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CLIMATE VARIABILITY, SHOCKS AND NON-FARM EMPLOYMENT: EVIDENCE FROM RURAL HOUSEHOLDS IN NORTHEAST THAILAND

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Abstract

This paper examines the impact of climate variability and shocks on non-farm employment in rural areas of Northeast Thailand. The paper utilizes a large panel data set that includes detailed and retrospective information about shock experience and a corresponding twenty-year historical village-level monthly rainfall data set from rural Northeast Thailand. The paper finds that the labor market is heterogeneous in terms of adapting to climate variability and coping with shocks. Households use non-agricultural wage and self-employment as a means of adapting to rainfall variability while they use agricultural wage to cope with agricultural and demographic shocks. We also show that there is a concave relationship between rainfall variability and both non-agricultural wage and non-farm self-employment. Economic slowdown and idiosyncratic shocks, such as demographic shocks, lead to substantial non-agricultural wage employment reduction. Overall, our findings show that the labor market can be less effective as a means for adapting to severe rainfall variability, economic and demographic shocks. It is also observed that poorer households are less able to exploit the high returns of the labor market to cope with shocks because of a lack of start-up assets.

Keywords

Climate Variability, Shocks, Non-farm Employment, Asset, Rural Thailand

JEL classification codes: Q120, Q540, J220

1 Introduction

Climate variability can put various sectors at risk, threaten households' livelihoods and undermine attempts to reduce poverty. The implications of climate variability are especially important for people in Southeast Asian regions who rely on agricultural and natural resources for their primary income and for heavily populated coastlines and large sections of the population who live on less than $2 a day (ADB, 2009). The negative effects of climate variability can be compounded by incomplete insurance and credit markets, which affect the behavior of households with regard to their adaptation strategies and responses to shocks. Even in emerging market economies such as Thailand, where the rapid and broad-based economic development and reduction of chronic poverty have been realized, and rural households are still vulnerable to climate change and extreme events in agriculture remains (LUO and LIN, 1999; IPPC, 2007). More than two-thirds of agricultural production in rural Thailand is rain fed and largely dependent on monsoon rains for cultivation (LUO and LIN, 1999; ADB, 2009). Thus, climate change, including higher surface temperatures, floods, droughts, severe storms and rising sea levels, are more likely to increase the vulnerability of the agricultural systems (IGLESIAS et al., 2011).

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Rural households in developing countries attempt to reduce their overall vulnerability to climate shocks and manage the impacts of these climate shocks ex-post by changing their farm portfolios of crops and livestock (e.g., HOWDEN et al., 2007; DI FALCO and CHAVAS, 2009; SMALE et al., 2001), using the labor market (e.g., BANDYOPADHYAY and SKOUFIAS, 2012; ELLIS and ALLISON, 2004; BARRETT et al., 2001; ITO and KUROSAKI, 2009), and employing a wide range of agriculture-based practices and technologies such as new cultivars, fertilizer and soil and water management (e.g., MCCARTHY et al., 2011, DERCON and CHRISTIAENSEN, 2011). The labor market has been used as a useful adaptation and coping strategy in some developing societies to withstand climate variability (ELLIS and ALLISON, 2004; BARRETT et al., 2001; ROSE, 2001; ITO and Kurosaki 2009). Thus, the rural non-farm sector plays a critical role in promoting growth and welfare by providing alternative employment. Consequently, the share of non-farm income to total household income is significant and growing in many developing countries (BARRETT et al., 2005). For example, DAVIS et al. (2010) reported that the non-farm income share has grown to 40–60% of rural incomes in Africa, Latin America and Asia.

However, there are three possible challenges in using the labor market as an adaptation strategy for climate variability and coping with shocks. First, because the share of non-farm income to total household income is growing in many developing countries as they increasingly rely on non-farm income, agricultural production shocks are no longer the only source of risks: demographic shocks and shocks in the labor market, such as job loss or income reduction, can limit the effectiveness of the labor market as a means of adapting to climate variability. Studies (e.g., FALLON and LUCAS 2002; HUANG et al. 2010; Bowen et al, 2012) have indicated that financial crises have led to a substantial reduction in non-farm employment. HUANG et al. (2010) found that rural households that diversified into non-farm employment lost their jobs because of the recent global financial crisis in China. TONGRUKSAWATTANA et al. (2013) found that demographic shocks, particularly the illness of a household member, represent the second most common shock type experienced by households in rural Thailand. They also found that demographic shocks cause higher asset LOSSES than agricultural shocks.

Second, the labor market as an adaptation and coping strategy against climate variability can be limited when the labor market is also affected by the same types of shocks that make the returns from the labor market to be correlated with on-farm returns (BARRETT et al., 2001; Ito and KUROSAKI, 2009). Additionally, households in developing countries face imperfect capital markets that influence a household's liquidity constraint, which influences a household's decision to engage in the labor market (BEEGLE et al., 2006; BARRETT et al., 2005; DEMEKE et al., 2011). In particular, because poor households in developing countries are constrained in terms of liquidity and more risk averse, they have a greater incentive to use the labor market as an adaptation strategy and to cope with shocks. However, they face entry barriers in using the labor market because of the lack of necessary resources, such as skill and capital, thus allowing wealthier farm households to dominate the most remunerative non-farm employment (BARRETT et al., 2005; LANJOUW and LANJOUW, 2001). This situation applies to rural Thailand, where income inequality is particularly high (WARR, 2011).

In this regard, the contributions of this paper to the existing literature are three-fold. First, this study aims to contribute to the expanding literature (GREEN and WEATHERHEAD, 2014; DI FALCO et al., 2012; DI FALCO et al., 2014; BANDYOPADHYAY and SKOUFIAS, 2012) on the impact of climate variability on household non-farm employment by including demographic shocks and shocks in the labor market, such as job loss or income reduction. The emphasis on using demographic shocks and shocks in the labor market climate distinguishes this study from others that consider the impacts of climate variability on non-farm employment. Second, this paper examines the impact of climate variability and other sources of shocks on non-farm employment by distinguishing among different types of non-farm labor, such as agricultural wage[2], non-agricultural wage[3] and non-farm self-employment[4], to address the possible heterogeneity of the labor market as a means of adapting to climate variability and coping with shocks in terms of their returns and accessibilities. Third, most of the past studies have used cross-sectional data, which limits the conclusions with regard to the long-term impact of climate variability and shocks. This paper utilizes a large panel data set that includes detailed information on retrospective information about shock experience and historical climatic patterns, such as the long-term coefficients of variation and intensity in village level rainfall, respectively which allows us to examine how rural households cope with long-term changes in climatic parameters and other sources of shocks.

The article is organized as follows. The next section presents the conceptual framework underlying the model which explains non-farm strategies in the presence of risk and incomplete credit and insurance markets. Section 3 describes the data, including information on the incidence and consequences of shocks and non-farm employment. Empirical strategies to test our hypotheses are presented in section 4, and in section 5, we discuss the econometric results. In section 6, we conclude and forward policy implications.

2 Conceptual Framework

We framed our analysis using the standard unitary agricultural household model in the presence of risk. The risk-averse farm household chooses climate change adaptation and shock coping strategies that will yield the highest net income given the production function and land, labor, and other resource constraints as well as climate (GREEN and WEATHERHEAD, 2014; DI FALCO et al., 2012; DI FALCO et al., 2014; BOWEN et al., 2012). We add the role of asset endowments to explain climate variability adaptation and buffering against shocks. Because the poor have a low level of initial human and physical capital, are more liquidity constrained and are more risk averse, they may be less able to exploit non-farm employment opportunities and thereby adapt to climate variability (BEEGLE et al., 2006; BARRETT et al., 2005; DEMEKE et al., 2011). As shown in studies conducted in developing countries (e.g.; Amare et al., 2012; Barrett et al. 2005), skilled wage employment and relatively high-investment businesses yield higher average and marginal returns compared with farming or other non-farm activities but are not accessible to poorer households. Conversely, initially wealthier households often have access to credit and insurance markets and are situated in wealthier areas that tend to engage in high-return non-farm employment, with the result that non-farm employment ultimately has a tendency to increase inequality (LANJOUW and LANJOUW, 2001). Furthermore, it is observed that the livelihoods of rural households in developing countries increasingly rely on non-farm income (DAVIS et al., 2010). Hence, climate variability is no longer the only source of risks, and shocks related to economic slowdown in the industrial or services sectors and idiosyncratic shocks, such as demographic shocks, may also negatively affect rural households. Considering the findings from the literature, we can deduce that it is important to incorporate not only climate variability but also multiple sources of uncertainties stemming from non-farm employment and the asset endowments of rural households when examining the role of labor markets in a household's ability to adapt to climate variability and cope with shocks.

Adaptation measures for climate variability and coping strategies for various sources of shocks by a farmer over a given period of time are assumed to be derived from the maximiza-

[2] Agricultural wage employment refers to activities outside the own farm, such as agricultural wage laborer, logger or fisher.

[3] Non-agricultural wage employment includes jobs in the services sector, construction and production industries.

[4] We define non-farm self-employment as employment of households that have an own-account worker (e.g., handicraftsman, petty-trader) or households with an own business that employs family workers or other employees (e.g., restaurant, convenience shop, hair salon, transport business).

tion of a discounted expected utility function of farm profit subject to climate variability, various sources of shocks that can influence the non-agriculture sector and liquidity constraints. Assuming that each farmer makes his non-farm employment participation decision to maximize profit, the reduced form non-farm employment decision is given by

(1) $A_{jit} = A(x_{it}, c_{it}, s_{it}, z_{it}, v_{it}; \beta) + \mu_{it}$

where A_{itj} is the labor allocated[5] to different sectors (j) such as agricultural wage, non-agricultural wage and non-farm self-employment of household i in time t. x_{it} is a vector of household characteristics, c_{it} is a vector to capture climatic variables and s_{it} is a vector with various sources of shocks[6]: (i) demographic shocks and (ii) economic shocks. z_{it} is a vector of wealth indicators and v_{it} are vectors of village-level characteristics. β is the vector of coefficients, and μ_{it} is the household-specific random error term.

Following agricultural household theory and situation analysis, we establish the following hypotheses regarding how households use the labor market to adapt to climate variability and cope with various sources of shocks. First, we hypothesize that farmers use the labor market to adapt to climate variability by allocating more labor to non-agricultural wage and self-employment and less to agricultural wage employment, meaning that labor markets are heterogeneous adaptation strategies. Second, using income diversification to adapt to climate variability is a limited strategy in the presence of economic and idiosyncratic shocks, such as demographic shocks. Third, we hypothesize that poorer households are less able to exploit non-farm employment opportunities to adapt to climate variability because of a lack of start-up human and physical capital and incomplete insurance and credit markets.

3 Study Area and Data Description

The data used for this study originate from a longitudinal survey DFGFOR756[7] database that comprises two rounds (2008 and 2010) of household- and village-level surveys that were conducted in rural Northeast Thailand. The surveys were conducted in three deliberately selected provinces, i.e., Buriram, Nakhon Phanom and Ubon Ratchathani, based on the high importance of agriculture for household income despite a low agricultural potential, remoteness in some areas and a high potential in other economic sectors. The sample was designed in such a way that it is representative of the rural population and would allow conclusions to be drawn for the vulnerability of households in rural areas in Northeast Thailand and other areas with similar conditions (HARDEWEG et al., 2013). Within the provinces, a three-stage random cluster sampling procedure was used to obtain a sample that was representative of the rural populations of the three selected provinces. In the first stage, the sub-district was sampled with approximately proportional allocation. Next, the villages were sampled with a probability proportional to their size based on their population. Finally, a systematic random sample with equal probability from household lists ordered by household size was used, resulting in a total sample size of 2200 households and 220 villages (HARDEWEG et al., 2013). The survey instrument included modules on household characteristics, assets, income, consumption and hours worked in various types of non-farm employment. A comprehensive shocks and risks section to collect retrospective information about shock experience and current risk perception was also included. We match this data set with longitudinal monthly rainfall data collected from local meteorological stations by the Thailand Meteorological Agency from 1991

[5] We use log hour allocated because the error terms become less heteroscedastic after the logarithmic transformation.

[6] The question asked during the survey was as follows: considering the time during the year preceding the survey, did any event cause a shock that affected the household and subsequent welfare loss due to shocks?

[7] It has been implemented by a consortium of economic research institutes of four German universities, including those in Hannover, Göttingen, Giessen, and Frankfurt. http://www.vulnerability-asia.uni-hannover.de/

to 2010. The data set includes the amount of rainfall (in millimeters per day) for 52 weather stations in the three provinces. We use a straight-line distance between each village (200 villages) to link the survey data with the closest weather station.

Following the literature (ITO and KUROSAKI, 2009; ROSE, 2001; BANDYOPADHYAY and SKOUFIAS, 2012; DI FALCO et al., 2009), we focus on one aspect of climate variability, represented by the coefficient of variation of rainfall, rainfall abundance and self-reported agricultural shocks, such as drought, flood, crop pests and diseases, to address how rural households use the labor market to adapt to climate variability. The coefficient of variation (CV of rainfall) is measured as the standard deviation divided by the mean of the monsoon season (sum of rainfalls from June to October) for twenty years' worth (1991–2010) of rainfall data at the village level (200 villages), and rainfall abundance is measured as the lagged average monsoon rainfall. We use a dummy variable for positive welfare losses[8] due to drought, flood, bad weather, crop pests and diseases as an indicator of agricultural shocks during the year preceding the survey. Similarly, we use a dummy variable for positive welfare loss due to illness and death as an indicator of demographic shocks and a dummy variable for positive welfare loss due to job loss, price changes and market regulation during the year preceding the survey.

As revealed by the household surveys, in all three provinces, the most frequently experienced shocks are related to agriculture (Table 2). However, demographic and economic shocks also play a role. In the shock module, we obtain information on the estimated total loss of income and assets and the extra expenditures due to an event in the year of its occurrence. Table 2 also reports the consequences of the most commonly reported shocks on the estimated loss of household assets and income, extra expenditures and total welfare loss due to the event. In 2008, agricultural shocks were the main source of welfare loss, followed by demographic and economic shocks, whereas in 2010, demographic shocks were dominant, followed by agricultural and economic shocks. More than 85% of the sample households participated in non-farm employment during the survey periods. Approximately 72% participated in non-agricultural wage activities, and 31% participated in non-farm self-employment (Table 3). The higher proportion of non-agricultural wage employment may reflect the accessibility of non-agricultural wage activities in rural Thailand.

Table 3 presents the intensity of non-farm employment participation and returns to family labor. Although the proportion of households participated in nonagricultural and agricultural wage employment seems to have declined, the hours supplied in nonagricultural and agricultural wage increased by 10% and 11%, respectively. Non-farm self-employment has the highest return to family labor among all of the activities undertaken by farmers. The average return to labor for self-employment[9] is more than 5.02 PPP$ per hour, which is approximately six and twelve times higher than that observed for non-agricultural wage and agricultural wage labor, respectively. The results may suggest that non-farm employment is heterogeneous in terms of their returns.

Table 4 presents the household characteristics, assets and various sources of shocks by non-farm employment participation. The results show that approximately 54% of the top tercile of households based on assets participate in non-farm self-employment activities, whereas approximately half of the lowest tercile group of households based on assets are engaged in agricultural wage employment. Table 4 also presents the reported shocks, and the incidence of shocks differs by non-farm employment participation. Households that are mainly dependent on low-return non-farm employment and have lower initial asset holdings were more likely to report being adversely affected by various sources of shocks.

[8] The question asked during the survey was as follows: considering the time during the year preceding the survey, has any event caused a shock that affected the household and subsequent welfare loss due to shocks?

[9] For non-farm self-employment, return is defined as the net income (profit) from non-farm self-employment divided by the number of hours supplied for non-farm self-employment per year.

4 Estimation Techniques

To test our hypotheses developed above, we first aim to examine the impact of climatic variables such as rainfall variability and rainfall abundance at the village level as well as self-reported agricultural shocks on non-farm employment. The basic regression model, which estimates how rural household use the labor market to adapt to climate variability and cope with agricultural shocks, takes the following form:

(2) $$A_{jit} = \beta_c c_{it} + \mu_{it}$$

where c_{it} is a vector to capture climatic variables such as the coefficient of variation[10], lagged monsoon rainfall and shocks related to agricultural production such as flood, drought, bad weather, pests and diseases. We include quadratic terms of lagged monsoon rainfall levels and the coefficient of variation to allow for nonlinear relationships between rainfall patterns and non-farm employment.

Second, we examine the combined effect of climate variability, economic shocks and demographic shocks on non-farm employment. We specifically estimate the following specification:

(3) $$A_{jit} = \beta_c c_{it} + \beta_s s_{it} + \mu_{it}$$

where s_{it} is a vector of various sources of shocks, e.g., demographic shocks such as health and death shocks and economic shocks such as losing jobs, business failures and price changes.

Additionally, to examine whether the risk-bearing capacities of households differ with the level of assets and whether shocks have a smaller effect on households with a greater level of assets, we include non-land assets and their interaction with rainfall variability and shock variables. In this model, we also include a wide range of household- and village-level characteristics. We investigate this empirically as follows:

(4) $$A_{jit} = \beta_x x_{it} + \beta_c c_{it} + \beta_v v_{it} + \beta_s s_{it} + \beta_{cz}(c_{it} * z_{it}) + \beta_{sz}(s_{it} * z_{it}) + \beta_z z_{it} + \mu_{it}$$

where x_{it} is a vector of household characteristics such as education, age, gender of the household head, and household size. z_{it} is a vector of wealth indicators that include land size, irrigated land size, the value of livestock and the value of non-land assets. We also include initial village-level characteristics (v_{it}), such as the proportion of households with public electricity, public water supply, quality of the roads, time to market and number of enterprises in the village, to address the heterogeneity across villages in explaining non-farm employment. We expect asset holdings to mitigate the impact of climate variability and other shocks. Estimating the equations using OLS could cause bias if household-omitted characteristics that impact the labor market are also correlated with climate variability and other sources of shocks. Intrinsically similar households and sources of shocks can also lead to different non-farm employments. We therefore also employ a household fixed-effects version of the equations to control for household unobservable, such as nonlinearities in wealth indicators, and to reduce the potential for biased estimates on climate viability and other sources of shocks. Furthermore, a province-year dummy variable is included to control for unobserved province characteristics.

[10] The coefficient of variation (CV of rainfall) is calculated based on rain season (sum of rainfalls from June to October) on 20-years (1991–2010) rainfall data at village-level (200 villages). The data set includes the amount of rainfall (in millimeters) per month and total days. We use the straight-line distance method between each village in the sample.

5 Econometric Results and Hypothesis Testing

5.1 Impact of Climate Variability and Shocks on Non-farm Employment

Following our conceptual framework in section 3, we first examine the impact of climate variability on non-farm employment (Table 5) followed by the impact of climate variability and other sources of shocks (Table 6). We estimated the basic model (Equation 2) and the model with other sources of shocks (equation 3) using both fixed effects[11] and the semi-parametric fixed effects tobit[12] estimator to address the impact of climate variability and other sources of shocks[13] on non-farm employment. We find that most of the interest variables are similar in sign and significance level. Because we are interested in quantitative implications and the economic significance of the effect of climate variability and other sources of shocks on non-farm employment, we focus on the estimates from linear models using fixed effects for subsequent discussions. The direction and magnitude of the impact of climate variability and other sources of shocks are compared across three types of non-farm employment.

The results indicate that rainfall variability measured by CV of rainfall; rainfall abundance and self-reported agricultural shocks have a positive impact on non-agricultural wages, although rainfall abundance and self-reported agricultural shocks are not statistically significant. The results are in line with our hypothesis that rural households use non-farm agricultural wage as a means of adapting to rainfall variability. Given that the average coefficient of variation is approximately 0.52, a 0.1 increase in CV of rainfall from 0.52 to 0.62 implies that households' hours supplied to non-farm agricultural wage activities increase by 22%. Similarly, rural households use non-farm self-employment as a means of adapting to rainfall variability. Rainfall variability increasing by one-tenth of the coefficient of variation implies that rural households' hours supplied to self-employment increase by 19%. This finding is in line with previous studies in developing countries and Southeast Asia (ROSE, 2001; ITO and KUROSAKI, 2009). We also find a concave relationship between rainfall variability and labor hours in non-agricultural wage and non-farm self-employment. This finding suggests that there is a threshold of rainfall variability after which the use of the labor market as a means of adapting to rainfall variability is limited. This may be because higher rainfall variability not only influences own-agricultural activities but also displaces labor and reduces the demand for labor outside the farm. Rural households in our study area use agricultural wage employment to cope with agricultural shocks. Households experiencing demographic shocks increase their agricultural wage labor by 21%, but they do not use agricultural wage labor as a means of adapting to rainfall variability, which may occur because agricultural wage employment opportunities are highly affected by rainfall variability. The overall results of the impact of rainfall variability and agricultural shocks give strong support for our first hypothesis that the use of labor markets is heterogeneous in adapting to rainfall variability and coping with agricultural shocks.

Turning to the impact of shocks that are mainly in the labor market and demographic shocks, we find a positive and significant effect of demographic shocks on agricultural wage, which

[11] This test is based on both the Hausman and robust Hausman test using cluster-robust standard errors (Wooldridge 2002), which is equivalent to testing the joint significance of the means of various explanatory variables added to the POLS model. The test rejects the null hypothesis that individual effects are random.

[12] Honoré (1992) proposed for a trimming mechanism to restore the symmetry of the error distribution in censored regressions

[13] Self-reported shocks may suffer reporting bias when responses are correlated with wealth and education; we test for significant differences for households with and without shock experience. Results confirm our assumption that shock incidence is largely independent of wealth indicators and household characteristics. The p-value for the chi statistic testing the null hypothesis that the estimated coefficients on the household characteristics and wealth indicators are jointly zero are not rejected for all three models. These results lend some confidence to the validity and independence of the self-reported shocks information. The full estimation results using household fixed effects are available on request.

indicates that households in our study area use agricultural wage to cope with demographic shocks. Controlling other factors, households experiencing demographic shocks increase their agricultural wage labor by 21%. Our empirical results are consistent with the findings of WARD and SHIVELY (2011), who found that households in rural China that experienced demographic shock due to the death of a household member are less likely to participate in migration as an ex-ante income smoothing response to risk. We find a negative and significant effect of demographic and economic shocks on non-agricultural wage employment. Controlling other factors, households experiencing demographic shocks decrease their non-agricultural wage labor by 27%. Similarly, economic shocks lead to a substantial non-agricultural wage employment reduction of approximately 41%. This is in line with previous studies (e.g., FALLON and LUCAS, 2002 in Thailand; HUANG et al., 2010 in China), which found that rural households who diversified into non-farm employment lost their jobs because of economic shocks. Both demographic and economic shocks have led to substantial non-agricultural wage employment reduction (29% and 41% reduction in hours, respectively) compared to with percentage of hours (27%) allocated to non-agricultural wage employment as an adaptation strategy for rainfall variability. The finding supports our second hypothesis that using the labor market to adapt to rainfall variability is limited in the presence of economic and idiosyncratic shocks such as demographic shocks.

5.2 The Role of Assets in Explaining Non-farm Employment

To test the hypotheses that non-land assets may help in adapting to the effects of rainfall variability and whether shocks have a smaller effect on households with a greater level of assets, we include non-land assets and their interactions with rainfall variability and shock variables. We show the results of the fixed effects model that refer to the extended model (equation 4) in Table 7. A Wald test for the equality of the interaction terms is rejected in all models. We find that wealth indicators have the expected signs in all non-farm employment equations. There is a positive and significant relationship between the level of household assets and non-agricultural wage and non-farm self-employment hours, whereas there is a negative relationship between the level of assets and agricultural wage hours, although it is not significant. This finding may suggest that households with relatively low start-up capital find it hard to engage in higher return activities, though the richer households are able to take part in these activities. A one standard deviation increase in log per capita of non-assets leads to a 15% and 44% increase in non-agricultural wage and non-farm self-employment hours, respectively.

Considering the impact of interaction effects and other covariates, we find that the impact of rainfall variability on non-agricultural wage hours becomes smaller in magnitude and that the impact of rainfall variability becomes insignificant for non-farm self-employment hours when interacting with non-assets. The results indicate that adaptation to rainfall variability varies with a household's level of assets. Furthermore, the effects of demographic and economic shocks on non-agricultural wage hours become positive when they are interacted with non-land assets. The results may suggest that households with a low level of non-land assets are more likely to be affected by economic shocks and demographic shocks. This finding confirms our third hypothesis that poor households are less able to exploit non-farm employment opportunities and thereby adapt to climate variability and shocks.

Turning to the effect of other covariates, we find evidence of a significant negative effect of the level of education on non-agricultural wage hours and non-farm self-employment hours. This effect could indicate the unwavering role of qualified skills as a necessity for high-return non-farm activities. The significant contribution of the role of education in shaping employment outcomes, obtained from our empirical evidence, is a finding that is consistent with previous empirical studies such as those of JONASSON and HELFAND (2010) in Brazil and MATSUMOTO et al. (2006) in Ethiopia, Kenya, and Uganda. Analyzing the demand-side factors[14] provides additional insights. Villages with better access to public facilities, such as paved roads, the availability of enterprises and electricity, play an important role in the expansion of high-return activities such as non-farm self-employment. Similarly, villages with access to a public water supply and enterprises offer opportunities to households to engage in non-agricultural wage employment. This result also supports previous studies assessing the relationship between demand factors and the non-farm labor supply. JONASSON and HELFAND (2010) showed that the local availability of geographic variables in the village, such as quality (paved) roadways and a number of enterprises increases the labor hours of non-agricultural wage employment.

6 Conclusions and policy implications

This study explores the impact of climate variability and other sources of shocks on household non-farm employment using a comprehensive set of household- and village-level panel data from Northeast Thailand and a corresponding twenty-year historical rainfall data set. The contribution of this paper is three-fold. First, this study incorporates not only climate variability but also other sources of shocks in both own-farm activities and the labor market, including demographic and economic shocks. Second, we differentiate the labor market into agricultural wage, non-agricultural wage and non-farm self-employment to address the possible heterogeneity of the labor market as a means of adapting and coping measures for rainfall variability and coping with shocks. Third, we examine whether the risk-bearing capacity of households differs with the level of assets and whether shocks have a smaller effect on households with a greater level of assets. Using the household panel and the rainfall data sets from rural Thailand, we are able to test three hypotheses: (1) household use different types of labor markets as a means of adapting to climate variability and other sources of shocks, and the labor market is heterogeneous in terms of adapting to climate variability and coping with shock; (2) dealing with the labor market as a means of adapting to climate variability is less effective in the presence of severe climate variability, economic shocks and idiosyncratic shocks; and (3) the risk-bearing capacity of households differs with the level of assets.

The results support our hypotheses and confirm the empirical findings from other developing countries (e.g., ITO and KUROSAKI, 2009; ROSE, 2001; BANDYOPADHYAY and SKOUFIAS, 2012; DI FALCO et al., 2009). Several interesting messages can be extracted from our results. First, using a panel data methodology that controls for individual heterogeneity and time-invariant village characteristics, we find that rural households use non-farm agricultural wages and non-farm self-employment as a means of adapting to rainfall variability. Rainfall variability increasing by one-tenth of the coefficient of variation implies that rural households' hours supplied to non-farm agricultural wage and self-employment increase by 22% and 19%, respectively. Second, rural households in our survey area use agricultural wage employment to cope with agricultural shocks but do not use agricultural wage employment as a means of adapting to rainfall variability, which confirms our first hypothesis. Third, the paper shows that a concave relationship between rainfall variability and labor hours supplied to non-agricultural wage and non-farm self-employment exists. Fourth, we find that households in our study area use agricultural wage to cope with demographic shocks. Controlling for other factors, households experiencing demographic shocks increase their agricultural wage labor hours by 21%. In line with previous studies (e.g., WARD and SHIVELY, 2011; FALLON and LUCAS, 2002; HUANG et al., 2010), we find that both demographic and economic shocks lead to substantial reductions in non-agricultural wage hours. Households experiencing demographic shocks reduce their non-agricultural wage hours by 29% and economic shocks lead to

[14] Because we use a fixed effects model, the within-village variation over time is small, which is why some of the coefficients are insignificant. In our random effects model, most of the geographic capital variables were highly significant.

a 44% reduction in hours in non-agricultural wage employment. Employment reduction because of demographic and economic shocks in non-agricultural wage and self-employment is much higher than the increase in labor hours in these activities because of climate variability, which confirm our second hypothesis. Fifth, we show that non-land assets play a very important role in determining non-farm employment: households with lower levels of non-assets find it difficult to engage in labor markets, particularly in high-return activities such as non-agricultural wage and non-farm self-employment. We also confirm that risk-bearing capacity and buffering against shock differ across households. Poor households are more likely to be affected by climate variability and other sources of shocks, which suggests that climate variability and other sources of shocks can push certain households into chronic poverty.

Our findings can provide some insight into the impact of climate variability and shocks on non-farm emolument and into the possible policy options that are available to reduce the impact of climate variability and other sources of shock. First, the findings suggest the importance of simultaneously analyzing the impact of climate variability and both demographic and economic shocks on non-farm employment. Second, the labor market can be less effective as a means for adapting to severe rainfall variability, economic and demographic shocks. Third, because labor markets are heterogeneous in terms of adapting climate variability and coping with shocks, it is important to distinguish different types of labor market when we analyze how rural households use the labor market to adapt to climate variability and shock coping measures. Fourth, the paper identifies a need for complementary intervention in building private asset accumulation, education investments and efforts to stimulate small- and medium-scale enterprises; and investment in infrastructure and public services which could play a vital role in addressing the challenges of climate variability and other sources of shocks.

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Appendix:

Table 1: Description of variables

Variable	Description
Dependent variables	
Non-agric wage	Hours supplied to non-agricultural wage per month
Agric. wage	Hours supplied to agricultural wage per month
Non-farm self-empl.	Hours supplied to non-farm self-employment per month
Household characteristics	
Below primary	Number of household members with below primary education
Primary	Number of household members who have completed primary education
Secondary	Number of household members who have completed secondary education
Professional Training	Number of household members who have completed professional education
Age of adult	Average age of adult members in the household
Dependency ratio	The dependency ratio is the number of dependents relative to the total number of household members
Wealth indicators	
Land	Land size, in hectares
Livestock	Value of livestock (measured in PPP$ at 2005 prices)
Non-land asset	Value of non-land assets (measured in PPP$ at 2005 prices)
Irrigation	The proportion of irrigated land to total agricultural land
Lowest asset	Households that are asset poor are in the lowest tercile
Asset medium	Households that have medium assets are in the medium tercile
Asset non-poor	Households that are asset rich are in the top tercile
Village characteristics	
HHs Water supply	Households with access to public water supply in the village (%)
HHs electricity	Households with access to electricity in the village (%)
HHs sanitation	Households with access to sanitation in the village (%)
Paved road	The village has paved road (yes=1, no=0)
No. enter.	Number of enterprises that have more than 9 employees
Time to market	Time to reach the market in minutes
Climate variability	
Climate variability	Measured as the standard deviation divided by the mean of the monsoon seasons (sum of rainfalls from June to October) in the 20 years (1991–2010) village-level rainfall data
Lagged rainfall	Lagged average monsoon rainfall levels/1,000, in mm
Agric. shocks	A dummy variable for positive welfare losses because of drought, flood, bad weather, crop pests and diseases
Other sources of shocks	
Demo. shocks	A dummy variable for positive welfare loss because of illness and death
Econ. shocks	A dummy variable for positive welfare loss because of job loss, price changes and market regulation

Source: DFG Rural Household- and Village-Level Panel Surveys in Thailand.

Table 2: Incidence and welfare consequences of shocks by year

	Year	Agric. Shocks	Demo. Shocks	Econ. Shocks
Incidence of shocks (%)				
	2008	43	30	25
	2010	48	38	31
Welfare consequences of shocks (PPP$ in 2005)				
Loss of income	2008	1124.55	400.10	865.03
	2010	748.70	163.74	285.35
Extra expenditure	2008	223.08	774.01	133.68
	2010	115.03	864.93	518.39
Loss of assets	2008	164.90	169.71	140.82
	2010	127.80	258.10	211.35

Source: Own calculations based on the 2008 and 2010 DFG Rural Household Surveys in Thailand

Table 3: Proportion of participants (%), labor supply and returns to non-farm employment

	Year	Non-agric. Wage	Agric. Wage	Non-farm self-empl.
Participants (%)	2008	80	18	31
	2010	71	17	34
	Change t- test	*	***	**
Labor supply per month (Hour)	2008	315.29(246.16)	265.15(277.46)	393.58(323.15)
	2010	353.54(248.68)	294.29(253.46)	426.68(425.42)
	Change t-test	***	**	
Individual components	2008	1.34(1.31)	0.33(0.94)	0.39(0.66)
	2010	1.39(1.26)	0.28(0.79)	0.43(0.70)
	Change t-test	**	***	*
Return per hour	2008	0.64(4.04)	0.24 (0.80)	5.49(5.58)
	2010	0.78(3.30)	0.48(0.72)	4.60(4.59)
	Change t-test	***	**	

Source: Own calculations based on DFG rural household- and village-level panel surveys in Thailand. Figures in brackets are standard errors.

Table 4: Descriptive statistics variables used in the model by participation status (N=4134)

Variable	All sample	Non-participant (13%)	Participant: Non-agric. Wage (75%)	Participant: Agric. Wage (17%)	Participant: Non-Farm Self-empl.(32&)
Household characteristics					
Below primary	1.03(1.21)	1.36(1.16)	1.03(1.23)	1.40(1.14)	0.82(1.22)
Primary	2.06(1.41)	2.06(1.15)	2.11(1.50)	2.11(1.40)	1.80(1.45)
Secondary	0.90(1.05)	0.51(0.81)	1.03(1.04)	0.63(1.01)	1.12(1.08)
Professional training	0.27(0.63)	0.08(0.35)	0.23(0.71)	0.12(0.41)	0.36(0.69)
Dependency ratio	1.58(0.78)	1.42(0.94)	1.59(0.74)	1.60(0.69)	1.59(0.74)
Average age of adult	36.24(11.89)	43.36(16.35)	35.21(10.50)	34.76(10.80)	35.38(11.03)
Wealth indicator					
Livestock	3.44(67.52)	3.33(10.10)	2.30(4.50)	2.10(4.90)	5.50(118.30)
Land size	2.46(3.11)	2.90(3.30)	2.50(2.70)	1.60(1.80)	2.70(3.80)
Irrigation	0.15(0.75)	0.24(1.01)	0.12(0.60)	0.11(0.50)	0.18(0.85)
Non-land assets	68.31(130.97)	40.80(78.60)	52.70(87.90)	30.70(66.50)	114.30(188.40)
Non-land asset tercile (%)					
Bottom asset		47	32	49	21
Medium asset		30	35	32	25
Top asset		22	33	19	54
Village characteristics					
Paved road	86	80	90	80	90
HHs electricity	97	92	95	94	96
HHs water supply	91	90	89	88	92
HHs sanitation					
Time to market	17.23(12.88)	15.90(12.10)	17.80(13.40)	18.70(12.80)	16.30(12.50)
No. Enter.	0.14(0.64)	0.20(0.80)	0.20(0.70)	0.10(0.30)	0.10(0.50)
Climate variability					
CV of rainfall	0.48(0.08)	0.48(0.08)	0.49(0.08)	0.48(0.08)	0.49(0.08)
Lagged monsoon	1.18(0.42)		1.16(0.42)	1.08(0.39)	1.16(0.41)
Agric. shocks (%)	45	46	45	47	43
Other sources of shocks					
Demo. Shocks (%)	34	34	34	37	33
Econ. Shocks (%)	29	29	29	30	30
Buriram	38	30	73	22	30
Ubon	44	54	68	14	32
Nakhon Phanom	18	17	74	14	31

Source: Own calculations based on DFG rural household- and village-level panel surveys in Thailand. Figures in brackets are standard errors.

Table 5: The Impact of Climate Variability on Non-Farm Employment

	Fixed Effects Estimates						Honoré Fixed Effects Tobit Estimates					
	Non-agricultural wage		Non-farm self-employment		Agricultural wage		Non-agricultural wage		Non-farm self-employment		Agricultural wage	
	Coef	Se	Coef	Se	Coef	Se	Coef	Se	Coef	Se	Coef	Se
Climate variability												
CV rainfall	0.217***	0.074	0.191**	0.077	-0.026	0.073	0.613**	0.258	0.440***	0.145	-0.418	0.391
CV rainfall sqr.	-0.002**	0.001	-0.002*	0.001	0.000	0.001	-0.003**	0.001	-0.009***	0.002	0.005	0.003
Lagged rainfall	-0.452	0.540	0.302	0.945	-1.025	0.649	-0.514	1.191	1.971	0.923	0.518	5.068
Lagged rainfall sqr	0.088	0.184	-0.112	0.422	0.217	0.204	0.080	0.496	0.645	0.800	-0.240	2.113
Agric. shocks	0.067	0.117	0.180	0.134	0.217**	0.097	0.116	0.179	0.301	0.389	0.250*	0.140
Cons	1.341	2.037	-2.753*	1.556	2.916	1.966						
No. Obs.		4,128		4,128		4,128	4,128		4,128		4,128	

Source: DFG Rural Household- and Village-Level Panel Surveys in Thailand.

Note: Robust standard errors in parentheses. *** represents p<0.01. ** represents p<0.05. * represents p<0.10.

Table 6: The Impact of Other Sources of Shock on Non-farm employment

	Fixed Effects Estimates						Honoré Fixed Effects Tobit Estimates					
	Non-agric. Wage		Non-farm self-empl.		Agric. Wage		Non-agric. Wage		Non-farm self-empl.		Agric. Wage	
	Coef	Se	Coef	Se	Coef	Se	Coef	Se	Coef	Se	Coef	Se
Climate variability												
CV rainfall	0.267*	0.144	0.217***	0.074	-0.026	0.062	0.572**	0.256	0.713***	0.168	-0.445**	0.210
CV rainfall sqr.	-0.002*	0.001	-0.002*	0.001	0.000	0.001	-0.005*	0.003	-0.008***	0.002	0.005	0.003
Lagged rainfall	-0.839	0.721	0.320	0.947	-0.756	0.541	-1.078	0.881	3.694*	1.911	0.921	4.787
Lagged rainfall sqr	0.272	0.284	-0.121	0.423	0.224	0.177	0.355	0.337	0.670	0.796	-0.484	2.004
Agric. shocks	0.198	0.149	0.164	0.137	0.222**	0.102	0.248	0.190	-0.381	0.377	1.169**	0.506
Other Sources of shocks												
Demo. Shocks	-0.293**	0.141	0.118	0.160	0.206**	0.101	-0.313*	0.175	-0.436	0.438	0.332*	0.195
Econ. shocks	-0.409**	0.197	0.063	0.188	-0.096	0.123	-0.502**	0.242	0.702	0.452	0.299	0.611
Cons	-1.009	3.388	-2.797*	1.547	2.889*	1.670						
No.Obs.		4,128		4,128		4,128	4,128		4,128		4,128	

Source: DFG Rural Household- and Village-Level Panel Surveys in Thailand.

Note: Robust standard errors in parentheses. *** represents p<0.01. ** represents p<0.05. * represents p<0.10.

Table 7: The Role of Assets and Other Covariates in Explaining Non-Farm Employment

	FE Estimates						Honoré Fixed Effects Tobit Estimates					
	Non-agric. Wage		Non-farm self-empl.		Agric. Wage		Non-agric. Wage		Non-farm self-empl.		Agric. Wage	
	Coef	Se	Coef	Se	Coef	Se	Coef	Se	coef	Se	Coef	Se
Climate variability												
CV rainfall	0.209*	0.118	0.150*	0.084	-0.098	0.092	0.550**	0.262	0.653***	0.216	-0.432	0.291
CV rainfall sqr.	-0.002*	0.001	-0.002*	0.001	0.001	0.001	-0.005*	0.003	-0.006**	0.003	0.005	0.005
Lagged rainfall	-0.944	0.866	0.440	0.982	-0.620	1.008	-1.163	0.911	2.398	1.732	0.855	3.443
Lagged rainfall sqr	0.322	0.312	-0.119	0.439	0.402	0.419	0.412	0.345	-0.921	0.698	-0.445	1.229
Agric. shocks	0.289	0.185	0.088	0.139	0.436***	0.151	0.351*	0.210	-0.436	0.337	0.117	0.410
Other sources of shock												
Demo. shocks	-0.482***	0.169	0.046	0.165	0.305**	0.146	-0.570***	0.203	-0.110	0.404	1.361***	0.452
Econ. shocks	-0.444**	0.210	-0.177	0.203	-0.328	0.222	-0.555**	0.260	0.015	0.421	-0.046	0.497
Wealth indicators												
Non-land asset	0.147*	0.086	0.439***	0.090	-0.044	0.106	0.281*	0.127	1.516***	0.154	-0.815***	0.231
Land	-0.034	0.034	0.040	0.033	-0.004	0.022	-0.054	0.063	-0.031	0.043	-0.478***	0.088
Livestock	0.056*	0.032	0.037	0.301	0.034	0.030	0.068*	0.039	-0.150***	0.054	0.005	0.068
Irrigation	0.055	0.080	0.012	0.080	0.026	0.057	0.020	0.151	0.220	0.147	-0.052	0.329
Non-land assets and its interactions												
CV rainfall *non-land assets	-0.004*	0.002	0.000	0.002	-0.001	0.001	-0.006**	0.003	0.000	0.001	-0.007	0.007
Agric. shocks*non-land assets	-0.002	0.001	0.000	0.001	0.000	0.001	-0.002	0.001	-0.001	0.001	0.005	0.004
Demo. shocks*non-land assets	0.002*	0.001	0.000	0.001	-0.001	0.001	0.003*	0.001	0.000	0.002	-0.014**	0.006
Econ. shocks*non-land assets	0.000	0.001	0.003*	0.001	0.001	0.001	0.000	0.001	0.002*	0.001	0.005	0.005
Household characteristics												
Dependency ratio	0.111	0.126	0.098	0.101	0.178*	0.092	0.145	0.184	-0.092	0.222	0.443	0.331
Below primary	0.039	0.122	0.185	0.138	-0.077	0.113	0.036	0.155	0.337**	0.138	-0.385*	0.218
Primary	0.398**	0.175	0.421***	0.162	-0.006	0.147	0.480**	0.188	0.186*	0.113	0.699***	0.151
Second	0.526***	0.150	0.182*	0.104	-0.119	0.138	0.625***	0.165	0.134	0.158	0.314	0.210
Professional	0.765***	0.223	0.254	0.286	-0.219*	0.119	0.852***	0.244	0.245	0.279	-0.493	0.435
Age of adult	-0.007	0.012	-0.022	0.013	-0.016	0.013	-0.009	0.017	0.022	0.019	-0.118***	0.023

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Village level characteristics												
Paved road	0.119	0.103	0.110***	0.034	-0.086	0.111	0.150	0.146	0.260	0.208	0.409	0.397
HHs water supply	0.112**	0.042	0.004	0.015	-0.003	0.014	0.014	0.017	0.009	0.031	0.037	0.051
Time market	0.000	0.003	-0.001	0.002	-0.003	0.003	0.000	0.004	-0.002	0.007	-0.014	0.011
HHs electricity	0.000	0.001	0.005***	0.001	-0.002	0.002	0.000	0.002	0.009***	0.003	-0.009	0.007
HHs sanitation	-0.001	0.001	0.000	0.001	-0.001	0.001	0.001	0.001	0.001	0.001	-0.003	0.003
No. Enter.	0.153*	0.036	0.122**	0.040	-0.035	0.026	0.049	0.052	0.000	0.126	-0.248	0.283
Ubon* time	0.061	0.070	0.033	0.056	-0.067	0.063	0.062	0.089	0.067	0.135	-0.139	0.286
Buriram* time	0.049	0.068	0.002	0.070	-0.056	0.061	0.065	0.083	0.011	0.161	-0.117	0.209
cons	-1.738	2.760	-4.685*	2.598	4.105*	2.404						
No. Obs.		4,128		4,128		4,128	4,128		4,128		4,128	

Source: DFG Rural Household- and Village-Level Panel Surveys in Thailand.

Note: Robust standard errors in parentheses. *** represents p<0.01. ** represents p<0.05. * represents p<0.10.