The Australian Journal of
Agricultural and
Resource Economics

Australian Journal of Agricultural and Resource Economics, 63, pp. 866–880

Farmers' constraints, governmental support and climate change adaptation: Evidence from Guangdong Province, China*

Ying Xu and Christopher Findlay†

While climate change is widely acknowledged, the role of government support in adaptation is less understood. We narrow this knowledge gap by modelling adaptation as a three-stage process where a farmer sequentially decides: (i) whether there is a need for adaptation; (ii) whether there are constraints that prevent adaptation; and (iii) whether such constraints are removed through government support. We develop a triple-hurdle model to describe this decision-making process and empirically estimate the impact of government support using a rural household survey from Guangdong Province, China. It is found that government support is positively associated with raising the odds of adaptation by about one quarter. This magnitude is larger than the estimates in recent literature, suggesting government support is more effective for farmers bound by constraints. Therefore, for cost-effective policy outcomes there is a need to identify the constraints and the farmers facing them.

Key words: China, climate change adaptation, constraint, governmental support, triple-hurdle model.

1. Introduction

Climate change defined in terms of increasing numbers of extreme events has profound impacts on agricultural production (Mendelsohn and Dinar, 1999; Howden *et al.,* 2007; Lobell *et al.,* 2008). While the need for adaptation is widely recognised, economic incentives behind adaptation decisions are less explored beyond aggregate-level cost–benefit analyses (Few *et al.,* 2007; Agrawala *et al.,* 2008; Tompkins *et al.,* 2008). Climate change adaptation, by adopting specific technologies to hedge against climate risks, incurs direct costs for farm households. Usually, the lack of resources (credit, information, etc.) is found to impede technology adoption in developing countries (Croppenstedt *et al.,* 2003; Shiferaw *et al.*, 2015). While strategies to encourage climate change adaptation have been widely called for (Adger

* This work was funded by the Australian Centre for International Agricultural Research under the project 'Assessing Farmer Responses to Climate Change-Adjustment Policy Options' (ADP/2011/039). Thanks to staff at the Center for Chinese Agricultural Policy for access to the data used here, especially Kaixing Huang. There is no conflict of interest between the co-authors.

† Ying Xu (email: ying.xu03@adelaide.edu.au) is research fellow at Centre for Global Food and Resources, University of Adelaide, Adelaide, South Australia, Australia. Christopher Findlay is professor at Faculty of the Professions, University of Adelaide, Adelaide, South Australia, Australia.

doi: 10.1111/1467-8489.12321

et al., 2009; World Bank, 2010), how government support affects household adaptation decisions is not well understood. This information is needed since households are the primary units of agricultural production in many developing countries, and the impact of governmen support will both suggest the cost-effectiveness of existing interventions and assist future policy designs in this regard.

Empirical studies of household climate change adaptation have explored the roles of potential factors using discrete choice modelling (Chen *et al.,* 2014; Wang *et al.,* 2015; Van Aelst and Holvoet, 2016). Simple application of discrete choice models, relies on the assumptions that farmers have full information about the adaptation procedure(s) as well as unconstrained access to required resources (Feder *et al.,* 1985). Neither assumptions receive enough consideration in this literature, yet the violation of them would result in corner solutions and inconsistent coefficient estimates as the zero-generation process cannot correctly capture farmers' unwillingness to adapt (Shiferaw *et al*., 2015). This issue is not trivial as in many developing countries, smallholders lack access to resources needed for adaptation even if they intend to adapt (Croppenstedt *et al.,* 2003). A few technology adoption employ double-hurdle models to investigate adoption decisions under constraint (Croppenstedt *et al.,* 2003; Shiferaw *et al.,* 2008). These studies, being knowledge-advancing, generally focus on the single most important constraint. However, a farmer may face multiple constraints, and all of them need to be removed to stimulate adaptation. These knowledge gaps directly motivate the current study.

We build a triple-hurdle model that considers a farmer's adaptation decision as a three-stage process where a farmer sequentially decides: (i) whether there is a need for adaptation; (ii) whether there are constraints that prevent adaptation; and (iii) whether such constraints are removed through government support. It addresses the possible lack of information, the existence of constraint(s), and the role of government support in removing the constraint(s) and thus stimulating adaptation. We apply the modelling framework to China, where climate change has had profound impacts on agricultural production, and further research especially regional-level modelling is urgently called for (Challinor *et al.,* 2010; Piao *et al.,* 2010). Unlike other technologies such as improved crop varieties that have already been widely adopted in China (Lin, 1991; Pray *et al.,* 2001), climate change adaptation practices have only recently received significant attention (Challinor *et al.,* 2010; Piao *et al.,* 2010; Wang *et al.,* 2012). While the government has issued a set of policies to facilitate adaptation in agricultural production (National Development and Reform Commission 2007; 2012), their effectiveness has rarely been investigated from a socio-economic perspective. The lack of empirical findings in this regard also motivates the current analysis.

Our study is facilitated by a household survey in Guangdong Province, China, focused on climate change adaptation behaviour. Guangdong is the second southmost and the most populous province in China, where agriculture is highly intensive (China Statistics Press 2010). It is a humid region yet the precipitation is unevenly distributed with 60 per cent of rainfall from June to August. This often causes extreme climate events and generates a positive demand for the adaptation technology in the coastal terrain (Gao *et al.,* 2008). Drought occurrence is also increasing (Zhang *et al.,* 2011). Consequently, agriculture in southern China may suffer from the presence of these climate risks (Wang *et al.,* 2008; Chavas *et al.,* 2009). Hence, the need for climate change adaptation can be more urgent in Guangdong as compared to Northern provinces covered in recent climate change adaptation studies (Chen *et al.,* 2014; Wang *et al.,* 2015). It is therefore an interesting study context to identify the specific hypothesised effects.

The next section provides an analytical framework focused on the triple-hurdle model followed by description of data, empirical results, and discussion. We conclude the paper with policy implications of the findings.

2. Analytical framework

We consider a climate change adaptation decision as a three-step process. First, a farmer needs to have positive desired demand of the technology to adaptation, which is determined by an ex ante evaluation of his/her net benefit change with adaptation. One who does not have the positive desired demand due to limited profitability will not adapt. Second, the farmer with positive desired demand needs to consider possible constraints that impede adaptation. Farmers who do not have the constraints then adapt, while those facing one or more constraints may or may not adapt. In the final stage, the constrained farmer with positive desired demand will need to remove the constraints from external resources such as government support. Successful removal of constraints will lead to adaptation, yet remaining constraints will continue playing a role and result in final non-adaptation. Figure 1 represents the three-step adaptation decision-making process.

In the first stage, the farmer evaluates his/her desired demand for climate change adaptation to maximise expected profits. Use π^{A} to denote the subjective estimate of the expected net benefit with adaptation, and π^{NA} to denote the subjective estimate of the expected net benefit without adaptation. Both π^{A} and π^{NA} can be considered as the respective present value flows of benefits to occur over time. The farmer's expected net benefit differential, or the latent desired demand function, y_1^*, can be specified as:

$$y_1^* = E\left(\pi^{\mathrm{A}} - \pi^{\mathrm{NA}}\right) = X_1\beta + u, \tag{1}$$

where X_1 is a vector of explanatory variables that determine the latent desired demand function, β is the vector of coefficients to be estimated, and u is the stochastic error. Thus, the observed adaptation decision with no constraint (s), denoted by y_1, depends on the sign of the expected benefit differential:

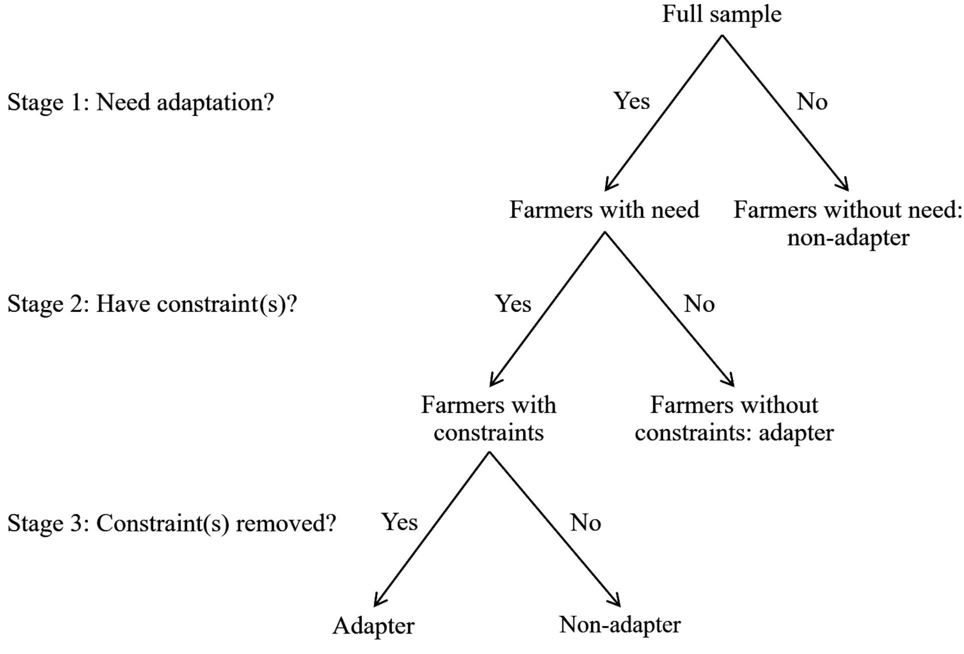

Figure 1 A graphical illustration of the triple-hurdle climate change adaptation decision process.

$$y_1 = \begin{cases} 1 \text{ if } y_1^* > 0, \text{ or } X_1\beta > u \\ 0 \text{ if } y_1^* \leq 0, \text{ or } X_1\beta \leq u. \end{cases} \tag{2}$$

The farmer may not adapt to climate change even with positive desired demand as they may still face constraint(s) and unconstrained access to all resources is a prerequisite of adaptation. Thus, the latent variable y_2^* that captures access to resources needed for adaptation depends on the original resources the farmer has, R^{o}, government support, R^{G}, and the resource threshold that needs to be met to allow adaptation, R^{T}. The binary indicator of observed resource access for the farmer, y_2, depends on whether available resources are enough to facilitate adaptation as captured by the sign of y_2^*:

$$y_2 = \begin{cases} 1 \text{ if } y_2^* = R^{\mathrm{o}} + R^{\mathrm{G}} - R^{\mathrm{T}} > 0 \\ 0 \text{ if } y_2^* = R^{\mathrm{o}} + R^{\mathrm{G}} - R^{\mathrm{T}} \leq 0. \end{cases} \tag{3}$$

Empirically, the latent variable y_2^* can be modelled as:

$$y_2^* = X_2\gamma + \epsilon, \tag{4}$$

where X_2 is a vector of explanatory variables that affect resource access; γ is the vector of coefficients to be estimated, and ϵ is the stochastic error.

As illustrated above, the farmer with positive desired demand of adaptation but constraint(s) still cannot adapt. Therefore, the latent variable y_3^* that predicts the final adaptation decision with possible change(s) of constraint status can be specified as:

$$y_3^* = X_3\delta + v, \tag{5}$$

where X_3 is a vector of the explanatory variables that affect final adaptation decision; δ is the vector of coefficients to be estimated, and v is the stochastic error term. The observed adaptation decision, y_3, is determined by the sign of y_3^*:

$$y_3 = \begin{cases} 1 \text{ if } y_3^* > 0, \text{ or } X_3\delta > v \\ 0 \text{ if } y_3^* \leq 0, \text{ or } X_3\delta \leq v. \end{cases} \tag{6}$$

The triple-hurdle model is then developed by Equations (1)-(6). In each hurdle, a Probit model is specified given the binary nature of the outcome variable, and the likelihood function combines the densities. Let $y = [y_1,\ y_2,\ y_3]$ and $X = [X_1,\ X_2,\ X_3]$. The density of y given X can be written as:

$$f(y|X) = [1 - \Phi(X_1\beta)]^{1[y_1=0]} \left[\Phi(X_1\beta)\begin{pmatrix} [1 - \Phi(X_{2\gamma})]^{1[y_2=0]} \\ [\Phi(X_{2\gamma}) \cdot \Phi(X_3\delta)^{1[y_3=1]} \cdot [1 - \Phi(X_3\delta)]^{1[y_3=0]}]^{1[y_2=1]} \end{pmatrix}\right]^{1[y_1=1]}, \tag{7}$$

where $\Phi(\cdot)$ is the standard normal cumulative density, and 1 [·] denotes the standard indicator function that takes the value of one (if the argument is true) or zero (if the argument is false).

Before the estimation of coefficients, formal test is needed to check whether the error terms of the three hurdle equations are independent conditional on the observed covariates, X. The triple-hurdle model is only valid when this assumption holds, or the coefficient estimates would be biased, and an alternative model would be needed. With conditionally independent errors, we can estimate all hurdle equations and derive the average partial (marginal) effect of each variable. To see this, it is helpful to present the probabilities in each of the hurdles [1]:

[1] It is farmers who have positive desired demand, but also constraints such as technology, capital and labour that prevent adaptation.

$$\begin{cases} \Pr(\text{do not need technology}) = \Pr(y_1 = 0|X) = 1 - \Phi(X_1\beta) \\ \Pr(\text{need with constraints}) = \Pr(y_1 = 1, y_2 = 1|X) = \Phi(X_1\beta)\Phi(X_2\gamma) \\ \Pr(\text{need without constraints}) = \Pr(y_1 = 1, y_2 = 0|X) = \Phi(X_1\beta)[1 - \Phi(X_2\gamma)]. \end{cases} \tag{8}$$

Thus, the probability of adaptation is:

$$E(\text{adaptation}) = E(y_3|X) = \Phi(X_1\beta)\Phi\left(X_{2\gamma}\right)\Phi(X_3\delta) + \Phi(X_1\beta)\left[1 - \Phi\left(X_{2\gamma}\right)\right]. \tag{9}$$

The average partial effect of X_k, k = 1, 2 or 3, is finally derived following Wooldridge (2010):

$$\begin{aligned} \frac{\partial E(y_3|X)}{\partial X_k} = {} & \beta_k\Phi(X_2\gamma)\Phi(X_3\delta) + \gamma_k\Phi(X_1\beta)\Phi(X_3\delta) + \delta_k\Phi(X_1\beta)\Phi(X_2\gamma) \\ & + \beta_k[1 - \Phi(X_2\gamma)] - \gamma_k\Phi(X_1\beta). \end{aligned} \tag{10}$$

It is therefore seen that the average partial effect is not equal to the conditional marginal effect of the coefficient estimate of any individual regression. Rather, it is jointly derived using regression estimates of all equations.

3. Data description

This study was facilitated by a rural household survey in Guangdong Province, China during the 2012-2013 period. The survey was specifically designed to uncover climate change adaptation in face of extreme events. The sampling took three steps. First, six counties were randomly selected among all counties in Guangdong Province which have experienced: (i) the most severe drought or flood at least once; and (ii) a relatively normal year with no worse than moderate weather shock(s) at least once during 2010–2012.[2] Next, within each county, townships were first stratified into three groups with varying agricultural production conditions and then randomly selected from each stratum. Three villages from each township were selected using a similar approach. Finally, 10 households from each village were randomly surveyed. This sampling strategy has been used in recent literature (Huang *et al.,* 2008; Wang *et al.,* 2015), where the stratification by the occurrence of climate extremes enhances data representativeness. Data variation is also guaranteed as farmers may or may not experience climate extreme events in the surveyed year. Moreover, it minimises the need for direct control for climate conditions, which is usually imprecise at the fine scale, and allows us

[2] Drought or flood is categorised as most severe, severe, moderate or small according to the national standard for natural disasters (NCC of CMA). Selected counties must have had at least one year with the most severe whether shock(s) and at least one year with no worse than moderate or small weather shock(s) during 2010-2012.

to see how individual farm households located in areas with varying agricultural production conditions responded to these events.

Descriptive statistics of variables employed in the triple-hurdle model are presented in Table 1. Multiple covariates are considered to predict the adaptation indicator, which is dichotomous and takes a value of one if the household take up any adaptation procedure(s), and zero otherwise. In addition to government support in climate change adaptation, we have included conventional demographic and socioeconomic indicators, along with measures of social network strength (number of relative households, having relative(s) working in town centre or not) and perception of climate risks (drought, flood, and heat injury). Abinary indicator of the existence of early warning service from the local government; and agricultural supply shop distance; to capture demand and supply side incentives of adaptation are incorprated following the literature (Chen *et al.,* 2014; Wang *et al.,* 2015). Village dummies are included in all stages of decision-making to capture any unobservable heterogeneities at that level. Climate condition measures, however, are not included given our sampling design has already fully accounted for such variation following recent studies (Huang *et al.,* 2008; Wang *et al.,* 2015).

As discussed above, our complex sample design consists of first-level cluster sampling and lower-level stratification to better capture cross-sectional climate adaptation variations. Since the design effect[3] of cluster sampling is no < 1 while the design effect of stratified sampling is no > 1, it is needed to check the 'net' design effect of these conflicting mechanisms. These are also reported in Table 1. It is seen that the design effect ranges from 1.097 to 1.474, suggesting reasonable sample efficiency.

Statistics of both full sample and subsamples categorised on the need for adaptation and the existence of constraint(s) in adaptation are also reported in Table 1. The overall adaptation rate is high (92.4 per cent) in face of climate change, as counties with climate shocks in the past 3 years were intentionally covered in our sampling strategy. There is a clear distinction between farmers without need (0 per cent adaptation) and farmers with need but no constraints (100 per cent adaptation). Farmers without need are the least educated (approximately 0.7 years less than full sample average), in largest households and with smallest land holding per capita. They have fewer relative households but a higher proportion of them worked in town centres. Living the farthest from agricultural supply shops (more than twice that of full sample average), those farmers are also more optimistic about their exposure to drought and flood risks while more likely to be anxious about heat injury. Farmers with need but no constraints are the best educated, and they have the largest number of relative households.

[3] The design effect is the ratio of the variance of an estimator accounting for the complex design to the variance of the estimator that would have been obtained with same-size simple random sampling (Skinner, 1989).

Table 1 Descriptive statistics of full sample and subgroups

Variable	Full sample (n = 541)	Design effect†	Farmers without need (n = 24)	Farmers with need but no constraints (n = 203)	Farmers with need and constraints (n = 314)
Adaptation (yes = 1; no = 0)	0.924 (0.265)	1.121	0.000 (0.000)	1.000 (0.000)	0.946 (0.227)
Governmental support (yes = 1; no = 0)	0.213 (0.377)	1.325	0.250 (0.442)	0.207 (0.416)	0.213 (0.410)
Head age (years)	54.31 (10.35)	1.193	54.92 (9.982)	54.85 (9.937)	53.92 (10.65)
Head gender (male = 1; female = 0)	0.965 (0.184)	1.097	1.000 (0.000)	0.970 (0.169)	0.959 (0.200)
Head education (years)	7.474 (2.948)	1.220	6.771 (3.605)	7.665 (2.697)	7.404 (3.046)
Village cadre (yes = 1; no = 0)	0.299 (0.458)	1.088	0.375 (0.494)	0.310 (0.464)	0.287 (0.453)
Farm experience (year)	32.19 (12.27)	1.205	33.83 (13.90)	33.85 (11.59)	30.99 (12.46)
Cooperative member (yes = 1; no = 0)	0.181 (0.385)	1.303	0.167 (0.381)	0.158 (0.365)	0.197 (0.399)
Household size	5.869 (2.417)	1.289	6.833 (2.929)	6.020 (2.437)	5.697 (2.344)
Land per capita (mu)	1.936 (4.323)	1.302	0.668 (0.647)	1.548 (3.502)	2.284 (4.895)
Durable assets per capita (thousand CNY)	1.798 (5.494)	1.334	1.851 (3.665)	1.409 (3.344)	2.045 (6.612)
Number of relative households	15.78 (6.891)	1.474	13.83 (6.638)	16.66 (6.846)	15.36 (6.889)
Relative(s) working in town centre (yes = 1; no = 0)	0.104 (0.305)	1.321	0.208 (0.415)	0.099 (0.298)	0.099 (0.299)
Drought perception (getting worse = 1; other = 0)	0.516 (0.500)	1.239	0.375 (0.495)	0.478 (0.501)	0.551 (0.498)
Flood perception (getting worse = 1; other = 0)	0.397 (0.489)	1.077	0.250 (0.442)	0.369 (0.484)	0.427 (0.495)
Heat injury perception (getting worse = 1; other = 0)	0.516 (0.500)	1.187	0.667 (0.482)	0.547 (0.499)	0.484 (0.501)
Early warning service (yes = 1; no = 0)	0.535 (0.499)	1.354	0.542 (0.509)	0.539 (0.500)	0.531 (0.500)
Agricultural supply shop distance (km)	2.247 (5.044)	1.166	5.925 (20.08)	1.848 (1.917)	2.224 (3.272)

Note: Standard deviations are reported in parentheses.
†The design effect is the ratio of the variance of an estimator accounting for the complex design to the variance of the estimator that would have been obtained with same-size simple random sampling (Skinner, 1989).

Farmers with need but also constraints are the least likely to be village cadre, having the least farm experience but the largest land and durable asset value per capita. About one fifth of them are cooperative members, which is the highest among subgroups. Finally, those farmers are more likely concerned about drought and flood conditions but are less likely concerned about heat injury.

4. Results and discussion

The triple-hurdle model results are empirically estimated with data described above. Standard errors are clustered at the county level, the primary sampling unit. Exclusion restrictions have been imposed across the regression equations of different stages in an intuitive manner. Specifically, perceived climate risks (drought, flood, and heat) are assumed to potentially affect the existence of positive desired demand of adaptation and the adaptation behaviour, but not the existence of constraint(s) in adaptation. Moreover, existence of government support is hypothesised to affect the final adaptation decision but not the existence of positive desired demand of adaptation or the existence of constraint(s) for similar intuitions. Before deriving the average partial effects with the non-linear likelihood function in Equation (10), it is necessary to check the sign and statistical significance of each single-equation coefficient estimate, which may help understand the decision-making at each stage.

4.1. Coefficient estimates of the triple-hurdle model

Table 2 reports the baseline results, where coefficient estimates of the three-stage adaptation decision process are reported in separate columns. Among all covariates, whether government support positively affects climate change adaptation decision is of our primary interest. This hypothesised relationship is confirmed in the third-stage regression with large coefficient magnitude and high statistical significance. While the coefficient does not necessarily reflect the average partial effect, it does confirm the role government support plays to stimulate adaptation. As the third-stage regression specifically uses the subsample of farmers with positive desired demand of adaptation but also with constraint(s), such relationship should be more appropriately established here as compared to earlier studies evaluating government support using all surveyed households including those unwilling to adapt and those without constraint(s) (Chen *et al.,* 2014; Wang *et al.,* 2015).

There is a gender disparity in the desire of adaptation, as female-headed households are more likely to report positive desired demand of climate change adaptation. Consequently, female-headed households are more likely to pursue anadaptation strategy. However, gender does not seem to be strongly related to the existence of constraint(s) that impede adaptation, which may imply that such gender disparity can largely arise from perceptions rather than actual socio-economic backgrounds. These patterns, however, can also result from the lack of variation in household head gender as most household has male heads and thus demands further investigation. In addition to gender, farm experience can help overcome constraint(s) and thus stimulate adaptation. This is also intuitive as human capital would likely improve farmer's skills and ease adaptation. Few coefficient estimates of other household head characteristics bear statistical significance, except that

Table 2 Triple-hurdle model estimation with clustered standard errors

	Stage 1: Need adaptation? (n = 541)	Stage 2: Have constraint(s)? (n = 527)	Stage 3: Constraint(s) removed? (n = 324)
Governmental support			4.697*** (0.415)
Head age	0.010 (0.022)	0.018* (0.010)	−0.023 (0.019)
Head gender	−4.282*** (0.317)	−0.207 (0.337)	−5.060*** (0.549)
Head education	0.074* (0.044)	−0.029 (0.021)	0.044 (0.050)
Village cadre	−0.251 (0.212)	−0.075 (0.129)	0.053 (0.274)
Farm experience	0.005 (0.017)	−0.027*** (0.009)	0.044*** (0.016)
Cooperative member	0.087 (0.276)	0.149 (0.151)	0.697 (0.468)
Household size	−0.055 (0.037)	−0.019 (0.025)	−0.063 (0.068)
Land per capita	0.336** (0.147)	0.020 (0.018)	0.077 (0.084)
Durable assets per capita	−0.009 (0.016)	0.019 (0.013)	0.047 (0.029)
Number of relative households	0.019 (0.015)	−0.020** (0.009)	0.018 (0.017)
Relative(s) working in town centre	−0.341 (0.304)	0.091 (0.198)	4.683*** (0.409)
Early warning service	0.072 (0.194)	−0.056 (0.118)	0.088 (0.257)
Agricultural supply shop distance	−0.027*** (0.009)	0.027 (0.021)	−0.002 (0.027)
Drought perception	0.394* (0.218)		−0.171 (0.271)
Flood perception	0.266 (0.240)		0.062 (0.261)
Heat injury perception	−0.515** (0.223)		0.396 (0.285)
Constant	4.677*** (0.772)	0.874 (0.621)	5.775*** (1.074)
Percentage of correct prediction	68.6	67.2	61.4
LR χ^2 statistic (P-value)	44.61 (0.000)	27.01 (0.001)	33.12 (0.000)

Note: Standard errors clustered at the county level are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

households with better educated heads are more likely to have positive desired demand and that households with older heads are more likely to face constraint(s) in adaptation. But these coefficients observe small magnitudes and are only marginally significant.

Several relationships also emerge between adaptation decisions and household characteristics. Relatively larger holders (with bigger plot area per person) tend to report the need for climate change adaptation. One may expect that in Guangdong Province, which is located around the Pearl River Delta and is highly industrialised, larger holders are highly specialised farmers and may suffer larger loss in face of climate extremes as compared with some smallholders who also supply off-farm labour off-season. However, the larger holders are not different from smaller holders regarding the existence of constraint(s) and the actual adaptation decision when both types of farmers face constraint(s). While the number of relative households does not matter at any stage, having relative(s) working in town centre is negatively associated with the existence of constraint(s) and positively associated with adaptation decision. A possible explanation may point towards information and resource advantages with this kinship. In addition, far distance to the nearest agricultural supply shop tends to suppress the positive desired demand of adaptation.

4.2. Average partial effects of the triple-hurdle model

To better understand the role of government support in climate change adaptation as well as those of other covariates, we compute the average partial effects using regression estimates of all stages according to Equation (10). Standard errors are obtained using delta method. Results are presented in Table 3. It is seen that government support in climate change adaptation increases the probability of adaptation for an average farmer by 0.244. Such effect is highly significant (at 1 per cent level). Moreover, it is larger than that of most of the other covariates (except for gender), confirming importance of the government's role in stimulating climate change adaptation among individual farmers.

Although gender disparity is again revealed given that female-headed households observe an average probability of adaptation that is 0.552 higher than male-headed households, there is limited variation in gender as discussed above and further research is needed with available data where female-headed households are better represented. In addition to gender, the number of relative households and whether the farmer has relative(s) working in town centre are both positively associated with climate change adaptation and jointly imply the importance of social network. Finally, education, farming experience, and land holding per household member are all positively associated with adaptation, yet the magnitudes of those correlations are small.

Table 3 Average partial effects of triple-hurdle model of climate change adaptation

Independent variable	Average partial effect
Governmental support	0.244*** (0.051)
Head age	−0.001 (0.002)
Head gender	−0.551*** (0.079)
Head education	0.008* (0.004)
Village cadre	−0.013 (0.021)
Farm experience	0.003** (0.001)
Cooperative member	0.039 (0.031)
Household size	−0.007 (0.004)
Land per capita	0.027** (0.011)
Durable assets per capita	0.001 (0.002)
Number of relative households	0.003* (0.001)
Relative(s) working in town centre	0.218*** (0.056)
Early warning service	0.011 (0.019)
Agricultural supply shop distance	−0.002 (0.002)
Drought perception	0.018 (0.021)
Flood perception	0.021 (0.021)
Heat injury perception	−0.015 (0.022)

Note: Standard errors computed using delta method are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

While these results are generally intuitive, there is a need to test their robustness. To do this, we alternatively estimate the triple-hurdle model using heteroskedasticity-robust standard errors instead of clustering standard errors at the county level. This procedure is followed given our complex sample design as discussed above. As reported in Table 4, the estimated robust standard errors are generally smaller than the clustered standard errors reported in Table 2. Therefore, our main estimates are conservative and thus robust, lending further credence to our computed average partial effects.

4.3. Discussion

The prominent effect of government support as compared with other covariates suggests the former can play a larger role in promoting climate change adaptation. From a practical perspective, most socio-economic factors, such as education, experience, landholding, and kinship resources, are largely predetermined at each cropping season when the farmer makes

Table 4 Triple-hurdle model estimates with heteroscedasticity-robust standard errors

	Stage 1: Need adaptation? (n = 541)	Stage 2: Have constraint(s)? (n = 527)	Stage 3: Constraint(s) removed? (n = 324)
Governmental support			4.697*** (0.393)
Head age	0.010 (0.017)	0.018** (0.008)	−0.023 (0.017)
Head gender	−4.282*** (0.287)	−0.207 (0.289)	−5.060*** (0.521)
Head education	0.074* (0.042)	−0.029 (0.021)	0.044 (0.040)
Village cadre	−0.251 (0.189)	−0.075 (0.114)	0.053 (0.219)
Farm experience	0.005 (0.011)	−0.027*** (0.008)	0.044*** (0.015)
Cooperative member	0.087 (0.259)	0.149 (0.134)	0.697 (0.451)
Household size	−0.055 (0.035)	−0.019 (0.025)	−0.063 (0.045)
Land per capita	0.336** (0.121)	0.018 (0.018)	0.077 (0.081)
Durable assets per capita	−0.009 (0.016)	0.019 (0.013)	0.047* (0.025)
Number of relative households	0.019 (0.013)	−0.020** (0.008)	0.018 (0.017)
Relative(s) working in town centre	−0.341 (0.242)	0.091 (0.182)	4.683*** (0.332)
Early warning service	0.072 (0.110)	−0.056 (0.110)	0.088 (0.191)
Agricultural supply shop distance	−0.027*** (0.005)	0.027 (0.020)	−0.002 (0.025)
Drought perception	0.394** (0.191)		−0.171 (0.222)
Flood perception	0.266 (0.187)		0.062 (0.178)
Heat injury perception	−0.515*** (0.176)		0.396 (0.205)
Constant	4.677*** (0.757)	0.874 (0.593)	5.775*** (0.886)
Percentage of correct prediction	68.6	67.2	61.4
LR χ^2 statistic (P-value)	42.59 (0.000)	28.33 (0.001)	31.75 (0.000)

Note: Heteroskedasticity-robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

adaptation decision, which may not be easily changed in the short run. Governmental support in terms of a set of policies, on the contrary, is flexible and can potentially be the most feasible and effective way to promote adaptation. Therefore, the importance of government support cannot be overemphasised in face of climate change that increasingly affects agricultural production (Mendelsohn and Dinar, 1999; Howden *et al.,* 2007; Lobell *et al.,* 2008).

The use of triple-hurdle model also adds insights to the existing small literature on government support and climate change adaptation in China. Chen *et al*. (2014) use 569 rural households from six provinces in China (excluding Guangdong) and find that the availability of village-provided policy supports against drought is associated with an increase in adaptation probability of 0.166 (marginal effect). Alternatively, Wang *et al*. (2015) use 870 households from five provinces in North China Plain and find that policy support against drought is associated with an increase in adaptation probability of 0.074 (marginal effect). Both studies use simple logit/probit models and fail to address the decision-making process under constraints as well as their possible removal by government support. Comparing to these results, our estimate of a 0.244 increase in adaptation probability is much larger. It is also intuitive that government support is more effective among those facing constraints. Therefore, it is necessary for future policy designs to carefully identify and then target the farmers in order to improve the effectiveness of interventions that aim to stimulate adaptation.

5. Concluding remarks

We have analysed the role of government support in farmers' climate change adaptation decision using a triple-hurdle model that depicts a three-stage decision process: (i) whether the farmer needs adaptation (ii) whether there are one or more constraints that prevent adaptation; and (iii) whether such constraints are removed through government support. It is found that government support is positively associated with an increase in the probability of adaptation of 0.244. While the non-experimental setting of the study does not allow us to establish a strong causal inference, it is highly probable that governmental support stimulates adaptation but not vice versa. Moreover, this positive change is much larger than the estimates in recent literature, suggesting government support can be effective among the farmers who wish to adapt but have constraints. These results suggest there is a need to correctly identify and target the subgroup of farmers who need support to remove existing constraint(s) in adaptation, in order to improve the effectiveness of governmental support.

Although we provide strong evidence regarding the role of government support in climate change adaptation, our estimation results should be rigorously treated as suggestive and indicative given certain limitations. While Guangdong Province is a typical agricultural region in southern China, external validity will only be established through evidence from different agro-ecological and socio-economic settings given the non-experimental nature of the current study. A sample larger than 541 households could also be more ideal. These limitations would call for further investigations into this issue that may provide better policy information to assist climate change adaptation among heterogeneous households.

References

Adger, W.N., Dessai, S., Goulden, M., Hulme, M., Lorenzoni, I., Nelson, D. R., Naess, L. O., Wolf, J. and Wreford, A. (2009). Are there social limits to adaptation to climate change?, *Climate Change* 93, 335-354.

Agrawala, S., Fankhauser, S., Hanrahan, D., Pope, G., Skees, J., Stephens, C. and Yasmine, S. (2008). Economic and policy instruments to promote adaptation, in Agrawala S and Fankhauser S*Economic Aspects of Adaptation to Climate Change*. pp. 85-133. Organization for Economic Co-operation and Development, Paris.

Challinor, A.J., Simelton, E.S., Fraser, E.D.G., Hemming, D. and Collins, M. (2010). Increased crop failure due to climate change: assessing adaptation options using models and socio-economic data for wheat in China, *Environmental Research Letters* 5, 034012.

Chavas, D.R., Izaurralde, C., Thomson, A.M. and Gao, X. (2009). Long-term climate change impacts on agricultural productivity in eastern China, *Agricultural and Forest Meteorology* 149, 1,118-1,128.

Chen, H., Wang, J. and Huang, J. (2014). Policy support, social capital and farmers' adaptation to drought in crop production of China, *Global Environmental Change* 24, 193-202.

China Statistics Press (2010). *Tabulation on the 2010 Population Census of the People's Republic of China*. Beijing, China.

Croppenstedt, A., Demeke, M. and Meschi, M.M. (2003). Technology adoption in the presence of constraints: the case of fertilizer demand in Ethiopia, *Review of Development Economics* 7, 58-70.

Feder, G., Just, R.E. and Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: a survey, *Economic Development and Cultural Change* 33, 255-298.

Few, R., Brown, K. and Tompkins, E.L. (2007). Public participation and climate change adaptation: avoiding the illusion of inclusion, *Climate Policy* 7, 46-59.

Gao, M., Qin, Z., Zhang, H., Lu, L., Zhou, X. and Yang, X. (2008). Remote sensing of agro-droughts in Guangdong Province of China using MODIS satellite data, *Sensors* 8, 4,687-4,708.

Howden, S.M., Soussana, J., Tubiello, F.N., Chhetri, N., Dunlop, M. and Meinke, H. (2007). Adapting agriculture to climate change, *Proceedings of the National Academy of Sciences* 104, 19,691-19,696.

Huang, J., Wang, Y. and Wang, J. (2008). Farmers' adaptation to extreme weather events through farm management and its impacts on the mean and risk of rice yield in China, *American Journal of Agricultural Economics* 97, 602-617.

Lin, J.Y. (1991). Education and innovation adoption in agriculture: evidence from hybrid rice in China, *American Journal of Agricultural Economics* 73, 713-723.

Lobell, D.B., Burke, M.B., Tebaldi, C., Mastrandrea, M.D., Falcon, W.P. and Naylor, R.L. (2008). Prioritizing climate change adaptation needs for food security in 2030, *Science* 319, 607-610.

Mendelsohn, R. and Dinar, A. (1999). Climate change, agriculture, and developing countries: does adaptation matter?, *The World Bank Research Observer* 14, 277-293.

National Development and Reform Commission (2007). *China's National Climate Change Program, National Development and Reform Commission*. People's Republic of China, Beijing, China.

National Development and Reform Commission (2012). *China's Policies and Actions for Addressing Climate Change*. National Development and Reform Commission, Beijing, China.

Piao, S., Ciais, P., Huang, Y., Shen, Z., Peng, S., Li, J., Zhou, L., Liu, H., Ma, Y., Ding, Y., Friedlingstein, P., Liu, C., Tan, K., Yu, Y., Zhang, T. and Fang, J. (2010). The impacts of climate change on water resources and agriculture in China, *Nature* 467, 43-51.

Pray, C., Ma, D., Huang, J. and Qiao, F. (2001). Impact of Bt cotton in China, *World Development* 29, 813-825.

Shiferaw, B., Kebede, T., Kassie, M. and Fisher, M. (2015). Market imperfections, access to information and technology adoption in Uganda: Challenges of overcoming multiple constraints. *Agric. Econ*. 46, 475– 488.

Shiferaw, B., Kebede, T., Kassie, M., and Fisher, M., (2015). Market imperfections, access to information and technology adoption in Uganda: Challenges of overcoming multiple constraints. *Agricultural Economics*, 46, 475– 488.

Shiferaw, B.A., Kebede, T.R. and You, L. (2008). Technology adoption under seed access constraints and the economic impacts of improved pigeonpea varieties in Tanzania, *Agricultural Economics* 39, 309-323.

Skinner, C.J. (1989). Introduction to part A, in Skinner, C.J., Holt, D. and Smith, T.M.F. (eds), *Analysis of Complex Surveys*. Wiley, New York, NY, pp. 23-58.

Tompkins, E.L., Few, R. and Brown, K. (2008). Scenario-based stakeholder engagement: incorporating stakeholders preferences into coastal planning for climate change, *Journal of Environmental Management* 88, 1,580-1,592.

Van Aelst K., and Holvoet N. (2016). Intersections of Gender and Marital Status in Accessing Climate Change Adaptation: Evidence from Rural Tanzania. *World Development* 79, 40–50.

Wang, J., Mendelsohn, R., Dinar, A., Huang, J., Rozelle, S. and Zhang, L. (2008). *Can China Continue Feeding Itself? The Impact of Climate Change on Agriculture*, Vol. 4470. World Bank Publications, Washington, D.C..

Wang, J., Wang, E., Yang, X., Zhang, F. and Yin, H. (2012). Increased yield potential of wheat-maize cropping system in the North China Plain by climate change adaptation, *Climatic Change* 113, 825-840.

Wang, J., Yang, Y., Huang, J. and Chen, K. (2015). Information provision, policy support, and farmers' adaptive responses against drought: An empirical study in the North China Plain, *Ecological Modelling* 318, 275-282.

Wooldridge, J.M. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, MA.

World Bank (2010). *Economics of Adaptation to Climate Change: Synthesis Report*. The World Bank, Washington DC.

Zhang, Q., Zhang, W., Chen, Y.D. and Jiang, T. (2011). Flood, drought and typhoon disasters during the last half-century in the Guangdong province, China, *Natural Hazards* 57, 267278.