Farmers' Adaptation to Extreme Weather Events through Farm Management and Its Impacts on the Mean and Risk of Rice Yield in China

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We explore how rice farmers adjust their farm management practices in response to extreme weather events and determine whether their adjustments affect the mean, risk, and downside risk of rice yield. Based on a survey of 1,653 rice farmers in China, our econometric analyses show that the severity of drought and flood in the study areas significantly increases the risk and downside risk of rice yield. The applied farm management measures respond to severe drought and flood and can be considered as adaptation to climate change, an issue often ignored in previous studies. We model adaptation and its impact on rice yield for adapters and non-adapters. Utilizing a moment-based approach, we show that adaptation through farm management measures significantly increases rice yield and reduces the risk and downside risk of rice yield. Several policies, including scaling up the cost-effective farm management adaptation and providing public services related to natural disasters, are recommended to improve adaptive capacity of farmers, particular the poor, in response to extreme events.

Key words: Adaptation, China, extreme weather, farm management, rice, risk exposure, yield.

JEL codes: Q18, Q54.

Overcoming the challenge of more frequent and extreme weather events has captured much attention from researchers (Howden et al. 2007; IPCC 2014). Forecasts show that the total area suffering from drought globally will increase between 15–44% by the end of the twenty-first century (IPCC 2012). The international community has called for incorporating climate change adaptation into national development plans (IPCC 2014; World Bank 2010). This is especially urgent for farmers in developing countries who are expected to bear the brunt of climate variability impacts (Seo and Mendelsohn 2008). In China, the annual average crop area suffering from drought has increased by nearly 120% since the 1950s, and the frequency of flood events has also increased (MWR 2012). China's government issued a national program at the end of 2013 to adapt to climate change, which shows that adaptation initiated by the government (NDRC 2013) is gaining momentum.

Although several studies of farmers' adaptation to climate change exist (Chen, Wang, and Huang 2014; Deressa et al. 2009; Seo and Mendelsohn 2008), there is inadequate analysis on the effectiveness of farm management and other adaptation practices; most studies have analyzed the determinants of adaptation decisions. For example, a survey in Ethiopia (Deressa et al. 2009) found that household characteristics and access to extensions influence farmers' adaptation decisions. Empirical studies in China found that farm characteristics and local government policies influence farmers' adaptation decisions (Chen, Wang, and Huang 2014; Wang, Huang, and Wang 2014). Exceptions include studies by Yesuf et al. (2008) and Di Falco, Veronesi, and Yesuf (2011). These studies treated farmer applications as adaptation measures

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and analyzed the impact of adaptation on crop yield. Several studies have also analyzed agricultural risk, including the mean-variance investigation of input effects (e.g., Abedullah and Pandey 2004; Just and Pope 1979) and technology adoption (Foudi and Erdlenbruch 2012). However, it remains unclear whether these applications mitigate the impact of extreme weather events.

Importantly, the influence of adaptation on downside risk exposure (e.g., the probability of crop failure) remains poorly understood. In general, downside risk refers to the risk located in the lower tail of the payoff distribution (Kim et al. 2014). While useful information about the risk effects of input adjustments can be obtained from understanding their impact on yield variance, analyzing the variance effect alone would not help differentiate between unexpected bad and good events (Di Falco and Veronesi 2014). Rising risks associated with climate variability has encouraged research on the role of downside risk in risk management for crop production (Kim and Chavas 2003).

Given the severity of extreme weather events and the potential role of farm management in mitigating risks, it is important to identify major farm management measures related to climate change and applied by farmers, whether these measures can be regarded as farmers' adaptation to climate variability, and whether adaptation measures can lower crop yield risks and increase the mean yield. This information is critical to better understand farmers' adaptation to extreme weather events and to provide empirical evidence for policy makers' climate change adaptation plans and investments.

The overall goals of this study are to explore how rice farmers adjust their farm management practices to extreme weather events, and to evaluate whether their adaptation reduces rice yield loss and risk, as well as downside risk in China. Rice is the main food staple in China, which produces nearly 30% of the world's total rice output (FAOSTAT 2011). Historical records in China document that the rice yield loss resulting from drought and flood increased at a rate of 4.6% and 3.8%, respectively, from 1951–2010 (NBSC 2012), suggesting that the potential for rice loss due to extreme weather events is a significant concern for food security in China. To our knowledge, no empirical study has investigated how farm management has adjusted to extreme weather events and the effects on the mean and risk of rice yield in China and other Asian countries.[1] The scope of this study is limited to drought and flood events because they are the most severe weather events faced by China's rice producers.

To achieve our goals, we have three specific objectives. The first is to gain a better understanding of extreme weather events (drought and flood) that affect rice production, and how farmers respond to these events by adjusting their farm management practices. The second objective is to identify the factors influencing farmers' adaptation to extreme weather events. Third, we aim to empirically examine the effects of major farm management measures, identified as adaptation to extreme weather events, on the mean, risk, and downside risk (skewness) of rice yield. We approximate downside risk exposure using the third moment of the crop yield distribution. An increase in yield skewness indicates a reduction in downside risk, that is, a decrease in the probability of crop failure (Di Falco and Chavas 2009).

We model adaptation as a selection process and estimate a simultaneous equations model with endogenous switching to account for heterogeneity in the decision to adapt or not, and to capture the differential impact of adaptation on adapters and non-adapters. This article differs from existing studies in two important ways. First, by designing a survey covering both normal and extreme weather years in recent years in the same counties for the same farmers, we are able to identify farmers' "true adaptations" for coping with the extreme weather events. To our knowledge, nearly all existing studies are unable to separate farmers' responses to climate change from their daily farm management practices. That is, many adjustments in farm management do not necessarily represent true adaptations (Lobell 2014). Second, most existing studies focus on farmer responses to the mean of climate change, while our study focuses on farmers' responses to extreme weather events such as drought and flood.

Based on a survey of 1,653 rice farmers in China, reseeding and fixing/cleaning seedlings are the main farm management measures related to climate change that have been

[1] To the best of our knowledge, Di Falco and Veronesi (2014) is the only economic study that attempts to formally measure the impact of farmer adaptation to climate change on downside yield risk in Ethiopia.

applied by rice farmers. The econometric results show that to a large extent the aforementioned measures used by farmers are responses to extreme weather events such as drought and flood, and can be regarded as adaptation to climate variability. Moreover, we show that these farm management measures contribute to a significant reduction in risk and downside risk of yield. The findings imply that adapting farm management measures at the early stage of rice production is an important risk management tool for rice farmers. The findings of this study have implications for the Chinese national adaptation plan to cope with extreme weather events, as well as for farmers' capacity-building programs in developing countries.

In the next section, we introduce the data used in this study. The following section illustrates the occurrence of extreme weather events and farmers' responses in the studied areas. After describing the conceptual framework we use to examine the impact of adaptation, we present the farm management measures applied in response to extreme weather events and their impact on rice yield, focusing on the effects on the mean, variance, and skewness (downside risk) of rice yield. The final section concludes with several policy implications.

Data and Sampling Methods

Except for secondary data on drought and flood discussed in the next section, all data used in this study is from a large-scale household survey on the impact of and adaptation to climate change on crop production conducted in China in late 2012 and early 2013. Based on regional crop production systems and climate situations, the survey covered nine provinces: Jilin in northeast China, Hebei in northern China, Henan in central China, Shandong and Jiangsu in the coastal area of eastern China, Anhui and Jiangxi in the inland area of eastern China, Yunnan in southwest China, and Guangdong in southern China. Five surveyed provinces have households that produced rice from 2010–2012. While these five provinces may not fully represent China's rice production overall, they do cover the following types of production: double-season dominated indica rice (early-season rice and late-season rice) in Guandong and Jiangxi; single-season dominated indica rice (middle rice) in Yunnan; single-season indica and japonica mixed rice (middle rice) in Henan; and single-season japonica rice (middle rice) in Jiangsu.

Within each province, we followed three steps to select counties to analyze the effects of extreme weather shocks. First, we selected all counties that had experienced the most severe drought or flood from 2010–2012. According to China's national standard for natural disasters (CMA 2004), the severity of a drought or flood has four categories: most severe, severe, moderate, and small. Second, from the counties identified in the first step, we kept only counties that also experienced a "normal year" in any of the three examined years.[2] Crop production often faces various weather shocks during any growing season; therefore, the term "normal year" is relative and describes an average year with no more than moderate (natural disaster level 3) weather shocks. Finally, from the list of counties identified in step two, three counties in each province except for Jiangxi (10 counties) and Guangdong (6 counties) were randomly selected for the study.[3] This sampling approach allowed us to examine differences in the two distinct years (severe disaster year and normal year), and we ended up with a sample of 25 counties.

Townships and villages were selected before we interviewed households. Within each of the 25 selected counties, all townships were divided into three groups based on the condition of the agricultural production infrastructure, and one township was randomly selected from each group. The same approach was used to select three villages

[2] During our sampling, the following two cases emerged during the previous three years (2010–2012): 1) some counties had experienced one severe disaster year and two normal years; and 2) some counties had experienced two disaster years and one normal year. In both cases, the rule is to select the most recent normal and disaster years for the survey so that the difficulty of farmers' recall can be reduced. Based on this rule, we had 48% data in 2012, 35% in 2011, and 17% in 2010. However, we admit that the above rule resulted in imbalances in respondents' information recall between the normal year and the disaster year (1:5), which may raise the concern of likely more recalling bias for the disaster year. A positive aspect was that 70% of recalled data for the disaster year were in 2011. In addition, we found that farmers had no difficulty recalling crop yield, farm management and major inputs in the disaster years of 2011 or 2010 because they had deep impressions of what had occurred during the most recent disaster year. Moreover, in the econometric analysis we will include year dummies for 2010 and 2011 to control for all systematic differences between 2010, 2011, and 2012, including the likely bias from farmers' recall.

[3] Jiangxi and Guangdong had more counties included because we had more funding to conduct the survey in these two provinces. Despite having more counties in these two provinces, the sampling approach and survey measures used are the exact same as those applied in the other provinces.

Table 1. Percentage of Plots Affected by Extreme Weather events (drought or flood) and Yield Loss Reported by Farmers, 2010–2012

	Plots affected by drought or flood (%)		Yield loss when suffered from drought or flood (%)	
	In severe disaster year	In normal year	In severe disaster year	In normal year
Drought[a]	41	16	24	23
Early rice	37	15	26	26
Middle rice	60	22	19	21
Late rice	49	20	26	22
Flood[b]	34	16	25	24
Early rice	44	25	30	27
Middle rice	54	19	17	21
Late rice	22	11	23	20

Note: The normalized difference for the percentages of rice plots affected by drought and by flood is 0.41 and 0.33, respectively. Superscript [a]indicates a total of 1,449 observations in 12 counties, while [b]indicates a total of 2,305 observations in 11 counties.

from each township. Finally, we randomly selected 10 households for face-to-face interviews in each sampled village. A total of 2,250 households were identified in the five studied provinces. In each household, two plots with grain production were randomly selected, resulting in 4,500 plots.

Although 2,250 households were interviewed, some households either did not plant rice or only planted one rice plot. Therefore, the final sample used in our analysis includes 1,653 households with rice production and 2,571 plots from 185 villages in 63 townships of 23 counties in five provinces. Because farmers in our samples also planted double-season rice (early and late-season rice), we analyzed data by type of rice: early-season rice, middle-season rice (single-season rice), and late-season rice. We thus arrive at the final number of 3,754 observations.[4] For each observation in each plot, we collected data for two time periods during the years 2010–2012, that is, a severe disaster year and a normal year; the time (or year) varies across counties.

While the survey covers a wide range of information, given the research objectives of the article, our analysis uses only the following data: 1) characteristics of households and farms; 2) detailed plot-level rice production data, especially production inputs (e.g., land, labor, fertilizer, machinery, crop varieties, and pesticide), outputs in both the severe disaster year and normal year, and soil quality; 3) farm management measures that may relate to adaptations to extreme weather events (e.g., drought or flood events) at the plot level; and 4) availability of government services at villages for fighting extreme weather events, which was collected in the village level survey.

[4] The number of observations is 1,349 for early rice, 950 for middle rice, and 1,455 for late rice.

Extreme Weather Events and Rice Farmers' Responses

Overall, the frequency of extreme weather events in the studied provinces exhibited a rising trend. Drought in Henan and Yunnan has become more severe, especially in Yunnan, which has witnessed several extreme drought shocks in recent years. The average annual crop area suffering from drought in Yunnan increased from 0.47 million hectares in the 1980s to 0.95 million hectares in the 2000s, with an average growth rate of 3.2% (NBSC 2012). On the other hand, the other three provinces, Jiangxi, Guangdong, and Jiangsu suffered flood more often, but drought has also been frequent (NBSC 2012).

The household surveys also demonstrate the severity of drought and flood reported by farmers in the study areas. For example, as shown in table 1, the percentage of samples that suffered from drought reached 41% in the severe disaster year (column 1). As expected, drought occurred much less frequently (16%) in the normal year (column 2). Likewise, the percentage of samples affected by flood increased from 16% in the normal year to 34% in the severe disaster year (row 5). For both drought and flood, the highest frequency of disaster occurred for middle rice (60% drought and 54% flood) in the severe disaster year (column 1). Interestingly, yield losses were similar when rice production faced drought (23–24%) or flood (25–24%) in either the severe disaster or normal year (columns 3 and 4). Because these results were reported by farmers, the figures in table 1 account for farmers' responses to drought and flood.

In response to the rising trend of extreme weather events, farmers may take various physical and non-physical measures. Physical measures include investments in and maintenance of irrigation facilities such as canals, tube wells, cisterns, ponds, and pump equipment; non-physical measures include farm management, crop insurance, and other measures that do not require large investments (Wang, Huang, and Wang 2014). This study specifically focuses on non-physical measures such as farm management, which are usually the most convenient type that farmers can implement during crop growing season. Based on field surveys, the most common farm management measures used by farmers related to drought and flood are reseeding, fixing, and cleaning seedlings. On average, 30% of our samples used these measures (table 2), which are crucial at the early stage of rice production when facing drought or flood. Importantly, the field surveys also revealed that the application rate of farm management measures was generally higher in the severe disaster year (33%) than in the normal year (26%). While we are unsure how extensively farm management measures were applied in response to drought and flood, we argue that the differences in applying measures between the severe disaster year and the normal year must largely result from farmers' adaptation to more severe drought and flood. For example, the 7% increment (33–26) in the application of reseeding, fixing, and cleaning seedlings represents an adaptation to extreme weather events. Meanwhile, farmers also applied other farm management measures such as changing rice varieties the following season and adjusting fertilizer use (table 2). However, the difference between the severe disaster year and the normal year was not large.

Table 2. Percentage of Plots with Major Farm Management Measures Applied by Rice Farmers, 2010–2012

	Reseeding, fixing or cleaning seedlings	Changing varieties in the next season or adjusting fertilize use
Severe disaster year	33	5
Normal year	26	4
Average	30	4.5

Note: Sample includes 3,754 observations.

Modeling and Estimation Procedure

We evaluate the impacts of farmers' adaptation to extreme weather events by adjusting farm management practices on the mean yield, risk, and downside risk of rice yield. To do this, we start with a moment-based approach (Antle 1983). The first moment is the mean yield. The second moment represents the variance of yield, measured by the square term of the error term estimated in the mean yield regression. The third moment represents the downside risk (skewness) of yield, measured by the third power of the error term estimated in the mean yield regression. We then incorporate the estimated three moments in an econometric model as independent variables and analyze how farmers' adaptation decisions affect the above three outcomes.

Econometric Model of Mean Yield, Risk, and Downside Risk

Following Antle (1983) and Antle and Goodger (1984), we adopt a moment-based approach that allows a flexible representation of the production risk. This approach has been widely used in agricultural economics to model the implications of weather risk and risk management (Di Falco and Chavas 2009; Kim and Chavas 2003; Koundouri, Nauges, and Tzouvelekas 2006). In our study, the rice yield function in $\log(y)$ under production uncertainty can be defined as:

$$(1) \qquad y = f_1(A, \boldsymbol{X}, \boldsymbol{\theta}_1) + u,$$

where A refers to adaptation, which takes a value of 1 if a farmer applies the farm management measures, and 0 otherwise. Further, $\boldsymbol{X}$ is a set of explanatory variables that includes the following: a) production inputs (labor, fertilizer, machinery, irrigation, pesticides, etc.) specified in log and a flood-tolerant rice variety (1 for the flood-tolerant variety, 0 otherwise); b) farm characteristics including characteristics of household head (gender, age, and education), household assets (land and durable consumption assets per capita), soil quality by category (low, moderate, and high), and rice by type planted (early, middle, and late); c) year dummies for 2011 and 2012 to control for the effects of other variables related to each of the three years (2010, 2011, and 2012); and d) province dummies (fixed effects at the provincial level) to control for the effects of province-specific factors that do not change over time. Moreover, $\boldsymbol{\theta}_1$ is a vector of parameters to be estimated and u is the error term that captures the uncertainty, including weather, faced by farmers, and satisfies $E(u) = 0$.

After estimating equation (1), we calculate the error term $u = y - f_1(A, \boldsymbol{X}, \boldsymbol{\theta}_1)$. The central moments of the yield can be defined as $E(y) = f_1(A, \boldsymbol{X}, \boldsymbol{\theta}_1)$ for the expected value of yield, $E[(u)^2] = f_2(A, \boldsymbol{X}, \boldsymbol{\theta}_2)$ for the variance of yield, and $E[(u)^3] = f_3(A, \boldsymbol{X}, \boldsymbol{\theta}_3)$ for the skewness of yield (Di Falco and Chavas 2009; Kim and Chavas 2003).

Modeling Adaptation to Extreme Weather Events

Two econometric challenges arise when estimating the impact of farmers' adaptation decisions on the three outcome variables: endogeneity of the application of farm management practice (A), and the sample selection bias due to unobserved heterogeneity. To deal with the sample selection bias problem, we employ an endogenous switching regression model to identify the impacts of adjusting farm management practices on the mean, variance, and skewness of rice yield. In the switching regression approach, farmers are partitioned into two regimes according to the application decision (e.g., adapters and non-adapters). Farmers typically choose to adapt when there is a net benefit from doing so (Abdulai and Huffman 2014). We can therefore represent farmer i's adaption decision (whether to take adaptation measures) by a latent variable A_i^* as

$$(2)\quad A_i^* = g(\boldsymbol{X}, Z, \boldsymbol{D}, \boldsymbol{\gamma}) + \boldsymbol{\eta}_i, \quad A_i = 1[A_i^* > 0],$$

where the variable Z is an instrument variable (IV) for A that is going to be an explanatory variable in the outcome equations (mean, variance, and skewness of rice yield) discussed below. Access to the government's technical services against drought or flood is an instrument variable used in the selection function (2).[5] This value is measured by determining whether a farmer can access the government's technical services against drought or flood at the village level, as well as using a dummy variable (1 = yes, 0 otherwise). The implication of $\boldsymbol{X}$ is similar to that in equation (1). Furthermore, $\boldsymbol{D}$ includes two dummy variables: the severe drought year (1 = yes, 0 otherwise), and the severe flood year (1 = yes, 0 otherwise) measured at the county level. Additionally, $\boldsymbol{\gamma}$ denotes a vector of parameters to be estimated. The error term $\boldsymbol{\eta}$ with mean zero and variance $\boldsymbol{\sigma}_\eta^2$ captures measurement errors and unobserved factors.

Given that the choice to apply farm management measures lies with the farmers, a separate outcome function is specified for adapters and non-adapters:

$$(3a)\quad \text{Regime 1 (Adapters)}: \quad Q_{1i} = f(A, \boldsymbol{X}, \boldsymbol{D}, \boldsymbol{\beta}_1) + \boldsymbol{\varepsilon}_{1i} \quad \text{if } A_i = 1,$$

$$(3b)\quad \text{Regime 2 (Non-adapters)}: \quad Q_{2i} = f(A, \boldsymbol{X}, \boldsymbol{D}, \boldsymbol{\beta}_2) + \boldsymbol{\varepsilon}_{2i} \quad \text{if } A_i = 0,$$

where Q_{1i} and Q_{2i} are the outcome variables (mean of rice yield in log, variance of rice in log, and skewness of rice yield) for adapters and non-adapters, respectively.[6] The vectors $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are parameters to be estimated.

The three error terms $\boldsymbol{\eta}, \boldsymbol{\varepsilon}_1$, and $\boldsymbol{\varepsilon}_2$ in equations (2), (3a), and (3b) are assumed to have a trivariate normal distribution, with zero

[5] There are two types of such services. The first is to provide early warning information on drought and flood through various dissemination methods such as television, village broadcast, text message, and meetings to urge farmers to pay attention to the upcoming or on-going drought or flood. The second is to send technicians from county or township extension stations to their villages to help farmers handle extreme weather events (drought and flood). Whether technical services are provided to a village is decided by governments (e.g., township, county, prefectural, or provincial governments) and these services are provided exclusively for extreme weather events (drought and flood); therefore, it is expected that the variable of "access to the government's technical services against drought or flood at village" influences rice yields only through its effects on farmers' adaptation decisions related to drought and flood.

[6] We explored different functional forms such as the linear and quadratic forms for the mean, variance, and skewness functions. Finally, we presented the most robust results based on a linear-log specification.

mean and the following covariance matrix:

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_\eta^2 & \sigma_{\eta 1} & \sigma_{\eta 2} \\ \sigma_{1\eta} & \sigma_1^2 & \sigma_{12} \\ \sigma_{2\eta} & \sigma_{21} & \sigma_2^2 \end{bmatrix},$$

where $Var(\varepsilon_1) = \sigma_1^2$, $Var(\varepsilon_2) = \sigma_2^2$, $Var(\eta) = \sigma_\eta^2$, $Cov(\varepsilon_1, \varepsilon_2) = \sigma_{12}$, $Cov(\varepsilon_1, \eta) = \sigma_{1\eta}$, and $Cov(\varepsilon_2, \eta) = \sigma_{2\eta}$. Note that since Q_{1i} and Q_{2i} are not observed simultaneously, the covariance between ε_1 and ε_2 is not defined. The sample selection bias may lead to nonzero covariance between the error term of the selection equation (2) and the outcome equation (3) (Maddala 1983). According to Lee and Trost (1978), the expected values of the error terms ε_1 and ε_2, conditional on the sample selection are given as:

$$(4) \quad E[\varepsilon_{1i} \mid A_i = 1] = E(\varepsilon_{1i} \mid \eta > -g(\boldsymbol{X}, Z, \boldsymbol{D}, \boldsymbol{\gamma})) = \sigma_{1\eta}\frac{\varphi[g(\boldsymbol{X}, Z, \boldsymbol{D}, \boldsymbol{\gamma})/\sigma)]}{\Phi[g(\boldsymbol{X}, Z, \boldsymbol{D}, \boldsymbol{\gamma})/\sigma]} \equiv \sigma_{1\eta}\lambda_{1i},$$

and

$$(5) \quad E[\varepsilon_{2i} \mid A_i = 0] = E(\varepsilon_{2i} \mid \eta \le -g(\boldsymbol{X}, Z, \boldsymbol{D}, \boldsymbol{\gamma})) = -\sigma_{2\eta}\frac{\varphi[g(\boldsymbol{X}, Z, \boldsymbol{D}, \boldsymbol{\gamma})/\sigma)]}{1 - \Phi[g(\boldsymbol{X}, Z, \boldsymbol{D}, \boldsymbol{\gamma})/\sigma]} \equiv \sigma_{2\eta}\lambda_{2i},$$

where $\varphi(\cdot)$ is the standard normal probability density function, and $\Phi(\cdot)$ is the standard cumulative distribution function. The terms λ_1 and λ_2 refer to the inverse Mills ratio evaluated at $g(\boldsymbol{X}, Z, \boldsymbol{D}, \boldsymbol{\gamma})$, and are incorporated into equations (3*a*) and (3*b*) to account for sample selection bias. In this study, the endogenous switching model with the probit model used in the first stage is estimated by the full information maximum likelihood (FIML) method (Lokshin and Sajaia 2004). To account for the possible heterogeneity in farmers' decisions on whether to adapt or not under the standard endogenous switching regression framework, we first included two dummy variables (middle rice and late rice) to capture the specificity of the different crops. Second, we used the Huber/White sandwich estimator for the robust heteroskedasticity variance estimation (Shen and Hartarska 2013). This approach yields consistent estimates of the covariance matrix without making distributional assumptions (Freedman 2006).

Of significant interest in this research is how farmers' adaptation of farm management measures affects rice yield and risks. This impact can be examined by first specifying the expected values of the outcome. For an adapter and a non-adapter of the farm management measures, the expected value of the outcome is calculated, respectively, as

$$(6) \quad E[y_{1i} \mid A_i = 1] = f(A, \boldsymbol{X}, \boldsymbol{D}, \boldsymbol{\beta}_1) + \sigma_{1\eta}\lambda_{1i}$$

and

$$(7) \quad E[y_{2i} \mid A_i = 0] = f(A, \boldsymbol{X}, \boldsymbol{D}, \boldsymbol{\beta}_2) + \sigma_{2\eta}\lambda_{2i}.$$

Accordingly, the expected value of the same adapter, had he chosen not to apply the farm management measures, and of the same non-adapter had he chosen to apply the measures is given, respectively, as

$$(8) \quad E[y_{2i} \mid A_i = 1] = f(A, \boldsymbol{X}, \boldsymbol{D}, \boldsymbol{\beta}_2) + \sigma_{2\eta}\lambda_{1i}$$

and

$$(9) \quad E[y_{1i} \mid A_i = 0] = f(A, \boldsymbol{X}, \boldsymbol{D}, \boldsymbol{\beta}_1) + \sigma_{1\eta}\lambda_{2i}.$$

The change in outcome due to the application of farm management measures can then be specified as the difference between application and non-application (Di Falco, Veronesi, and Yesuf 2011). These changes are termed the average treatment effect on the treated (ATT) as the difference between (6) and (8):

$$(10) \quad \text{ATT} = E[y_{1i} \mid A_i = 1] - E[y_{2i} \mid A_i = 1] = f(A, \boldsymbol{X}, \boldsymbol{D}, \boldsymbol{\beta}_1) - f(A, \boldsymbol{X}, \boldsymbol{D}, \boldsymbol{\beta}_2) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{1i}.$$

Similarly, we can also calculate the average effect of the treatment on the untreated (ATU) for farmers that did not adapt as the difference between (9) and (7):

$$(11) \quad \text{ATU} = E[y_{1i} \mid A_i = 0] - E[y_{2i} \mid A_i = 0] = f(A, \boldsymbol{X}, \boldsymbol{D}, \boldsymbol{\beta}_1) - f(A, \boldsymbol{X}, \boldsymbol{D}, \boldsymbol{\beta}_2) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{2i}.$$

Since sample selection is taken into account through the terms (λ_1, λ_2) of equations (10) and (11), ATT and ATU generate unbiased estimates of the effects of adjusting farm management practices.

Econometric Estimation

Here we present the estimation results of equations (2), (3*a*), and (3*b*). The basic descriptive statistics are presented in table A.1 of the appendix.

Estimation of Mean Rice Yield Function

We begin by estimating the determinants for the application of farm management measures and their impact on the mean rice yield. The results for the selection and mean yield equations that are jointly estimated by the FIML approach are reported in table 3. The first column reports the estimates of the selection function (1), which helps explain why some farmers apply farm management measures and others do not. The second and third columns present, respectively, the estimated coefficients of mean rice yield functions (3*a*) and (3*b*) for farmers that did and did not apply farm management measures. In the results of the selection function, we are interested in the effects of severe flood and drought on the application decision. Previous studies found there is not a strong relationship between climate change variables and farmers' adaptation decisions (Di Falco, Veronesi, and Yesuf 2011). Our results show that compared to normal years, more farmers adjust their farm management practices when facing severe drought or flood (rows 1 and 2, table 3). This result empirically confirms that the application of farm management measures identified in this study is a type of adaptation to extreme weather events.

We also determine that the impacts of various inputs and farm characteristics on farmers' adaptation decisions are statistically significant (column 1, table 3). Labor, fertilizer, and other inputs, as well as using a flood-tolerant seed variety have significant positive effects on the probability of adapting the farm management measures. The estimated coefficient for male head of households is negative and statistically significant, suggesting that women tend to be more motivated to adjust farm management practices related to extreme events. Both land per capita and durable consumption assets per capita have significant and positive effects on adaptation. This result confirms that the poor may be more vulnerable in the face of climatic shocks (Wang, Huang, and Wang 2014). We also find that the estimated parameters for the 2011 and 2012 year dummy variables are positive and significant. However, direct interpretation of these parameters is not easy because the differences could be due to many systematical variations among different years.

The instrument variable (IV) has a significant and positive effect on adaptation. This suggests that farmers in villages with access to the government's technical services against drought or flood were more likely to practice adaptation against these extreme weather events. The result implies that having access to government technical services against drought or flood can reduce farmers' constraints on applying adaptation measures, and can thereby increase the possibility of adaptation. We also checked the validity of the IV by conducting the following three tests. First, we made a balance test on pre-treatment characteristics of farmers who do and do not have access to the technical services against drought or flood. Results indicate that the sample is not imbalanced on observables. Second, the results of an F-statistics test shows that despite statistical significance at the 1% level of the IV in the first-stage selection model, we cannot reject the presence of a weak instrument (F-stat. = 8.1, which is less than the threshold of 10). However, because the IV here is only related to the government's technical services against drought or flood, and the selection variable is farmers' adaptation measures in response to extreme drought and flood events, intuitively the impact of this IV on rice yield should be only (or largely) through its impact on farmers' adaptation measures. To show there is no direct impact of the IV on rice yield, we conducted the third test to determine whether this IV does not directly affect rice yield, but has an indirect effect on rice yield through its effect on adaptation. To do this, the rice yield among farmers that did not adapt is regressed on the IV along with all other variables. The t test statistic is 1.13, suggesting evidence of no direct impact of the IV on rice yield.

In yield equations, most estimated coefficients are statistically significant with the expected signs. For example, rice yield is lower for both adapters and non-adapters when extreme weather events are presented (rows 1 and 2, table 3). In particular, the

Table 3. Estimations of Farmer's Adaptation and Its Impact on Mean Rice Yield

	Selection	Rice yield (log) Adapters	Rice yield (log) Non-adapters
Severe disaster years			
Drought	0.117**	0.009	−0.124***
	(0.053)	(0.027)	(0.023)
Flood	0.277***	−0.095***	−0.273***
	(0.044)	(0.021)	(0.023)
Inputs			
Labor (log)	0.100***	−0.000	0.016
	(0.019)	(0.000)	(0.010)
Fertilizer (log)	0.087***	0.079***	0.021
	(0.027)	(0.019)	(0.016)
Machinery (log)	0.001	0.000	0.014***
	(0.006)	(0.000)	(0.004)
Other inputs (log)	0.031***	0.010	0.015**
	(0.012)	(0.007)	(0.006)
Flood-tolerant variety	0.122***	0.049**	0.015
	(0.035)	(0.020)	(0.016)
Farm characteristics			
Male of household head	−0.245**	0.147*	0.128*
	(0.119)	(0.089)	(0.076)
Age of household head	−0.003	−0.003***	−0.003***
	(0.002)	(0.001)	(0.001)
Education of household	0.007	0.001	0.008***
	(0.005)	(0.003)	(0.003)
Land per capita	0.138***	−0.002	−0.028**
	(0.024)	(0.015)	(0.013)
Durable consumption assets per capita	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Moderate soil quality	0.010	0.033	0.098***
	(0.049)	(0.021)	(0.025)
High soil quality	−0.034	0.086***	0.146***
	(0.056)	(0.027)	(0.028)
Middle rice	−0.046	0.218***	0.257***
	(0.046)	(0.026)	(0.024)
Late rice	−0.050	0.079***	0.144***
	(0.036)	(0.022)	(0.019)
D2011	0.174***	0.220***	0.131***
	(0.052)	(0.041)	(0.028)
D2012	0.112**	0.143***	0.113***
	(0.049)	(0.032)	(0.022)
Instrument variable			
Access to the government's technical services against drought or flood	0.108***		
	(0.039)		
Constant	−0.479	8.055***	8.243***
	(0.323)	(0.223)	(0.166)
Province dummies	Yes	Yes	Yes
σ_i		0.382***	0.542***
		(0.047)	(0.023)
ρ_j		0.085	−0.045
		(0.225)	(0.040)

Note: Robust standard errors appear in parentheses. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The sample consists of 7,508 observations (3,754 × 2 years).

impact of flood on the rice yield of non-adapters is larger than that of the adapters. These results suggest that flood events are more severe than drought for rice production. Adapters suffer less yield loss than non-adapters, indicating the effective impact of adaptation. An exception is found for adapters in the severe drought year: the estimated coefficient is not statistically significant. This may be because rice is generally planted in areas where the availability of irrigation water is more ensured. Having less significant coefficients for input variables (rows 3–7, table 3) is consistent with previous findings on intensive or excessive use of production inputs in China (e.g., Huang et al. 2008; Holst, Yu, and Grun 2013).

Regarding farm characteristics, most estimated coefficients are statistically significant. Households headed by men, youths, and highly educated people tend to improve rice yield for both adapters and non-adapters (middle section, table 3). The negative impact of land per capita suggests the average yield is negatively correlated with farm size, a finding similar to that of many existing studies (e.g., Abdulai and Huffman 2014). Other variables such as wealth (durable consumption assets per capita) and better soil quality also positively impact rice yield. The order of yield from early rice to middle rice and then to late rice is also expected.

Estimation of Risk Functions

The estimation of farmers' adaptation decisions and their impacts on the variance and skewness of rice yield are shown in table A.2 (appendix) and table 4. Because the results on the selection (or adaptation) equation (column 1, tables A.2 and 4) are similar to those presented in table 3, here we focus on the estimates of the variance and skewness functions.

Most of the estimated coefficients in the variance function are statistically significant (table A.2). The signs of many of the coefficients reveal some interesting findings. For example, severe flooding is found to have a statistically positive impact on the variance of rice yield for non-adapters, but no significant impact for adapters (row 2, table A.2). This suggests that the adaptation does mitigate rice yield risk or variance when severe flooding occurs. The impact of severe drought on the variance is positive but not statistically significant. This may be because rice is produced in regions with good irrigation infrastructure. The impacts of several inputs and farm characteristics on the variance of yield also differ (middle section, table A.2).

Regarding the skewness of rice yield, we first test normality of the error term u with a null hypothesis that the yield distribution is symmetric using a Wald statistic. The mean skewness of u is -0.35 and the Wald statistic is statistically different from zero with a p-value of 0.000. This implies that the distribution yield is skewed to the left, which corresponds to a significant exposure to downside risk. In this case, if negative skewness increases, the probability of crop failure would increase (Torriani et al. 2007).

The results of the estimated skewness function suggest that both severe flooding and drought have significantly negative effects on the skewness of rice yield, and thus increase the exposure to downside risk for both adapters and non-adapters (rows 1 and 2, table 4). We also find that inputs such as labor, machinery, and better soil quality have different effects on the skewness of yield for adapters and non-adapters (middle section, table 4). The differences in the coefficients of the variance and skewness functions between adapters and non-adapters illustrate the presence of heterogeneity in the sample.

The estimated results show that the covariance term ρ_j in the skewness function for both adapters and non-adapters is not statistically different from zero (table 4), while ρ_j in the variance function has a positive sign and is statistically significant in the equation for non-adapters (table A.2).[7] This information suggests that non-adapters have significantly higher variance of rice yield than a random household in the sample. On the other hand, ρ_j has a negative sign and is statistically significant in the adapters' equation, indicating that adapters have lower variance of rice yield than a random household in the sample (Akpalu and Normanyo 2014).

[7] The estimates presented in the last two rows of tables 3, 4, and A.2 account for the endogenous switching in the mean, variance, and skewness of rice yield functions, respectively. Although the estimated coefficients of the correlation term ρ_j are not statistically significant in the mean and skewness of rice yield functions (tables 3 and 4), it is statistically significant in the variance of rice yield function (table A.2). In addition, the estimated coefficients of many variables in the mean, variance, and skewness of yield functions between adapters and non-adapters differ. The above results suggest that we would have encountered estimation problems if we had not used the endogenous switching regression model.

Table 4. Estimations of Farmer's Adaptation and Its Impact on Skewness of Rice Yield

		Skewness of rice yield	
	Selection	Adapters	Non-adapters
Severe disaster years			
Drought	0.115**	−0.130***	−0.201**
	(0.053)	(0.048)	(0.088)
Flood	0.278***	−0.347***	−0.781***
	(0.044)	(0.078)	(0.092)
Inputs			
Labor (log)	0.101***	−0.059*	0.089**
	(0.019)	(0.032)	(0.041)
Fertilizer (log)	0.085***	0.079*	−0.012
	(0.027)	(0.041)	(0.058)
Machinery (log)	0.001	−0.017***	0.045***
	(0.005)	(0.006)	(0.014)
Other inputs (log)	0.033***	−0.015	0.028
	(0.012)	(0.014)	(0.026)
Flood-tolerant variety	0.124***	0.066	0.043
	(0.035)	(0.057)	(0.067)
Farm characteristics			
Male of household head	−0.245**	0.326	0.044
	(0.119)	(0.380)	(0.260)
Age of household head	−0.003*	−0.003	−0.008***
	(0.002)	(0.004)	(0.003)
Education of household	0.007	0.000	0.006
	(0.005)	(0.000)	(0.012)
Land per capita	0.138***	−0.056	−0.076
	(0.024)	(0.051)	(0.056)
Durable consumption assets per capita	0.001***	0.001*	0.002***
	(0.000)	(0.001)	(0.001)
Moderate soil quality	0.010	−0.087**	0.150
	(0.050)	(0.035)	(0.103)
High soil quality	−0.034	−0.120*	0.070
	(0.056)	(0.067)	(0.121)
Middle rice	−0.042	0.408***	0.589***
	(0.047)	(0.108)	(0.113)
Late rice	−0.070*	0.262***	0.466***
	(0.036)	(0.080)	(0.077)
D2011	0.175***	0.482***	0.505***
	(0.052)	(0.108)	(0.124)
D2012	0.112**	0.324***	0.422***
	(0.049)	(0.086)	(0.092)
Instrument variable			
Access to the government's technical services against drought or flood	0.105***		
	(0.037)		
Constant	−0.421	−0.781	−1.457**
	(0.325)	(0.689)	(0.597)
Province dummies	Yes	Yes	Yes
σ_i		1.226***	2.299***
		(0.099)	(0.040)
ρ_j		0.024	−0.013
		(0.027)	(0.033)

Note: Robust standard errors appear in parentheses. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The sample consists of 7,508 observations.

Table 5. Impacts of Farm Management Measures on Mean, Risk, and Downside Risk Exposure of Rice Yield

Sub-samples	Decision stage: To adapt	Decision stage: Not to adapt	Treatment effects
Average expected rice yield (kg/ha)			
Rice plots that adapted	5,571	4,908	ATT = 663***
Rice plots that did not adapt	5,161	5,086	ATU = 74***
Average expected variance (risk)			
Rice plots that adapted	0.028	0.049	ATT = −0.021***
Rice plots that did not adapt	0.016	0.035	ATU = −0.019***
Average expected skewness (downside risk exposure)			
Rice plots that adapted	−0.136	−0.438	ATT = 0.302***
Rice plots that did not adapt	−0.173	−0.487	ATU = 0.314***

Note: ATT represents the effect of the treatment (i.e., adaptation) on the treated (i.e., farmers that adapted), while ATU represents the effect of the treatment (i.e., adaptation) on the untreated (i.e., farmers that did not adapt). Asterisks *** denote significance at the 1% level.

Effects of Adaptation on Mean, Variance, and Skewness of Rice Yield

The estimates for the average treatments effects (ATT and ATU) on the mean, variance, and skewness of rice yield are presented in table 5. The results reveal that the adaptation significantly increases rice yield (rows 1 and 2). Unlike the mean differences presented in table A.1, which may confound the impact of farmers' adaptation decisions on yield through the influence of other characteristics, these average treatment effect estimates account for selection bias arising from the fact that adapters and non-adapters may be systematically different. Specifically, in the counterfactual case represented by equation (8), farmers who adapted would reduce rice production by 663 kg/ha (about 14%) if they had not adapted (row 1). If we extrapolate such loss to the national level, it implies that China would reduce rice production by 9%, equivalent to $8.4 billion USD. In the counterfactual case, equation (9), for farmers who did not adapt, they would increase rice production by 74 kg/ha (about 2%) if they did adapt (row 2). This implies that China would increase crop revenue by $0.99 billion USD due to adaptation measures taken by rice farmers. These findings suggest adapting to extreme weather events through farm management measures does benefit China through increased rice production.

Table 5 also presents the average treatment effects of adaptation on the variance and skewness of rice yield. We find that farm management measures taken by farmers in response to extreme weather events significantly decreased both variance (rows 3–4) and downside risk of rice yield (rows 5–6). For example, the risk (variance measure) faced by farmers who adapted would have had an increase of 0.021 units (about 43%) if they had not adapted (row 3). The impact of taking adaptation measures on the downside risk of rice yield is similar to its impact on the variance case. The downside risk faced by farmers who adapted would have had an increase of 0.302 units (about 69%) if they had not adapted (row 5). These estimates show that farmers' adaptation to extreme weather events hedges against the risk of crop failure.

Conclusions

Using data from a survey conducted in five provinces in China, this article investigates the contribution of applying farm management measures in response to extreme weather events on the mean, variance, and downside risk of rice yield. The survey results show that more farmers adjust their farm management practices (e.g., reseeding, fixing, and cleaning seedlings) in severe drought and flood years than in normal years. The econometric analysis confirms that the applied farm management measures respond to severe drought and flood and can be considered an adaptation to climate change, an issue often ignored in previous studies. The extent of applying farm management measures is closely correlated with crop input levels and varies across households with differences in the characteristics of both farmers and their farms. Moreover, improving farmers' access to governmental services for drought and flood facilitates farmers to adapt by adjusting their farm management practices. Existing farm management measures can help farmers adapt to extreme weather events, and adjusting farm management helps increase the mean rice yield and reduces risks, including the variance and downside risk of rice yield.

The findings from this study have several policy implications. First, the farm management measures can be used for adaptive risk management in rice production. Currently, plans for enhancing national adaptation strategies have mainly focused on new investment and new technology (IPCC 2014). While these are important, national adaptation plans should also focus on existing farm practices, such as the farm management measures discussed in this study, which can reduce climate risks and can be easily applied by farmers. However, our survey shows that even during severe drought and flood years, only one-third of farmers are able to use farm management measures to cope with extreme weather events. Since the cost of this kind of adaptation is low, the potential to scale it up to more farmers is high.

Second, public services can play an important role in helping farmers adapt to extreme events, thereby increasing their adaptive capacity. Our results suggest that the government's services for drought and flood (e.g., the dissemination of warning information during/after disasters and providing technical guidance by sending technical experts to the fields) is of paramount importance in determining the implementation of farmers' adaptation measures. Further, the availability of disaster warning information may increase farmers' awareness of threats posed by extreme weather events. Providing technical guidance can reduce farmers' constraints on applying adaptation measures and increase the possibility of adaptation. However, only one-fourth of rice farmers in our study areas can access these services. Clearly, there is room to incorporate climate change adaptation services into China's public extension system.

Third, another crucial area where farmers' adaptive capacity can be improved is the development of large family farms in China. The results show that land per household is a significant driver of the decision to adapt. For those farmers who have adapted, this seems to indicate that the scale management of agriculture helps to decrease rice production risks posed by extreme events. Policy makers should therefore mainstream climate change adaptation into the modernization of agriculture symbolized by scale management. Accordingly, policy makers may also need to intervene to encourage land transfer to promote the emerging rental market in rural areas of China.

Fourth, enhancing the adaptive capabilities of the poor in response to extreme events should be another prioritized area for policy interventions. The positive influence of household assets on adaptation decisions suggests that the poor, who generally lack sufficient capital or labor, may be more vulnerable in the face of extreme events. Hence, governmental support such as technical services for droughts or flooding should particularly be given to the poor to enhance their adaptation of farm management measures.

Finally, as farmers have been suffering increasingly frequent and severe extreme weather events in many developing countries, we believe the findings of this study also have implications for other countries in terms of their national adaptation plans and farmers' crop risk management.

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Appendix

Table A.1. Descriptive Statistics of Variables by Adapters and Non-adapters of Farm Management Measures

Variables	Total	Adapters	Non-adapters	Diff.
Rice yield (kg/ha)	5,631.13	5,854.71	5,537.50	317.21***
Variance of rice yield	0.25	0.15	0.30	−0.15***
Skewness of rice yield	−0.35	−0.14	−0.44	0.30***
Severe flood year (1 = yes; 0 = no)	0.31	0.36	0.29	0.07***
Severe drought year (1 = yes; 0 = no)	0.19	0.21	0.19	0.02**
Labor (days/ha)	125.41	138.72	119.83	18.89***
Fertilizer (kg/ha)	405.56	413.97	402.03	11.94***
Machinery (yuan/ha)	1,807.27	1,778.93	1,819.14	−40.21*
Other inputs (yuan/ha)	1,173.78	1,235.09	1,148.11	86.98***
Flood-tolerant variety (1 = yes; 0 = no)	0.28	0.32	0.26	0.06***
Male of household head (1 = male; 0 = female)	0.98	0.98	0.98	0.00
Age of household head (years)	54.13	53.88	54.23	−0.35
Education of household head (years)	6.63	6.78	6.57	0.21***
Land per capita (ha)	0.34	0.40	0.32	0.08***
Durable consumption assets per capita (1,000 yuan)	23.98	26.94	22.73	4.21***
High soil quality (1 = yes; 0 = no)	0.22	0.21	0.23	−0.02
Moderate soil quality (1 = yes; 0 = no)	0.66	0.67	0.65	0.02
Middle rice (1 = yes; 0 = no)	0.25	0.26	0.25	0.01
Late rice (1 = yes; 0 = no)	0.39	0.38	0.39	−0.01
2012 (1 = yes; 0 = no)	0.47	0.44	0.49	−0.05***
2011 (1 = yes; 0 = no)	0.30	0.35	0.28	0.07***
Access to the government's technical services against drought or flood (1 = yes; 0 = no)	0.24	0.26	0.23	0.03**

Note: There are 7,508 total observations. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.2. Estimations of Farmer's Adaptation and Its Impact on Variance of Rice Yield

		Variance of rice yield (log)	
	Selection	Adapters	Non-adapters
Severe disaster years			
Drought	0.065	0.254	0.167
	(0.051)	(0.211)	(0.125)
Flood	0.214***	−0.225	0.662***
	(0.041)	(0.167)	(0.104)
Inputs			
Labor (log)	0.076***	−0.236***	0.130***
	(0.017)	(0.071)	(0.043)
Fertilizer (log)	0.045*	−0.000	−0.032
	(0.025)	(0.000)	(0.058)
Machinery (log)	−0.001	−0.021	−0.064***
	(0.005)	(0.023)	(0.014)
Other inputs (log)	0.030***	−0.156***	0.025
	(0.011)	(0.048)	(0.026)
Flood-tolerant variety	0.081**	−0.282**	0.046
	(0.032)	(0.132)	(0.083)
Farm characteristics			
Male of household head	−0.211*	0.537	−0.886***
	(0.108)	(0.434)	(0.284)
Age of household head	−0.002	0.011*	0.001
	(0.001)	(0.006)	(0.003)
Education of household	0.008	−0.045**	−0.016
	(0.005)	(0.021)	(0.013)
Land per capita	0.116***	−0.346***	0.336***
	(0.022)	(0.085)	(0.058)
Durable consumption assets per capita	0.001***	−0.005***	0.002***
	(0.000)	(0.001)	(0.001)
Moderate soil quality	0.019	0.023	−0.281**
	(0.044)	(0.180)	(0.111)
High soil quality	−0.055	0.399*	−0.538***
	(0.051)	(0.211)	(0.127)
Middle rice	−0.075*	−0.208	−1.034***
	(0.043)	(0.175)	(0.107)
Late rice	−0.054	−0.199	−0.556***
	(0.034)	(0.138)	(0.084)
D2011	0.089*	−0.890***	−0.946***
	(0.048)	(0.200)	(0.121)
D2012	0.068	−0.965***	−1.129***
	(0.045)	(0.183)	(0.111)
Instrument variable			
Access to the government's technical services against drought or flood	0.085***		
	(0.020)		
Constant	−0.317	−0.512	0.412
	(0.290)	(1.158)	(0.834)
Province dummies	Yes	Yes	Yes
σ_i		3.810***	2.855***
		(0.085)	(0.035)
ρ_j		−0.965***	0.908***
		(0.004)	(0.006)

Note: Robust standard errors appear in parentheses. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The sample consists of 7,508 observations.