credits – become better known. Further, we discover that technician density and job training can alleviate farm households' risk aversion and facilitate the diffusion of technology, highlighting the importance of technicians' assignment and job training in developing effective interventions.

Finally, in the light of the pre-trend test in Section 5, it is noteworthy that China's post-famine generation – which never experienced famine or severe material deprivation – is replacing the older generation as the main labour force in agricultural production. Thus, the Great Famine's significantly strong, negative effects on technology adoption will eventually fade as the younger generation takes over.

## References


Abay, K.A., Berhane, G., Taffesse, A.S., Abay, K. & Koru, B. (2018) Estimating input complementarities with unobserved heterogeneity: evidence from Ethiopia. *Journal of Agricultural Economics*, 69, 495–517.

Abebe, G. & Alemu, A. (2017) Role of improved seeds towards improving livelihood and food security at Ethiopia. *International Journal of Research-Granthaalayah*, 5, 338–356.

Adnan, N., Nordin, S.M. & Ali, M. (2018) A solution for the sunset industry: Adoption of Green Fertilizer Technology amongst Malaysian paddy farmers. *Land Use Policy*, 79, 575–584.

Ager, P., Eriksson, K., Hansen, C.W. & Lønstrup, L. (2019) How the 1906 San Francisco Earthquake Shaped Economic Activity in the American West. Explorations in Economic History. Working Paper.

Alem, Y., Bezabih, M., Kassie, M. & Zikhali, P. (2010) Does improved fertilizer use respond to rainfall variability? Panel data evidence from Ethiopia. *Agricultural Economics*, 41, 165–175.

Ambrus, A., Field, E. & Gonzalez, R. (2020) Loss in the time of cholera: long-run impact of a disease epidemic on the urban landscape. *American Economic Review*, 110, 475–525.

Angrist, J.D. & Pischke, J.S. (2008) *Mostly harmless econometrics: an empiricist's companion*. Princeton, NJ: Princeton University Press.

Ashton, B., Hill, K., Piazza, A. & Zeitz, R. (1984) Famine in China, 1958–61. *Population and Development Review*, 10, 225–271.

Barker, D.J. (1990) The fetal and infant origins of adult disease. *British Medical Journal*, 301, 1111.

Barker, D.J. (2004) Developmental origins of adult health and disease. *Journal of Epidemiology and Community Health*, 58, 114–115.

Baron, R.M. & Kenny, D.A. (1986) The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51, 1173–1182.

Bhattamishra, R. & Barrett, C.B. (2010) Community-based risk management arrangements: a review. *World Development*, 38, 923–932.

Binswanger, H.P. & Sillers, D.A. (1983) Risk aversion and credit constraints in farmers' decision-making: a reinterpretation. *The Journal of Development Studies*, 20, 5–21.

Borooah, V.K. (2002) *Logit* and probit: ordered and multinomial models. London, UK: Sage.

Cameron, L.A. (1999) The importance of learning in the adoption of high-yielding variety seeds. *American Journal of Agricultural Economics*, 81, 83–94.

Cao, S.J. (2005) Death and its causes in China from 1959 to 1961. *Chinese Journal of Population Science*, 1, 14–28.

Cassar, A., Healy, A. & Von Kessler, C. (2017) Trust, risk, and time preferences after a natural disaster: experimental evidence from Thailand. *World Development*, 94, 90–105.

Chayanov, A.V. (1974) La organización de la unidad económica campesina. Available from URL http://www.sidalc.net.

Chen, Y. & Zhou, L.A. (2007) The long-term health and economic consequences of the 1959–1961 famine in China. *Journal of Health Economics*, 26, 659–681.

Cheng, L.G. & Zhang, Y. (2011) Does famine experience in childhood influence one's saving decision—a new explanation of China's high household saving rate. *Economic Research Journal*, 8, 120–133.

Damon, W. & Hart, D. (1991) *Self-understanding in childhood and adolescence*. Cambridge, UK: Cambridge University Press.

Dercon, S. (2008) Fate and fear: risk and its consequences in Africa. *Journal of African Economies*, 17, 97–127.

Dudycha, G.J. & Dudycha, M.M. (1941) Childhood memories: a review of the literature. *Psychological Bulletin*, 38, 668–682.

Duflo, E. (2006) Poor but rational. *Understanding Poverty*, 24, 367–379.

Duflo, E., Kremer, M. & Robinson, J. (2011) Nudging farmers to use improved fertilizer: theory and experimental evidence from Kenya. *American Economic Review*, 101, 2350–2390.

Evenson, R.E. & Gollin, D. (2003) Assessing the impact of the Green Revolution, 1960–2000. *Science*, 300, 758–762.

Fafchamps, M. (2010) Vulnerability, risk management and agricultural development. *African Journal of Agricultural and Resource Economics*, 5, 243–260.

Feng, X. & Johansson, A.C. (2018) Living through the great Chinese famine: early-life experiences and managerial decisions. *Journal of Corporate Finance*, 48, 638–657.

Franken, J.R.V., Pennings, J.M.E. & Garcia, P. (2014) Measuring the effect of risk attitude on marketing behavior. *Agricultural Economics*, 45, 1–11.

Freud, S. (1905) Three essays on the theory of sexuality. The standard edition of the complete psychological works of Sigmund Freud, volume VII. (1901-05): a case of hysteria, three essays on sexuality and other works, 123-246

Freud, S. (1915) *Paper on metapsychology: the unconscious*. London, UK: Hogarth Press.

Giedd, J.N., Blumenthal, J., Jeffries, N.O., Castellanos, F.x., Liu, H., Zijdenbos, A. *et al.* (1999) Brain development during childhood and adolescence: a longitudinal MRI study. *Nature Neuroscience*, 2, 861–863.

Giné, X. & Yang, D. (2009) Insurance, credit, and technology adoption: Field experimental evidence from Malawi. *Journal of Development Economics*, 89, 1–11.

Gneezy, U. & Potters, J. (1997) An experiment on risk taking and evaluation periods. *Quarterly Journal of Economics*, 112, 631–645.

Gollin, D. (2010) Agricultural productivity and economic growth. *Handbook of Agricultural Economics*, 4, 3825–3866.

Harrison, G.W., Humphrey, S.J. & Verschoor, A. (2010) Choice under uncertainty: evidence from Ethiopia, India and Uganda. *Economic Journal*, 120, 80–104.

Hertwig, R., Barron, G., Weber, E.U. & Erev, I. (2004) Decisions from experience and the effect of rare events in risky choice. *Psychology Science*, 15, 534–539.

Hess, E.H. (1959) Imprinting. *Science*, 130, 133–141.

Huaibin Government (1987) *Prefecture gazetteer of Huaibin from 1951 to 1983*. Zhengzhou, China: Henan Renmin Press.

Huang, C. & Martorell, R. (2009) Long-Term Health Consequences of Early Life Exposure to the 1959-61 Chinese Famine. CCER Working Paper.

Huang, P.C. (1990) *The peasant family and rural development in the Yangzi Delta, 1350–1988*. Redwood, US: Stanford University Press.

Humphrey, S.J. & Verschoor, A. (2004) Decision-making under risk among small farmers in East Uganda. *Journal of African Economics*, 13, 44–101.

Jacobs, J.E. & Klaczynski, P.A. (2002) The development of judgment and decision making during childhood and adolescence. *Current Directions in Psychological Science*, 11, 145–149.

Jedwab, R., Johnson, N.D. & Koyama, M. (2019) Negative shocks and mass persecutions: evidence from the Black Death. *Journal of Economic Growth*, 24, 345–395.

Josselyn, S.A. & Frankland, P.W. (2012) Infantile amnesia: a neurogenic hypothesis. *Learning and Memory*, 19, 423–433.

Kihlstrom, J.F. & Harackiewicz, J.M. (1982) The earliest recollection: A new survey. *Journal of Personality*, 50, 134–148.

Lamb, R.L. (2003) Improved fertilizer use, risk and off-farm labor markets in the semi-arid tropics of India. *American Journal of Agricultural Economics*, 85, 359–371.

Li, G.J. (1988) Dynamic analysis of women's mean age at childbearing in China (1960–1981). *Chinese Journal of Population Science*, 05, 2–17.

Li, R.J. (2016) An assessment of the quality of population data of 1957–1963 in Henan Province. *South China Population*, 06, 1–10.
Lin, J.Y. (1990) Collectivization and China's agricultural crisis in 1959–1961. *Journal of Political Economy*, 98, 1228–1252.
Liu, E.M. & Huang, J. (2013) Risk preferences and pesticide use by cotton farmers in China. *Journal of Development Economics*, 103, 202–215.
Malmendier, U. & Nagel, S. (2011) Depression babies: do macroeconomic experiences affect risk taking. *The Quarterly Journal of Economics*, 126, 373–416.
Mao, H., Zhou, L., Ifft, J. & Ying, R. (2019) Risk preferences, production contracts and technology adoption by broiler farmers in China. *China Economic Review*, 54, 147–159.
McGuire, S. & Sperling, L. (2011) The links between food security and seed security: facts and fiction that guide response. *Development in Practice*, 21, 493–508.
Meng, X. & Qian, N. (2009) The long term consequences of famine on survivors: evidence from a unique natural experiment using China's great famine. National Bureau of Economic Research. NBER Working Paper.
Minten, B., Koro, B. & Stifel, D. (2013) The Last Mile (s) in Modern Input Distribution: Evidence from Northwestern Ethiopia. Working Paper.
Moser, C.M. & Barrett, C.B. (2006) The complex dynamics of smallholder technology adoption: the case of SRI in Madagascar. *Agricultural Economics*, 35, 373–388.
Nadel, L. & Zola-Morgan, S. (1984) *Infantile amnesia*. Boston, MA: Springer.
National Bureau of Statistics of China (2006) Bulletin of 2005 national survey on 1% population sampling. Available from URL: http://www.stats.gov.cn.
Ofreneo, R. (2004) From the Green Revolution to the Gene Revolution: Agriculture, AFTA and the TNCs. Asian Development Bank Regional. Working Paper.
Quibod, I.L., Atieza-Grande, G. & Oreiro, E.G. (2020) The Green Revolution shaped the population structure of the rice pathogen Xanthomonas oryzae pv. oryzae. *The International Society for Microbial Ecology Journal*, 14, 492–505.
Roodman, D. (2011) Fitting fully observed recursive mixed-process models with cmp. *The STATA Journal: Promoting Communications on Statistics and Stata*, 11, 159–206.
Schultz, T.W. (1964) *Transforming traditional agriculture*. New Haven, US: Yale University Press.
Scott, J.C. (1977) *The moral economy of the peasant*. New Haven, US: Yale University Press.
Shaffer, D.R. & Kipp, K. (2013) *Developmental psychology: childhood and adolescence*. New York, US: Cengage Learning.
Song, J. & Zhang, J.W. (2017) Parity, timing of birth, and fertility: A comparative study on the trends and differential mechanism of the mean age at childbearing in China, Japan, and Korea. *Population Research*, 03, 3–14.
Spiegel, A., Britz, W. & Finger, R. (2018) Risk, Risk Aversion and Agricultural Technology Adoption a Combination of Real Options and Stochastic Dominance. Working Paper.
Victora, C.G., Adair, L., Fall, C., Hallal, P.C., Martorell, R., Richter, L. *et al.* (2008) Maternal and child undernutrition: consequences for adult health and human capital. *The Lancet*, 371, 340–357.
Weber, E.U., Böckenholt, U., Hilton, D.J. & Wallace, B. (1993) Determinants of diagnostic hypothesis generation: effects of information, base rates, and experience. *Journal of Experimental Psychology. Learning Memory and Cognition*, 19, 1151–1164.
Weigelin-Schwiedrzik, S. (2003) Trauma and memory: the case of the great famine in the people's Republic of China (1959–1961). *Historiography East & West*, 1, 39–67.
Wen, Z.L. & Ye, B.J. (2014) Analyses of mediating effects: the development of methods and models. *Advances in Psychological Science*, 22, 731–745.
Whatley, W.C. (2018) The gun-slave hypothesis and the 18th century British slave trade. *Explorations in Economic History*, 67, 80–104.
Yapa, L. (1993) What are improved seeds? An epistemology of the Green Revolution. *Economic Geography*, 69, 254–273.