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Being a happy farmer: Technology adoption and subjective well-being

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ABSTRACT

This paper empirically investigates the impact of technology adoption on farmers' subjective well-being, as measured by happiness and life satisfaction. A theoretical framework is constructed to link farmers' subjective well-being to technology adoption, with a particular emphasis on mechanization services in agricultural production. By fitting a nationally representative panel dataset – China Family Panel Studies – into an endogenous switching regression model that addresses potential selection bias, we find that technology adoption leads to a 0.194 standard deviation increase in happiness and a 0.065 standard deviation increase in life satisfaction. Further analysis reveals that the effect is more pronounced for individuals engaged in off-farm employment and varies across farm sizes. To underpin the causal effect, we test three plausible mechanisms – absolute income, relative income, and leisure – which are well-documented in the literature for their correlations with happiness and life satisfaction. Our empirical analysis indicates that the adoption of agricultural mechanization services indeed increases the absolute income of farmers and allows them to allocate more time to leisure activities.

1. Introduction

People's self-assessment of their lives, often referred to as "subjective well-being" that encompassing aspects of happiness and/or life satisfaction, is fundamental to a good life (Wilson, 1967; Diener, 1984; Ferrer-i-Carbonell, 2005; Frey and Stutzer, 2010). The 2021 World Happiness Report highlights that the bottom 1/3 least happy countries are predominantly developing nations with agricultural population comprising the majority (Helliwell et al., 2021), underscoring the importance of improving farmers' subjective well-being. Nonetheless, although the empirical studies of factors contributing to people's subjective well-being have been numerous (Easterlin, 1974; Benjamin et al., 2012; Diener et al., 2018), less emphasis has been put particularly on farmers in developing countries.

This paper delves into the role played by agricultural technology adoption in improving farmers' subjective well-being. Existing literature extensively demonstrates that adopting various agricultural technologies significantly boosts productivity and income (Zhang et al., 2016; Nakano and Magezi, 2020), alleviates poverty (Minten and Barrett, 2008; Kassie et al., 2011), and improves food security and human development (Self and Grabowski, 2007; Pan et al., 2018) in developing countries (Feder et al., 1985; Birkhaeuser et al., 1991; Gollin et al., 2002). Yet, little empirical evidence has been documented about how technology adoption influences

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farmers' subjective well-being.

The technology that this paper emphasizes is mechanization services in agricultural production. Mechanization itself is one of the most successful technologies that has seen significant diffusion in the agricultural sector, particularly since the Green Revolution in developing countries (Evenson and Gollin, 2003). The recent diffusion of such a technology in developing countries is marked by the widespread adoption of agricultural mechanization services (hereafter AMS) in countries like China (Yang et al., 2013), Ghana (Benin, 2015), Bangladesh (Mottaleb et al., 2016), and Myanmar (Belton et al., 2021). In the AMS arrangement, farmers opt for a fee-for-service that pays service providers (like machinery owners, farm cooperatives, or agribusiness firms) for a blend of specialized labor and mechanized production. AMS provides an alternative to owning machinery or relying on manual labor, especially beneficial for smallholders with limited financial resources and technical skills. Its impact on agriculture, in terms of such as labor substitution (Takeshima et al., 2013), farm size (Huang and Ding, 2016), yield and total factor productivity (Yamauchi *et al*., 2016), factor misallocation (Chen et al., 2022), and agricultural income (Wang et al., 2016), is an increasingly vital area of study, as highlighted by Justice and Biggs (2020).[1]

In this paper, we develop a simple model to explore the farmer's decision-making in allocating labor for on-farm, off-farm and leisure activities. This model posits that a farmer's subjective well-being is influenced by personal consumption (from both on-farm and off-farm incomes), consumption comparisons with others, and leisure time. We propose that AMS can enhance the farmer's subjective well-being through three primary effects: the absolute income effect (increased productivity and total income due to AMS adoption), the relative income effect (income growth surpassing the average due to AMS adoption), and the leisure effect (reduced need for labor on farm and/or off-farm by AMS adoption).

Building upon this theoretical framework, we empirically estimate the impact of AMS adoption on farmers' subjective well-being, using a nationally representative panel dataset – China Family Panel Survey (CFPS) – that was collected in 2014 and 2018. China serves as our research setting, primarily due to its sheer number of farmers and extensive AMS adoption (see Yang et al., 2013; Huang and Ding, 2016). The individual-level subjective well-being is measured with two widely studied dimensions: happiness and life satisfaction (Dolan and Metcalfe, 2012; Diener et al., 2018). To address the potential endogeneity from self-selection in AMS adoption, we employ an endogenous switching regression (ESR) model, integrating instrumental variable (IV) techniques and counterfactual analysis in estimation (see Lokshin and Sajaja, 2004). In particular, the endogeneity of AMS adoption is instrumented using the interaction between village-level terrain dummy and county-level monthly minimum wage indicators.

We find, first, that farmers' subjective well-being does improve as a result of adopting AMS once selection bias has been addressed. Specifically, farmers who switch from non-adopters to adopters experience an average increase of 0.044 in happiness (ranging from 0 to 1, with a mean of 0.737) and 0.016 in life satisfaction (ranging from 0 to 1, with a mean of 0.689). These are equivalent to a notable increase in standard deviation of 19.4 % and 6.5 %, respectively. Second, the effect of technology adoption on subjective well-being, as measured by the average treatment effect on the treated (ATT), exhibits heterogeneity based on farmers' work types and farm sizes. Farmers engaged in off-farm employment tend to experience greater increases in happiness and life satisfaction from adoption, compared to those solely involved in farming. This is also true for large farms compared to small farms in happiness. In general, the impact of AMS adoption on life satisfaction is much smaller than on happiness, reflecting the adaptive and habitual nature of technology adoption (Karahanna et al., 1999). Lastly, the robustness of the baseline results persists even after we control for any unobserved temporal factors that may vary across provinces. We accomplish this by introducing province-by-year fixed effects. Additionally, we address the potential reverse causality by incorporating lagged technology adoption into our analysis.

Validating the mechanisms through which technology adoption affects subjective well-being poses another challenge in comprehending the empirical results. In theory, farming as self-employment allows flexible time allocation between farming and non-farming activities (e.g., off-farm employment or leisure) to maximize farmers' utility (Singh et al., 1986; Kool and Botvinick, 2014). On the one hand, self-employment in farming offers nonpecuniary benefits such as autonomy, competence and relatedness, which boost farmers' subjective well-being (Howley, 2015). On the other hand, the drudgery of farming, coupled with income disparity issues between farming and non-farm activities, may adversely affect farmers' subjective well-being (Belton et al., 2021; Markussen et al., 2018). AMS, as a labor-saving technology, alters farmers' time allocation by reducing farm labor needs (Hayami and Ruttan, 1970; Nickols and Fox, 1983). Intuitively, AMS adopters may feel happier and be more satisfied with their life due to the increase in their earnings from alternative off-farm employment and/or the more leisure time (Diener and Biswas-Diener, 2002; Newman et al., 2014). However, the income growth from technology adoption can vary, possibly widening income disparities. This, in turn, could lead to a reduction in the subjective well-being of farmers with relatively lower incomes (Perez-Truglia, 2020).

We further test the abovementioned mechanisms to substantiate the causal relationship between AMS adoption and subjective well-being. Empirical evidence confirms that technology adoption has indeed elevated farm and off-farm incomes. However, it's important to note a caveat: this adoption has also widened the relative income gap between farmers, which has countered some of the positive effects on subjective well-being. Additionally, we observe that technology adoption has enabled farmers to allocate more time to leisure activities, while reducing time spent for unpaid housework.

This paper pertains to various strands of literature. First, it relates to the ongoing debate on the effects of technology adoption. While current literature primarily focuses on agricultural technology's impact on production and objective well-being indicators (Pan

[1] Apart from developing countries, some developed countries also had mechanization services in the early days. A limited number of markets for mechanization services existed in American agriculture during the period of 1930-1970, affected the size of farm operations (Kislev and Peterson, 1982). Additionally, mechanization services, a key part of the hire of capital services, increased the productivity levels of small farms compared to larger counterparts in Australian grains industry (Sheng and Chancellor, 2019).

et al., 2018, also see Ruzzante et al., 2021 for a review), the influence on subjective well-being remains underexplored. Our study bridges this gap by not only theorizing the link between technology adoption and farmers' subjective well-being but also providing empirical evidence to support this relationship.[2]

Second, it also aligns with the literature on technology and inequality. Existing research highlights technological progress's role in exacerbating income inequality, particularly in the context of trade and financial globalization at the country level (Greenwood, 1997; Jaumotte et al., 2013). However, micro-level and agriculture-specific evidence remains scarce. Our study extends beyond the typical focus on the direct effects of agricultural technology on farmers' absolute income (Birkhaeuser et al., 1991; Kassie et al., 2011; Nakano and Magezi, 2020). We also delve into its impact on relative income, uncovering that technology adoption, while increasing absolute income through farming and off-farm earnings, also intensifies income disparities among farmers. This phenomenon could potentially offset the positive effects of technology adoption on subjective well-being, which should be noted.

Last, the paper relates to the literature on understanding the effects of technology adoption from the perspective of time allocation, particularly in relation to leisure. Leisure is recognized as a vital component of subjective well-being (Brajša-Žganec et al., 2011; Newman et al., 2014), with activities like watching television and using the internet being positively correlated to happiness and life satisfaction (see Kuykendall et al., 2015, Wiese et al., 2018 for meta-analysis). In addition to those, we introduce detailed components of time allocation including paid work, unpaid work and leisure. This contributes to the literature by exploring how agricultural technology adoption may enhance farmers' subjective well-being through increased leisure time and investigate which specific leisure activities are involved to this effect.

The remainder of the paper is organized as follows. Section 2 outlines a theoretical framework. Section 3 delineates the empirical strategy, data source and measures. Section 4 presents and discusses the empirical results. Section 5 delves into the analysis of the underlying mechanisms. Finally, Section 6 concludes the paper.

2. Theoretical framework

This section provides a simple model to investigate how AMS adoption may affect farmers' subjective well-being. The model focuses on three key channels: absolute income, relative income, and leisure effects, which have been notably emphasized in subjective well-being literature (Brajša-Žganec et al., 2011; Diener et al., 2018) and are closely tied to the studies concerning technology adoption (Birkhaeuser et al., 1991; Self and Grabowski, 2007; Zhang et al., 2016).

In this model, a representative farmer allocates his/her labor endowment L across on-farm work (denoted by L^f), off-farm work (denoted by L^o), as well as entertainment or leisure (denoted by L^e), where $L^f + L^o + L^e \leq L$. On-farm work yields agricultural income, which depends on the production function $Y(L^f, M)$, where M represents AMS availability, the cost of which is denote by s per unit. $Y_L > 0$; $Y_M > 0$ and $Y_{LL} < 0$. Off-farm work generates non-agricultural income wL^o, where w is the exogenous off-farm wage rate. The farmer's problem is to maximize utility subject to budget constraint and labor constraints. Taking into account the subjective well-being, the farmer derives utility from three sources (i) own consumption c; (ii) the consumption relative to the local average $c/\bar{c}$;[3] and (iii) leisure time L^e.[4] Formally, the farmer's utility maximization problem can be constructed as follows:

$$\max_{\{c, L^f, L^o, L^e\}} U = \beta \ln(c) + \gamma \ln\left(\frac{c}{\bar{c}}\right) + (1 - \beta - \gamma)\ln(L^e) \tag{1}$$

subject to

$$\begin{aligned} &\textit{Budget constraint}: c \leq Y\left(L^f, M\right) + wL^o - sM \\ &\textit{Labor allocation constraint}: L^f + L^o + L^e \leq L \end{aligned} \tag{2}$$

where $0 < \beta < 1,\ 0 < \gamma < 1,$ and $0 < \beta + \gamma < 1$.

The budget constraint and labor allocation constraint are binding, leading to:

$$\max_{L^f, L^o} \beta \ln\left(Y\left(L^f, M\right) + wL^o - sM\right) + \gamma \ln\left(\frac{Y\left(L^f, M\right) + wL^o - sM}{\bar{c}}\right) + (1 - \beta - \gamma)\ln\left(L - L^f - L^o\right) \tag{3}$$

The first-order conditions of Eq. (3) result in a straightforward condition:

[2] Outside the agricultural sector, the impact of technological affluence and individual subjective well-being has been an ongoing debate in Europe (Kavetsos and Koutroumpi, 2011). More recently, Singh et al. (2022) discussed the excessive use of technology for work and personal activities, such as digital platforms, may cause technostress and decrease subjective well-being of employees.

[3] Relative consumption is important for subjective well-being and is a universal human trait observed in both developed and developing countries, irrespective of their lifestyle orientation towards market activities (Luttmer, 2005; Fafchamps and Shilpi, 2008; Perez-Truglia, 2020). It is typically modeled as $(c - \bar{c})$ or $c/\bar{c}$, both of which produce qualitatively similar effects. For ease of exploitation, we use the relative term $c/\bar{c}$.

[4] The study aims to explore the impact of AMS adoption on farmers' subjective well-being through changes in labor allocation. The model is set up as if AMS is predetermined before farmers decide on labor allocation and consumption. Recognizing that AMS adoption, while endogenous, is influenced by factors like market prices, terrain conditions and other unobservables, the study considers AMS can be predicted in advance of labor allocation decisions. We thank the anonymous reviewer for this comment.

$$Y_L(L^f, M) = \frac{\partial Y}{\partial L} = w \tag{4}$$

That is, the equilibrium labor allocation is determined such that the marginal product of on-farm labor equates to the off-farm work wage. This condition determines the equilibrium on-farm labor input $L^f = L^f(M)$, which is depended on the availability of AMS.

The effect of AMS adoption can be derived as

$$\frac{dL^f}{dM} = -\frac{Y_{LM}}{Y_{LL}} \tag{5}$$

Clearly, the sign of Eq. (5) depends on whether AMS availability and on-farm labor input are complements or substitutes. If they are complements, i.e., $Y_{LM} > 0$, then $\frac{dL^f}{dM} > 0$, implying that AMS adoption leads to an increased on-farm labor input. Alternatively, if they are substitutes, i.e., $Y_{LM} < 0$, then $\frac{dL^f}{dM} < 0$, indicating that AMS adoption has a negative impact on-farm labor input.

From the first order condition with respect to L^o in Eq. (3):

$$\frac{\partial U}{\partial L^o} = (\beta + \gamma)\frac{w}{Y + wL^o - sM} - (1 - \beta - \gamma)\frac{1}{L - L^f - L^o} = 0 \tag{6}$$

We can thus express the equilibrium off-farm labor input as:

$$L^o(M) = (\beta + \gamma)\left(L - L^f(M)\right) - (1 - \beta - \gamma)\frac{Y\left(L^f(M), M\right) - sM}{w} \tag{7}$$

Using the equilibrium condition in Eq. (4),[5] simple algebra can derive the impact of mechanization on off-farm labor:

$$\frac{dL^o}{dM} = -\frac{dL^f}{dM} - (1 - \beta - \gamma)\frac{Y_M - s}{w} \tag{8}$$

The condition suggests that the impact of AMS adoption on off-farm labor allocation depends on $\frac{dL^f}{dM}$, i.e., its influence on-farm labor, and $(Y_M - s)$, representing the marginal net benefit of AMS. If $\frac{dL^f}{dM} > 0$ and $(Y_M - s) > 0$, suggesting that AMS adoption complements on-farm labor and generates a positive marginal net benefit, then $\frac{dL^o}{dM} < 0$. In this scenario, AMS adoption depresses the off-farm labor allocation. However, if $\frac{dL^f}{dM}$ and $(Y_M - s)$ have opposing signs, the impact of AMS on off-labor is undetermined, depending on which of these effects is stronger.

Investigating the impact of AMS adoption on leisure, given that $L^e = L^e(M) = L - L^f(M) - L^o(M)$, we can derive:

$$\frac{dL^e}{dM} = -\frac{dL^f}{dM} - \frac{dL^o}{dM} = (1 - \beta - \gamma)\frac{Y_M - s}{w} \tag{9}$$

Thus, the effect of AMS adoption on leisure hinges on the marginal net benefit of AMS on farming income. If $(Y_M - s) > 0$, indicating a net benefit from AMS adoption, the influence on leisure time is positive and hence the subjective well-being of farmers is likely to rise.

Moreover, setting the total income of the farmer as $I(M) = Y(L^f(M), M) + wL^o(M) - sM$, taking into account Eqn. (5), (8) and (9), we can derive the effect of AMS on total income:

$$\frac{dI}{dM} = \frac{\partial Y}{\partial L^f}\frac{dL^f}{dM} + \frac{\partial Y}{\partial M} + w\frac{dL^o}{dM} - s = (\beta + \gamma)(Y_M - s) \tag{10}$$

Therefore, the household's total income moves in the same direction as the farming income.

Finally, inserting the equilibrium income $I(M)$, and the equilibrium leisure $L^e(M)$ into the utility function (3), we derive the indirect utility function as follows:

$$V = \beta\ln(I(M)) + \gamma(\ln I(M) - \ln\bar{c}(M)) + (1 - \beta - \gamma)\ln(\mathrm{L}^e(M)) \tag{11}$$

It can be derived that:

[5] Here, we investigate the off-farm labor allocation in a partial equilibrium setting, assuming constant non-farm wages. However, if mechanization leads to large fluctuation of off-farm labor supply, it is likely that the non-farm wages will be affected, which, in turn, may strengthen or weaken the effect of AMS depending on the extent to which the off-farm labor are freed out. Additionally, the overall general equilibrium impact of AMS is not a straightforward boost; it also depends on demand side, which, in the Chinese context, is a result of urbanization, economic trends and industrial structural changes (Wang et al., 2016) and is not the focus of our current paper. Thus, we opted for a partial equilibrium framework and offered a suggestion for thoroughly exploring general equilibrium effects in conclusion for future study. We thank the anonymous reviewer suggesting this general equilibrium discussion.

$$\frac{dV}{dM} = \underbrace{\beta\frac{\frac{dI}{dM}}{I(M)}}_{absolute\ \ income\ \ effect} + \underbrace{\gamma\left(\frac{\frac{dI}{dM}}{I(M)} - \frac{\frac{d\bar{c}}{dM}}{\bar{c}(M)}\right)}_{relative\ \ income\ \ effect} + \underbrace{(1-\beta-\gamma)\frac{\frac{dL^e}{dM}}{L^e(M)}}_{leisure\ \ effect} \tag{12}$$

In words, Eq. (12) indicates that AMS affects the subjective well-being of the farmer through three distinct channels:

Absolute income effect. The first term captures the absolute income effect of AMS adoption. As highlighted in condition (10), this effect follows the same direction of the marginal net benefit of AMS adoption. If $(Y_M - s) > 0$, then, $\frac{dI}{dM} > 0$, implying a rise of the total income following the increased farming income with the AMS adoption.

Relative income effect. The second term captures the relative income effect: a farmer's utility increase if AMS adoption leads to a higher income (or consumption) growth than the average, $(\frac{\frac{dI}{dM}}{I(M)} > \frac{\frac{d\bar{c}}{dM}}{\bar{c}(M)})$. Although some evidence indicates that this effect might be less pronounced at low-income levels (McBride, 2001), research indicates its significance in rural China, especially regarding income within a village and over time (Knight et al., 2009). This study extends these insights by underscoring the importance of relative income (or consumption) growth, which takes into account both on-farm and off-farm sources, driven by AMS adoption and its impact on subjective well-being. In practice, the net effect of AMS adoption on relative income growth is undetermined and deserves a further empirical investigation.

Leisure effect. The third term captures the leisure effects. As condition (9) shows, if the marginal net benefit of AMS is positive, the leisure time available to the farmer increases because AMS adoption frees the farmer from working on-farm and/or off-farm. This leisure time increase further contributes positively to the subjective well-being of farmers, echoing the findings in Newman et al. (2014).

To sum up, the overall effect of AMS adoption on SWB remains uncertain and depends on several factors. In the following section, we will provide empirical evidence regarding the effects of AMS adoption, and specifically test the validity of these three channels.

3. Empirical strategy and data source

3.1. Empirical strategy

The main task of this study is to unbiasedly estimate the effect of AMS adoption on farmers' subjective well-being. This is challenged because farmers' decision to adopt or not is voluntary and may be influenced by a set of unobserved characteristics. For example, a farmer's capability in organizing agricultural production, often an unobservable factor, might influence both the demand for AMS and subjective well-being (Sheng and Chancellor, 2019). Neglecting to account for such factors could lead to biased estimates. Specifically, if less skilled farmers are more likely to adopt AMS and simultaneously have lower life satisfaction, this could result in a downward bias in our estimates.

We address the potential issue of selection bias by accounting for both observed and unobserved heterogeneities with the widely-adopted endogenous switching regression (ESR) model (Lokshin and Sajaia, 2004). In particular, ESR models the decision of AMS adoption and its impact on subjective well-being within a two-stage framework. The first stage estimates a Probit model to determine the probability of adopting AMS, and the second stage estimates the determinants of subjective well-being respectively for adopters and non-adopters. To mitigate the problem of inconsistent standard errors caused by heteroskedastic residuals in this two-stage approach, a full information maximum likelihood (FIML) estimator is frequently utilized to simultaneously estimate the selection equation and outcome equations (Lee, 1982; Lokshin and Sajaja, 2011). Compared to other nonlinear regressions with instrumental variables (such as IV-Probit and IV-Tobit) and propensity score matching (PSM), ESR is more suitable for handling endogenous binary variables and correcting for selection bias originating from both observed and unobserved factors. Moreover, its coefficient estimates facilitate the calculation of the average treatment effect on the treated (ATT).

Considering the fact that farmers voluntarily choose to adopt AMS or not, we construct a selection model in which a risk-neutral farmer decides to adopt AMS if it generates net benefits. Let $D^*_{ihc,t} = D^*_{aihc,t} - D^*_{nihc,t}$ be the latent variable that captures the expected net benefits from the adoption ($D^*_{aihc,t}$) with respect to non-adoption ($D^*_{nihc,t}$), where i indexes individual, h represents household, c denotes county, and t is time. If $D^*_{ihc,t}$>0, the farmer will adopt AMS. We specify the latent variable as follow:

$$D^*_{ihc,t} = \mathbf{Z}_{ihc,t}\boldsymbol{\alpha}_1 + \mathbf{Z}_{hc,t}\boldsymbol{\alpha}_2 + \delta_t + \tau_c + \varepsilon_{ihc,t},\ \ with\ D_{ihc,t} = \begin{cases} 1, & if\ D^*_{ihc,t} > 0 \\ 0, & otherwise \end{cases} \tag{13}$$

$D_{ihc,t}$ is the observed counterpart of $D^*_{ihc,t}$, which equals 1 if farmer i adopts AMS. The vectors $\mathbf{Z}_{ihc,t}$ and $\mathbf{Z}_{hc,t}$ donate individual-level and household-level variables influencing the expected benefits of AMS adoption. $\boldsymbol{\alpha}_1$ and $\boldsymbol{\alpha}_2$ are unknown parameters to be estimated, δ_t denotes year fixed effects, τ_c indicates county fixed effects, and $\varepsilon_{ihc,t}$ is error term.[6]

[6] County fixed effects absorb all time-invariant county-level characteristics that are associated with AMS adoption and also affect subjective well-being. For instance, local culture, employment environment and other implicit factors based on the characteristics of counties. Year fixed effects are included to account for any temporal shocks to AMS adoption and subjective well-being that are beyond the level of a county.

In the second stage, we specify two separate outcome equations, one for AMS adopters and the other for non-adopters:

$$\mathbf{Y}_{\mathrm{aihc,t}} = \mathbf{X}_{\mathrm{ihc,t}}\boldsymbol{\beta}_{1\mathrm{a}} + \mathbf{X}_{\mathrm{hc,t}}\boldsymbol{\beta}_{2\mathrm{a}} + \delta_{\mathrm{t}} + \tau_{\mathrm{c}} + \mu_{\mathrm{aihc,t}},\ if \mathrm{D}_{\mathrm{ihc,t}} = 1 \tag{14a}$$

$$\mathbf{Y}_{\mathrm{nihc,t}} = \mathbf{X}_{\mathrm{ihc,t}}\boldsymbol{\beta}_{1\mathrm{n}} + \mathbf{X}_{\mathrm{hc,t}}\boldsymbol{\beta}_{2\mathrm{n}} + \delta_{\mathrm{t}} + \tau_{\mathrm{c}} + \mu_{\mathrm{nihc,t}}, if \mathrm{D}_{\mathrm{ihc,t}} = 0 \tag{14b}$$

where $\boldsymbol{Y}_{aihc,t}$ and $\boldsymbol{Y}_{nihc,t}$ represent the subjective well-being of AMS adopters and non-adopters. $\boldsymbol{X}_{ihc,t}$ and $\boldsymbol{X}_{hc,t}$ denote covariates at individual and household levels, respectively, that may influence the outcome variables. $\mu_{aihc,t}$ and $\mu_{nihc,t}$ are random disturbance terms associated with the outcome variables. It is worth noting that ESR permits a partial overlap between $\boldsymbol{Z}_{ihc,t}$ and $\boldsymbol{Z}_{hc,t}$ in the selection Eq. (13) with $\boldsymbol{X}_{ihc,t}$ and $\boldsymbol{X}_{hc,t}$ in the outcome Eqs. (14a) and (14b), respectively. However, for proper identification, it is essential to include at least one instrumental variable (IV) in the selection equation that does not appear in the outcome equations (Lokshin and Sajaja, 2004), and this IV should correlate with farmers' technology adoption decisions and be orthogonal to omitted variables impacting subjective well-being. In this study, we estimate the selection Eq. (13) using all specified explanatory variables in outcome Eqs. (14a) and (14b), along with a valid IV.

The three error terms, $\varepsilon_{ihc,t}$, $\mu_{aihc,t}$, and $\mu_{nihc,t}$, from the selection Eq. (13) and outcome Eqs. (14a), and (14b), are assumed to follow a trivariate normal distribution with a mean vector of zero and a specific covariance matrix.

$$\sum = \begin{bmatrix} \sigma_\eta^2 & \sigma_{a\eta} & \sigma_{n\eta} \\ \sigma_{a\eta} & \sigma_a^2 & \cdot \\ \sigma_{n\eta} & \cdot & \sigma_n^2 \end{bmatrix}$$

where σ_η^2 denotes a variance of the error term in the selection Eq. (13), σ_a^2 and σ_n^2 are variances of the error terms in the outcome Eqs. (14a) and (14b), respectively. The covariances between the error terms of the selection equation and each outcome equation are denoted by $\sigma_{a\eta}$ and $\sigma_{n\eta}$. The covariance between $\mu_{aihc,t}$ and $\mu_{nihc,t}$ is undefined (dots in the covariance matrix), as $\boldsymbol{Y}_{aihc,t}$ and $\boldsymbol{Y}_{nihc,t}$ are never observed simultaneously for the same farmer. As the error term in selection Eq. (13) is correlated with the error terms of the outcome Eqs. (14a) and (14b), the expected values of error terms $\mu_{aihc,t}$ and $\mu_{nihc,t}$ conditional on the sample selection are non-zero and are defined respectively as follows:

$$E\left[\mu_{\mathrm{aihc,t}}\middle|\mathrm{D}_{\mathrm{ihc,t}} = 1\right] = \sigma_{a\eta}\frac{\varnothing\left(\mathbf{Z}_{\mathrm{ihc,t}}\boldsymbol{\alpha}_1, \mathbf{Z}_{\mathrm{hc,t}}\boldsymbol{\alpha}_2\right)}{\oint\left(\mathbf{Z}_{\mathrm{ihc,t}}\boldsymbol{\alpha}_1,\ \mathbf{Z}_{\mathrm{hc,t}}\boldsymbol{\alpha}_2\right)} = \sigma_{a\eta}\lambda_{\mathrm{aihc,t}} \tag{15a}$$

$$E\left[\mu_{\mathrm{nihc,t}}\middle|\mathrm{D}_{\mathrm{ihc,t}} = 0\right] = \sigma_{n\eta}\frac{\varnothing\left(\mathbf{Z}_{\mathrm{ihc,t}}\boldsymbol{\alpha}_1, \mathbf{Z}_{\mathrm{hc,t}}\boldsymbol{\alpha}_2\right)}{1 - \oint\left(\mathbf{Z}_{\mathrm{ihc,t}}\boldsymbol{\alpha}_1, \mathbf{Z}_{\mathrm{hc,t}}\boldsymbol{\alpha}_2\right)} = \sigma_{n\eta}\lambda_{\mathrm{nihc,t}} \tag{15b}$$

where $\varnothing(\cdot)$ represents the standard normal probability density function, and $\oint(\cdot)$ denotes the standard normal cumulative density function. The inverse Mills ratios (IMR), $\lambda_{aihc,t}$ and $\lambda_{nihc,t}$, are estimated from the selection equation. A notable implication of the error structure is that if the estimated covariance $\widehat{\sigma_{a\eta}}$ and $\widehat{\sigma_{n\eta}}$ are statistically significant, then the decision of AMS adoption and the outcomes are correlated. Such a correlation points to the presence of endogenous switching, thereby leading to the rejection of the null hypothesis of the absence of selection bias. In light of this, IMR ($\lambda_{aihc,t}$ and $\lambda_{nihc,t}$) are calculated and incorporated into second stage to account for selection bias.

Of significant interest in this paper is the ATT of adopting AMS on subjective well-being of farmers. To obtain ATT, we follow Lokshin and Sajaja (2004) and compare the expected outcome values for adopters in both observed and counterfactual scenarios. More specifically, the observed outcomes and unobserved counterfactuals for adopters are constructed as follows:

$$E\left[\mathbf{Y}_{\mathrm{aihc,t}}\middle|\mathrm{D}_{\mathrm{ihc,t}} = 1\right] = \mathbf{X}_{\mathrm{ihc,t}}\boldsymbol{\beta}_{1\mathrm{a}} + \mathbf{X}_{\mathrm{hc,t}}\boldsymbol{\beta}_{2\mathrm{a}} + \sigma_{a\eta}\lambda_{\mathrm{aihc,t}} + \delta_{\mathrm{t}} + \tau_{\mathrm{c}} \tag{16a}$$

$$E\left[\mathbf{Y}_{\mathrm{nihc,t}}\middle|\mathrm{D}_{\mathrm{ihc,t}} = 1\right] = \mathbf{X}_{\mathrm{ihc,t}}\boldsymbol{\beta}_{1\mathrm{n}} + \mathbf{X}_{\mathrm{hc,t}}\boldsymbol{\beta}_{2\mathrm{n}} + \sigma_{n\eta}\lambda_{\mathrm{aihc,t}} + \delta_{\mathrm{t}} + \tau_{\mathrm{c}} \tag{16b}$$

where Eq. (16a) represents the expected outcomes of farmer $\boldsymbol{i}$ who has adopted AMS. Eq. (16b) refers to the counterfactual expected outcomes for the same farmer if he/she had not adopted. In this way, ATT is easily obtained as:

$$\begin{aligned} ATT &= E\left[\boldsymbol{Y}_{aihc,t}\middle|D_{ihc,t} = 1\right] - E\left[\boldsymbol{Y}_{nihc,t}\middle|D_{ihc,t} = 1\right] \\ &= \boldsymbol{X}_{ihc,t}(\boldsymbol{\beta}_{1a} - \boldsymbol{\beta}_{1n}) + \boldsymbol{X}_{hc,t}(\boldsymbol{\beta}_{2a} - \boldsymbol{\beta}_{2n}) + (\sigma_{a\eta} - \sigma_{n\eta})\lambda_{aihc,t} \end{aligned} \tag{17}$$

3.2. Data and measures of variables

This study utilizes a nationally representative, longitudinal survey dataset – China Family Panel Studies (CFPS) of Peking University – to estimate (Eqn. (13)–(17)). The CFPS employs a multi-stage probability proportional sampling strategy and randomly selected 162 counties in 25 provinces across China (for detail information, see Xie and Hu, 2014); its baseline survey was conducted in 2010, and follow-up surveys were conducted every other year, and the latest available data is up to 2018. The CFPS collects rich data on individual, family, and community characteristics. However, information related to AMS adoption did not enter the questionnaire until 2014, and that of happiness was seriously missing in 2016. To ensure data validity, we rely on the data collected in 2014 and 2018. As our primary objective is to investigate the effect of technology adoption on farmers' subjective well-being, it is natural to exclude all urban samples and the segment of rural samples that have entirely rented out land (i.e., those who were not engaged in farming). [7] The final dataset used is an unbalanced panel data consisting of 20,899 adults from 5,558 rural households. The main variables are defined below.

3.2.1. Subjective well-being

In assessing the subjective well-being of farmers, we use individual-level happiness and life satisfaction measures, aligning with methodologies employed in Zhang et al. (2017) and Perez-Truglia (2020).[7] Happiness often captures short-term perceptions of daily life and has a more emotional aspect, while life satisfaction reflects long-term aspirations and expectations regarding one's life as a whole (Dolan and Metcalfe, 2012; Diener et al., 2018). Information on happiness is collected in the CFPS questionnaire through the question "Are you happy?", where respondents are required to rate their happiness on a scale from 0 (lowest) to 10 (highest). Life satisfaction is determined by asking, "Are you satisfied with your life?" with possible responses ranging from 1 (very unsatisfied) to 5 (very satisfied). To facilitate the interpretation of the regression findings, we normalize both measures to a range of 0 to 1. Notably, a significant positive correlation (0.271) between these measures corroborates existing literature, suggesting a consistent link between different subjective well-being dimensions (Vermunt et al., 1989; Tsou and Liu, 2001; Selim, 2008).

Figs. 1 and 2 depict the density distribution of happiness and life satisfaction stratified by AMS adoption status. These visual representations reveal a notable trend: farmers who have adopted AMS generally report higher levels of happiness and life satisfaction, with their responses skewing toward the middle and/or right side of the spectrum. This suggests that AMS adoption may have a positive influence on the subjective well-being of farmers.

3.2.2. AMS adoption

To assess AMS adoption, we utilized the household survey question from CFPS, which inquires about the household's decision to adopt AMS. This binary variable is assigned a value of 1 if the respondent's family adopted AMS, and 0 if not. This variable is pivotal in our econometric framework, severing as the dependent variable in the selection equation of the ESR model.

3.2.3. Control variables

The selection of control variables is guided by extensive literature on AMS adoption (e.g., Mottaleb et al., 2016; Belton et al., 2021) and subjective well-being (e.g., Dolan et al., 2008; Diener et al., 2018; Perez-Truglia, 2020). Specifically, we include individual characteristics such as age, gender, educated year, religion, marital status, and off-farm employment. Additionally, household level features, such as household size, children ratio, non-child dependency ratio, annual income per capita, income sharing, value of durable goods, value of machinery, and contract land are integrated.

To gauge the potential impact of unobserved factors on our results, we implement the sensitivity analysis proposed by Oster (2019). We use the suggested level of 1.3 times of the R-square in the regression with controls as the maximum R-square. The test results indicate that, the explanatory power of unobservables needs to be 4.18 times (in the case of the dependent variable being happiness) and 13.53 times (in the case of the dependent variable being life satisfaction) larger than that of the observables to overturn our empirical findings, which we argue is very unlikely given that a rich set of covariates have been controlled in our analysis (also see Satyanath et al., 2017).

3.2.4. Descriptive statistics

Table 1 presents variables definitions and their descriptive statistics. The last column in Table 1 justifies whether the means of the selected variables significantly differ between AMS adopters and non-adopters. Overall, the results suggest systematic differences in characteristics between adopters and non-adopters. In comparison to non-adopters, AMS adopters are typically more educated, married, engaged in off-farm employment, and tend to have larger households, higher incomes, more assets, a lower possibility to own agricultural machinery, but a higher possibility to own contracted land. These significant differences indicate that these indicators may influence farmers' adoption decision and highlight the presence of selection bias in technology adoption, which should be addressed in the empirical analysis.

3.3. Instrumental variable and its validation

To address the potential endogeneity in AMS adoption, we interact village-level terrain dummy (1 for plain, 0 otherwise) and

[7] Happiness and life satisfaction are the two most widely used measures of subjective well-being in the literature. A growing body of evidence have examined that subjective well-being is positively correlated to objective measures of well-being (Urry et al., 2004), and also positively correlated with decision utility (Benjamin et al., 2012). Thus, the subjective well-being measures contain significant information about the true well-being of individual.

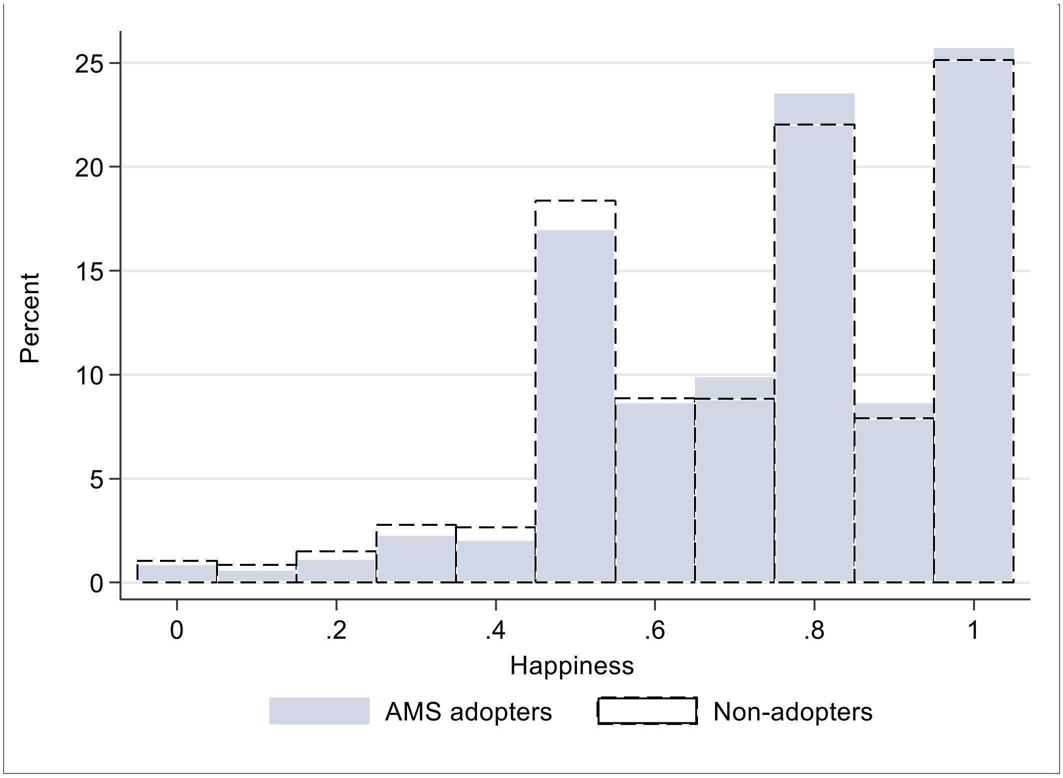

Fig. 1. The distribution of happiness by AMS adoption status, Data source: CFPS, 2014 and 2018.

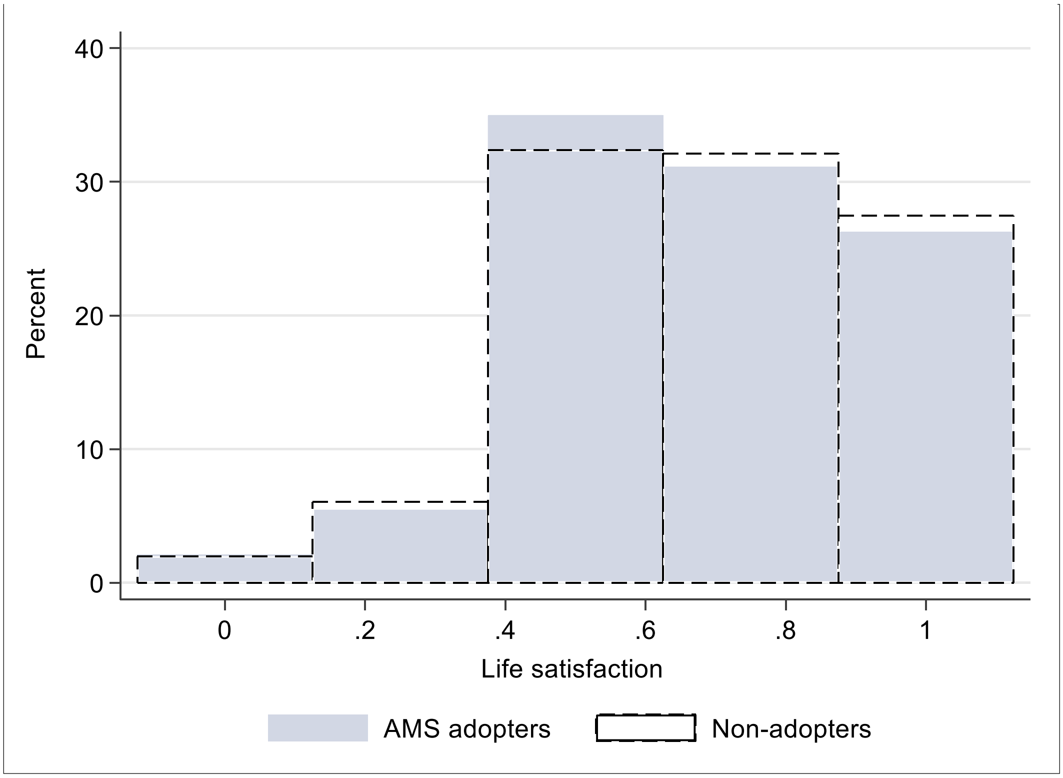

Fig. 2. The distribution of life satisfaction by AMS adoption status, Data source: CFPS, 2014 and 2018.

Table 1
Variables definition and descriptive statistics.

Variable	Definition	Full sample		AMS adopter		Non-adopter		Diff.
		Mean	S.D.	Mean	S.D.	Mean	S.D.	
Dependent variables								
Happiness	Self-reported happiness: 0–10, from very unhappiness to very happiness, and then normalized to have 0 minimum and 1 maximum.	0.737	0.227	0.746	0.221	0.729	0.233	0.017***
Life satisfaction	Self-reported happiness: 1–5, from very unsatisfaction to very satisfaction, and then normalized to have 0 minimum and 1 maximum.	0.689	0.245	0.685	0.244	0.693	0.246	−0.008**
Independent variables								
AMS adoption	1, if farmer adopted agricultural mechanization services; 0, otherwise	0.468	0.499					
Instrumental variables								
Plain×MW	Multiply the county minimum wage (RMB/month, log) by the dummy of whether the village terrain is plain (1, if plain; 0, otherwise)	3.235	3.561	4.639	3.425	2.001	3.215	2.638***
Control variables								
Age	Age (years)	48.519	15.018	48.405	15.176	48.618	14.879	−0.213
Gender	1, if Male; 0, Female	0.494	0.500	0.489	0.500	0.498	0.500	−0.009
Education	Educated year (years)	6.149	4.358	6.589	4.271	5.759	4.398	0.830***
Religion	1, if religious; 0, otherwise	0.174	0.379	0.173	0.378	0.176	0.381	−0.003
Marriage	1, if in the marriage; 0, otherwise	0.862	0.345	0.868	0.338	0.857	0.350	0.011**
Off-farm	1, if participate off-farm employment; 0, otherwise	0.225	0.417	0.241	0.428	0.209	0.407	0.032***
Household size	Number of household members	4.721	2.080	4.770	2.057	4.678	2.098	0.092***
Children ratio	Ratio of children (age <16) to family	0.066	0.135	0.065	0.133	0.066	0.137	−0.001
Non-child dependency ratio	Ratio of non-children members exited labor markets	0.116	0.197	0.115	0.193	0.117	0.200	−0.002
Income per capita	Per capita income of household members (RMB/year), log	8.938	1.075	9.023	0.979	8.863	1.147	0.160***
Income sharing	Received transfer payments of household from both the government or private sector and income sharing from family relatives (RMB), log	5.159	3.051	5.372	2.837	4.971	3.216	0.401***
Durable goods value	Value of household's durable goods (RMB), log	8.743	1.917	8.901	1.821	8.604	1.987	0.297***
Machinery value	Value of household's agricultural machinery (RMB), log	4.010	4.006	3.761	3.979	4.228	4.017	−0.467***
Contract land	1, if household obtained contracted land from the village collective; 0, otherwise	0.965	0.184	0.951	0.137	0.981	0.216	0.030***

Note: The dataset is an unbalanced panel data consisting of 20,899 adults from 5,558 rural households. The unit of observation is an individual. 6.14RMB=1 dollar (2014); 6.18RMB=1 dollar (2018).
Data source: CFPS, 2014 and 2018.

county-level monthly minimum wage for non-agricultural work (log-transformed) to construct the instrumental variable (IV).[8] While these two IV components are discussed in previous studies (e.g., Gerritsen and Jacobs, 2020; Bao et al., 2024), neither one can effectively provide the intended variation for our empirical study. This is easily seen by noting that terrain exhibits no variation over time and minimum wage varies only at the county level. The interaction of them (Plain × MV), however, creates a village-level variable with time variation for panel analysis. We delve into the validity of this IV in the following.

First, the correlation condition requires that AMS adoption is correlated to terrain and minimum wage. Previous studies have demonstrated that terrain is a significant determinant in the application of agricultural mechanization (Feder et al., 1985; Takeshima et al., 2013). Plains, conducive to mechanized farming, contrast sharply with hilly or mountainous areas, where steep and fragmented terrain impedes efficient machinery operation. This distinction in terrain types plays a pivotal role in influencing the adoption of AMS.[9]

Beyond terrain, the relative costs of labor and machinery also influence AMS adoption (Yamauchi, 2016; Sheng and Chancellor, 2019). Variation in such costs is well reflected in the cross-county differences in urban sector minimum wages, which are determined exogenously by local governments, giving farmers little control over them (Kong et al., 2021). We therefore use the minimum wage to

[8] Minimum wage data are collected directly from the Ministry of Human Resources and Social Security and the Chinese Academy of Labor and Social Security. We manually collected minimum wage data at the county-level. The final dataset covers minimum wage data of all counties in the sample of CFPS from 2014 to 2018, including both units of the monthly minimum wage and the hourly minimum wage. In empirical work, we also used the minimum wage rate in hours, and the estimated results and ATT are robust.

[9] We thank one anonymous reviewer for highlighting the potential differences in subjective well-being between households residing in plain and hilly regions, which may threaten the exclusivity of our constructed IV. Upon incorporating individual and household control variables, and county and year fixed effects, we observe that the OLS estimates of the impact of terrain on subjective well-being are insignificant—0.001 ($p = 0.851$) for happiness and 0.011 ($p = 0.107$) for life satisfaction. This suggests that the variations in subjective well-being associated with terrain have been effectively mitigated by the inclusion of these controls and fixed effects.

represent the earning incentive from non-agricultural sector and to reflect the scarcity of agricultural labor (Bhorat et al., 2014). It is expected that a higher minimum wage positively affects AMS adoption. This forms the basis of the IV, exhibiting a strong positive correlation with AMS adoption, as evidenced in column 2 of Appendix Table A1. This correlation aligns with the assumption that farmers in plains with relatively higher labor wages are more inclined to adopt AMS.

Second, the exclusion restriction condition requests that the IV has no direct impact on the outcome variables with its influence channeled exclusively through AMS adoption. In case that the IV may violate the exact exclusion restriction and directly affect subjective well-beings to some extent or through channels other than affecting AMS adoption, we examine whether our IV is "plausibly exogenous" (Conley et al., 2012). We use the zero-first-stage method suggested by Van Kippersluis and Rietveld (2018) to estimate the IV's impact on subjective well-being of farmers not adopting AMS. The results reported in the last two columns of Table A1 largely confirm that the IV has no statistically significant impact on happiness and life satisfaction of non-adopters, suggesting no serious direct effect of the IV on farmers' subjective well-being.

The statistical validity of the IV is further confirmed through under-identification and weak-identification tests. The Kleibergen-Paap rk LM statistic (10.24, $p < 0.01$) and Cragg-Donald Wald F statistic (148.81) strongly indicate that we can reject the null hypothesis of under/weak identification, providing evidence of the statistical validity of the IV.

To assess the suitability of the chosen IV compared to other potential instruments, we employ a machine learning method – IVLASSO – to scrutinize the instrument setting. This approach estimates structural parameters in the presence of many potential instruments, utilizing techniques for estimating sparse high-dimensional models (Belloni et al., 2014; Chernozhukov et al., 2015). It relies on an approximate sparsity assumption and employs high-quality variable selection along with appropriate moment functions. In our analysis, we include various variables like minimum wage, terrain, and contracted land area, in addition to the primary IV, drawing upon theoretical analysis and existing literature (e.g., Wang et al., 2016; Justice and Biggs, 2020). The IVLASSO results, presented in Table A2, validate our selection of the primary IV. In light of the exclusion restriction, the ideal set of instruments identified using IVLASSO provides a high-quality prediction of the endogenous variable – AMS adoption. This result, combined with the preceding discussions on correlation and exclusion restriction, highlights that the chosen IV in this study is not simply spuriously correlated to the endogenous variable but possesses true predictive power.

4. Empirical results

4.1. The estimated results of ESR model

The estimates of the factors influencing farmers' AMS adoption decisions and their impact on happiness and life satisfaction are presented in Tables 2 and 3, respectively. As discussed in Section 3.1, we utilized the FIML estimator to simultaneously estimate the selection equation and two outcome equations. The lower parts of Tables 2 and 3 display the estimated correlation coefficients ($\boldsymbol{\rho}$) between the error term in the selection equation ($\boldsymbol{\varepsilon}$) and the error terms in the outcome equations ($\boldsymbol{\mu}$). For AMS adopters, $\boldsymbol{\rho_{a\eta}} = \boldsymbol{\sigma_{a\eta}}^2/\boldsymbol{\sigma_a \sigma_\eta}$, represents the correlation coefficient between $\boldsymbol{\varepsilon_{ihc,t}}$ and $\boldsymbol{\mu_{aihc,t}}$. Similarly, for non-adopters, $\boldsymbol{\rho_{n\eta}} = \boldsymbol{\sigma_{n\eta}}^2/\boldsymbol{\sigma_n \sigma_\eta}$, represents the correlation coefficient between $\boldsymbol{\varepsilon_{ihc,t}}$ in selection equation and $\boldsymbol{\mu_{nihc,t}}$.[10] In specific, $\boldsymbol{\rho_{n\eta}}$ is significant and negative in Table 2, indicating that the happiness of non-adopters significantly differs from a random individual in the sample. In Table 3, $\boldsymbol{\rho_{a\eta}}$ is significant and negative implying a positive selection bias, suggesting that farmers with above-average life satisfaction are more likely to adopt AMS. Additionally, the results of the Wald test, i.e., the likelihood-ratio test for the joint independence of the three equations, in Tables 2 and 3 confirm that the equations are indeed dependent, and it is appropriate to estimate selection and outcome equations jointly. We discuss the results of the selection equation, outcome equations, and average treatment effect on treated (ATT) in the following.

4.1.1. Results of selection equations

The estimated coefficients of the Probit model for the selection Eq. (13) are provided in the second columns of Tables 2 and 3 for happiness and life satisfaction, respectively. It should be noted that the magnitudes of these estimates may differ slightly for the same adoption decision in the two tables. This is primarily due to the joint estimation of different outcome Eqs. (14a) and (14b) for each subjective well-being measure.

The results of the selection equation reveal that the effects of selection variables on the decision to adopt AMS are statistically similar in both tables. Firstly, the estimated coefficients of the IV, which is the interaction of terrain and minimum wage (Plain × MW), are statistically significant and positive in both tables, suggesting that farmers are more likely to adopt AMS if their farms are located in plain areas with relatively high minimum wages in the non-agricultural sector. This result aligns with previous research findings that have shown the rapid expansion of AMS in the plains and the promotion of AMS adoption due to rising wages (Wang et al., 2016; Yamauchi, 2016). Secondly, some of the control variables are estimated to be significantly different from zero, indicating that farmers' adoption decisions are not entirely exogenous and are influenced by individual and household characteristics. For instance, religious farmers or those owning contracted land are more inclined to adopt AMS, whereas owning valuable agricultural machinery reduces this likelihood, implying a substitution effect between owned machineries and AMS adoption. Overall, these findings underscore the necessity of addressing selection bias in assessing the impact of adopting AMS.

[10] To make sure that estimated ρ is bounded between -1 and 1 and the estimated σ is always positive, the maximum likelihood directly estimates $\ln \sigma$, and atanhρ. More details see Lokshin and Sajaia (2004).

Table 2
ESR results of AMS adoption and its impact on happiness.

Variable	Selection equation	Happiness	
		AMS adopters	Non-adopters
Plain×MW	0.063***		
	(0.016)		
Age	0.001	0.000	0.000**
	(0.001)	(0.000)	(0.000)
Gender	−0.031**	−0.007	−0.015***
	(0.016)	(0.005)	(0.005)
Education	0.009**	0.002**	0.002**
	(0.004)	(0.001)	(0.001)
Religion	0.181***	0.000	0.011
	(0.047)	(0.008)	(0.008)
Marriage	0.017	0.023***	0.040***
	(0.033)	(0.008)	(0.007)
Off-farm	0.047	−0.007	−0.009
	(0.034)	(0.005)	(0.006)
Household size	0.009	0.006***	0.005***
	(0.010)	(0.002)	(0.002)
Children ratio	0.265*	0.002	0.010
	(0.152)	(0.025)	(0.024)
Non-child dependency ratio	−0.125	0.015	0.019
	(0.093)	(0.017)	(0.015)
Income per capita	0.019	0.017***	0.016***
	(0.019)	(0.003)	(0.003)
Income sharing	0.017**	−0.001	−0.001
	(0.008)	(0.001)	(0.001)
Durable goods value	0.014	0.007***	0.007***
	(0.011)	(0.002)	(0.001)
Machinery value	−0.021***	0.001	0.001
	(0.006)	(0.001)	(0.001)
Contract land	0.445***	−0.014	0.016
	(0.113)	(0.017)	(0.016)
Constant	−1.671***	0.513***	0.452***
	(0.308)	(0.061)	(0.030)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
σ_i		0.212***	0.223***
		(0.003)	(0.002)
ρ_j		0.060	−0.124**
		(0.043)	(0.057)
Wald test of indep. eqns.	6.51**		
Log likelihood	−7504.164		
Observations	19,748	19,748	19,748

Note: The unit of observation is an individual. The robust standard errors clustered at the village level are shown in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. Data source: CFPS, 2014 and 2018.

4.1.2. Results of outcome equations

The last two columns of Tables 2 and 3 report the results of estimating Eqs. (14a) and (14b), regarding happiness and life satisfaction for both AMS adopters and non-adopters. In Table 2, the coefficient estimates for age and gender are significantly different from zero for non-adopters, aligning with the notion that mechanization substitutes for on-farm labor (Hayami and Ruttan, 1970; Yamauchi, 2016). In contrast, the coefficients estimate for education and marriage at the individual level, as well as for household size, income per capita, and durable goods value at the household level, are statistically significant and positive for both adopters and non-adopters, implying that both individual and household characteristics are crucial to farmers' happiness. These results of the positive relationship between these indicators of objective well-being and happiness are largely consistent with the findings summarized by Diener et al. (2018).

In Table 3, the significant positive coefficient for agricultural machinery value, a crucial agricultural asset, for AMS adopters underlines its key role in enhancing life satisfaction. Conversely, owning contracted land has a negative effect on adopters' life satisfaction, suggesting a need for further analyses on the potential heterogeneous effects across farm sizes. It's worth noting that, unlike the results for happiness, the estimated coefficients of off-farm employment are statistically negative significant for both AMS adopters and non-adopters. These suggest that the experience of off-farm employment often implies long-term migration and a perception of an obvious income gap between rural and urban areas, which may, over the long term, reduce farmers' subjective well-being (Markussen et al., 2018). Additionally, the estimated coefficients of education on life satisfaction are negative, contrary to its impact on happiness. One plausible explanation is that while education may enhance short-term subjective well-being through better employment and income, it may also lead to increased life stress and a heightened perception of income disparities, and hence negatively affect long-term subjective well-being.

Table 3
ESR results of AMS adoption and its impact on life satisfaction.

Variable	Selection equation	Life satisfaction	
		AMS adopter	Non-adopter
Plain×MW	0.051***		
	(0.012)		
Age	0.000	0.003***	0.002***
	(0.001)	(0.000)	(0.000)
Gender	−0.032**	0.005	0.004
	(0.016)	(0.006)	(0.005)
Education	0.007*	−0.004***	−0.003***
	(0.004)	(0.001)	(0.001)
Religion	0.189***	−0.012	0.013*
	(0.045)	(0.011)	(0.007)
Marriage	0.021	0.010	0.015**
	(0.035)	(0.010)	(0.007)
Off-farm	0.042	−0.014*	−0.013**
	(0.033)	(0.008)	(0.006)
Household size	0.003	−0.001	−0.000
	(0.009)	(0.002)	(0.001)
Children ratio	0.291**	−0.015	0.017
	(0.148)	(0.037)	(0.028)
Non-child dependency ratio	−0.163	−0.017	−0.008
	(0.105)	(0.027)	(0.021)
Income per capita	0.014	0.002	0.012***
	(0.018)	(0.004)	(0.003)
Income sharing	0.017**	−0.003*	−0.002*
	(0.007)	(0.002)	(0.001)
Durable goods value	0.011	0.001	0.004***
	(0.010)	(0.002)	(0.001)
Machinery value	−0.020***	0.004***	0.001
	(0.006)	(0.001)	(0.001)
Contract land	0.405***	−0.052*	−0.009
	(0.110)	(0.028)	(0.012)
Constant	−1.514***	0.971***	0.393***
	(0.291)	(0.080)	(0.045)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
σ_i		0.286***	0.227***
		(0.011)	(0.002)
ρ_i		−0.858***	−0.067
		(0.038)	(0.071)
Wald test of indep. eqns.	82.26***		
Log likelihood	−7867.219		
Observations	18,654	18,654	18,654

Note: The unit of observation is an individual. The robust standard errors clustered at the village level are shown in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. Data source: CFPS, 2014 and 2018.

The observed differences in how happiness and life satisfaction are affected suggest that these two measures of subjective well-being are not consistently influenced by the same factors. This reinforces the importance of using both measures. Aligning with Dolan and Metcalfe (2012) and Diener et al. (2018), the findings suggest that happiness tends to reflect emotional well-being, while life satisfaction encompasses a broader, evaluative perspective.

4.1.3. Results of the average treatment effects on the treated (ATT)

The results in Table 4 regarding ATT elucidate a significant enhancement in farmers' happiness and life satisfaction upon adopting

Table 4
ATT of AMS adoption on happiness and life satisfaction.

Variable	Mean outcome				ATT	Economic significance
	AMS Adopter		Non-adopter			Change in terms of S.D.
Happiness	0.745	(0.061)	0.701	(0.069)	0.044***	0.194
Life satisfaction	0.682	(0.093)	0.666	(0.096)	0.016***	0.065

Note: The table is calculated using ESR results from Tables 2 and 3. ATT, average treatment effect on the treated. Change in terms of S.D. is the proportion of the mean change in the dependent variable to its standard deviation associated with the AMS adoption status changing from 0 to 1. The standard deviation of happiness and life satisfaction is 0.227 and 0.245. The robust standard errors clustered at the village level are shown in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. Data source: CFPS, 2014 and 2018.

AMS, with effect sizes considerably larger than those depicted in Table 1. These effects are not only statistically significant but also economically meaningful. Specifically, the ATT in terms of happiness is 0.044 when switching from non-adopters to adopters of AMS, equivalent to a 0.194 standard deviation increase. Regarding life satisfaction, which encapsulates long-term and overall subjective well-being, the increase due to AMS adoption is 0.016, equivalent to a 0.065 standard deviation increase. Notably, these effect sizes are substantial and, in some cases, exceed those found in previous studies focused on indirect factors affecting subjective well-being. For instance, Zhang et al. (2017) found that air quality, measured by the air pollution index (ranging from 0 to 500 and represented by API/100), had a treatment effect size on happiness (rated on a scale of 0–4) ranging from 0.044 to 0.094 in China between 2010 and 2014. Han and Gao (2020)) observed an increase in life satisfaction (rated on a scale of 1–5) among recipients of China's rural subsistence allowance program between 2012 and 2014, with increase ranging from 0.061 to 0.093. Additionally, Lindqvist et al. (2020) reported a 0.037 standard deviation increase in life satisfaction from winning a $100,000 lottery in Sweden.

4.1.4. Robustness

To ensure the robustness of our main findings, we perform a series of empirical exercises. First, we include province-year fixed effects into our baseline specification to account for any unobserved trending variables that may vary by province-specific agricultural policies, as detailed in Panel A of Table A3. This adjustment did not significantly alter the ATT results, which remained consistent with our baseline estimates. Second, to mitigate potential reverse causality between subjective well-being and technology adoption, we use a lagged period of AMS adoption in Panel B of Table A3. In this case, happiness, life satisfaction, and control variables are from the 2018 CFPS data, while AMS adoption and the IV are from 2014. The positive effects of technology adoption on farmers' happiness and life satisfaction were reaffirmed, even though the effect size for life satisfaction increases significantly.

4.2. Heterogeneous analysis

To gain a deeper understanding of the impact of adopting AMS on various groups of farmers, we delve into the heterogeneous effects of AMS adoption on farmers' subjective well-being. Building on the findings in this study and the existing literature, which emphasizes the significance of labor endowments and farm sizes as determinants of agricultural technology adoption (see Kislev and Peterson, 1982; Feder et al., 1985; Mwangi and Kariuki, 2015), we segment the sample based on farmers' employment types and farm sizes, respectively. We re-estimate the ESR model and reported the calculated ATT in Table 5.

In Panel A of Table 5, the results reveal that adopting AMS has positive and statistically significant effects on farmers' happiness and life satisfaction, regardless of whether they have involved in off-farm employment. However, the effect size varies: the ATT for the off-farm group is larger than that for the on-farm group, indicating a greater increase in subjective well-being in the former group when AMS is adopted. The ATT results indicate that AMS adoption leads to a 0.052 increase in the happiness of on-farm individuals, which is equivalent to a 0.229 standard deviation increase, and a 0.077 increase for those engaged in non-farm employment, which is equivalent to a 0.339 standard deviation increase. A similar trend is observed for life satisfaction. The transition from non-adopters to adopters is associated with a significant 0.007 increase in life satisfaction, equivalent to a 0.029 standard deviation increase for on-farm individuals, and a 0.042 increase for non-farm employment individuals, equivalent to a 0.171 standard deviation increase. One possible explanation for these heterogeneous effects is that AMS adoption reduces the demand for seasonal on-farm labor, which in turn reduces the frequency of migration of farmers engaged in off-farm employment, ultimately enhancing their subjective well-being.

The study further examines the impact of technology adoption on farmers' happiness and life satisfaction, depending on whether or not they expand their farms by renting additional farmland.[11] The results presented in Panel B of Table 5 reveal that AMS adoption positively influences happiness, regardless of whether farmers have expanded their farms or not. Nonetheless, the influence varies significantly across subgroups: farmers who expanded their farms experience a larger increase in happiness (ATT increases by 0.076 and equivalent to a 0.330 standard deviation) compared to those who did not (ATT increases by 0.045 and equivalent to a 0.198 standard deviation). The increase in life satisfaction for farmers who have expanded their farms is statistically insignificant, while there is indeed a significant increase for those without expanded farms. Considering that expanded farms typically have larger operational sizes, these findings suggest that AMS adoption tends to enhance the subjective well-being of farmers managing relatively large farms over a relatively short period. This effect may be attributed to the fact that larger farms are more prone to on-farm labor shortages and thus stand to gain more from the labor-saving benefits provided by AMS compared to smaller farms, which primarily rely on family labor.

5. Mechanism analysis

The preceding section of the study highlighted the significant positive impact of adopting AMS on farmers' subjective well-being in China. We also observed variations in the effects of happiness and life satisfaction based on farmers' employment types and farm sizes. In this section, we aim to offer suggestive evidence to establish potential causal mechanisms that underlie this relationship. Consistent with the theoretical framework, we will investigate the roles of income (both absolute and relative incomes) and time allocation, particularly the leisure effect, to understand how AMS adoption influences farmers' subjective well-being. The regression equation is

[11] Considering that the initial farm size of Chinese farmers, i.e., the area of contract land, is similar within villages, farmers who rented in land means that the operational farm size is relatively large. We therefore use whether farmers rented in land as the cut-off of farm size.

Table 5
Heterogeneity in ATT of AMS adoption on happiness and life satisfaction.

Variable	Mean outcome				ATT	Economic significance
	AMS adopters		Non-adopters			Change in terms of S.D.
Panel A: Work type						
Happiness effects						
On-farm	0.741	(0.066)	0.689	(0.077)	0.052***	0.229
Off-farm	0.747	(0.074)	0.670	(0.095)	0.077***	0.339
Life satisfaction effects						
Farming	0.690	(0.097)	0.683	(0.102)	0.007***	0.029
Off-farm	0.677	(0.100)	0.635	(0.112)	0.042***	0.171
Panel B: Farm size						
Happiness effects						
Large farm	0.743	(0.083)	0.667	(0.141)	0.076***	0.330
Small farm	0.751	(0.073)	0.706	(0.098)	0.045***	0.198
Life satisfaction effects						
Large farm	0.676	(0.107)	0.672	(0.043)	0.005	0.020
Small farm	0.627	(0.084)	0.565	(0.097)	0.062***	0.253

Note: The table is calculated using ESR results for different subsamples. Panel A divides sub-samples by the cut-off of whether the farmer is involved in off-farm employment. Panel B divides sub-samples by the cut-off of whether the farmer rented-in land to expand farm size. The unit of observation is an individual. ATT is the average treatment effect on the treated. The fixed effects of year and county are controlled. Change in terms of S.D. is the proportion of the mean change in the dependent variable to its standard deviation associated with the AMS adoption status changing from 0 to 1. The standard deviation of happiness and life satisfaction is 0.227 and 0.245. The robust standard errors clustered at the village level are shown in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. Data source: CFPS, 2014 and 2018.

formulated as follows:

$$\boldsymbol{M}_{aihc,t} = \boldsymbol{D}_{ihc,t}\gamma_1 + \boldsymbol{X}_{ihc,t}\gamma_2 + \boldsymbol{X}_{hc,t}\gamma_3 + \boldsymbol{\delta}_t + \boldsymbol{\tau}_c + \boldsymbol{\omega}_{aihc,t} \tag{18}$$

where $\boldsymbol{M}_{aihc,t}$ represents the mechanism variables. The setting of $\boldsymbol{D}_{ihc,t}$, $\boldsymbol{X}_{ihc,t}$, $\boldsymbol{X}_{hc,t}$, $\boldsymbol{\delta}_t$ and $\boldsymbol{\tau}_c$ still same with Eqn. (13)–(17). $\boldsymbol{\omega}_{aihc,t}$ is random disturbance term associated with the outcome variables. γ_1, γ_2 and γ_3 are unknown parameters to be estimated.

5.1. Income mechanism: absolute income effect and relative income effect

Following the established literature that both absolute income and relative income are crucial for subjective well-being (Easterlin, 1974; Diener et al., 1993; Ferrer-i-Carbonell 2005; Perez-Truglia, 2020), our first set of mechanism analyses involve both. Particularly, absolute income is measured at the household level, including income from major livelihood activities of farmers in developing countries, such as farm income, off-farm income, and family business income. To measure relative income, we use an individual's perceived local income ranking, a method akin to approaches in McBride (2001), Clark and Senik (2010), and Noy and Sin (2021). The definition and descriptive statistics of these variables can be found in Panel A of Table A4 in the Appendix.

The income channels are estimated using the OLS estimation of Eq. (18), with the dependent variables being the absolute income and relative income, respectively. The results are presented in Panel A of Table 6.[12] The results indicate a positive but marginally significant correlation between AMS adoption and total family income, particularly through farm and off-farm income. Aligned with the absolute income effect outlined in the theoretical framework, these empirical results imply that the marginal net benefit of AMS adoption is positive. The positive effect of mechanization services on absolute income has also been found in South Asia and sub-Saharan Africa (Takeshima et al., 2013; Justice and Biggs, 2020). In addition, the study finds a negative effect of AMS adoption on relative income, suggesting a reduced perceived income ranking or increased perceived income inequality. This suggests that the relative income growth resulting from AMS adoption does not exceed the rate of increase in peers' income, which may partially offset the positive effects of AMS adoption on the subjective well-being of farmers.

In summary, the empirical evidence suggests that AMS adoption positively influences absolute income, mainly through farm income and off-farm income, yet may have a negative impact on relative income among farmers. Moreover, we present the results of ESR model and the calculated ATT without the inclusion of the income control variable (referred to as income per capita) in Appendix Tables A5-A8. This specification also captures the indirect effect of AMS working through income, though it can be problematic because the exclusion restriction for the instrument is arguably not valid here. Nonetheless, the findings are consistent with the baseline results in Tables 2–5.

5.2. Time allocation mechanism: leisure effect

The study also examines the role of time allocation in the relationship between technology adoption and farmers' subjective well-being, focusing on leisure activities. Existing studies showed positive correlations between subjective well-being and various leisure

[12] Note, we only report the results for the key independent variable – technology adoption – due to space limitations.

Table 6
Mechanism analysis: the impact of AMS adoption on income and time allocation.

Panel A: Income			
Total income	Absolute income	Relative income	
AMS adoption	0.052*	−0.039*	
	(0.030)	(0.020)	
Activity income	Farm income	Off-farm income	Business income
AMS adoption	0.290***	0.347***	0.011
	(0.108)	(0.123)	(0.079)
Panel B: Time allocation			
Paid work	Family farm	Off-farm	Family business
AMS adoption	−0.007	0.019**	0.008*
	(0.281)	(0.008)	(0.004)
Unpaid work	Household chores	Care grandchildren	Care parents
AMS adoption	−0.052	−0.202*	−0.138
	(0.037)	(0.107)	(0.087)
Leisure activities	Internet	TV & Movie	Reading
AMS adoption	0.197*	0.018	0.135
	(0.113)	(0.186)	(0.085)
Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: Panel A, unpaid work and leisure activities in Panel B report OLS estimates. Paid work in panel B employs Probit model since the dependent variables are dummies and marginal coefficients are reported. The unit of observation is an individual. The control variable of *income per capita* is highly consistent with the dependent variables for panel A, and is therefore excluded from panel A. Similarly, the control variable of *off-farm* is excluded in the regression with the dependent variable of off-farm in panel B. The robust standard errors are shown in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. Data source: CFPS, 2014 and 2018.

activities, such as watching television and surfing online (Brajša-Žganec et al., 2011; also see the meta-analysis in Kuykendall et al., 2015 and Wiese et al., 2018). Time-based data connects individuals reported subjective well-being to actual events that occurred in lives (Newman et al., 2014). In this study, time allocation is defined based on the work of Dong and An (2015) and includes three components: paid work, unpaid work, and leisure activities. Paid work encompasses participation in family farming, off-farm employment, and family business.[13] Unpaid work includes the amount of time spent on household chores and the frequency of caregiving for grandchildren and parents per week. Leisure encompasses weekly time spent surfing the internet, watching TV and movies, and annual reading. These components, detailed in Table A4 of the Appendix, help understand the impact of AMS adoption on farmers' time allocation.

Panel B of Table 6 presents the effects of AMS adoption on farmers' time allocation. First, the findings suggest that while AMS adoption marginally impacts on family farming engagement, it significantly increases participation in off-farm and family business activities. This indicates that technology adoption can facilitate farm households to reallocate more labor outside of farm. Second, AMS adoption has a negative and significant effect on the frequency of caring for grandchildren, possibly due to the reduced on-farm labor needs for grandparents. Finally, AMS adoption has a positive and significant effect on online activities, indicating technology adoption encourages farmers to allocate more time to leisure activities. Combined with findings that mobile internet use has a positive impact on the subjective well-being of older individuals in China (Lu and Kandilov, 2021), this suggests that increased leisure time is a key channel through which technology adoption affects farmers' subjective well-being.

In summary, the results suggest that AMS adoption enables farmers to allocate more time to paid work and leisure activities while reducing time spent on unpaid work. Therefore, the increase in absolute income and enhanced leisure time are both identified as important channels for increasing subjective well-being of farmers through technology adoption.

6. Conclusion

The study estimates the impact of technology adoption on farmers' subjective well-being, which is largely overlooked in the current literature. Utilizing the 2014 and 2018 CFPS data and employing an endogenous switching model, we find that farmers switching from non-adopters of AMS to adopters experience significant increase in happiness and life satisfaction. We also explore the heterogeneous impact of AMS adoption based on farmers' work types and farm sizes. The results indicate that those who engaged in off-farm employment or with expanded farm size benefit more in terms of happiness. Furthermore, our analysis identifies key mechanisms driving this enhanced subjective well-being, including increased absolute income, more leisure time, and less time spent on unpaid work.

The findings of this study suggest that the adoption of mechanization services effectively enhances the subjective well-being of

[13] The CFPS questionnaire did not contain information on the detailed time input for the different types of paid work. Therefore, a general measure, i.e., whether the farmer participated in each paid work, is used to reflect whether the farmer allocated time to this work.

farmers. This underscores the necessity for more research on the different technological advancements and their influence on farmers' subjective well-being. Understanding how various agricultural technologies affect farmers' subjective well-being is essential for developing countries to make informed decisions on technology diffusion. It is worth noting that our model and analysis are partial equilibrium in nature. To the extent that massive rural-urban migration induced by AMS adoption may lead to labor surplus and a decrease in equilibrium wage rate in the non-farm sector, this could influence the general equilibrium effect of AMS adoption. While this aspect falls outside the scope of our farmer-centric study, we believe it is an important avenue for future research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. There's no financial/personal interest or belief that could affect their objectivity.

Data availability

The authors do not have permission to share data.

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Appendix

Table A1
The correlation condition of the IV and the results of zero first stage test.

Variable	AMS adoption	Zero first stage	
		Happiness	Life satisfaction
Plain×MW	0.063***	0.014	0.007
	(0.016)	(0.014)	(0.006)
Age	0.001	0.005**	0.014
	(0.001)	(0.002)	(0.020)
Gender	−0.031*	−0.152***	−0.011***
	(0.016)	(0.047)	(0.003)
Education	0.009**	0.017**	0.056*
	(0.004)	(0.008)	(0.030)
Religion	0.181***	0.130*	0.060**
	(0.047)	(0.075)	(0.028)
Marriage	0.017	0.404***	−0.051*
	(0.033)	(0.070)	(0.026)
Off-farm	0.048	−0.089	−0.001
	(0.034)	(0.060)	(0.006)
Household size	0.009	0.049***	0.073
	(0.010)	(0.016)	(0.115)
Children ratio	0.264*	0.137	−0.036
	(0.152)	(0.235)	(0.083)
Dependency ratio	−0.125	0.178	0.050***
	(0.093)	(0.148)	(0.011)
Income per capita	0.020	0.167***	−0.006*
	(0.019)	(0.025)	(0.004)
Income sharing	0.017**	−0.006	0.018***
	(0.008)	(0.009)	(0.006)
Durable goods value	0.014	0.070***	0.003
	(0.011)	(0.014)	(0.003)
Machinery value	−0.021***	0.006	−0.026
	(0.006)	(0.008)	(0.047)
Contract land	0.448***	0.203	−0.031
	(0.113)	(0.155)	(0.047)
Constant	−1.679***	4.523***	2.576***
	(0.308)	(0.304)	(0.184)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
R^2	0.291	0.081	0.137
Observations	19,752	10,538	9,958

Note: The table reports Probit estimate in the second column and marginal coefficients. The last two columns are OLS regression of the IV direct effects on subjective well-beings of farmers without AMS adoption. The unit of observation is an individual. The robust standard errors adjusted for clusters in village are shown in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. Data source: CFPS, 2014 and 2018.

Table A2
Instrumental variables selecion with IVLASSO.

Variable	Definition	Mean	S.D.	LASSO coefficient
Panel A: high dimensionality instrumental variables				
MW	County minimum wage (RMB/month, log)	2.535	0.193	0.011
Plain	1, if plain; 0, otherwise	1.992	1.170	0.107
Plain×MW	Multiply the county minimum wage (RMB/month, log) by the dummy of whether the village topography is plain	5.857	6.658	0.858
Contract land	Contract land area at village level (mu)	3250.012	4284.573	−0.054
Panel B: Selection result				
Selected instrumental variable: Plain×MW				

Note: The unit of observation is an individual. 15 mu = 1 hectare. Data source: CFPS, 2014 and 2018. The last column of LASSO displays coefficients after lasso estimation results.

Table A3
Robustness tests: ATT of AMS adoption on subjective well-being.

Variable	Mean outcome AMS adopters		Non-adopters		ATT	Economic significance Change in terms of S.D.
Panel A: Added provinces by year fix effects						
Happiness	0.746	(0.063)	0.703	(0.071)	0.043***	0.442
Life satisfaction	0.681	(0.095)	0.671	(0.100)	0.010***	0.041
Panel B: Lagged technology adoption						
Happiness	0.747	(0.064)	0.707	(0.073)	0.040***	0.176
Life satisfaction	0.685	(0.080)	0.639	(0.088)	0.046***	0.187

Note: The table is calculated using ESR results for different equation settings. In panel A, the province-by-year fixed effects was added to control for any unobserved trending variables that could vary by province. In panel B, technology adoption is used from a lagged period of 2014 and the other variables are 2018. In panel C, the fixed effects are controled at household level. The unit of observation is an individual. The fixed effects of time and county are controlled in panel A and panel B. Change in terms of S.D. is the proportion of the mean change in the dependent variable to its standard deviation associated with the AMS adoption status changing from 0 to 1. The standard deviation of happiness and life satisfaction is 0.227 and 0.245. The robust standard errors clustered at the village level are shown in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. Data source: CFPS, 2014 and 2018.

Table A4
Mechanism variables definition and descriptive statistics.

Variable	Definition	Mean	S.D.
Panel A: Income			
Total income	Household total income (RMB/year), log	10.252	1.235
Relative income	Perceived rank of personal income: ranging from 1(much lower than average) to 5 (much higher than average)	2.764	1.059
Farm income	Household income from farm (RMB/year), log	6.748	4.023
Off-farm income	Household income from salaried jobs (RMB/year), log	5.727	4.938
Business income	Household income from own business (RMB/year), log	0.729	2.619
Panel B: Time allocation			
Paid work			
Family farm	1, if worked on family farm; 0, otherwise	0.738	0.440
Off-farm	1, if participated off-farm employment; 0, otherwise	0.234	0.424
Family business	1, if operated non-farm family business; 0, otherwise	0.036	0.186
Unpaid work			
Housework	Housework time for own family (hours/week)	2.516	2.162
Care grandchildren	Frequency of care grandchildren, ranging from 1 (once every few months) to 6 (almost every day)	5.152	1.441
Care parents	Frequency of care parents, ranging from 1 (once every few months) to 6(almost every day)	4.236	1.629
Leisure activities			
Internet	Spare time online (hours/week)	2.831	7.398
TV	Time spent watching TV and movies (hours/week)	10.634	9.458
Reading	Total reading (books/year)	0.810	7.138

Note: The unit of observation is an individual. 6.14RMB=1 dollar (2014 data) and 6.18RMB=1 dollar (2018 data). Data source: CFPS, 2014 and 2018.

Table A5
ESR results of AMS adoption and its impact on happiness, without control income.

Variable	Selection equation	Happiness

(*continued on next page*)

Table A5 (*continued*)

Variable	Selection equation	Happiness	
		AMS Adopters	Non-adopters
		AMS Adopters	Non-adopters
Plain×MW	0.060***		
	(0.016)		
Age	0.000	0.000	0.001**
	(0.001)	(0.000)	(0.000)
Gender	−0.034**	−0.008	−0.017***
	(0.016)	(0.005)	(0.005)
Education	0.009**	0.002***	0.002***
	(0.004)	(0.001)	(0.001)
Religion	0.181***	0.000	0.015*
	(0.045)	(0.007)	(0.008)
Marriage	0.021	0.021***	0.040***
	(0.032)	(0.008)	(0.007)
Off-farm	0.053	−0.002	−0.004
	(0.034)	(0.005)	(0.006)
Household size	0.003	0.005***	0.005***
	(0.009)	(0.002)	(0.002)
Children ratio	0.285*	−0.000	0.010
	(0.148)	(0.025)	(0.023)
Non-child dependency ratio	−0.136	0.017	0.019
	(0.090)	(0.017)	(0.015)
Income sharing	0.016**	−0.001	−0.000
	(0.007)	(0.001)	(0.001)
Durable goods value	0.015	0.009***	0.008***
	(0.011)	(0.002)	(0.001)
Machinery value	−0.019***	0.001*	0.001
	(0.006)	(0.001)	(0.001)
Contract land	0.472***	−0.020	0.011
	(0.118)	(0.017)	(0.016)
Constant	−1.486***	0.660***	0.573***
	(0.279)	(0.053)	(0.022)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
σ_i		0.212***	0.225***
		(0.003)	(0.002)
ρ_j		0.053	−0.133**
		(0.043)	(0.054)
Wald test of indep. eqns.	7.45**		
Log likelihood	−7892.971		
Observations	20,355	20,355	20,355

Note: The unit of observation is an individual. The robust standard errors clustered at the village level are shown in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. Data source: CFPS, 2014 and 2018.

Table A6
ESR results of AMS adoption and its impact on life satisfaction, without control income.

Variable	Selection equation	Life satisfaction	
		AMS Adopter	Non-adopter
Plain×MW	0.049***		
	(0.012)		
Age	−0.000	0.003***	0.002***
	(0.001)	(0.000)	(0.000)
Gender	−0.034**	0.005	0.003
	(0.016)	(0.006)	(0.005)
Education	0.007*	−0.004***	−0.002***
	(0.004)	(0.001)	(0.001)
Religion	0.191***	−0.012	0.014*
	(0.044)	(0.010)	(0.008)
Marriage	0.031	0.009	0.016**
	(0.034)	(0.009)	(0.007)
Off-farm	0.045	−0.013*	−0.010
	(0.032)	(0.007)	(0.006)
Household size	−0.001	−0.001	−0.001
	(0.008)	(0.002)	(0.001)
Children ratio	0.269*	−0.012	0.015
	(0.146)	(0.037)	(0.028)

(continued on next page)

Table A6 (*continued*)

Variable	Selection equation	Life satisfaction	
		AMS Adopter	Non-adopter
Dependency ratio	−0.133	−0.019	−0.007
	(0.102)	(0.027)	(0.020)
Income sharing	0.016**	−0.003*	−0.002**
	(0.007)	(0.001)	(0.001)
Durable goods value	0.012	0.002	0.006***
	(0.010)	(0.002)	(0.001)
Machinery value	−0.018***	0.004***	0.001
	(0.006)	(0.001)	(0.001)
Contract land	0.430***	−0.054**	−0.013
	(0.113)	(0.028)	(0.012)
Constant	−1.412***	0.968***	0.484***
	(0.262)	(0.067)	(0.038)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
σ_i		0.283***	0.228***
		(0.010)	(0.002)
ρ_i		−0.842***	−0.082
		(0.038)	(0.062)
Wald test of indep. eqns.	88.18***		
Log likelihood	−8148.229		
Observations	19,193	19,193	19,193

Note: The unit of observation is an individual. The robust standard errors clustered at the village level are shown in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. Data source: CFPS, 2014 and 2018.

Table A7
ATT of AMS adoption on happiness and life satisfaction, without control income.

Variable	Mean outcome				ATT	Economic significance
	AMS Adopter		Non-adopter			Change in terms of S.D.
Happiness	0.745	(0.060)	0.697	(0.067)	0.049***	0.216
Life satisfaction	0.680	(0.092)	0.658	(0.096)	0.022***	0.090

Note: The table is calculated using ESR results from Tables A5 and A6. ATT, average treatment effect on the treated. Change in terms of S.D. is the proportion of the mean change in the dependent variable to its standard deviation associated with the AMS adoption status changing from 0 to 1. The standard deviation of happiness and life satisfaction is 0.227 and 0.245. The robust standard errors clustered at the village level are shown in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. Data source: CFPS, 2014 and 2018.

Table A8
Heterogeneity in ATT of AMS adoption on happiness and life satisfaction, without control income.

Variable	Mean outcome				ATT	Economic significance
	AMS adopters		Non-adopters			Change in terms of S.D.
Panel A: Work type						
Happiness effects						
Farming	0.741	(0.065)	0.684	(0.074)	0.057***	0.251
Off-farm	0.747	(0.071)	0.676	(0.094)	0.071***	0.313
Life satisfaction effects						
Farming	0.689	(0.096)	0.669	(0.102)	0.020***	0.082
Off-farm	0.675	(0.099)	0.623	(0.113)	0.052***	0.212
Panel B: Farm size						
Happiness effects						
Large farm	0.743	(0.079)	0.657	(0.143)	0.086***	0.379
Small farm	0.751	(0.071)	0.711	(0.097)	0.040***	0.176
Life satisfaction effects						
Large farm	0.674	(0.107)	0.661	(0.139)	0.013***	0.053
Small farm	0.628	(0.081)	0.561	(0.096)	0.067***	0.312

Note: The table is calculated using ESR results for different subsamples. Panel A divides sub-samples by the cut-off of whether the farmer is involved in off-farm employment. Panel B divides sub-samples by the cut-off of whether the farmer rented-in land to expand farm size. The unit of observation is an individual. ATT, average treatment effect on the treated. The fixed effects of time and county are controlled. Change in terms of S.D. is the proportion of the mean change in the dependent variable to its standard deviation associated with the AMS adoption status changing from 0 to 1. The standard deviation of happiness and life satisfaction is 0.227 and 0.245. The robust standard errors clustered at the village level are shown in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. Data source: CFPS, 2014 and 2018.

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