Adaptation Potential of Farmers' Own Risk Management Strategies in Smallholder Agriculture: Some Evidence from India

Pratap Singh Birthal (ps.birthal@icar.gov.in)

National Institute of Agricultural Economics and Policy Research https://orcid.org/0000-0002-7287-6269

Jaweriah Hazrana

NCAP: National Centre for Agricultural Economics and Policy Research

Digvijay Negi

Indira Gandhi Institute of Development Research

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Pratap S Birthal (ps.birthal@icar.gov.in; psbirthal@yahoo.com)
ICAR-National Institute of Agricultural Economics and Policy Research, New Delhi, 110 012, India

Jaweriah Hazrana (jaweriah.harzana@gmail.com)
ICAR-National Institute of Agricultural Economics and Policy Research, New Delhi, 110 012, India

Digvijay S Negi(digvijay@igidr.ac.in; digvijaynegi12@gmail.com)
Indira Gandhi Institute of Development Research, Mumbai 400 065, India

Abstract

Farmers in developing countries are more exposed to frequent climatic shocks, and they, in the absence of a well-functioning market for crop insurance, rely on their own risk management strategies to reduce adverse effects of climatic shocks on agricultural production. This study evaluates adaptation benefits of farmers' own risk management strategies in Indian agriculture, and comes out four key highlights. One, farmers, based on their historical exposures to climatic shocks, resource endowments and access to information and credit, often use more than one risk management measure at a time. Two, all risk management strategies, including the mitigation, transfer and coping, contribute towards improving agricultural productivity and reducing downside risk exposure, but it is the risk mitigation strategy that is more efficient. Three, joint adoption of risk management strategies generates even larger adaptation benefits. Four, although joint adoption of these strategies is positively associated with farm size, with information and liquidity constraints relaxed probability of their joint adoption is likely to increase on smaller farms.

Keywords Risk management strategies, Agricultural productivity, Downside risk

JEL classification Q10, Q54, Q18

1 Introduction

Farmers' frequent exposure to climatic shocks is one of the main causes of low agricultural productivity, food and nutrition insecurity, and persistent poverty in developing countries (Bhandari et al. 2007, Hill and Mejia-Mantilla 2015, Duong et al. 2019, Hansen et al. 2019). For example, In India the negative rainfall shocks (or droughts) in India are found to reduce household income by 25-60% and increase head-count poverty by 12-33% (Bhandari et al. 2007). Similarly, the negative rainfall shock have been reported to reduce household consumption by 37% in Nigeria (Amare et al. 2018) and 15% in Uganda (Hill and Mejia-Mantilla 2015).

Further, poor people and poor economies suffer more from climatic shocks. Dell et al. (2012) show growth effect of climatic shocks highly negative for agriculture in developing countries than in developed countries. In India, climatic hazards have been found to reduce agricultural growth by about 25%, and the impact being larger in low-income and more agrarian states (Birthal et al. 2021). On the other hand, these lack access to financial resources, institutions and technologies for risk management (Hansen et al. 2019, Ali et al. 2020). Formal markets for crop insurance are underdeveloped (Binswanger-Mkhize 2012, Ali et al. 2020), that compel smallholder farmers to use their own risk management strategies (Mendelsohn 2010) such as the diversification into high-value and stress-tolerant crops, animal husbandry and non-farm activities; climate-resilient agronomic practices; out-migration, borrowings and sale of assets (Deressa et al. 2010, Kakraliya et al. 2018, Birthal and Hazrana 2019, Collins-Sowah and Henning 2019, Aryal et al. 2020). Based on an extensive review of empirical literature, Altieri and Nicholls (2013) conclude that smallholder farmers use a number of traditional

52 strategies to deal with climate variability, and it is now increasingly recognized that a
53 combination of traditional practices and scientific innovations is a robust path to increase
54 productivity, sustainability and resilience of smallholder agriculture.

55 Several studies have assessed adaptation potential of traditional risk management measures,
56 but most of these focus either one or two measures, while in practice farmers use multiple
57 measures at a time (Jodha et al. 2012, Amondo et al. 2019). Only a few studies have
58 investigated adaptation benefits of multiple risk management measures (Kassie et al. 2014,
59 Teklewold et al. 2017, Vigani and Kathage 2019, Collin-Sowah and Henning 2019, Amondo et
60 al. 2019). This study assesses adaptation benefits of farmers' own risk management strategies
61 in India[1] utilizing information from a large-scale nationally representative farm survey (GoI
62 2015). The survey, although, not targeted at risk management, provides useful information
63 on several farm and non-farm activities that provide farmers a cushion against climatic and
64 non-climatic shocks. We identify such activities from this survey, and based on their risk
65 functions classify these into risk avoidance/mitigation, risk transfer and risk coping strategies.

66 The study employs multinomial endogenous switching regression technique, and finds that
67 (i) often the farmers adopt more than one risk management measure at a time, and (ii) the
68 mitigation-based measures more efficient at reducing risk and improving agricultural
69 productivity, but their joint adoption along with risk transfer and coping measures generates
70 even larger adaptation benefits. These findings have two important policy implications. One,
71 these serve as a guide for farmers to take informed decisions on the choice of different risk
72 management measures. Two, at policy level the evidence on the productivity-risk tradeoffs

[1] More than 86% of the landholdings in India are of size less than or equal to two hectares.

between risk management strategies provides a feedback to policymakers to identify efficient and inclusive adaptation measures and mainstream these into the risk management policy.

Rest of the paper is structured as follows. Following section describes data sources, and section 3 discusses empirical approach. Section 4 provides descriptive statistics of the variables that may differentiate farmers in their choice of risk management strategies and their outcomes. The factors influencing farmers' choice of risk management strategies and their adaptation benefits are presented in section 5, and section 6 discusses these in relation to the available empirical evidence. Concluding remarks are made in the last section.

2 Data sources

The study utilizes data from a large-scale nationally representative farm survey conducted in 2012-13 by the National Sample Survey Office (NSSO) of the Government of India (GoI 2015). The survey collected information from 35200 households spread throughout the country. It provides information on several aspects of farming and farm households, including the area under crops, their outputs and monetary values; landholding size, land-lease; irrigation; livestock ownership and sales; participation in labor markets and non-farm activities; and agricultural information, institutional credit and crop insurance. We exploit this survey to identify important agricultural practices that farmers follow as a part of their farm management and livelihoods, but also provide a cushion against climatic shocks.

To understand farmers' adaptive response to climate shocks, the household-level variables are integrated with climate variables (i.e., precipitation and temperature) at district-level. The climate data have been extracted from the gridded data on daily minimum and maximum temperature (at 0.5 x 0.5 grid) and precipitation (at 0.25 x 0.25 grid) sourced from the India

Meteorological Department (IMD), Ministry of Earth Sciences, Government of India. We derive district-level estimates of climate variables assigning each weather station to a district whose centroid is nearest to it, and then calculate average of the concerned variable recorded at all the weather stations assigned to the district. Our climate dataset pertains to the period from 1980 to 2011, and from this we estimate positive and negative deviations in temperature and rainfall from their respective historical means.

Literature shows that farmers adopt several measures of risk management (see, Birthal and Negi 2012, Amare et al. 2018, Birthal et al. 2019, Call et al. 2019, Birthal and Hazrana 2019, Duong et al. 2019, Hansen et al. 2019), and based on their risk functions these can be categorized as (i) risk mitigating, (ii) risk transferring, and (iii) risk coping. From the farm survey data, we identify diversification into high-value crops, animal husbandry and non-farm business activities as important risk mitigation measures. Crop insurance and renting-out land to comprise our risk transfer strategy. Guaranteed wage employment, out-migration, remittances and livestock sales are found as important risk coping measures. A few of these have been in use traditionally as component of farm management, while others might have been adopted instantaneously in response to a climatic shock.

3 Empirical approach

A risk-averse will adopt a risk management measure if it the expected utility from its adoption is higher than without its adoption. Further, given the resource endowment, he/she will choose amongst the available measures the one that provides higher expected utility. Since risk management measures are adopted *a priori* without knowing their actual outcomes, these can be expressed as an *ex-ante* comparison of their expected utilities (Koundouri et al. 2006, Mukasa 2018). Thus, the farmer chooses a measure from the available alternatives, j =

1, ..., N, that maximizes his/her expected utility, i.e., $\mathrm{E}[\mathrm{u}(\mathrm{k})] = \int \mathrm{kf}(\mathrm{k})\mathrm{u}(\mathrm{k})$; where $\mathrm{u}(\mathrm{k})$ is a real-valued function that represents the utility from measure k, and $\mathrm{f}(\mathrm{k})$ is the probability density function of k.

Following recent literature (e.g., Di Falco and Veronesi 2013, Teklewold et al. 2013, Kassie et al. 2015, Teklewold et al. 2017) this study employs multinomial endogenous switching regression (MESR) technique to evaluate adaptation potential of different risk management strategies. MESR belongs to the category of instrumental variable (IV) approaches that correct for the unobserved heterogeneity and the selection bias in the outcome generating process (Bourguignon et al. 2007, Vigani and Kathage 2019).

MESR is a two-step econometric procedure. It first evaluates the choice of a measure *j* from *N* mutually exclusive measures, i.e., *j = 1, ..., N*. Assuming that the choice of a risk management measure is a function of exogenous variables, and all the observations are independent, the expected utility from adoption of multiple measures can be defined by a latent variable Y_{ij}^* as:

$$Y_{ij}^* = \boldsymbol{C_i \alpha_j} + \xi_{ij} \qquad \ldots (1)$$

$$Y_i = \begin{cases} 1 \;\; iff \;\; Y_{i1}^* > \max_{k \neq 1}(Y_{ik}^*) \;\; \text{or} \;\; \varepsilon_{i1} < 0 \\ \;\; \vdots \;\; \vdots \qquad\qquad \vdots \\ N \;\; iff \;\; Y_{iN}^* > \max_{k \neq N}(Y_{ik}^*) \;\; \text{or} \;\; \varepsilon_{iN} < 0 \end{cases} \qquad \ldots (2)$$

Where, $\varepsilon_{ij} = \max_{k \neq j}\left(Y_{ik}^* - Y_{ij}^*\right) < 0$, that is, the farmer *i* selects measure *j* if it provides more utility than an alternative measure *k*; and $k \neq j$.

In selection equation, $\boldsymbol{C_i\alpha_j}$ is the deterministic component that influences probability of choosing measure *j* through observable household characteristics and/or risk factors. ξ_{ij}, is an idiosyncratic stochastic component that captures effect of unobservable factors.

Parameters of the latent variables in Eq. (1) are estimated using maximum likelihood estimator (MLE). Under the assumption that ξ_{ij} is identically and independently Gumbel distributed the probability that farmer *i* with a set of characteristics $\boldsymbol{C_i}$ adopts measure *j* can be specified as a multinomial logit function:

$$P_{ij} = P\left(\varepsilon_{ij} < 0 | \boldsymbol{C_i}\right) = \frac{\exp\left(\boldsymbol{C_i\alpha_j}\right)}{\sum_{k=1}^{N} \exp\left(\boldsymbol{C_i\alpha_j}\right)} \qquad \ldots (3)$$

Equation (3) assumes independence of irrelevant alternatives (IIA), i.e., probability of choosing a measure is independent of other measures. Bourguignon et al. (2007) show that a multinomial logit function provides robust selection bias correction for outcome equation even if the assumption of IIA is violated.

In its second step, MESR generates bias-corrected outcomes. With multiple adaptation measures, the vector of outcome variables is assumed to be a linear function of the explanatory variables. Hence, the stochastic function to evaluate outcome of each measure can be expressed as:

$$\begin{cases} Regime\ 1: & I_{i1} = \boldsymbol{X_i\beta_i} + u_{i1} \quad if \;\; Y_i = 1 \qquad \ldots (4a) \\ \quad \vdots & \qquad\qquad\qquad \vdots \\ Regime\ \mathrm{N}: & I_{iN} = \boldsymbol{X_i\beta_N} + u_{iN} \quad if \;\; Y_i = \boldsymbol{N} \qquad \ldots (4n) \end{cases}$$

Where, I_i is the outcome variable for regime 1 to N, $\boldsymbol{X_i}$ is a vector of exogenous variables that impact the outcome, and u_i is the random error term.

If error terms in selection and outcome equations are correlated, then OLS estimates of Eq. (4) are inconsistent. The MESR takes into consideration correlation between error terms (Bourguignon et al. 2007). The correction for endogenous selection of risk management measures can be expressed as:

$$\begin{cases} Regime\ 1: \quad I_{i1} = \boldsymbol{X_i\beta_i} + \sigma_1\lambda_1 + \theta_{i1} \quad if\ \ Y_i = 1 & \ldots(5a) \\ \quad \vdots \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \vdots \\ Regime\ \mathrm{N}: \quad I_{iN} = \boldsymbol{X_i\beta_N} + \sigma_N\lambda_N + \theta_{iN} \quad if\ \ Y_i = N & \ldots(5\mathrm{m}) \end{cases}$$

Where, σ_j is the covariance between ε_i and u_i, θ_i is an error term with an expected value of zero, and λ_j is the inverse Mills ratio (IMR) estimated from the probabilities generated from Eq. (3).

A single selectivity correction term is generated for each risk management measure, and it is included in the relevant outcome equation. To account for the possible heteroscedasticity due to λ_j the standard errors in Eq. (5) are bootstrapped.

The proper identification of MESR requires that order condition to be satisfied, i.e., vector $\boldsymbol{C_i}$ should contain at least one variable that is not included in vector $\boldsymbol{X_i}$. The additional variables serve as instruments, i.e., these are correlated with farmer's adoption of a risk management measure, and not with its outcome.

The estimates of MESR are utilized to calculate average treatment effects (ATT) on the treated. For the purpose, we construct the following counterfactuals for the treated, i.e., those who had adopted a risk management measure:

Adopters with adoption (actual adoption in the sample):

$$E(I_{iN\neq1}|Y_i = N_{\neq1}) = \boldsymbol{X_i\beta}_{N\neq1} + \sigma_{N\neq1}\lambda_{iN\neq1} \quad \ldots (6a)$$

Non-adopters without adoption (actual non-adoption in the sample):

$$E(I_{1i}|Y_i = 1) = \boldsymbol{X_i\beta}_1 + \sigma_1\lambda_{i1} \quad \ldots (6b)$$

Adopters deciding not to adopt (counterfactual):

$$E(I_{1i}|Y_i = N_{\neq1}) = \boldsymbol{X_i\beta}_1 + \sigma_1\lambda_{iN\neq1} \quad \ldots (6c)$$

Non-adopters deciding to adopt (counterfactual):

$$E(I_{iN\neq1}|Y_i = 1) = \boldsymbol{X_i\beta}_{N\neq1} + \sigma_{N\neq1}\lambda_{i1} \quad \ldots (6d)$$

Équations (6a) and (6b) respectively provide expected utility for adopters and non-adopters of a risk management measure, and Eq. (6c) and (6d) the corresponding expected utility for counterfactual cases. The expected outcomes are then used to obtain unbiased treatment effects on the treated, i.e., the difference between Eq.(6a) and Eq.(6c).

$$ATT = E(I_{iN\neq1}|Y_i = N_{\neq1}) - E(I_{1i}|Y_i = N_{\neq1}) = \boldsymbol{X_i}(\boldsymbol{\beta}_{N\neq1} - \boldsymbol{\beta}_1) + \lambda_{1i}(\sigma_{N\neq1} - \sigma_1) \quad \ldots (7)$$

Our outcome variables are the agricultural productivity (measured as the value of output per hectare of cropped area), and its higher-order moments, i.e., variance and skewness (Antle1983, Di Falco and Chavas 2009).

4 Descriptive statistics

Table 1 shows frequency distribution of risk management measures. Risk mitigating measures are the most exploited — over 62% of the farm households practiced animal husbandry, 31% cultivated horticultural crops (i.e., vegetables, fruits, spices, medicinal and aromatic plants), and 5% had owned non-farm business activities. Adoption of risk transfer measures is extremely limited — 6.3% had purchased a crop insurance contract, and 4.1% had rented-out land.

Farmers also adopt the measures that help them absorb or recover from the risk impacts. Out-migration (defined as staying-away of a household-member from his/her permanent residence at least for 15 day-employment), was reported by 6.7%, and receipt of remittances by 10.6% of the households. Livestock sales were limited to only 2.3% of the households. Wage employment is one of the means of consumption smoothening during an agricultural crisis. The Government of India implements a country-wide employment scheme known as Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) that provides guaranteed employment of 100 days to a willing household. About 13% of the households had availed benefits of this scheme. This scheme is not designed for risk management, yet it helps its participants to cope with climatic shocks (Fischer 2020). Other risk coping measures too do not directly influence farm performance, but these ease liquidity constraints on the adoption of direct risk management measures (Hansen et al. 2019).

Most farm households had adopted more than one measure at a time. Based on similarity of their risk functions these are grouped as: (i) risk mitigating, (ii) risk transferring, and (iii) risk coping. These strategies are combined to know the extent of their joint adoption (Table 2). Overall, 85% households had adopted one or other measure. Risk mitigation was a common

212 strategy — it was adopted by more than three-fourths of the households, either alone or in
213 conjunction with other strategies. Risk coping strategy was adopted by 31% households and
214 mostly in conjunction with risk mitigation measures. Risk transfer strategy was limited to one-
215 tenth of the households.

216 To have an idea about the adaptation potential of different risk management strategies, first
217 we look at unconditional kernel density of agricultural productivity under different adaptation
218 regimes (Figure 1). Distribution of agricultural productivity under risk mitigation and transfer
219 strategies and also their joint adoption is skewed towards right, which indicates that these
220 have potential to reduce downside risk exposure.

221 Table A1 (in the appendix) compares means of key characteristics of adopters and non-
222 adopters of risk management strategies. There are three sets of variables. The first set
223 includes the risk characteristics as represented by standardized deviations of rainfall and
224 temperature from their respective long-term means. The second set includes the
225 demographic (i.e., household size, age, gender and education) and institutional (i.e., access
226 to credit, information and social safety nets, and awareness of the government-determined
227 minimum support prices) characteristics that are anticipated to influence farmers' attitude
228 towards risk, and thus their choice of a risk management strategy (Cole et al. 2013). Social
229 networks may also differentiate them in their adoption decisions (Negi et al. 2020). Caste is
230 an important form of social network in India. Broadly, there are four broad caste groups, viz.,
231 scheduled castes (SC), scheduled tribes (ST), other backward castes (OBCs) and upper or other
232 castes, with SC/ST at the bottom of hierarchy and upper caste at the top. The third set includes
233 the farm and location characteristics, viz., farm size, irrigation status, crop portfolio (number
234 of crops grown), and slope and altitude of the districts. Farm size and irrigation shape farmers'

attitude towards risk, directly or mediated through crop yields. Sherrick et al. (2004) find that the larger the farms, the lesser is the requirement for risk management. Irrigation, besides its yield-enhancing role, also reduces the requirement for risk management (Birthal et al. 2015).

Further, we also control for the unobserved heterogeneity across farms by including the means of important inputs, viz, fertilizers, seeds, pesticides and labor in our econometric model.

A comparison of the characteristics of non-adopters and adopters of risk management shows that a larger proportion of the adopter-households is headed by the females and the older persons, rank higher in social status and have larger families. Their landholding size is larger and crop portfolio is more diversified. Other factors that differentiate adopters from non-adopters is their better access to information and institutional credit, and awareness about minimum support prices (MSP).

MESR requires correction of selection bias through an instrumental variable (IV) which is correlated with adoption of a strategy but not with its outcome. Following the extant literature (e.g., Di Falco et al. 2011, Di Falco and Veronesi 2014, Kassie et al. 2015) we include farmers' training in agriculture and their net asset position as the instruments. All variables (except dummies and proportions) are transformed into their log equivalents.

The selection of instrumental variables is validated by estimating OLS and multinomial logit equations, and the test-statistics (Table 3) confirms appropriateness of our selected instruments. Further, we also conduct an exogeneity test and estimate two-stage least square (2SLS) and generalized method of moments (GMM) (Table 4). The Durbin and Wu-Hausman

256 tests for the 2SLS, and C-statistic for the GMM could not reject the null hypothesis that
257 selected instruments are exogenous. The full set of the results are given in Tables S1 and S2.

258 **5 Results**

259 **5.1 Determinants of adoption of risk management strategies**

260 'No risk management' is the base category in our selection equations; hence, the regression
261 coefficients need to be interpreted in relation to it. Table 5 presents estimates of the
262 selection equations. The diagnostics show a good fit of the model. The Wald statistic is highly
263 significant, rejecting the null hypothesis that regression coefficients are jointly equal to zero.
264 The chi-squared test for the joint significance of instruments is also significant.

265 In most selection equations, regression coefficient on the negative as well as positive rainfall
266 deviations is significant but opposite in direction — positive on deficit rainfall, and negative
267 on excess rainfall. The probability of joint adoption of risk management strategies is higher in
268 case of both the positive and negative deviations in temperature. These results suggest that
269 farmers' adaption decisions are driven by their historical exposures to climatic shocks.

270 Farm size has a positive and significant effect on the adoption of most risk management
271 strategies. This means that the larger the farm size, the higher is the farmers' risk taking
272 capacity. It should be noted that farm activities such as horticulture and animal husbandry
273 are labor-intensive, while large farmers are less-endowed with labor, discouraging them to
274 adopt labor-intensive activities. Our finding is contrary to that of Sherrick et al.(2004) who
275 find that larger farms have less requirements for risk management.

276 Irrigation discourages adoption of risk management, as is suggested by its negative sign in
277 most selection equations. The number of crops grown have a mixed effect on farmers' choice

278 of risk management strategies. For example, adoption of a more diverse crop portfolio
279 discourages use of risk coping and risk transfer strategies, but motivates adoption of risk
280 mitigating strategy.

281 The influence of the household-level factors is as expected. The probability of adoption
282 increases with age and education of household-heads. Further, female-headed households
283 are more conscious towards risk management probably because of their greater concern for
284 household food security. Household size (i.e., availability of labor) too has a positive and
285 significant influence on the adoption of risk management strategies. Further, the probability
286 of adoption of most risk management strategies is higher among the lower-caste households.

287 The coefficient on information and institutional credit is consistently positive and significant
288 across all risk management strategies and their portfolios. This implies that with information
289 and liquidity constraints relaxed, the probability of adoption of risk management strategies
290 would increase. So, does the farmers' awareness about MSP. It should be noted that the
291 Government of India procures farm commodities, mainly paddy and wheat, at their minimum
292 support prices. This insulates farmers from price fluctuations and also acts as an incentive to
293 adopt new technologies and agronomic practices. On the other hand, the household's access
294 to food security nets[2] seems to reduce the requirements for risk management.

[2] The Government of India implements the National Food Security Act, 2013 that provides an affordable access to food to about two-thirds of the country's population. Presently, an eligible household can purchase his/her entitlement of food from the public distribution system at heavily subsidized prices, i.e., rice at Rupees 3/kg and wheat at 2/ kg.

295

296

297 **5.2 Adaptation benefits of risk management strategies**

298 Regression estimates of the outcome equations are presented through Tables A2-A4 (in the
299 appendix). The bias correction term is statistically significant in most outcome equations,
300 indicating that bias correction was important in our analysis.

301 A few factors that influence farm performance merit attention. In all outcome equations,
302 agricultural productivity is positively influenced by irrigation, information and institutional
303 credit; and negatively by farm size and food security nets. Irrigation, crop counts, and
304 information are found to reduce variance in it, while farm size, institutional credit and food
305 security nets increase it. A positive sign on a variable in skewness function means a reduction
306 in downside risk exposure. We find farm size, irrigation, credit and food security nets to
307 reduce downside risk exposure.

308 Table 5 presents adaptation benefits of different risk management strategies. All risk
309 management strategies lead to an improvement in agricultural productivity. Risk mitigation
310 strategy, however, causes a larger improvement (25%) compared to risk transfer (14%) and
311 the risk coping (10%). Nonetheless, their joint adoption, in general, has a larger potential to
312 enhance agricultural productivity.

313 All the risk management strategies, individually or jointly, also contribute towards reducing
314 variance in agricultural productivity, and the reduction is larger in case of their joint adoption.
315 Further, joint adoption of all the strategies (e.g., MTC) causes the highest reduction in

316 downside risk exposure (16%). These findings clearly demonstrate that joint adoption of risk
317 management strategies is more efficient at improving agricultural productivity and reducing
318 downside risk exposure.

319

320 **6 Discussion**

321 Do our estimates match with those reported in the literature? In Ethiopian context, Di Falco
322 and Veronesi (2014) treating use of multiple risk management measures as a single binary
323 indicator in their econometric analysis demonstrate that these reduce downside risk
324 exposure. Similarly, Shahzad and Abdulai (2019) find that in Pakistan the adaptation to
325 climate change reduces downside exposure to risk, but does not influence much the returns
326 from farming.

327 Yesuf et al. (2009) considering chemical fertilizers and soil-water conservation technology as
328 important adaptations to climate change in Ethiopian agriculture find fertilizers to reduce
329 variance but increasing downside risk exposure; and soil-water conservation reducing
330 downside risk exposure but no significant impact on variance. The adoption of drought-
331 tolerant maize is found efficient at improving yield and reducing downside risk in Nigeria and
332 Zambia (Wossen et al. 2017, Amondo et al. 2019).

333 A few studies have also investigated the impact of joint adoption of different risk
334 management measures or strategies. Kassie et al. (2015) demonstrate higher yield and risk
335 benefits from the joint adoption of crop diversification and minimum tillage practices in
336 Malawi. Similar evidence is reported by Issahaku (2020) from the joint adoption of crop
337 diversification and soil-water conservation technology in Ghana. In Ehiopia, Teklewold et al.

338 (2017) find joint adoption of water management, improved varieties and fertilizers being
339 more efficient at improving yield and reducing downside risk exposure in maize.

340 On the other hand, some studies provide a mixed evidence on the impact of joint adoption of
341 risk management measures. Vigani and Kathage (2019) in their assessment of the impact of
342 crop insurance, production contract, production diversification and crop variety, and their
343 portfolios on total factor productivity of wheat in France and Hungary report their positive as
344 well negative impacts on downside risk exposure. They find larger negative impacts in the
345 case of more complex risk management portfolios. Collins-Sowah and Henning (2019) too
346 report similar evidence from Senegal.

347 The ambiguity in the impacts of different risk management strategies is probably due to the
348 context specificities in the probability of occurrence of climatic shocks and farmers' risk
349 preferences. Evidently, most of the above mentioned studies are location-specific based on
350 small samples. Our results are based a large dataset that allows us to control for spatial
351 contexts. Further, it covers fairly a large number of measures of risk management that are
352 typical of smallholder agriculture where farmers due to lack of a market for crop insurance
353 often use their own risk management measures, knowingly or unknowingly, as a part of their
354 farm Our findings support the claim that in smallholder agriculture a combination of
355 traditional practices and scientifically sound innovations is a robust path to increase
356 productivity, sustainability and resilience of agriculture (Altieri and Nicholls 2017).

357 **7 Conclusions and implications**

358 This study has evaluated the adaptation potential of farmers' own risk management
359 strategies. It highlights four key findings. One, farm households, based on their historical
360 exposure to climatic shocks use several risk management measures and often more than one

361 at a time. Two, although farmers benefit from all risk management strategies, the risk
362 mitigation strategy generates relatively larger adaptation benefits. Three, joint adoption of
363 different risk management strategies provides even higher adaptation benefits than do the
364 individual strategies. Four, joint adoption of risk management strategies is positively
365 associated with farm size. However, with information and liquidity constraints relaxed the
366 smallholder farmers will go for adoption of multiple risk management strategies.

367 These results offer an important insight into the ways the farm households manage
368 production risks and have some important policy implications. These findings can serve as a
369 guide for farmers to take informed decisions on the use of different risk management
370 measures subject to their risk preferences and resource constraints. At policy level, the
371 evidence on productivity-risk tradeoffs between different risk management strategies
372 provides an important feedback to policymakers to identify economically more efficient and
373 inclusive risk management measures and mainstream these into agricultural research and
374 development policies, especially when the uptake of crop insurance is poor.

375

376 **Declarations**

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Availability of data and material: The data are available in the public domain and can be obtained at cost from the concerned agencies as indicated in the section on Data sources in this manuscript.

Code availability: Authors shall be happy to share the software codes.

Authors' contributions:

Dr Pratap Singh Birthal conceptualized and the idea and developed it for its implementation by the team, and wrote the manuscript.

Dr Jaweriah Hazrana compiled the data and undertook the required econometric analysis.

Dr Digvijay Singh Negi helped refine the econometric results and write-up of the manuscript.

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Figures

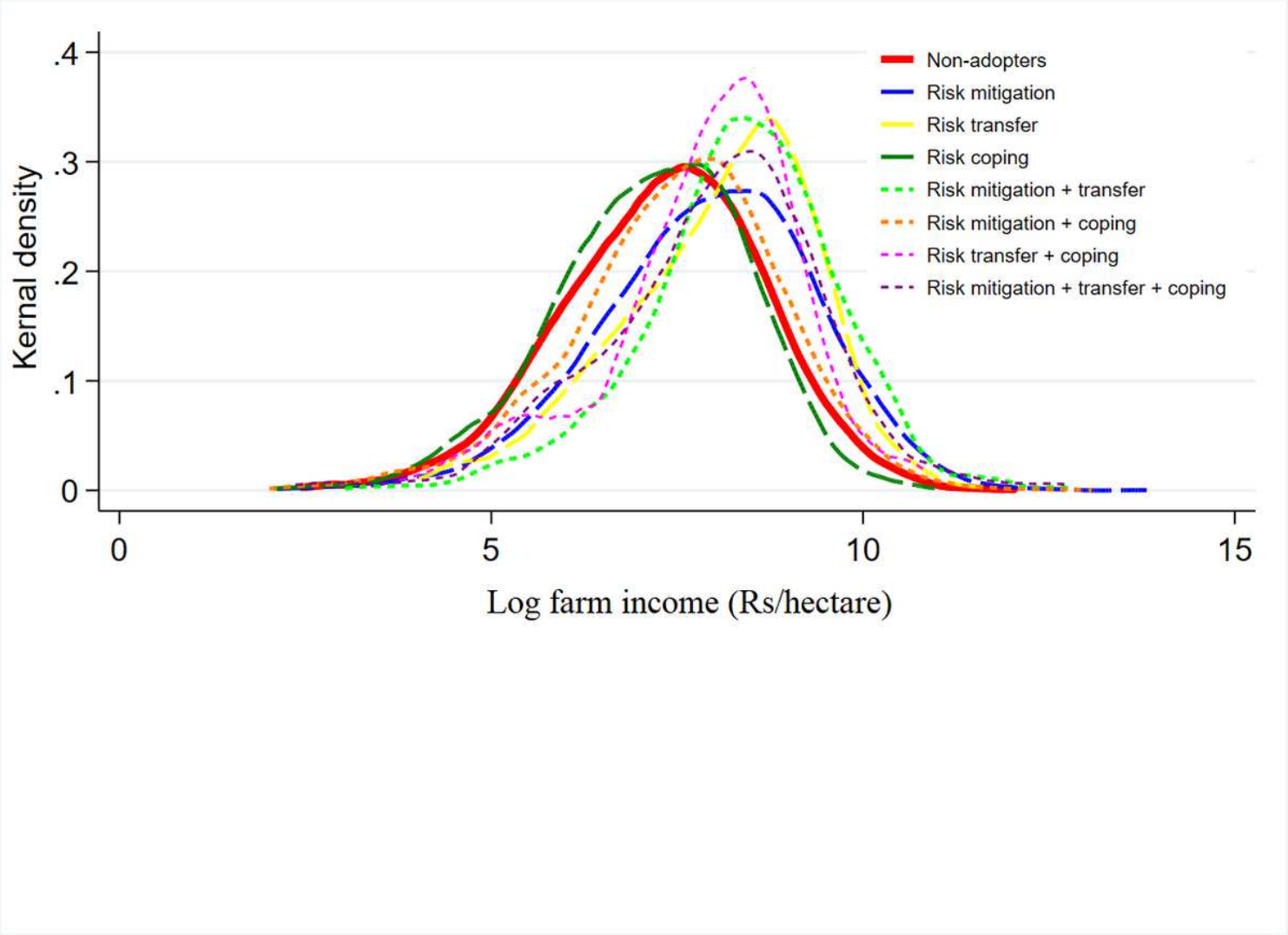

Figure 1

Unconditional kernel densities

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