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Off-farm Labor Supply and Health Impact of Pesticide Use: An Economic Analysis

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OFF-FARM LABOR SUPPLY AND HEALTH IMPACT OF PESTICIDE USE: AN ECONOMIC ANALYSIS

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An Abstract of the Thesis Presented
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By employing data from Vietnam Household Living Standard Surveys (VHLSS) and weather data from different sources, this thesis aims to fill the gaps in the literature on off-farm labor supply, health effect of pesticide use and the economic returns to communist party membership in Vietnam.

This thesis consists of four chapters. The first chapter provides a brief introduction. The second chapter considers the effect of weather on the risk perception of farmers in Vietnam by examining labor allocation decision and its effect on household income. I started by building a theoretical framework with the assumption that off-farm wage per hour is fixed and there is a risk factor in the farm production. As the result, the model shows that the farming risk pushes farmers to allocate more time for the off-farm sector in order to cope with the farming risk. On the other hand, higher marginal revenue of farm production increases the amount of time working in agricultural sector.

However, the question of whether off-farm participation betters farmers cannot be answered theoretically. With data from VHLSS and weather data from the Vietnamese Ministry of Agricultural and Rural Development and Unisys.com, I attempt to answer this question by using a Heckman correction model. Results from the econometric model show that weather affects the off-farm participation decision of agricultural households

and off-farm participation associates with higher household income. In addition, long-term climate patterns show stronger effects than short-term ones on the labor allocation decision. I also found that distance to town center reduces the possibility of off-farm participation and reduces income.

The third chapter focuses on the relationship between pesticide use and health burden of farmers in Vietnam. By using the number of hospital visits and health expenditure as a proxy for health status, we found that lagged pesticide use associates with the increasing needs of medical services. Particularly, lagged pesticide uses for rice and industrial crops have the strongest effects on the health status of farmers. This is one of the most recent attempts to examine the association between pesticide use and health burden on farmers in Vietnam. In the near future, I would like to work more on confirming the causal effect of pesticide use on the health status of farmers with better data.

Chapter 4 concludes.

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CHAPTER 1
INTRODUCTION

Vietnam is a developing country with a large agricultural sector. As farmers in other developing countries, most of them lack knowledge and capital to be less dependent on nature. Consequently, farmers in Vietnam and developing countries, in general, are more vulnerable to the farming risk coming from time-varying weather conditions and diseases than their colleagues in developed economies. Off-farm jobs become an insurance to reduce the income risk for agricultural households.

In Vietnam, after the land reforms carried out in North Vietnam (1954–1956) and in South Vietnam (1967–1970), each rural household owns a small area of agricultural land. For this reason, off-farm participation is not just a kind of insurance to reduce income risk, but also a measure to improve living standards. Off-farm participation is not fully studied in Vietnam, and there is also a big gap in the literature on the correlation between weather and labor allocation decision. With an attempt to fill these vacuums, the second chapter provides theoretical and empirical evidence on the effect of risk associated with weather on labor allocation decisions and how it affects household income.

Another problem that comes to my attention is the health effect of pesticide use on farmers. Even though pesticides bring higher productivity in the agricultural sector, most of them are very poisonous to both humans and animals. However, the adverse effect of pesticide use for farmers would not be recognized easily until years of pesticide exposure through food, air and water, because the level of pesticide exposure from agricultural production is usually not high enough to have any immediate effect. It would be challenging to quantify the health effects on pesticide use. This might be the reason why most recent studies on this subject stop at providing the negative correlation between pesticide use and health status. Chapter 3 provides more detail on our study conducted by Dr. Chen and I about the relationship between pesticide use and health burden in Vietnam. It has suggested harmful health effects of pesticide use on Vietnamese farmers.

CHAPTER 2
CLIMATE AND OFF-FARM LABOR SUPPLY OF AGRICULTURAL HOUSEHOLDS: EVIDENCE FROM RURAL VIETNAM

This chapter investigates the effects of weather conditions on labor allocation and total income of rural Vietnamese households. Like farmers in other developing countries, rural families in Vietnam are highly dependent on nature for farm production. Changes in long term weather patterns, such as temperature, rainfall and storm, are among the primary sources of hazards affecting farming yield. Thus, climate change often influences a farmer's decision whether to take an off-farm job. High risk in agricultural production sometimes forces farmers to seek for off-farm jobs, which in turn affect the household income. By using data from 2008, 2010, 2012 and 2014 Vietnam Household Living Standard Surveys (VHLSS), we consider the association between off-farm employment and household income and estimate both effects of weather on the income of rural families through farm production and off-farm labor participation decisions. Long-term climate-related risks are found to have a stronger impact on farmers' risk perceptions than short-term ones, leading to higher off-farm participation rates and higher income in the long run. Distance from a town center also plays an important role, which reduces off-farm employment opportunities and household income.

2.1 Introduction

This study focuses on the off-farm labor supply and household income of farmers in a southeastern Asian country, Vietnam, with special attention to weather risks. Like its peers in this region, Vietnam is a developing country with a prominent share of the labor force (48%) working in the agricultural sector (Central Intelligence Agency, 2015). One one hand, like farmers in other low-income countries, farmers in Vietnam are vulnerable to risks associated with weather and disease. According to Fay et al. (2010), Vietnam is one of the most vulnerable countries to climate change. Income from non-farm sources, on the other hand, is less affected by the natural hazards. In this study, we investigate the impact of climate risks on the Vietnamese farmer' off-farm employment decision and household income.

Off-farm activities play a significant role in the rural economy of Vietnam, generating most of the income for rural families (Davis et al., 2010). In comparison to off-farm income, the income from farming is relatively low partially because of the inefficient scale of farming production. In particular, diseconomy of scale in Vietnam's agricultural sector widely exists because of the land fragmentation policies during the last century (Pham et al., 2007). Even worse, from 1975 to 1986, the ban on private ownership and trading by the ruling communist party negatively affected agricultural output (Central Intelligence Agency, 2015). However, since Vietnam launched an economic reform in 1986, well-beings of farmers have been improved due to less government interventions in the market (Benjamin and Brandt, 2002). But living standard of farmers is still low. Hence, income diversification is important in enhancing the welfare of rural households (Ivrin, 1997).

The off-farm jobs are improving the living standard of rural households. van de Walle and Cratty (2004) and Hoang et al. (2014) suggested that participation in the off-farm job market can reduce poverty rates among rural communities. In particular, Hoang et al. (2014) found off-farm employment increased household spending by 14% and reduced the likelihood of poverty by around 10%. In addition, off-farm employment is associated with higher food consumption (Mishra et al., 2016). In our sample, off-farm activities account for around 40% of family income. There is also evidence that farm families engaging in off-farm activities have a higher amount of spending on their farm production, including seeds, hired labor, services, and livestock inputs (Stampini and Davis, 2009).

Off-farm employment is a way to reduce income uncertainty caused by variations in farm output. Mishra and Goodwin (1997) and Mishra and Holthausen (2002) provided the theoretical and empirical evidence that farm income variability increases non-farm activities. In developing countries where a farmer is more likely to face income shocks, an off-farm job can be considered as an insurance (Ferreira, 2001). Because the off-farm sector provides a diversified source of income for farmers, it reduces uncertainty in household income. There is also evidence that off-farm activities could lessen credit constraints of farmers in developing countries (Oseni and Winters, 2009; Hoang et al., 2014).

There exists a significant gap in the literature that assesses the farmers' decisions to participate the off-farm labor market in response to climate changes in the countryside of Vietnam. The existing literature on off-farm activities in Vietnam concentrate on the impact of off-farm jobs on poverty and credit constraints (van de Walle and Cratty, 2004; Stampini and Davis, 2009; Hoang et al., 2014). The only relevant study we found is an unpublished report (Tu et al., 2008) evaluated off-farm labor supply with data collected in 1997. However, their work solely focused on the risks of the off-farm jobs, while the correlation between farming income uncertainty and off-farm labor supply was not addressed. This chapter aims to fill the gap in the literature by providing an empirical analysis of the labor supply decisions of farmers with special attention to the farming-related weather risks.

In this study, we focus on the direct (via farming) and indirect (via off-farm employment) effects of climate conditions on household income. Natural disasters have a strong adverse effect on the economy of Vietnam. Natural disasters are causing a loss of 1-1.5% of Vietnam's Gross Domestic Product (GDP) each year (Global Facility for Disaster Reduction and Recovery, 2013) while lowering the national output growth rates (Noy and Vu, 2010). At the micro-level, households are found to be negatively affected by storms, droughts and floods (Thomas et al., 2010; Bui et al., 2014; Le, 2015; Arouri et al., 2015). Natural disasters also exacerbate poverty and inequality (Bui et al., 2014). Nevertheless, there is evidence that households always attempt to adapt to risks of natural disasters (Arouri et al., 2015; Thomas et al., 2010). Off-farm employment, which is less affected by the climate, is one of the channels used to build resilience to risks from natural hazards (Awondo et al., 2017). For example, Off-farm labor supply in developing countries has been found to be related with rainfall fluctuations (Ito and Kurosaki, 2009; Demeke and Zeller, 2012).

We aim to quantify the effects of temperature, rainfall, rain shadow wind (Foehn wind), and storms on off-farm labor participation and income of rural households in Vietnam. Specifically, we estimate the off-farm labor supply based on family characteristics and weather conditions. We focus on climate changes over three different time spans: the past year (short-run), the past three years (medium-run) and the past five years (long-run). We investigate the correlation between off-farm participation and family income, and assess household revenue function. To achieve these objectives, we apply the Heckman correction method using Vietnam Household Living Standard Surveys (VHLSS) data in 2008, 2010, 2012 and 2014, and weather data from more than 100 hydro-meteorology stations around the country and storm tracks data from UNISYS (unisys.com).

The results suggest that off-farm employment is associated with a higher household income. In addition, it shows that the impacts of climate changes on the labor allocation decisions of farmer households are stronger in the long term than in short term. In particular, average weather conditions in the previous five years have a larger impact than the weather conditions in the previous year. It suggests that the long term climate trend may have more deeply affected the risk perceptions of individual farmers than short term fluctuations. There is also evidence that households attempt to reduce the risks of storm hits by participating the off-farm labor market. We found that although storms affect families' income negatively, households affected by the storms are more likely to take off-farm jobs. Hence, Vietnamese farmers tend to utilize off-farm employment to mitigate the negative impact of natural hazards.

The contributions of this chapter to the current literature are in several folds. First, even though off-farm labor supply is not a entirely new topic among agricultural economists, such a topic has rarely been visited in southeastern Asia, a booming region with a huge agricultural population. This chapter fills the gap among studies about labor allocation of Vietnamese rural households by drawing a link between off-farm participation and household income. Further, in our model, we evaluate the effects of weather conditions on farmers' income, which has been a critical topic as we face rising challenges of worldwide climate changes. Such a topic, though, has not been studied as far as Vietnamese farmers concern.

Second, our study finds weather risks affect agricultural households' labor allocations differently across various time spans. Weather conditions in a longer period generally have a stronger impact. For example, even if agricultural yields were disappointing last year because of the unfavorable weather conditions, this year farmers might still chose to work exclusively on farmland as they may view it as a one time shock. However, when weather risks are consistently high in the previous 5 years, farm households are more likely to seek for off-farm income sources instead.

Last but not the least, our study provides important policy implications for policy makers and development agencies in Vietnam. We find weather risks have a significant adverse impact on on-farm labor supply and income of rural households. However, such a negative effect can be lessened by off-farm jobs. Since off-farm income is less susceptible to weather, farmers' participation in the off-farm labor market usually can boost their income. Such findings may assist Vietnam's legislators to better understand farmers' behavior. In order to improve the income of agricultural households in Vietnam, the government could choose to provide them better access to off-farm employment opportunities in rural areas. Further, our results also suggest that government assistance programs are necessary in remote areas where off-farm jobs are limited.

The rest of this chapter is organized as follows. Section 2 provides an overview of the theoretical framework. Section 3 introduces the econometric model with the description of data. Section 4 presents the empirical results and further discussions on the effects of weather on the labor market and households' income. Section 5 concludes.

2.2 Theoretical framework

Agriculture sector are extremely sensitive to weather conditions. This creates an income risk on farmers since it can affects farm production. In this section, we develop a simple model showing that riskier farm production increases the amount time spent in the off-farm sector. We assume that each household act like an individual agent. Each household are assumed to maximize their utility with income and time constraints. The household's utility depends on their total income and leisure time. We have the indirect utility function as

$$U = U\big(\pi, L\big), \tag{2.1}$$

where π is the household income and L is the amount of leisure time. The utility function of the household U is a concave function where $U' \geq 0$ and $U'' < 0$. Besides, $U_{\pi L} = U_{L\pi} \geq 0$ as an agent desires more leisure time when he has more money, and vice versa. The income function consists of two components. The first component represents the farming income $(1-\alpha)PQ(F) - C(Q(F))$ where P is the price of agricultural product, $Q(F)$ is its production function, F is the amount of time working in the farm, and α is the remaining fraction of output after being affected by weather and other natural hazards. Other factors that might affect α are plant pests and epidemic, however, we are specifically interested in weather. Thus, we assume that α is a function of weather conditions. Note that α is bounded from 0 to 1, $\alpha \in [0, 1]$.

The production function $Q(\cdot)$ is a function of technology, labor, capital and other factors. Since we only examine the effect of income risk α in the farm production to household allocation of labor, labor-unrelated factors, namely technology, capital, etc., are the characteristics of the production function. We assume that $Q(F)$ is concave so that $Q_F \geq 0$, and $Q_{FF} < 0$. The second component is income from off-farm labor WH, in which W is the hourly wage rate and H is the number of hours that farmers work in the off-farm sector. We also assume that the wage rate of the off-farm job is constant and the demand for off-farm labor is perfectly elastic. The total amount of time is fixed as $L+F+H=T$. In this chapter, we focus on the risks of agricultural production, so we assume that P and W are exogenous. As a result, the household income function can be written as

$$\pi = (1-\alpha)PQ(F) - C(Q(F)) + WH. \tag{2.2}$$

We assume that the household aims to maximize their income with the time constraint. Then we are able to obtain the Lagrangian equation as

$$\mathscr{L}(L,F,H) = U\Big(\pi(F,H),L\Big) - \lambda(L+F+H-T). \tag{2.3}$$

We can take the derivatives to obtain the first-order conditions as

$$\frac{\partial \mathscr{L}}{\partial L} = U_L - \lambda = 0, \tag{2.4}$$

$$\frac{\partial \mathscr{L}}{\partial F} = U_\pi\big((1-\alpha)PQ_F - C_Q Q_F\big) - \lambda = 0, \tag{2.5}$$

$$\frac{\partial \mathscr{L}}{\partial H} = U_\pi W - \lambda = 0. \tag{2.6}$$

$$\frac{\partial \mathscr{L}}{\partial \lambda} = L+F+H-T = 0 = 0. \tag{2.7}$$

From the equation (2.5) and equation (2.6), we have $U_\pi\big((1-\alpha)PQ_F - C_Q Q_F\big) = U_\pi W$, or

$$Q_F\big((1-\alpha)P - C_Q\big) = W. \tag{2.8}$$

Note that at the solution point F^* shown in Figure 2.1, $(1-\alpha)P - C_Q > 0$ because $W > 0$ and $Q_F > 0$. The marginal profit of farming is $Y^F = Q_F\big((1-\alpha)P - C_Q\big)$. We have that: $\frac{\partial Y^F}{\partial F} = Q_{FF}((1-\alpha)P - C') - C'' Q_F$. As $Q_{FF} < 0$, $(1-\alpha)P - C_Q > 0$, $C_{QQ} > 0$ and $Q_F > 0$, then $\frac{\partial Y^F}{\partial F} < 0$. Hence, we can illustrate the solution of equation (2.8) on Figure 2.1. Figure

2.2 shows other two extreme cases of the equation (2.8). In Figure 2.2a, it is more profitable for a household to leave the agricultural sector. However, if wage from off-farm sector is always lower than the marginal income from farm production in Figure 2.2b, the household would spend all the time in the agricultural sector. The allocation of time between off-farm employment and farm work depends on the relative comparison between the off-farm wage and marginal income from agricultural sector. It is also noticeable that a higher α means a higher damage from unpredictable factors such as weather and natural hazards. Those hazards often lead to a smaller fraction of time on farming, and a higher possibility to take off-farm job.

Figure 2.1. The optimal allocation of farm labor

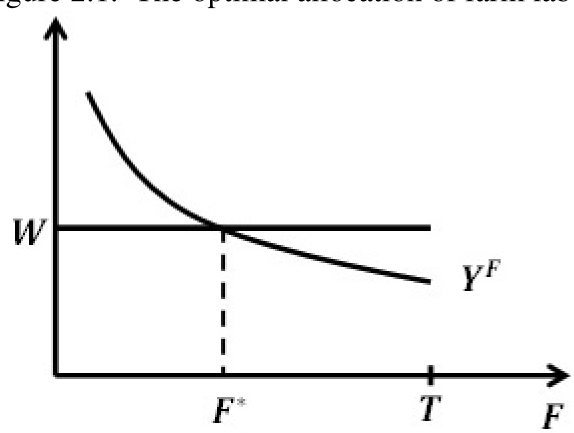
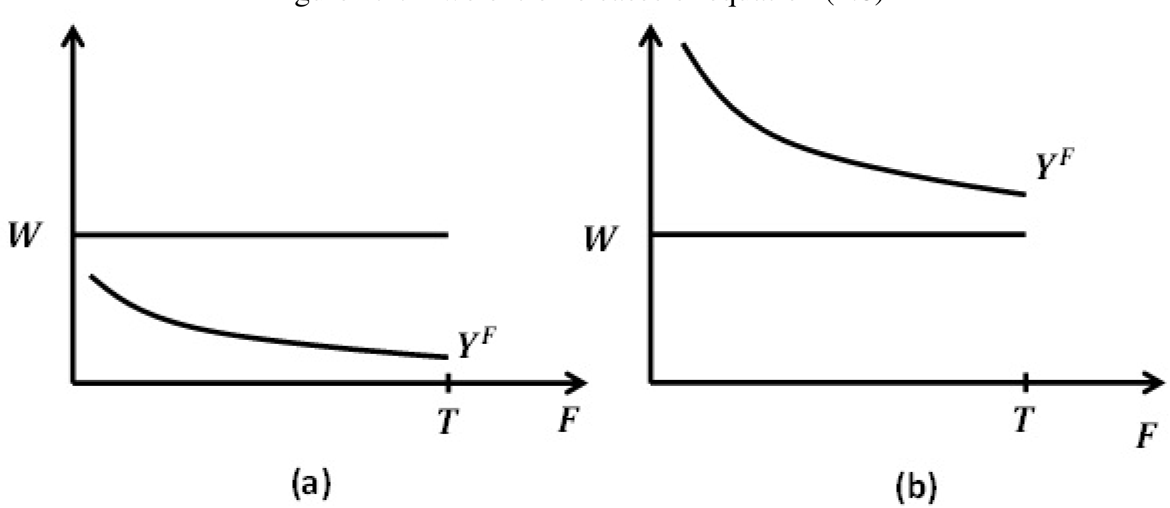


Figure 2.2. Two extreme cases of equation (2.8)



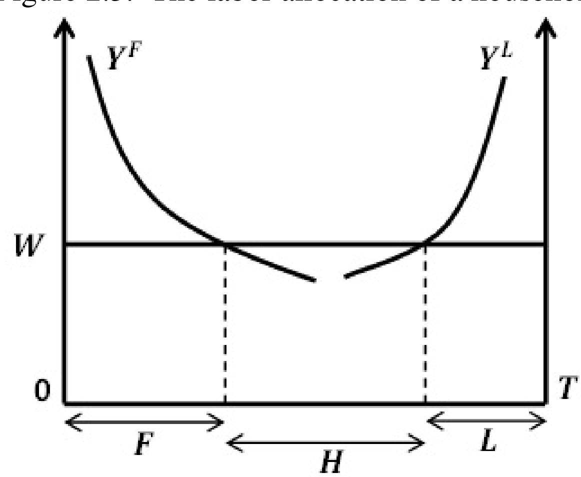
We have assumed that the household rationally desires to increase their household income, given the amount of time allocating for farm production and off-farm employment. Hence, spending more time on leisure would reduce the household income $\pi_L < 0$. Using the first order conditions (2.4) and (2.6), we obtain

$$U_L = U_\pi W \Leftrightarrow \frac{U_L}{U_\pi} = W. \tag{2.9}$$

Denoting $Y^L = U_L/U_\pi$, we get

$$\frac{\partial Y^L}{\partial L} = \frac{U_{LL}U_\pi - U_{\pi L}U_L}{U_\pi^2} = \frac{U_{LL}U_\pi - (U_{\pi\pi}\pi_L + U_{\pi L})U_L}{U_\pi^2}. \tag{2.10}$$

Figure 2.3. The labor allocation of a household



Since $U_{LL} < 0$, $U_\pi > 0$, $U_{\pi\pi} < 0$, $\pi_L < 0$, $U_{\pi L} > 0$, and $U_L > 0$, then $\frac{\partial Y^L}{\partial L} < 0$. Using this result along with the result shown in the Figure 2.1, we plot Figure 2.3 which illustrates the time allocation of a household. From the graph, there are three factors that affect the likelihood of taking an off-farm job. The first factor to consider is the wage of off-farm job W. As the wage increases, it is more profitable for farmer to allocate more time towards off-farm jobs and less time on leisure. Another factor is the production function of the farm $Q(F)$. A household with more capital endowment and other inputs other than labor would have a higher Y^F, which decreases the possibility of taking off-farm jobs. The last factor is the farming risk. Higher risks of weather, natural hazards and other uncontrollable factors would lead to a higher value of α resulting in a higher value of Y^F. It means a household must be more likely to take an off-farm job when facing elevated farming-related risks.

The theoretical framework confirms the results of Mishra and Goodwin (1997) and Mishra and Holthausen (2002). Our model is an extension of Mishra and Goodwin (1997) but with different assumptions of leisure time and utility function. In our model, we assume that households also consider how much leisure time they can spend when evaluating utilities. Our model shows that household's assets, labor, farm income risk and off-farm wage all affect a household's labor allocation.

The theoretical model also shows that the loss ratio α due to weather conditions can also increase the possibility of off-farm participation. Moreover, farmers do not know exactly the size of loss ratio α of the current crop, consequently they would make an expectation of α based on their observations of weather in the past. Thus, the risk estimated based on the weather conditions in the past affects on the off-farm labor supply of households. In the following section, we will test these hypotheses by using a sample data set of Vietnamese farm households.

2.3 Research methodology

2.3.1 Econometric model

To investigate the effects of weather risk and off-farm participation on farm households' income, the Heckman correction model is deployed. There are two reasons to use this econometric model. First, endogeneity may exist in the household income estimation since some covariates might not be completely exogenous. Examples include the binary variable whether a household has any member taking an off-farm job. Secondly, there is potentially sample selection bias which is a common problem in survey studies. The data we obtained are from the surveys conducted every two years by the Vietnamese government. The survey recollects approximately 50% of the households they interviewed in the previous survey. Due to the constrained resources, the survey cannot collect data from households that migrate to another location. This might lead to a selection bias. All these concerns make the Heckman correction method a reasonable choice. Later in the results table, the test for the correlation between error terms in the household income equation and the off-farm job equation is provided, which confirms the legitimacy of using the Heckman correction model.

The first stage is the Probit model, which assesses off-farm employment decisions of farm households. The binary dependent variable Y_i takes the value of 1 when a household, who own agricultural land, have at least one member having off-farm jobs, and 0 otherwise. The off-farm job can be part-time or full-time, including working in the household's non-farm business. The econometric specification is as follows.

$$Y_i = \begin{cases} 1, & \text{if } Y_i^* > 0 \\ 0, & \text{if } Y_i^* \leq 0 \end{cases}, \tag{2.11}$$

where $Y_i^* = Z_i\gamma + \varepsilon_i$, $\varepsilon_i \sim \mathcal{N}(0,1)$. Z_i consists of control variables and weather conditions. Weather in the past may shape a farmer's risk perceptions and through this channel it affects the farmer's off-farm labor supply (Ito and Kurosaki, 2009; Demeke and Zeller, 2012). Thus information of weather conditions from the previous t year(s) are utilized. t can take the values of 1, 3 or 5 years. Temperature, rainfall, rain shadow wind and storm are usually found to have significant effects on farm income (Mendelsohn et al., 1994). Higher variations in climate may also lead to higher risks in farmland's output (Mendelsohn et al., 1996; Ito and Kurosaki, 2009). Furthermore, natural disasters may also adversely affect off-farm sectors in rural regions as it affects the whole economy.

The demographic variables, such as age, gender, years of schooling, and number of dependents, are expected to have strong effects on households' supplies in off-farm labor markets due to their correlation with working ability and demand for good and services. For example, a larger number of non-working age dependents leads to a higher off-farm participation rate in India (Ito and Kurosaki, 2009). In addition, years of schooling is an important measure of human capital accumulation. People receiving higher education would be more likely to have vocational training or tertiary education, which leads to better off-farm job prospects. Therefore, education provides a better access to off-farm employment opportunities. Age is also considered, as it is often related to the farming experience.

Alesina et al. (2013) and Hansen et al. (2015) demonstrated that there is a gender-based division of labor force due to different physical strengths. There are other empirical evidence from the studies of Fan (2003), and Mendola and Carletto (2012) in China and Albania to confirm that gender discrimination does exist in developing countries' labor markets. Yet Su et al. (2016) did not find such evidence in China's agricultural sector. In this study, we examine whether gender difference, which is a result of either gender discrimination or sexual division of labor, exists in the rural labor market of Vietnam. Therefore, the variable of male fraction among working age members is included in the econometric model.

Size of land that a rural household own, which is associated with income from farming, also plays an important role in the labor supply decision (Ito and Kurosaki, 2009; Demeke and Zeller, 2012). Families with more land would be less likely to leave their farms. Besides, families owning more land are observed to spend more time on the crops or cultivation (Su et al., 2016). Smaller farm land often leads to a lower farming productivity, which in turn might increase off-farm labor supply (Jia and Petrick, 2014). Asset, which is the total present value of a household's properties, is also included in the empirical model. In rural Vietnam, for some families the most valuable asset is a motorcycle or car, which can be observed in the data.

Distance to the nearest town center is expected to negatively affect a household's off-farm participation and income. With more off-farm opportunities in populated areas, people living closer to the town are expected to have a higher off-farm participation rate.

Inversely, people living far away from the town might find it hard to get an off-farm job. Social network is one of the key factors in getting off-farm jobs (Tu et al., 2008), yet people living in a remote area have fewer chances to build enough connections to acquire hiring information.

We also include the proportion of household members with health insurance as an explanatory variable. Health insurance coverage is often observed to affect occupation choice, wage and other aspects of labor markets (Currie and Madrian, 1999; Buchmueller et al., 1999; Garthwaite et al., 2014). Thus, we use health insurance coverage as a control variable in our model. Additionally, we also use year and regional dummies as control variables.

We expect differentiated estimates and significant levels of coefficients for weather conditions across different spans of time. Previous weather conditions can shape the mindset of farming households on agricultural risks. Thus, it later affects the off-farm employment decision.

The probability that a household takes an off-farm job is $\Pr(Y_i = 1|Z_i) = \Pr(\varepsilon_i < \widehat{Y_i^*}) = \Phi(Y_i^*)$, in which $\Phi(.)$ is the cumulative distribution function of standard normal distribution. Below is the functional form of the second stage regression:

$$I_i = X_i\beta + u_i, \quad u_i \sim \mathcal{N}(0, \sigma), \tag{2.12}$$

where I_i is the natural logarithm of total household income, from both off-farm job and farming. We assume there is a correlation between ε_i and u_i, so that $cov(\varepsilon_i, u_i) = \rho$. Then

$$E[I_i|X_i, Y_i = 1] = X_i\beta + E[u_i|X, Y_i = 1] = X_i\beta + \rho\sigma\lambda(Z_i\gamma), \tag{2.13}$$

where λ is the inverse Mill ratio.

Like Z_i in equation (2.11), X_i consists of control variables and weather conditions. We control for the variation in the demographic and socio-economic variables, including age, square of age, highest year of education, number of dependents, total asset, number of working age members, and size of land. Land, assets and labor are in the logarithm form like income, which is consistent with the Cobb-Douglas production function. Age is expected to have a quadratic relation with both income and off-farm participation. We also take into account the effect of year of schooling, which is a proxy of human capital. As mentioned above, years of schooling affects the job choice of a farmer, as higher education leads to better chance to access to vocational training or tertiary education. As shown in the theoretical framework, off-farm jobs can reduce the variations in farm income. The fraction of members having health insurance is also included in the model as an explanatory in the second stage. However, in equation (2.12) the information of weather conditions is for the current year, because agricultural income is expected to be directly affected by contemporaneous weather conditions.

In addition, we also control for the regional and yearly fixed effects by using dummy variables in 2nd stage as well as the first stage. Regions across the country are inherently different, not only in the way how the government administrates, but also in socio-economic and demographic distributions, weather and other natural conditions that we cannot comprehend in our model. It is worth noting that there is a North-South difference in term of weather conditions. The northern part is colder, has higher fluctuations in temperature, and bears more disasters. Further details will be discussed in the result section.

2.3.2 Data

To assess factors affecting off-farm participation, our empirical analysis employs data obtained from the Vietnam Household Living Standard Surveys (VHLSS) from 2008 to 2014. The survey has been conducted in 1993, 1997, and every two years since 2002 by the Vietnamese General Office of Statistics. With stratified random sampling, the survey collects information about demographics, education, health care, labor market, income, household expenditure, microcredit, social welfare and so on. There are about 10,000

Table 2.1. Data description.

Variables	Definition
Household income	Total household income from farm, wage and household business, adjusted by CPI data from World Bank (unit: thousand VND)
Off-farm	Dummy variable, 1: household has offered off-farm labor in the previous 12 months, 0: otherwise
Number of working-age adults	Number of people whose age from 16 to 65 and not attending school
Total land area	Total farming area (unit: meter square)
Assets	Total present value of total assets, adjusted by CPI (unit: 1,000 VND)
Distance to town center	Distance to Town Center in kilometers
Insurance proportion	The proportion of household members having health insurance in the last 12 months
Age	Average age of members whose age from 16 to 65
Highest year of schooling	Highest year of school among family member whose age from 16 to 65 and not attending school
Number of dependents	Number of members whose age under 16 or above 65 or still attending school
Male proportion	The fraction of male among family members whose age is from 16 to 65
Temperature	Average temperature at the year of observation (unit: Celcius)
Temperature SD	Temperature standard deviation based on monthly average temperature
Rainfall volume	Average monthly rainfall volume (unit: meter)
Rainfall SD	Rainfall standard deviation based on monthly average
Rain shadow wind	Number of days having rain shadow wind at the year of observation
Storm hits	Number of storm hits at the year of observation. A commune is defined to be affected if there is a moment that the distance from the commune to the center of a storm is less than 50 kilometers and wind speed at that time is above 60 knots
Temperature in the previous t years	Average temperature in the last t years prior to the year of observation
Temperature standard deviation in the previous t years	Temperature's standard deviation in the last t years prior to the year of observation based on year average temperature
Rainfall volume in the previous t years	Montly average rainfall volume in the last t years prior to the year of observation (unit: meters)
Rainfall standard deviation in the last t years	Rainfall standard deviation based ot yearly average for monthly rainfall of the t years prior to the year of observation
Rain shadow wind in the last t years	Yearly average number of days having rain shadow wind in t years prior to the year of observation
Storm hits in the last t years	Yearly average number of storm hits in t years prior to the year of observation

household observations in each survey. Additionally, VHLSS interviews commune-level administrators for information such as education, healthcare and off-farm opportunities. Since the surveys were conducted to collect previous year's information, the years of observation are actually 2007, 2009, 2011 and 2013. We focus on the subset of the data which only consist of agricultural households who own farmland. In total, there are about

30,000 observations across 63 provinces from 2007 to 2013. It is worth noting that the data is cross-sectional.

We also use the weather data from Vietnamese Ministry of Agricultural and Rural Development and storm track data from UNISYS (unisys.com) to examine the effects of temperature, precipitation, and storm on the off-farm job market. Over one hundred weather stations across Vietnam provide information about temperature, rainfall and rain shadow wind. The climatic conditions of a commune are considered to be same as the nearest station. A storm hit at the commune level will be counted only when the distance from the commune to the center of the storm is less than 50 kilometers and the wind speed is at least 60 knots. Table 2.1 presents the definition of variables in the model while associated summary statistics are presented in Table 2.2.

Table 2.2. Summary statistics of household level variables.

Variable	Obs	Mean	Std. Dev.	Median	Min	Max
Household income	29,782	75,187.17	160,604.3	45049	46.9	9,693,504
Off-farm	29,782	0.7455	0.4356	1	0	1
Number of working-age adults	29,782	2.5317	1.0931	2	1	9
Total land area (unit: m^2)	29,782	10,526.7	139,111.7	3,852	16	16,927,850
Assets (unit: VND)	29,782	12,945.26	18,513.93	8,660.563	15.1743	698,436.8
Insurance proportion	29,782	0.5706	0.3705	0.5	0	1
Age	29,782	37.2239	8.0619	35.5	16	65
Highest year of school	29,782	9.1185	3.4168	9	0	21
Number of dependents	29,782	1.7821	1.2811	2	0	9
Male fraction	29,782	0.4825	0.1918	0.5	0	1

We find 75% of households in the sample have at least one off-farm job. However, this number is not the same in different regions. As shown in Figure 2.4, families from northern mountainous areas are less likely to take off-farm jobs compared with those in Red River delta, southern central coast, central highland and southeastern regions. On the other hand, Figure 2.5 shows a significant income disparity between northern and southern parts of Vietnam. From 2007 to 2013, household income is increasing in the whole country. However, the household income in southern Vietnam is much higher than that in the north. Families in Red River Delta have similar income as their counterparts in the South.

Figure 2.4. The percentage of household having off-farm job in the sample (%)

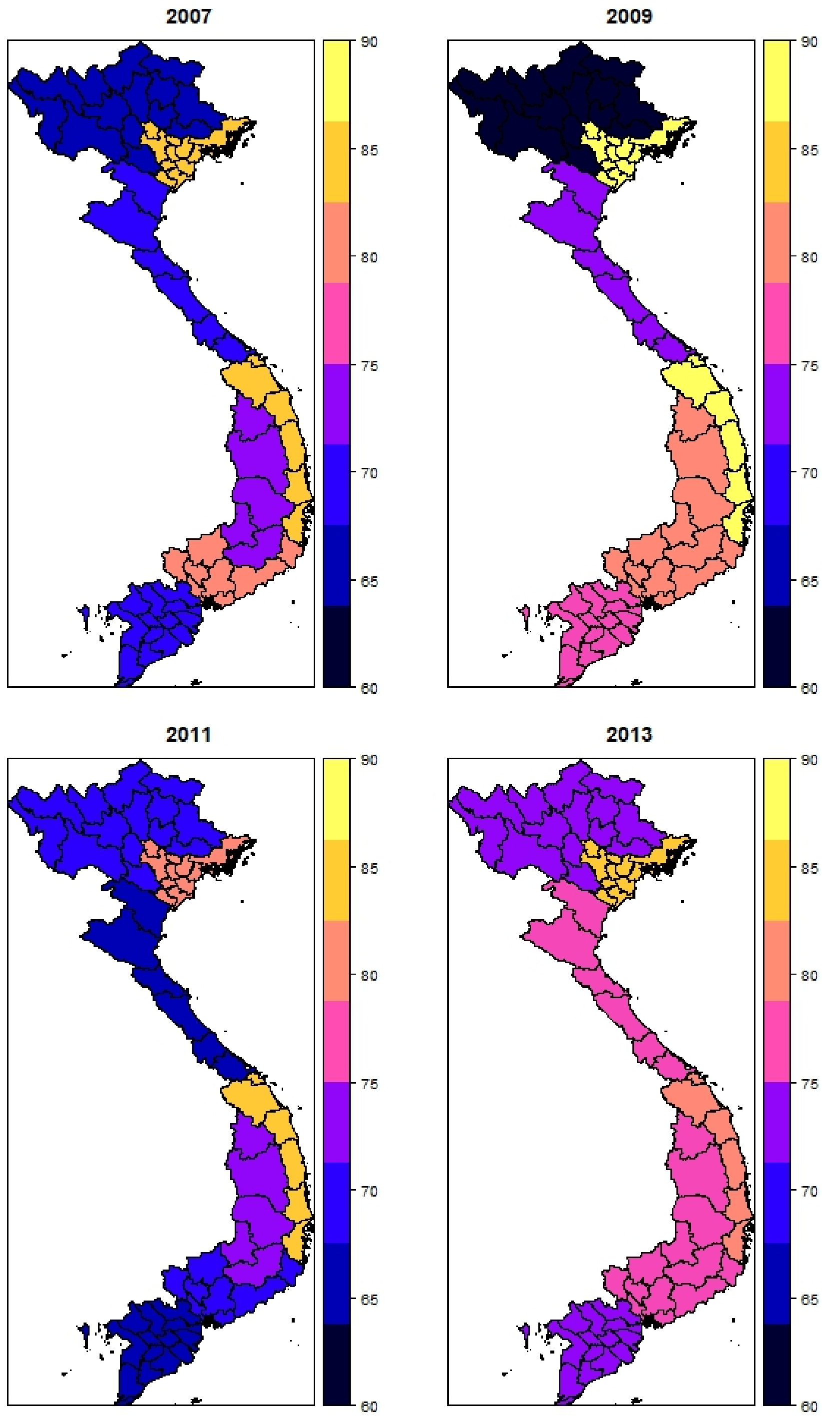


Figure 2.5. Average household income in the sample by provinces and years, adjusted by CPI (unit: 1,000 VND)

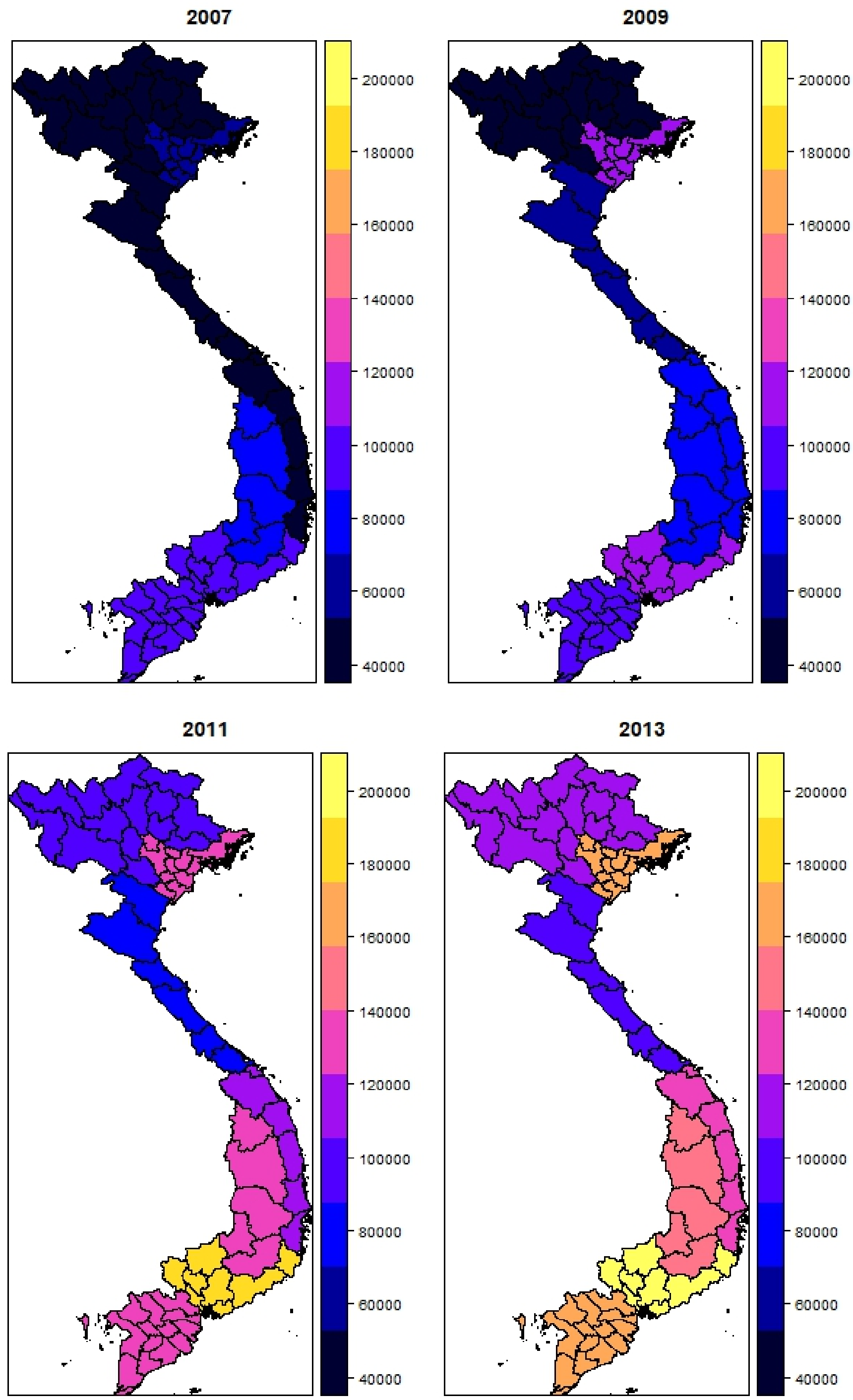


Table 2.3. Summary statistics of commune level variables.

Variable	Obs	Mean	Std. Dev.	Median	Min	Max
Distance to town center (unit: km)	5,792	12.2369	12.3456	10	0	160
Temperature (unit: °C)	5,792	24.5135	2.1670	24.0333	14.1833	28.4667
Temperature in the last 1 years (°C)	5,792	24.8212	2.1306	24.4167	14.55	28.625
Temperature in the last 3 years (°C)	5,792	24.6276	2.1036	23.9944	15.1694	28.3917
Temperature in the last 5 years (°C)	5,792	24.6354	2.0881	24.0283	15.1417	28.1842
Temperature standard deviation	5,792	3.3542	1.7216	4.0518	0.7133	6.3838
Temperature standard deviation in the last 3 years	5,792	0.4826	0.2274	0.5047	0.0048	1.2533
Temperature standard deviation in the last 5 years	5,792	0.4092	0.1720	0.5048	0.0612	1.1036
Rainfall volume (unit: meter)	5,792	0.2070	0.0915	0.1868	0.0836	0.4761
Rainfall volume in the last 1 year	5,792	0.1833	0.0635	0.1738	0.0586	0.4879
Rainfall volume in the last 3 year	5,792	0.1864	0.0621	0.1717	0.0941	0.5705
Rainfall volume in the last 5 year	5,792	0.1892	0.0634	0.1624	0.0999	0.5227
Rainfall standard deviation	5,792	0.2135	0.1240	0.1788	0.0758	0.7570
Rainfall standard deviation in the last 3 years	5,792	0.0378	0.0267	0.0319	0.0015	0.3382
Rainfall's standard deviation in the last 5 years	5,792	0.0400	0.0254	0.0334	0.0068	0.2572
Rain shadow wind (unit: day)	5,792	13.6407	18.4036	6	0	120
Rain shadow wind in the last 1 years	5,792	19.7343	24.6926	9	0	126
Rain shadow wind in the last 3 years	5,792	17.5151	20.6159	8	0	98.3333
Rain shadow wind in the last 5 years	5,792	16.5621	19.8500	6.2	0	87.2
Storm hits	5,792	0.0192	0.1371	0	0	1
Storm hits in the last 1 years	5,792	0.0331	0.1790	0	0	1
Storm hits in the last 3 years	5,792	0.0204	0.0802	0	0	0.6667
Storm hits in the last 5 years	5,792	0.0176	0.0568	0	0	0.4

In this model, we only consider the income from farming, off-farm jobs and/or household business. The median and the mean of years of schooling are around 9, suggesting that the majority of households in our sample might do low-skilled jobs, in agriculture or off-farm sector. Most households are young since the average age is 37 years old and median age is less than 36 years old. Consistently, the average number of working-age household members is roughly 2.5 and the average number of dependents is less than 2. In an average family, more than half of the households have health insurance.

As has been discussed in the econometric specifications, distance to the nearest town center may negatively affect households' income and off-farm participation. As shown in Table 2.3, there are some villages that are around 160 kilometers away from town centers. In our sample, there are 67 communes located more than 50 kilometers away from their closest town centers. Those communes are often separated from populated areas because of jungles, mountainous terrain or rivers without bridge. Families in those communes cannot take off-farm opportunities in a nearby town, and also have less chance to access the education system.

Table 2.4. The average weather's condition by regions from the North to the South.

Area	Average Temperature	Temperature's Fluctuation	Rainfall Volume	Rainfall Fluctuation	Rain Shadow Wind
Northern Mountainous Area	22.56	4.67	0.15	0.15	7.92
Red River Delta	23.69	4.86	0.15	0.16	6.37
Northern Central Coast	24.2	4.29	0.19	0.22	32.61
Southern Central Coast	22.3	2.51	0.25	0.30	27.03
Central Highland	23.19	1.64	0.26	0.27	8.69
Southeastern Area	26.31	1.06	0.29	0.27	25.92
Mekong River Delta	27.27	0.99	0.30	0.27	7.03

Figures 2.6-10 are the maps illustrating the commune-level weather conditions. North-south disparities are documented in Figures 2.6 and 2.7. In particular, the northern part tends to have a lower mean but higher fluctuation of temperature than the south. Such trend is evident in Table 2.4, which presents the yearly average weather information from north (upper) to south (bottom). Figures 2.8 and 2.9 illustrate the monthly rainfall volume and rainfall's fluctuation. Even though precipitation varies year by year, rainfall volume tends to be consistently lower in the northern area. The rainfall's fluctuation shows the same tendency, which is confirmed in Table 2.4. Figure 2.10 shows the number of days with rain shadow wind in 2007, 2009, 2011, and 2013. The regions suffer most from rain shadow wind are the central coast area and the southeastern area.

2.4 Results

We run the Heckman correction model using three scenarios which correspond to agricultural households' labor allocation decisions facing short-term, medium-term or long-term weather risks respectively. Table 2.5 provides the regression results of household income estimation. With a highly significant correlation $\rho = 0.81$, there is a positive and vigorous relationship between u_i and ε_i. To be precise, farm households,

Figure 2.6. The average temperature, unit: Celcius

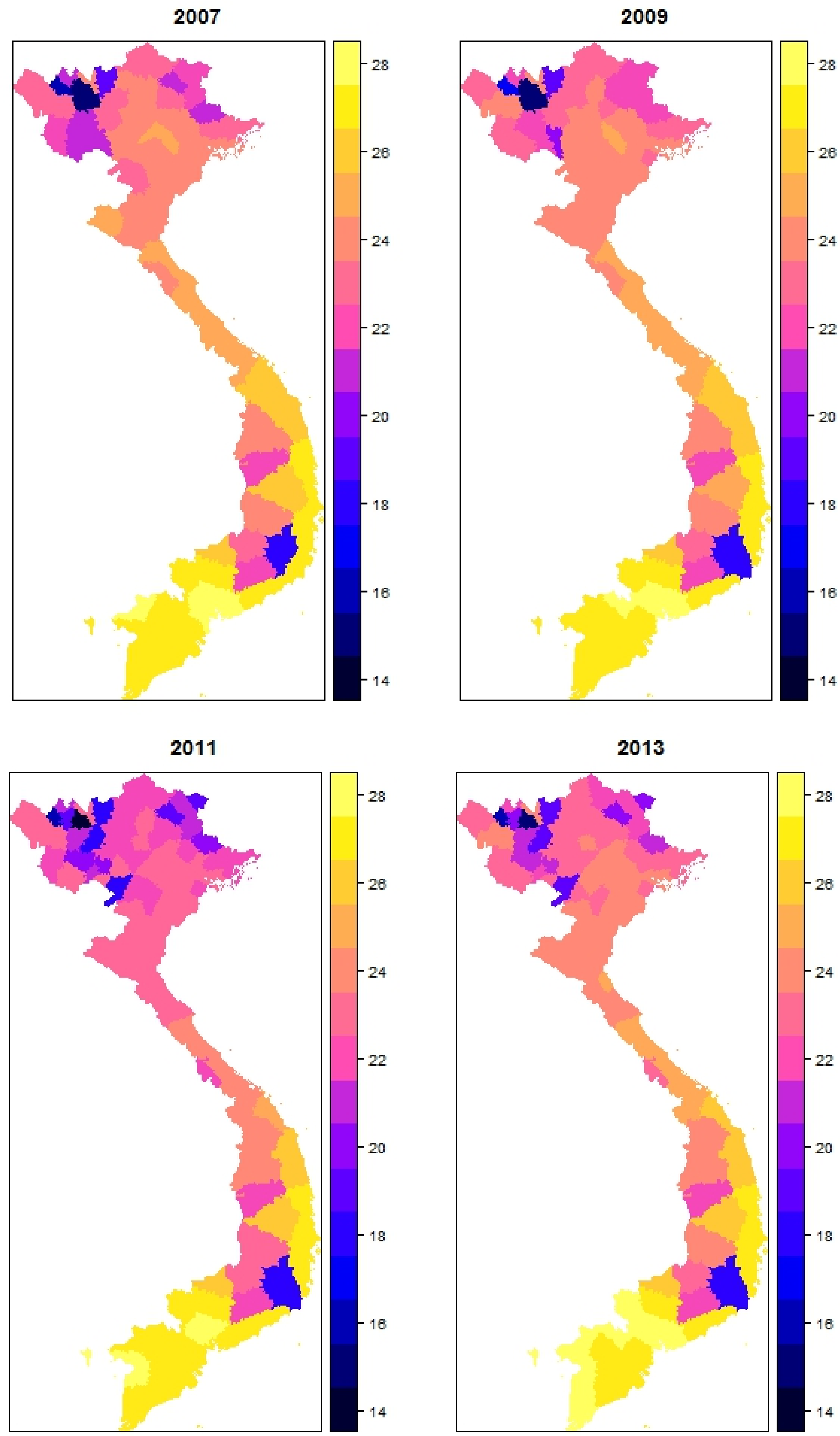


Figure 2.7. The temperature's standard deviation

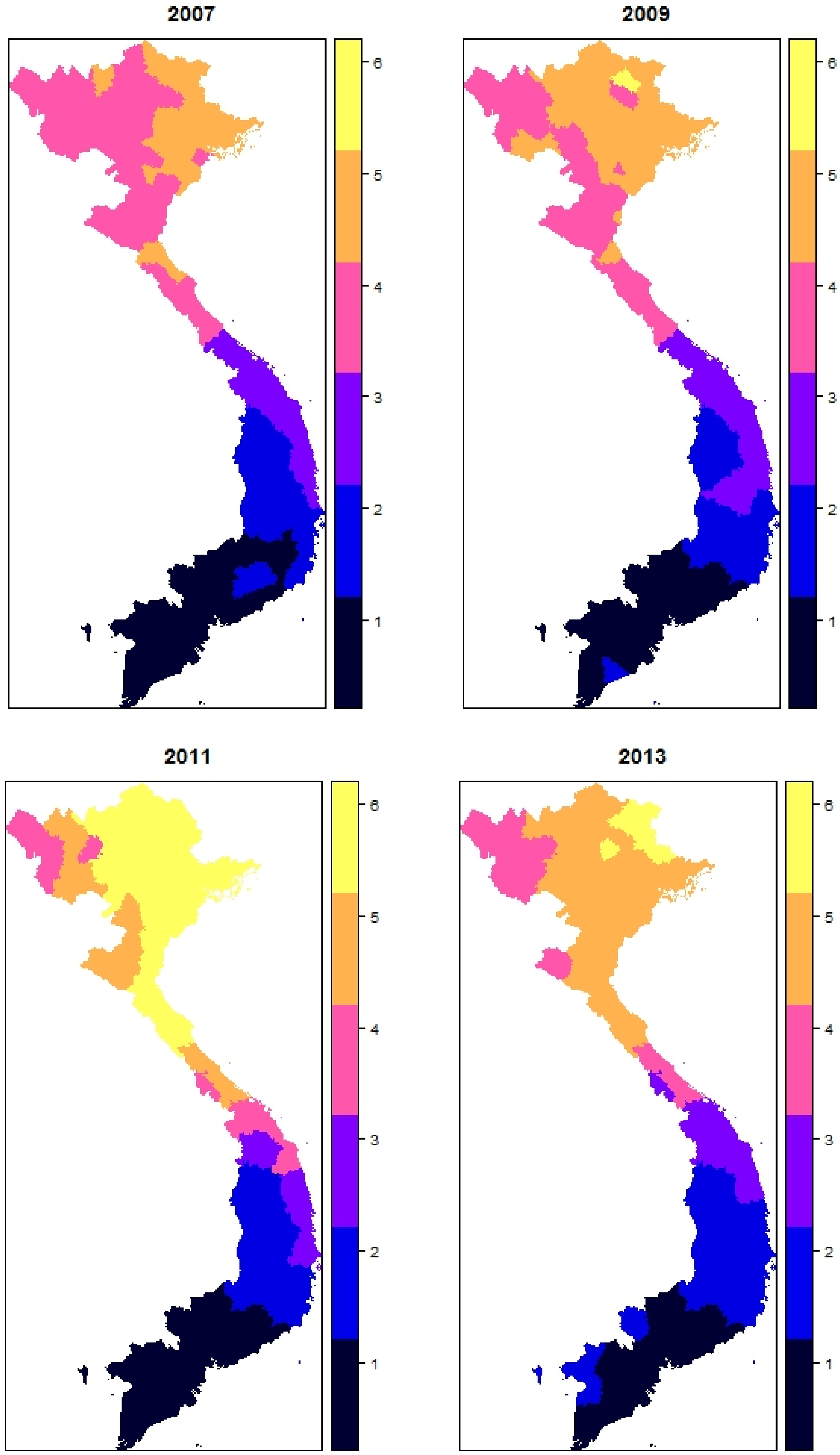


Figure 2.8. The average monthly rainfall volume, unit: mm

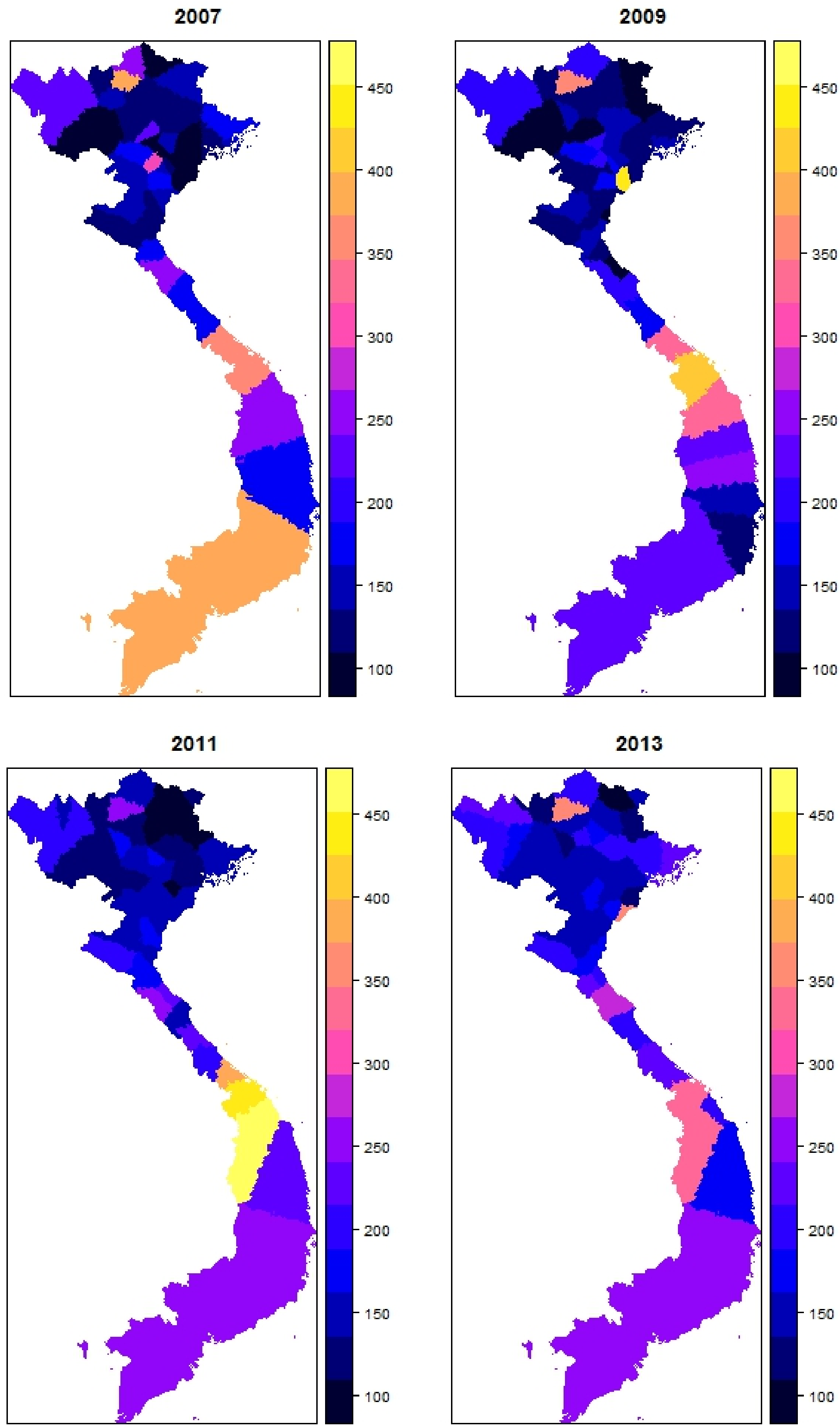


Figure 2.9. The rainfall's standard deviation

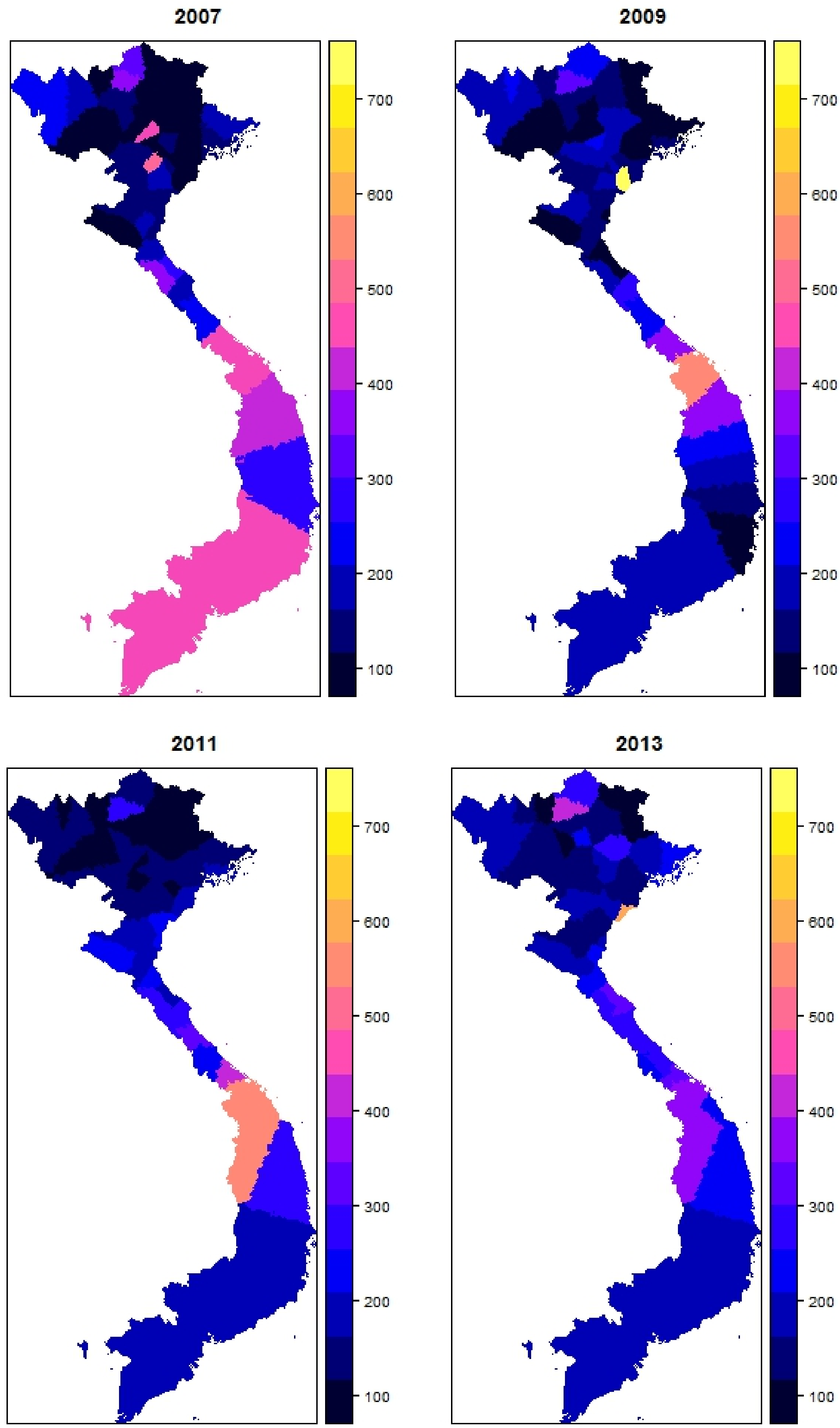
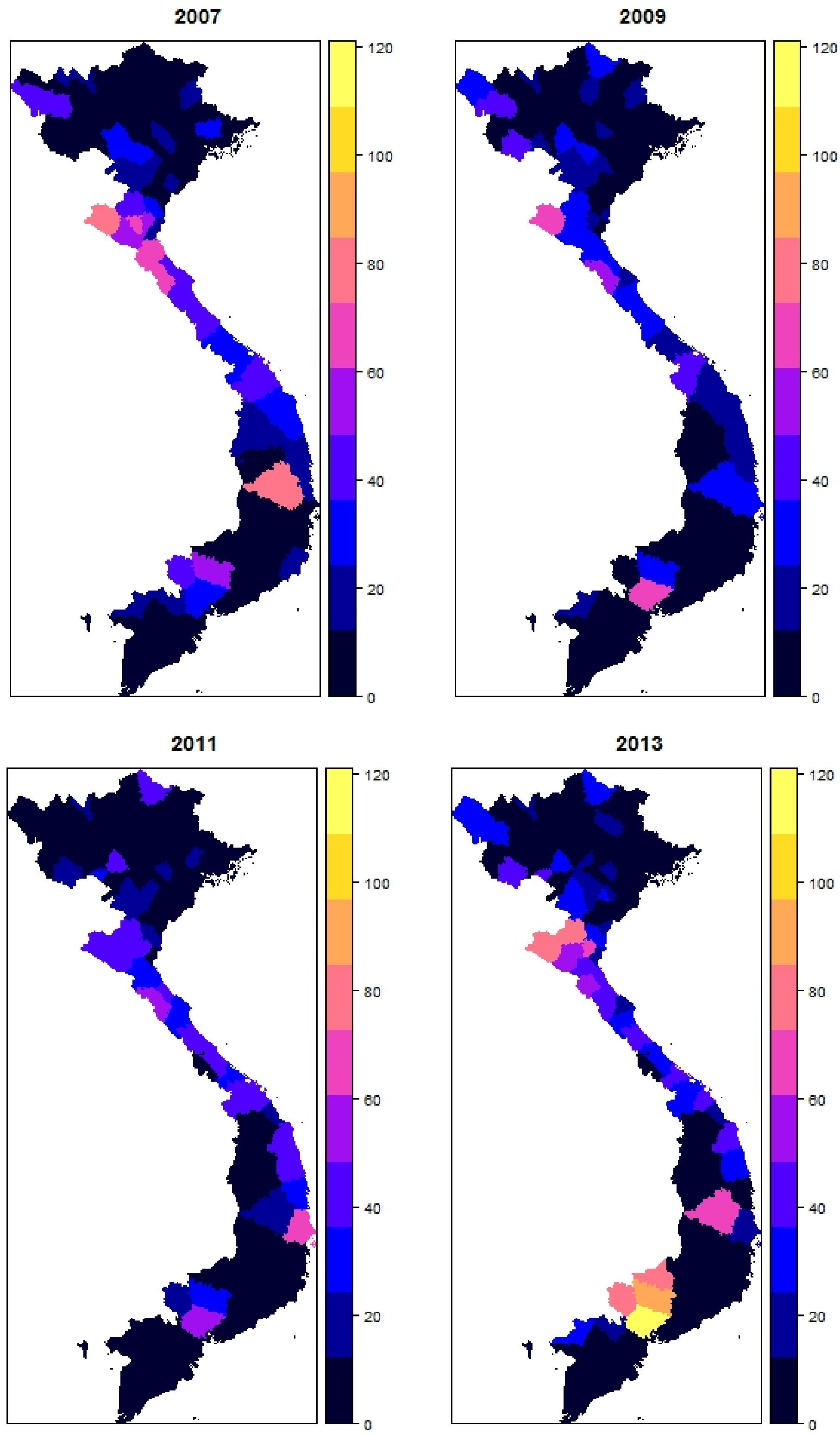


Figure 2.10. The number of days having rain shadow wind



whose members have off-farm jobs, are expected to have higher total income. The null hypothesis of independent equations ($H_0 : \rho = 0$) is rejected. Moreover, farm household with off-farm jobs, are expected to have higher total income. The results confirm the validity of using the Heckman correction method in this study.

The relationship between temperature of the preceding t year(s) and off-farm employment is not linear, as the coefficients of temperature and temperature squared are both significant. It turns out the off-farm participation will reach minimum at around 21 degree Celsius in all three scenarios. However, coefficients of temperature squared are larger at $t = 3$ and the largest at $t = 5$. It implies that the effect of long-term temperature pattern is higher. The trend is also true for temperature's fluctuation, rainfall volume, and rainfall's fluctuation.

Such patterns might be due to the fact that farming households need to observe weather patterns for some time before they begin to shape their expectation of future agricultural risks. This affects their perception of whether the adverse climate effects are temporary or persistent. Farmers might hesitate to search for off-farm jobs if they believe the adverse climate effects are a temporary phenomenon.

The standard deviation of yearly average temperature in the last 5 years is associated with the highest probability of taking off-farm jobs. The change in temperature partially reflects the fluctuation in weather conditions, thus it increases agricultural risk. As a result, locations with higher fluctuation in temperature in the past have the greater uncertainty of farm income. This leads to higher participation rates in the off-farm sector.

Higher rainfall volume in the past is associated with higher off-farm employment, and the correlation is the strongest for the rainfall observed in the last 5 years. In contrast, the coefficient of yearly rainfall's standard deviation is negative, which implies that higher rainfall fluctuation is associated with lower off-farm participation rate. However, yearly rainfall fluctuation might not be important since it is only significant in the 5 years period. Rain shadow wind, which delivers dry and hot air, mostly during summer, rarely has

Table 2.5. Result of Heckman correction model estimating household total income and off-farm labor supply in rural area

	$t=1$		$t=3$		$t=5$	
VARIABLE	Income	Off-farm	Income	Off-farm	Income	Off-farm
Log of number of working-age adults	0.3722***	0.4320***	0.3718***	0.4335***	0.3719***	0.4313***
	(0.0127)	(0.0235)	(0.0127)	(0.0235)	(0.0127)	(0.0235)
Log of total land area (unit: m^2)	0.0670***	-0.3356***	0.0672***	-0.3378***	0.0668***	-0.3380***
	(0.0045)	(0.0087)	(0.0045)	(0.0087)	(0.0045)	(0.0087)
Log of total asset (unit: 1,000 VND)	0.2746***	0.0850***	0.2746***	0.0855***	0.2745***	0.0851***
	(0.0043)	(0.0080)	(0.0043)	(0.0080)	(0.0043)	(0.0080)
Distance to town center (unit: km)	-0.0078***	-0.0052***	-0.0077***	-0.0053***	-0.0078***	-0.0054***
	(0.0005)	(0.0008)	(0.0005)	(0.0008)	(0.0005)	(0.0008)
Insurance proportion	-0.1570***	0.1139***	-0.1567***	0.1148***	-0.1571***	0.1186***
	(0.0131)	(0.0240)	(0.0131)	(0.0240)	(0.0131)	(0.0240)
Age	0.0769***	0.0902***	0.0768***	0.0897***	0.0768***	0.0897***
	(0.0046)	(0.0074)	(0.0046)	(0.0074)	(0.0046)	(0.0074)
Age squared	-0.0011***	-0.0014***	-0.0011***	-0.0014***	-0.0011***	-0.0014***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Highest year of schooling	0.0371***	0.0254***	0.0371***	0.0256***	0.0372***	0.0256***
	(0.0015)	(0.0028)	(0.0015)	(0.0028)	(0.0015)	(0.0028)
Number of Dependents	0.0854***	0.0518***	0.0854***	0.0515***	0.0854***	0.0514***
	(0.0041)	(0.0075)	(0.0041)	(0.0075)	(0.0041)	(0.0075)
Male Fraction	0.2186***	0.3293***	0.2175***	0.3322***	0.2177***	0.3316***
	(0.0245)	(0.0422)	(0.0245)	(0.0423)	(0.0245)	(0.0422)
Temperature (unit: °C)	-0.2403***		-0.2436***		-0.2447***	
	(0.0393)		(0.0398)		(0.0397)	
Temperature squared	0.0057***		0.0058***		0.0058***	
	(0.0009)		(0.0009)		(0.0009)	
Temperature standard deviation	0.0337***		0.0331***		0.0319***	
	(0.0111)		(0.0112)		(0.0111)	
Rainfall Volume (unit: m)	0.2854*		0.3224*		0.3711**	
	(0.1657)		(0.1650)		(0.1659)	
Rainfall standard deviation	-0.1994*		-0.2133**		-0.2384**	
	(0.1022)		(0.1021)		(0.1021)	
Rain shadow wind (unit: day)	-0.0007**		-0.0008***		-0.0007**	
	(0.0003)		(0.0003)		(0.0003)	
Storm hits	-0.0020		-0.0011		-0.0008	
	(0.0446)		(0.0446)		(0.0447)	
Temperature in the last t years (unit: °C)		-0.2388***		-0.2637***		-0.2861***
		(0.0723)		(0.0735)		(0.0739)
Temp squared in the last t year		0.0056***		0.0063***		0.0068***
		(0.0016)		(0.0017)		(0.0017)
Temp. deviation in the last t years				0.2178***		0.3712***
				(0.0690)		(0.0961)
Rainfall Volume in the last t years		0.4639***		0.7525***		1.1063***
		(0.1644)		(0.2311)		(0.2652)
Rainfall Deviation in the last t years				-0.2208		-1.3217***
				(0.3678)		(0.5095)
Rain shadow wind in the last t years		-0.0002		-0.0009*		-0.0005
		(0.0005)		(0.0005)		(0.0005)
Storm hits in the last t year(s)		0.2311***		0.3987***		0.3259**
		(0.0481)		(0.0993)		(0.1387)

significant effect on off-farm employment. Among all scenarios, only the coefficient of previous 3 years' rain shadow wind is significant.

Table 2.5. – *Continued from previous page*

	$t=1$		$t=3$		$t=5$	
VARIABLE	Income	Off-farm	Income	Off-farm	Income	Off-farm
Constant	7.7510***	2.7690***	7.7827***	2.9500***	7.7888***	3.0846***
	(0.4356)	(0.8163)	(0.4400)	(0.8161)	(0.4396)	(0.8162)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regionaly dummies	Yes	Yes	Yes	Yes	Yes	Yes
ρ	0.8149***		0.8133***		0.8149***	
	(0.0073)		(0.0074)		(0.0073)	
σ	0.6760***		0.6755***		0.6760***	
	(0.0042)		(0.0042)		(0.0043)	
λ	0.5509***		0.5494***		0.5509***	
	(0.0077)		(0.0077)		(0.0077)	
Observations	29,782		29,782		29,782	
AIC	67,173.67		67170.62		67174.03	

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The effects of storm are always significant. The coefficient of storm hits in the last year is 0.23. This figure is 0.40 for storms in the previous three years and and 0.33 for storms in the previous five years. Given the positive impact of storm hits on off-farm participation and the positive effect of off-farm participation on household income, storms may also indirectly increase household income of farmers.

While evaluating the effect of weather on household income, we find both temperature and rainfall have similar effects as they do in the off-farm participation estimation. There is also a U-shaped relationship between temperature and household income. Furthermore, there is a positive correlation between precipitation and household income while we failed to find statistically significant impact of storm on household income. Moreover, despite having no effect on off-farm participation, rain shadow wind has a negative effect on income. For an additional day of having downside wind in a year, the total income reduces by 0.07%.

Socio-economic and demographic variables are found to have different impacts. Households possessing more farm land would be more likely to stick with farm work as shown in the off-farm participation estimation. Meanwhile, for a 1% increase in total land size, household income expands by 0.07%. In addition, a larger number of working-age adults in the family would lead to a higher probability of taking off-farm jobs, since the amount of time needed for the farm is almost fixed. At the same time, families with more working-age adults also have higher income. On the other hand, the number of dependents increases the off-farm participation. More dependents often cause higher demand for food, medical care and education. Such households may be under higher financial pressure to seek for employment opportunities outside their farms. Meanwhile, dependents can also provide assistance in both farming and off-farm jobs. For each additional dependent, household income increases by 8.5%.

A larger present value of assets leads to a higher off-farm participation rate. This is because that a larger endowment of capital can reduce the need for farm labor. Besides, a larger value of assets might mean a higher amount of spending on private vehicles, which helps household members to access off-farm opportunities. A 1% increase of total asset value is expected to increase household income by 0.27%.

Gender also plays a significant role, as a higher portion of male members leads to more off-farm participation. This might be because of two possible reasons. First, gender-based favoritism widely exists in rural areas, where girls are often discouraged to attend school and they have to bear a larger burden of housework. Second, many off-farm jobs are non-technical jobs such as construction labor which prefer males. On the other hand, the results show that families with a higher proportion of health insurance coverage have higher off-farm participation rates. However, in the household income function, insurance proportion is found to be negatively associated with family income.

It is found a household's average age is non-linearly associated with both off-farm participation and income. *Ceteris paribus*, families, whose average age is 30 years old, are expected to have the highest off-farm participation rate and the highest income . At this age, the families are more likely to have kids, thus the financial pressure they are facing may be at its peak. Meanwhile, since many households are multi-generational, working-age adults above 30 in the older generation might not be able to work as much as they used to.

As expected, we find that years of schooling matter. More years of schooling lead to a higher probability of working outside the agricultural sector and it is also correlated with a higher household income. Such an effect of schooling on income is not only because of increasing off-farm employment, but also due to higher human capital. People with more vocational training or tertiary education often have more employment options.

We also see the regional heterogeneity in household income and off-farm participation rates. Compared with the Mekong delta, families in the Red River delta, southern central coast, central highland and southeastern Area are expected to more actively participate the off-farm job market. However, in terms of household income, rural families in the central coast and the northern mountainous area have lower income than their counterparts in the Mekong river delta. Should everything else be equal, a family in the southeastern area is expected to have the highest income, mostly because the southeastern region has more non-farm opportunities than any other part of the country.

Finally, with the econometric model, we are able to predict the off-farm participation rates and household income based on the regression with weather risks from the previous 5 years. The expected values are illustrated in Figures 2.11 and 2.12. Households in southern Vietnam seem to have higher income and off-farm participation rates than their peers in the north, except households in Red River delta have relatively high income close to those in the south.

Figure 2.11. The predicted probability of off-farm participation (%)

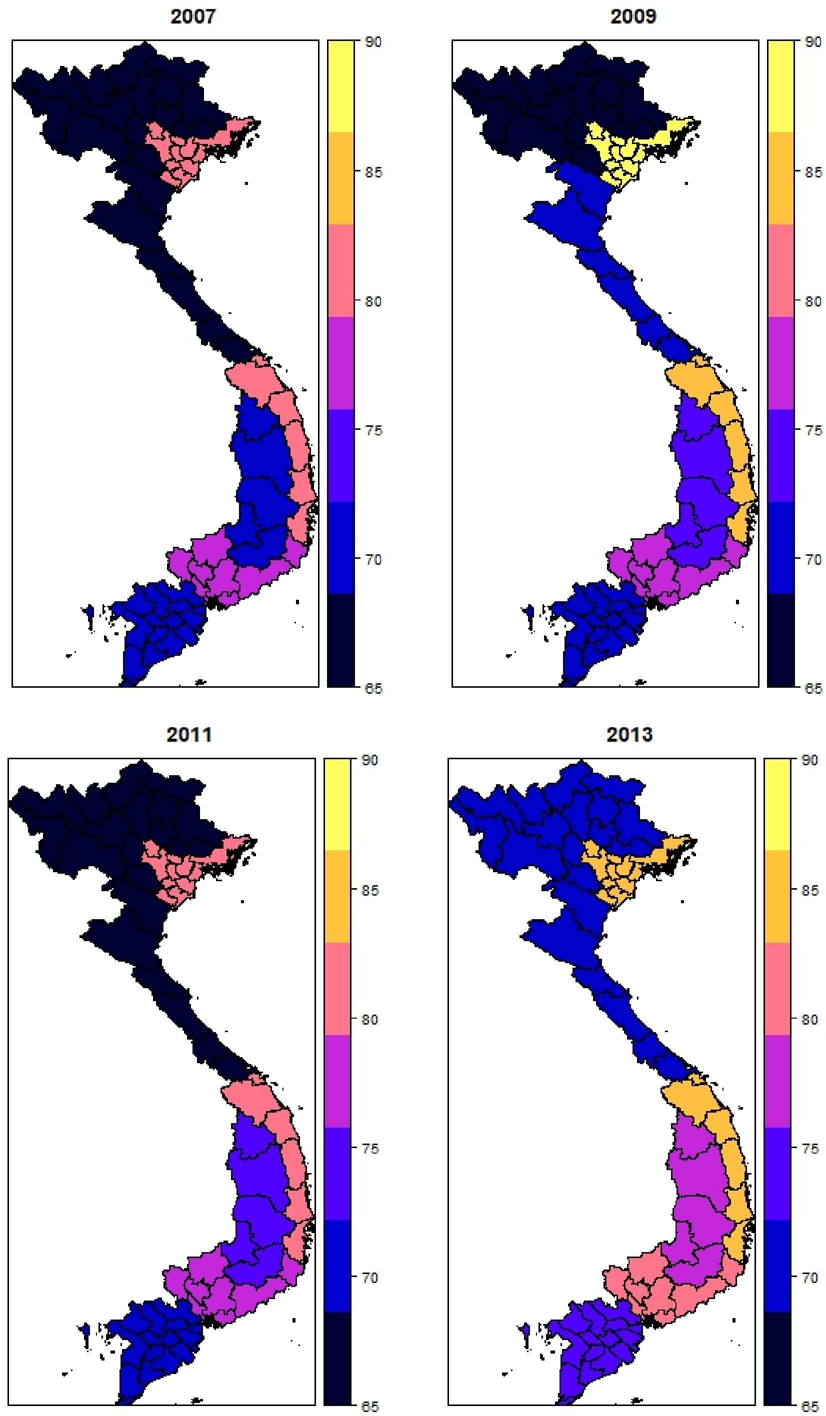
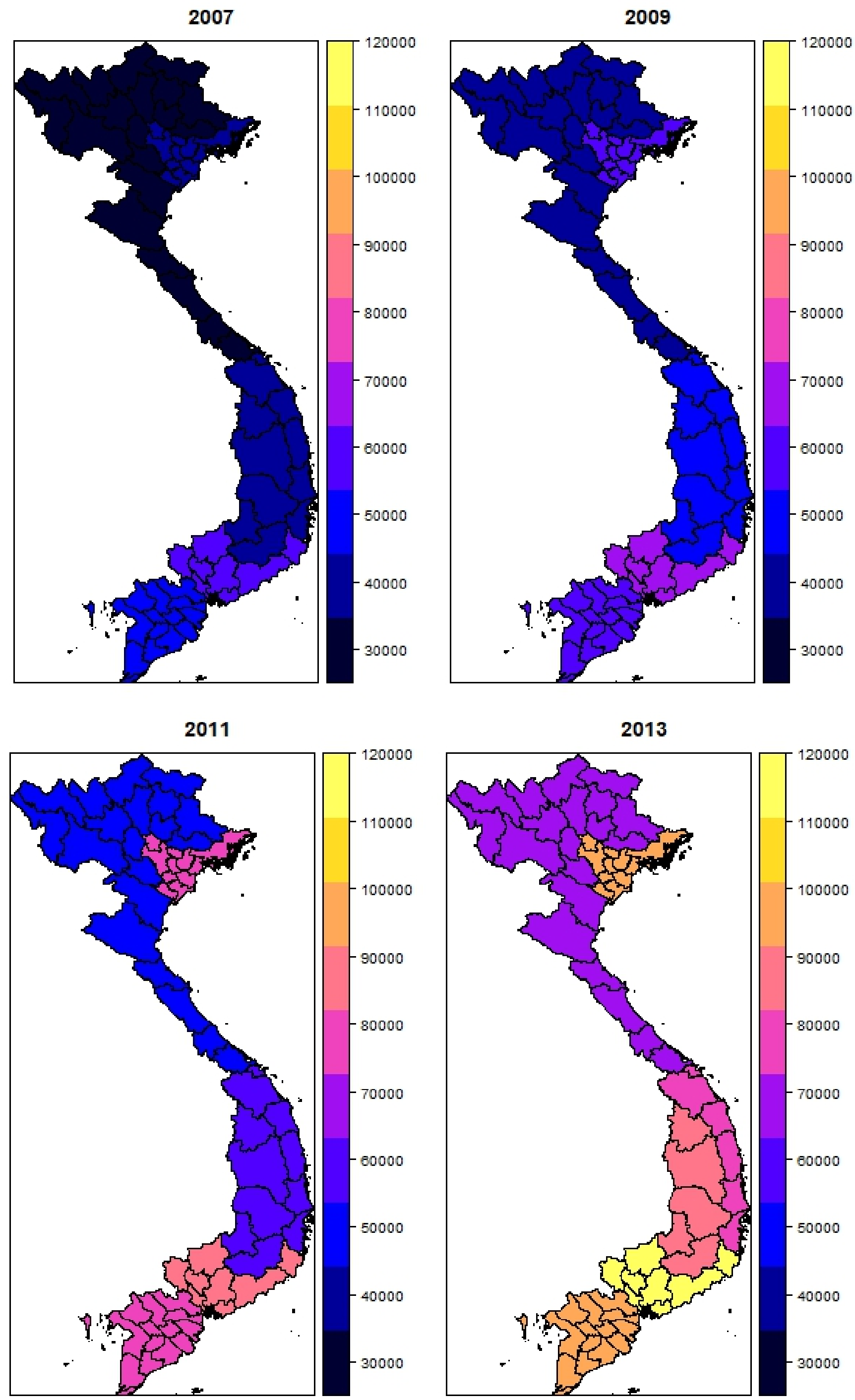


Figure 2.12. Average predicted household income by provinces and years, adjusted by CPI (unit: 1,000 VND)



2.5 Conclusions

Our research contributes to the current literature of agricultural households' labor allocation in several folds. First, we studied off-farm labor supply in a developing country in Southeastern Asia, Vietnam, of which the topic is rarely evaluated. We examined the determinants of farming household's total income with a focus on weather and natural disasters and their impacts on off-farm employment participation. With the available data, we adopted the Heckman correction method to overcome endogeneity and the potential selection bias of the survey. We also found significantly positive correlation between off-farm employment and household income. Families whose members take off-farm jobs tend to have higher income.

The second contribution is that we have identified temporally variant impacts of weather on off-farm labor supply. The results of our econometric models demonstrate that climate patterns observed over a longer period (i.e., five years) generally have a stronger effect on the off-farm job participation rate than weather observed over a shorter period of time (i.e., one year or three years). This may be because farmers' risk perceptions of weather are based on observations over several years rather than just one year.

Further, this study reaffirms the argument of Arouri et al. (2015) regarding the resilience of rural households affected by natural disasters. In particular, we find exposure to storms leads to more off-farm participation, thus resulting in higher income. Another interesting result is the negative effect of rain shadow wind on household income. For each additional day with rain shadow wind, annual household income decreases by 0.13% even though the wind does not affect the off-farm participation. Proximity to town center is also found to be an important determinant. A longer distance to the populated area may impair a rural household's ability to access employment opportunities in off-farm sectors and thus reduce their income.

In all, this study has provided a detailed framework of analyzing off-farm labor supply in a developing country with a huge rural population such as Vietnam with a focus on weather. Our findings confirm that weather risks have played a vital role in labor allocations of agricultural households. Since nearly 50% of the workforce in Vietnam are in the agricultural sector, our study should provide important insights for policymakers and stakeholders in Vietnam and other similar developing countries in Southeastern Asia. On one hand, efforts to prevent or mitigate the weather risks would be important to retain farmers on their land. Such efforts shall include, but are not limited to, improving irrigation system and providing crop insurance. On the other hand, the government may also consider encouraging agricultural households to engage in off-farm jobs in order to improve their income. Supporting the development of manufacturing factories in the countryside and building a better transportation system shall improve the economic opportunities available to the rural households.

CHAPTER 3
PESTICIDE USE AND HEALTH BURDEN OF FARMERS IN VIETNAM

Though pesticide is capable of enhancing the productivity in the agricultural sector, it may have an adverse effect on human health. It is often found to affect vulnerable populations such as children and pregnant women. However, the relationship between pesticide use and health burden of farmers is still unknown. This study aims to answer this question by investigating the correlation between agricultural households' pesticide use and household members' health in Vietnam. The results show that for an additional million Vietnam Dong (VND - approximately US $65 in 2004) annual spending on pesticide in the previous years, the current year's number of hospital visits increases by 2.6%. This figure for pesticide use of rice crop is 3.3%. For the young people, one additional million VND of pesticide use in non-rice food crop, industrial and fruit crops is associated with a 15.2%, 23.6% and 59.9% increase in the number of hospital visits respectively. Besides, a million VND increase in lagged pesticide use leads to 2.2% increase in the health care cost. For rice and industrial crops,the numbers are 2.4% and 22.1% respectively. These results provide an evidence for the negative association between pesticide use and health status of farmers in Vietnam.

3.1 Introduction

Pesticides can increase productivity in the agricultural sector. However, there are potential adverse health effects of pesticide on both farmers and consumers. In the Mekong Delta of Vietnam, Dasgupta et al. (2007) found that farmers do not fully perceive the risks of toxic substances of herbicide and insecticide that they are exposed to. However, it is still unknown to what extent pesticide consumption affects farmers' health and related expenditure. In this study, we estimate the correlation between pesticide use on the health burden of farmers by employing data from Vietnam Household Living Standard Surveys.

Pesticide pollution could be a severe problem in Vietnam since there is a large population in its agricultural sector. According to Central Intelligence Agency (2015), 50% of the Vietnamese workforce is in the agricultural sector. Even though dangerous pesticides were banned in 1995, the authority still found 2,500 kilograms of DDT in 2000, with approximately 50 metric tons of other pesticides which are classified as highly toxic by WHO (PPD, 2000). Pham et al. (2011) found DDTs, HCHs, Drin and other insecticides in the sample of fish, vegetable, tea and soil from two rural communes in northern Vietnam. Based on the Acceptable Daily Intake Level (ADI), Pham et al. (2011) suggest that farmers living in that area should not consume tea, fish, and vegetables more than 3 gram a day. There is also evidence for the abusive use of pesticides from the case study conducted by Lamers et al. (2011). They found that the amount of insecticides sprayed by the farmers is nearly twice the maximum dosage recommended by the producers.

There are many other studies about pesticide pollution in Vietnam. Dang et al. (1999) found high concentrations of DDT and PCB in the samples taken along the coast in the Gulf of Tonkin in the rainy season of 1997. Hong et al. (2008) found similar results by measuring the concentration level of organochlorine in the water from Ha Long Bay, Hai Phong Bay, and Ba Lat Estuary. DDT can also be detected in the sewer water of Hanoi, the capital city of Vietnam (Pham et al., 2010). The increasing trend of the DDT/DDE ratio reflected the recent usage of DDT even though it was banned for more than a decade. Even worse, Nguyen et al. (2004) found the pesticide residuals in the human breast milk in Hanoi and Ho Chi Minh city. The concentration level of DDT compound is the highest among all the pesticides found in the human milk, and this figure is also one of highest among developing countries.

Pesticide pollution is also a severe issue in other countries. Zhu et al. (2005), Bai et al. (2006), Zhou (2000) and Jiang et al. (2009) found the residuals of organochlorine (DDTs, HCHs, etc.) or organophosphorus pesticides in soil, food, and surface water in different locations of China. The results from Cobb-Douglass function estimations by Widawsky et al. (1998) showed that insecticides and herbicides are overused by Chinese farmers, while the host-plant resistance is underestimated. Meanwhile, the pesticide residuals are also found in water (Tariq et al., 2004; Ahad et al., 2006) and food (Parveen et al., 2005; Saqib et al., 2005) in Pakistan.

Given the risks of toxic pesticides, researchers were concerned with their impact on farmers' health. In the Philippine, Pingali et al. (1994) found that pesticide consumption endangers the health of farmers, and thus increases their health expenditure. Antle and Pingali (1994) had the same conclusion on the effect of pesticides on farmers health in the Philippine, which also reduces farmers' productivity. Crissman et al. (1994), Antle et al. (1998), Maumbe and Swinton (2003), and Sheahan et al. (2017) have the similar results with different data sets from Ecuador, Zimbabwe, and Sub-Sahara regions. In the U.S., Hill et al. (1995) found the pesticide residues in the urine samples of adults. But the level of pesticide pollution in the US is relatively low (Kolpin et al., 1998). Nevertheless, pesticide use in the US costs about $1.1 billion a year in the filed of public health, $1.5 billion due to pesticide resistance in pests, $1.4 billion of crop losses, $2.2 billion of bird losses and $2.0 billion because of groundwater contamination (Pimentel, 2005).

Even though toxic pesticides are widely and in some cases illegally used in Vietnam, there is a huge gap in the literature about the effect of pesticide on the health condition of Vietnamese farmers. As far as we know, Nguyen and Tran (2003) is the only study attempting to address this issue. By using data collected in 1997 in the Mekong Delta, Nguyen and Tran (2003) provided evidence for the effect of insecticide and herbicide on farmer health and health care cost. Their results show that pesticides are overused and recommended a 33.4% tax on pesticide sale. However, we believe the simple OLS model that they employed would not be enough to control for many potential issues. One of them might be the endogeneity issue where the pesticide consumption might depend on other variables. Another problem possibly arising might be a selection bias.

In this study, we focus on how pesticide use affects Vietnamese farmers' health conditions and health expenditures. We investigate the effect of household-level pesticide use on individuals' number of hospital visits and health spending with data from Vietnam Households Living Standard Surveys. To ensure the validity of our analysis, we employ data of lagged pesticide use from previous years, which are relatively exogenous to the current year's health condition. However, it is still possible that an unobserved factor can affect both lagged pesticide use and health condition. Since the number of hospital visits is a count variable of which a significant portion of observations are zeros, we use zero-inflated models for our analysis. The result of Vuong test prefers using zero-inflated negative binomial model rather than using standard negative binomial model. There is also a test for overdispersion implying that zero-inflated Poisson model is less suited in this analysis. In addition, we use the log-linear OLS model to investigate the association between farmers' pesticide use and their healthcare cost.

We also evaluate some relevant variables that previous literature overlooked unintentionally. For example, a big collection of literature on health economics in Vietnam concentrated on the impact of health insurance on health care. Jowett et al. (2003) and Sepehri et al. (2006a) found that health insurance reduces out-of-pocket payments by about 20-30%, with data collected before 2003. The evidence provided by Sepehri et al. (2006b) shows that people having health insurance, especially the low- and middle-income classes, care more about their health. Nevertheless, health insurance scheme in Vietnam is still useful in reducing the financial burden of many households (Hoang et al., 2013). Additionally, there are studies considering the effects of health shocks on living standards. Wagstaff (2007) measured health shocks as a recent death of a working-age household member, a long inpatient spell and a decrease in the body mass index. These variables were found to be positively correlated with the unearned income but negatively related to the earned income. It was also reported that households' medical spending increased even with insurance. Households can cope with health shocks by increasing loan and selling assets while simultaneously decreasing other expenditure (Mitra et al., 2016). There is also a study by Lohmann and Lechtenfeld (2015) that considers the effect of drought on health care expenditure. Therefore, to account for the above mentioned factors, our study consider both health insurance and weather shocks.

The estimations have shown the adverse effect of pesticide on agricultural household. For a million of 2004 VND increase in lagged pesticide consumption, which is about US$65, the number of hospital visits raises by 2.6%. For people whose age is from 35 to 49 and whose age is above 49, this number is only 2.8% and 2.9%. Pesticide use on rice crop has the same trends, a million VND increase in the lagged consumption would increase the number of hospital visits by 3.3%. Particularly, this figure are 4.4% and 4.8% for middle-age and old household members, respectively. Meanwhile, the number of hospital visits of the young group increases by 15.2%, 23.6% and 59.9% for every million VND of pesticide spent on non-rice food crop, industrial and fruit crops.

Moreover, a million VND increase in lagged pesticide consumption has raise individuals' healthcare cost by around 2.2%. This figure for the rice crop's pesticide use is 2.4% for the whole sample and around 3.2% and 3.1% for the sample of middle-age and senior household member. The coefficients for pesticide on non-rice food crops is only about 9.1% in the young group. On the other hand, the figure is 20% for the pesticide use in industrial crop.

3.2 Econometrics Models and Data Description

3.2.1 Econometrics Models

In this study, we use two variables as proxies for the health conditions of farmers, namely the number of hospital visits and individual-level health care cost. In the health care cost estimations, we use the log-linear OLS. However, there is the potential endogeneity issue because pesticide increases agricultural output as well as household income, thus it might improve heath status. Therefore, we use the data for pesticide use from the previous surveys as the pesticide spending in the past is exogenous. Since the available data is collected every two years and only approximately 50% of sample is interviewed in the next survey, use annual pesticide spending in the previous 2 years reduce the sample size significantly. And the sample size would be much smaller if we use 4-years lagged pesticide use as independent variable. Hence, we only use two-years lagged pesticide use in our econometric model. Below is the econometric specification:

$$\log(h_{it}) = \beta_0 + \beta_1 . p^{total}_{i(t-2)} + \sum \gamma_j . x_{ijt} + \sum \theta_t . t + \varepsilon \tag{3.1}$$

In the equation (1), h_{it} is health expenditure of person i at the year t. Variable $p^{total}_{i(t-2)}$ is the total lagged value of pesticide use in million VND that his family uses at year $t-2$. Besides, x_{ijt} is the list of control variables including individual income, dummies for being part of ethnic minorities, for living in urban or rural, for either having health insurance or receiving free treatment, for being part-time and full-time farmer. In this research, we include observations of non-farmers living the farm households. Because these non-farmers also participate in household farm works and exposed to pesticide use through food, air and water.

Other control variables are gender, marital status, age, year of school and household consumption on alcohol and tobacco per adults. Since this is not panel data, we include the dummy variables for the year of observation t in the model, particularly for 2008, 2012 and 2014. The base year is 2006. Besides, variables about income, health expenditure, pesticide use, tobacco consumption and alcohol consumption are adjusted by Consumer Price Index to the value of million VND in 2004. The detailed variable description is in Table 3.1.

We also examine the effect of pesticide consumption for different crops on farmers' health. These crops are rice, non-rice staple crops, industrial crops such as cacao or pepper, and fruit crops whose the pesticide consumption are denoted as p^r_{it}, p^s_{it}, p^i_{it} and p^f_{it}. With

Table 3.1. List of variables and definitions

Variable	Definition
Health care cost	Cost for health care service and purchasing medicine without prescription, unit: 1 million VND, CPI adjusted to price level in 2004
Visit	The number of visits to health care facility in a year
Total pesticide consumption	Yearly household total spending on pesticide, unit: 1 million VND, CPI adjusted to price level in 2004
Total lagged pesticide consumptin	Yearly household total spending on pesticide in previous survey, unit: 1 million VND, CPI adjusted to price level in 2004
Pesticide for rice crop	Yearly household total spending on pesticide for rice crop, unit: 1 million VND, CPI adjusted to price level in 2004
Lagged pesticide for rice crop	Yearly household total spending on pesticide for rice crop in previous survey, unit: 1 million VND, CPI adjusted to price level in 2004
Pesticide for the non-rice food crop	Yearly household total spending on pesticide for non-rice food crop, unit: 1 million VND, CPI adjusted to price level in 2004
Lagged pesticide for the non-rice food crop	Yearly household total spending on pesticide for non-rice food crop in previous survey, unit: 1 million VND, CPI adjusted to price level in 2004
Pesticide for industrial crop	Yearly household total spending on pesticide for industrial crop, unit: 1 million VND, CPI adjusted to price level in 2004
Lagged esticide for industrial crop	Yearly household total spending on pesticide for industrial crop in previous survey, unit: 1 million VND, CPI adjusted to price level in 2004
Pesticide for fruit crop	Yearly household total spending on pesticide for fruit crop, unit: 1 million VND, CPI adjusted to price level in 2004
Lagged pesticide for fruit crop	Yearly household total spending on pesticide for fruit crop in previous survey, unit: 1 million VND, CPI adjusted to price level in 2004
Income	Individual income, CPI adjusted to price level in 2004
Ethnic	Dummy variable whether being part of any minority group, 1: ethnic minorities, 0: Kinh and Chinese
Urban	Dummy variable whether living in urban or rural areas, 1: urban, 0: rural
Health insurance	Dummy variable for having health insurance or free healthcare booklet, 1: Yes, 0: No
Part-time farmer	Dummy variable whether being farmer and having off-farm job, 1: Yes, 0: No
Full-time farmer	Dummy variable whether being farmer and having no off-farm job, 1: Yes, 0: No
Married	Dummy variable for marital status, 1: married, 0: otherwise
Age	Years of age
Year of school	The number of years receiving education, including tertiary education
Female	Dummy for gener, 1 is for Female and 0 is for Male
Average alcohol spending	Yearly household spending on alcoholic beverage per adults whose age is from 18 to 70 (unit: 1 million VND/adult), CPI adjusted to price level in 2004
Average tobacco spending	Yearly household spending on tobacco per adults whose age is from 18 to 70 (unit: 1 million VND/adult), CPI adjusted to price level 2004

the same time dummies and control variables, we have the econometric specification:

$$\log(h_{it}) = \beta_0 + \sum_{j=r,s,i,f} \beta_j . p^j_{i(t-2)} + \sum \gamma_j . x_{ijt} + \sum \theta_t . t + \varepsilon \tag{3.2}$$

To estimate the number of hospital visits, we decide to use Zero-inflated Negative Binomial Regression. In this study, we define the number of hospital visit as the frequency of visiting health care facility for medical in the last 12 months, including clinics and commune-level health care station. There are two reasons for this decision. Firstly, we observe an overdispersion of the number of hospital visits from the descriptive statistics in Table 3.2. We will provide the result of overdispersion test, which confirms the legitimacy of using Negative Binomial Regression instead of Poisson Regression. Secondly, there are a number of household members who did not visit healthcare facility for treatment in a year. There are many reasons to decide to not visit hospital. For instance, income can be an important factor, since people with low income are less likely to seek treatment from hospital as their budget are tight and health is not their top priority. Thus, zero-inflated model is appropriate in this case. The result of Vuong's test will be provided to confirm that zero-inflated negative binomial model is more suitable than the standard negative binomial model.

Equations (3.3) and (3.4) illustrate the zero-inflated negative binomial model for estimating the number of hospital visits. Equation (3.3) is the likelihood function of negative binomial distribution, in which $\mu_{it} = \exp\left(\beta_0 + \beta_1 . p^{total}_{i(t-2)} + \sum \gamma_j . x_{ijt} + \sum \theta_t . t\right)$. Given the probability density function from the equation (3.3), $\alpha = 0$ would lead to an equality between the mean and the variance as α is dispersion parameter, which makes Poisson distribution a better choice. Thus, negative binomial model is more appropriate than Poisson regression if we are able to reject the null hypothesis that $\alpha = 0$.

$$g(v_{it}) = P(V = v_{it}) = \frac{\Gamma(v_{it} + 1/\alpha)}{\Gamma(v_{it} + 1)\Gamma(1/\alpha)} \left(\frac{1}{1 + \alpha\mu_{it}}\right)^{1/\alpha} \left(\frac{\alpha\mu_{it}}{1 + \alpha\mu_{it}}\right)^{v_{it}} \tag{3.3}$$

Table 3.2. Summary statistics

VARIABLES	Obs	Mean	S.E.	Min	Median	Max
Health care cost	30,364	0.379	1.784	0.000143	0.0583	86.57
Visit	30,364	1.266	3.365	0	0	85
Total lagged pesticide use	30,364	0.426	1.932	0	0.0560	139.8
Lagged pesticide for rice crop	30,364	0.301	1.460	0	0	55.58
Lagged pesticide for non-rice food crop	30,364	0.0500	1.192	0	0	139.8
Lagged pesticide for fruit crop	30,364	0.0295	0.266	0	0	12.10
Lagged pesticide for industrial crop	30,364	0.0455	0.289	0	0	16.21
Income	30,364	13.83	23.23	-904.6	9.612	599.9
Ethnic	30,364	0.356	0.479	0	0	1
Urban	30,364	0.280	0.449	0	0	1
Health insurance	30,364	0.487	0.500	0	0	1
Part-time farmer	30,364	0.251	0.434	0	0	1
Full-time farmer	30,364	0.287	0.452	0	0	1
Marital status	30,364	0.747	0.435	0	1	1
Age	30,364	39.87	13.77	18	40	70
Year of school	30,364	8.071	3.963	0	9	21
Female	30,364	0.513	0.500	0	1	1
Alcohol consumption	30,364	0.0370	0.0905	0	0.00857	2.715
Tobacco consumption	30,364	0.0608	0.139	0	0.00857	3.085

The zero-inflated component of our model is in the equation (3.4). In which, $g(v_{it})$ is the likelihood function given from equation (3.3). Meanwhile, $\pi_{it} = \frac{\lambda_{it}}{1+\lambda_{it}}$, which $\log(\lambda_{it}) = \beta_0 + \beta_1.p^{total}_{i(t-2)} + \sum \gamma_j.x_{ijt} + \sum \theta_t.t$.

$$Pr(v_{it} = j) = \begin{cases} \pi_{it} + (1-\pi_{it})g(v_{it} = 0), & \text{if } j = 0 \\ (1-\pi_{it})g(v_{it}), & \text{if } j > 0 \end{cases} \tag{3.4}$$

To investigate the effect of pesticide consumption of different crops on the number of hospital visits, we just use the same zero-inflated negative binomial model but replace the total value of pesticide use $\beta_1.p^{total}_{i(t-2)}$ by the value of pesticide use for each crops $\sum_{j=r,s,i,f} \beta_j.p^j_{i(t-2)}$.

3.2.2 Data

To assess the effect of pesticide consumption on health condition of farmer, the empirical analysis employs data obtained from Vietnam Household Living Standard Survey (VHLSS) from 2004 to 2014. With stratified random sampling, the survey has been conducted in 1993, 1997, and every two years since 2002 by the Vietnamese General Office of Statistics. The sample consists of individuals belonging to agricultural households whose age from 18 to 70. In total, there are more than 30,000 observations collected from VHLSS 2006, 2008, 2012 and 2014. The descriptive statistics of the sample are in table 3.2.

In the samples, individuals, who do not visit hospital for a year, would have zero health care expenditure. However, households still spend on medicine without prescription or instruments for health care purpose. Since we only have household-level non-hospital health expenditure, we decide to add the household average value of other health expenditure on individual's health expenditure.

It is noticeable that there is negative income in table 3.2, which happens due to our estimation of individual income. Within a household, we estimate an income for an individual would be his salary along with his share from the profit of household business and agricultural activities. We assume that anyone involving in household business would have the equal share of profit as other household members. This is also applied to any other household-level economic activities, like farming. Since profit can be negative, it is unavoidable to have negative value for individual income.

3.3 Results and Discussion

3.3.1 Effect of Pesticide Use on Health Care Expenditure

Tables 3.3 and 3.4 shows the OLS estimations of health expenditure. As mentioned in the introduction, we provide estimation results for different age groups in addition to the pooled estimations. These age groups are young, middle-age and old. The young group

Table 3.3. Health expenditure estimations with total lagged pesticide use

VARIABLES	Whole sample	Young	Middle-age	Old
Total lagged pesticide use	0.0220***	0.0211***	0.0245***	0.0184**
	(0.0045)	(0.0079)	(0.0077)	(0.0082)
Urban	0.0834***	0.1962***	0.0404	-0.0581
	(0.0224)	(0.0329)	(0.0394)	(0.0471)
Ethnic minorities	-0.1926***	-0.1787***	-0.1708***	-0.2635***
	(0.0243)	(0.0338)	(0.0431)	(0.0560)
Health insurance	-0.0464***	-0.1666***	-0.0100	0.0816**
	(0.0179)	(0.0267)	(0.0307)	(0.0381)
Income	0.0037***	0.0040***	0.0033***	0.0044***
	(0.0004)	(0.0007)	(0.0006)	(0.0009)
Part-time farmer	-0.2961***	-0.2563***	-0.2733***	-0.4003***
	(0.0241)	(0.0358)	(0.0397)	(0.0568)
Full-time farmer	-0.3174***	-0.3194***	-0.2762***	-0.3917***
	(0.0235)	(0.0367)	(0.0427)	(0.0452)
Marital status	-0.0731***	0.0210	-0.2536***	-0.0225
	(0.0248)	(0.0337)	(0.0568)	(0.0543)
Age	0.0088**	0.0541*	0.0195	0.1572**
	(0.0045)	(0.0316)	(0.0759)	(0.0683)
Age squared	0.0002***	-0.0006	0.0001	-0.0011*
	(0.0001)	(0.0006)	(0.0009)	(0.0006)
Female	0.2024***	0.1317***	0.1898***	0.3203***
	(0.0176)	(0.0266)	(0.0303)	(0.0389)
Year of schooling	0.0203***	0.0241***	0.0131***	0.0305***
	(0.0025)	(0.0038)	(0.0043)	(0.0051)
Alcohol consumption	0.2388**	0.5445***	0.2249	-0.0638
	(0.1054)	(0.1725)	(0.1561)	(0.2479)
Tobacco consumption	0.3255***	0.1845*	0.2094**	0.8836***
	(0.0698)	(0.1081)	(0.1059)	(0.1719)
Year dummies	Yes	Yes	Yes	Yes
Constant	-3.5662***	-4.0790***	-3.6278**	-7.9870***
	(0.0846)	(0.4010)	(1.5849)	(2.0026)
Observations	30,364	11,640	10,599	8,125
R-squared	0.0828	0.0542	0.0372	0.0563

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.4. Health expenditure estimations with lagged pesticide use for different crops

VARIABLES	Whole sample	Young	Middle-age	Old
Lagged pest. used for rice crop	0.0243***	0.0131	0.0323***	0.0313**
	(0.0060)	(0.0083)	(0.0115)	(0.0125)
Lagged pest. used for non-rice food crop	0.0054	0.0909**	0.0061	0.0011
	(0.0073)	(0.0431)	(0.0106)	(0.0111)
Lagged pest. used for industrial crop	0.2206***	0.2008***	0.2392***	0.1962***
	(0.0302)	(0.0505)	(0.0463)	(0.0652)
Lagged pest. used for fruit crop	0.0590*	0.0235	0.0908	0.0581
	(0.0326)	(0.0497)	(0.0575)	(0.0638)
Urban	0.0885***	0.1986***	0.0436	-0.0506
	(0.0224)	(0.0330)	(0.0393)	(0.0472)
Ethnic minorities	-0.1908***	-0.1777***	-0.1677***	-0.2618***
	(0.0243)	(0.0338)	(0.0431)	(0.0560)
Health insurance	-0.0427**	-0.1623***	-0.0044	0.0836**
	(0.0179)	(0.0267)	(0.0307)	(0.0381)
Income	0.0036***	0.0039***	0.0030***	0.0041***
	(0.0004)	(0.0007)	(0.0006)	(0.0009)
Part-time farmer	-0.3010***	-0.2632***	-0.2846***	-0.4019***
	(0.0241)	(0.0358)	(0.0397)	(0.0568)
Full-time farmer	-0.3310***	-0.3331***	-0.3010***	-0.4011***
	(0.0236)	(0.0368)	(0.0430)	(0.0453)
Marital status	-0.0694***	0.0241	-0.2506***	-0.0235
	(0.0247)	(0.0337)	(0.0567)	(0.0543)
Age	0.0090**	0.0555*	0.0194	0.1548**
	(0.0045)	(0.0316)	(0.0759)	(0.0683)
Age squared	0.0002***	-0.0007	0.0001	-0.0010*
	(0.0001)	(0.0006)	(0.0009)	(0.0006)
Female	0.2028***	0.1323***	0.1900***	0.3216***
	(0.0176)	(0.0266)	(0.0303)	(0.0389)
Year of schooling	0.0201***	0.0236***	0.0131***	0.0308***
	(0.0025)	(0.0038)	(0.0043)	(0.0051)
Alcohol consumption	0.2286**	0.5370***	0.2039	-0.0572
	(0.1054)	(0.1724)	(0.1561)	(0.2479)
Tobacco consumption	0.3186***	0.1695	0.2048*	0.8634***
	(0.0698)	(0.1081)	(0.1058)	(0.1719)
Year dummies	Yes	Yes	Yes	Yes
Constant	-3.5738***	-4.1006***	-3.6228**	-7.9300***
	(0.0845)	(0.4008)	(1.5837)	(2.0023)
Observations	30,364	11,640	10,599	8,125
R-squared	0.0843	0.0556	0.0395	0.0576

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

contains people whose age is from 18 to 34 years old. Meanwhile, people which is 35-49 years old are in the middle-age group and the rest of the sample (50-70 years old) are in the old group.

In table 3.3, every million VND increase in total laggaed pesticide use associate with 2.2% raise of health expenditure. This effect is similar among age groups. Particularly, in the group of people under 35 years old, the health expenditure increases by 2.11% for every one million VND of household-level lagged pesticide used. This number for the middle-age and old groups are 2.45% and 1.84%, respectively.

We also estimate the effect of lagged pesticide use for different crops on health expenditure. These crops are rice, non-rice food crop, industrial crop and fruit crop. Among these crops, pesticide use for industrial crop have a strongest effect on health expenditure. A million VND of lagged pesticide use for industrial crop associates with 22.06% increase in health expenditure. This figure is 20.08%, 23.92% and 19.62% in young, middle-age and old groups, respectively.

Meanwhile, the coefficient of lagged pesticide use for rice crop in the pooled sample is only 2.43%. However, it is insignificant in the young group, and the figure is 3.23% and 3.13% in the middle-age and old groups, respectively. Additionally, lagged pesticide use for non-rice food crop only affects the health expenditure in the young group, which is about 9.09%. The pesticide use for fruit crop is also included in our model, but its effect is modest. Particularly, for every million VND of lagged pesticide use for fruit crop, the health spending increases by 5.9% in the pooled sample, but it is insignificant among age groups.

In addition to the effect of pesticide use, we also observe strong correlations between tobacco consumption and alcohol consumption with health expenditure. In the pooled sample, every million VND of alcohol consumption per adults increases health expenditure by 23-24%. However, alcohol consumption does not effect the middle-age and old groups since the coefficients are insignificant. Alcohol consumption only affects the young by increase health expenditure by 54-55%.

On the other hand, health expenditure, on average, raises by 32% for every million VND spent on tobacco per adults. Among age groups, it seems that the old people are affected severely from the tobacco consumption, since the coefficients is 87-88% in the old group. Meanwhile, in the middle-age group, every million VND of tobacco per adult associate with 21% increase in health expenditure, and it is 18.5% in the young group.

3.3.2 Effect of Pesticide Consumption on the Number of Hospital Visits

Tables 3.5 and 3.6 show the estimation results for the impact of lagged pesticide use on the number of hospital visits. Wit both tables, we reject the null hypothesis that $\alpha = 0$; it implies that negative binomial distribution is more suitable than the Poisson distribution with our count data. On the other hand, in all regressions, the result of Vuong's test always prefers the zero-inflated negative binomial model over the standard one. These two tests shown that using zero-inflated negative binomial model is appropriate given our data.

From table 3.5, the number of hospital visits increases by 2.6% for every million VND of lagged pesticide use. Among age groups, the effect of lagged pesticide use is significant only in the middle-age and old groups, which are 2.84% and 2.86%. However, as shown in inflate components, pesticide use increases the probability of visiting hospital in a year in all age groups.

In table 3.6, the effect of lagged pesticide used for industrial crop is not as strong as it is in the health expenditure estimations. Lagged pesticide used for industrial crop is significant only in the young group, which is about 23.63%. Surprisingly, lagged pesticide for fruit crop has a huge impact on the number of hospital visits in the young group, which increase the number of hospital visits by about 60% for every million VND of pesticide use.

Table 3.5. The zero-inflated negative binomial regression for the number of hospital visits with total lagged pesticide use

VARIABLES	Whole sample		Young		Middle-age		Old	
	NBREG	Inflate	NBREG	Inflate	NBREG	Inflate	NBREG	Inflate
Total lagged pesticide use	0.0260***	-0.2288***	0.0129	-0.2365**	0.0284**	-0.5207**	0.0286**	-0.8483**
	(0.0084)	(0.0736)	(0.0154)	(0.0978)	(0.0136)	(0.2224)	(0.0119)	(0.4092)
Urban	0.0172	0.1710**	-0.0017	-0.0896	-0.0538	0.4914***	0.0890	0.6403***
	(0.0363)	(0.0773)	(0.0747)	(0.1300)	(0.0625)	(0.1651)	(0.0558)	(0.1893)
Ethnic minorities	-0.4784***	-0.7908***	-0.5390***	-0.7489***	-0.4825***	-1.2558***	-0.5193***	-1.8474***
	(0.0486)	(0.1375)	(0.0898)	(0.1752)	(0.0734)	(0.3072)	(0.0732)	(0.3259)
Health insurance	0.2864***	-0.4951***	0.1664***	-0.2755***	0.3605***	-0.7564***	0.3109***	-1.3145***
	(0.0301)	(0.0676)	(0.0604)	(0.1047)	(0.0520)	(0.1635)	(0.0464)	(0.1763)
Income	0.0008	0.0004	0.0010	0.0020	0.0002	-0.0012	0.0010	0.0026
	(0.0005)	(0.0011)	(0.0011)	(0.0021)	(0.0008)	(0.0017)	(0.0008)	(0.0022)
Part-time farmer	-0.2037***	-0.0947	-0.0126	-0.1339	-0.1557**	0.0763	-0.3770***	0.4427*
	(0.0389)	(0.0887)	(0.0762)	(0.1392)	(0.0630)	(0.1859)	(0.0676)	(0.2299)
Full-time farmer	-0.2297***	0.1241	-0.1258	0.2021	-0.1944***	0.1739	-0.2890***	0.5389***
	(0.0358)	(0.0892)	(0.0805)	(0.1441)	(0.0662)	(0.2076)	(0.0507)	(0.2030)
Marital status	0.0018	-0.1721**	0.2165***	-0.1933	-0.1727**	-0.0738	-0.0510	0.4622
	(0.0381)	(0.0852)	(0.0813)	(0.1421)	(0.0875)	(0.2626)	(0.0597)	(0.3142)
Age	0.0277***	0.0042	0.1228*	0.3581***	-0.0305	-0.2555	0.3280***	0.2248
	(0.0069)	(0.0188)	(0.0691)	(0.1332)	(0.1211)	(0.3402)	(0.0782)	(0.3371)
Age squared	-0.0001	-0.0007***	-0.0024*	-0.0079***	0.0006	0.0023	-0.0027***	-0.0024
	(0.0001)	(0.0002)	(0.0013)	(0.0026)	(0.0014)	(0.0041)	(0.0007)	(0.0029)

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Table 3.5 – continued from previous page

VARIABLES	Whole sample		Young		Middle-age		Old	
	NBREG	Inflate	NBREG	Inflate	NBREG	Inflate	NBREG	Inflate
Female	0.1088***	-0.6462***	0.2198***	-0.4983***	0.0085	-0.9219***	0.1361***	-0.6692***
	(0.0291)	(0.0648)	(0.0636)	(0.1152)	(0.0510)	(0.1561)	(0.0473)	(0.1566)
Year of schooling	-0.0417***	0.0721***	-0.0408***	0.0750***	-0.0608***	0.0628***	-0.0326***	0.0654***
	(0.0039)	(0.0094)	(0.0078)	(0.0146)	(0.0072)	(0.0208)	(0.0060)	(0.0213)
Alcohol spending	-0.0237	-0.1614	-0.5952*	-2.7348***	0.4486*	1.3684**	0.0051	0.1974
	(0.1577)	(0.4674)	(0.3038)	(1.0592)	(0.2470)	(0.5676)	(0.2451)	(0.7147)
Tobacco spending	0.4408***	-0.1723	0.3552*	-0.4312	0.3533**	-0.1575	0.5761***	-1.1062
	(0.1086)	(0.2554)	(0.2091)	(0.5174)	(0.1640)	(0.3901)	(0.1824)	(0.8715)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.1360	-0.1769	-1.2475	-4.6861***	1.2016	4.9083	-8.8055***	-7.6288
	(0.1392)	(0.3393)	(0.8851)	(1.7113)	(2.5422)	(7.0412)	(2.3010)	(9.6370)
Log of dispersion parameter	0.7961***		0.9155***		1.0117***		0.6706***	
	(0.0313)		(0.0863)		(0.0509)		(0.0409)	
Vuong test	13.41***		7.68***		5.50***		7.15***	
Observations	30,364	30,364	11,640	11,640	10,599	10,599	8,125	8,125

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.6. The zero-inflated negative binomial regression for the number of hospital visits with lagged pesticide use for different crops

VARIABLES	Whole sample		Young		Middle-age		Old	
	NBREG	Inflate	NBREG	Inflate	NBREG	Inflate	NBREG	Inflate
Lagged pest. use for rice crop	0.0331***	-0.2745***	0.0054	-0.3193***	0.0442***	-0.4509**	0.0484***	-0.6043*
	(0.0094)	(0.0915)	(0.0143)	(0.1080)	(0.0159)	(0.1867)	(0.0158)	(0.3118)
Lagged pest. use for non-rice food crop	0.0098	-0.0242	0.1517*	0.0284	0.0091	-0.1241	0.0088	-0.0181
	(0.0084)	(0.0389)	(0.0790)	(0.1301)	(0.0125)	(0.3131)	(0.0100)	(0.0289)
Lagged pest. use for industrial crop	-0.0295	-1.8039***	0.2363*	-0.0216	-0.0348	-6.7151***	0.0241	-4.3290**
	(0.0382)	(0.6410)	(0.1393)	(0.1951)	(0.0519)	(2.5448)	(0.0724)	(1.7912)
Lagged pest. use for fruit crop	0.0785	0.0422	0.5986**	0.5187***	0.0193	-6.2304*	-0.0081	-1.6506
	(0.0685)	(0.1292)	(0.2937)	(0.1824)	(0.0702)	(3.2826)	(0.0641)	(1.7608)
Urban	0.0165	0.1529*	0.0181	-0.0690	-0.0418	0.5415***	0.0876	0.6023***
	(0.0363)	(0.0786)	(0.0749)	(0.1277)	(0.0623)	(0.1660)	(0.0556)	(0.1853)
Ethnic minorities	-0.4635***	-0.7717***	-0.5253***	-0.7310***	-0.4486***	-1.0924***	-0.5170***	-1.8257***
	(0.0491)	(0.1404)	(0.0896)	(0.1725)	(0.0742)	(0.3070)	(0.0730)	(0.3314)
Health insurance	0.2888***	-0.4973***	0.1861***	-0.2477**	0.3541***	-0.7606***	0.3075***	-1.3085***
	(0.0301)	(0.0687)	(0.0605)	(0.1041)	(0.0510)	(0.1611)	(0.0460)	(0.1764)
Income	0.0007	0.0003	0.0010	0.0018	0.0001	-0.0009	0.0009	0.0025
	(0.0005)	(0.0011)	(0.0011)	(0.0021)	(0.0009)	(0.0017)	(0.0008)	(0.0021)
Part-time farmer	-0.2041***	-0.0799	-0.0127	-0.1260	-0.1479**	0.2350	-0.3807***	0.4217*
	(0.0389)	(0.0900)	(0.0761)	(0.1374)	(0.0627)	(0.1829)	(0.0674)	(0.2307)
Full-time farmer	-0.2355***	0.1492*	-0.1594**	0.1520	-0.2018***	0.3160	-0.2858***	0.5879***
	(0.0360)	(0.0906)	(0.0808)	(0.1434)	(0.0655)	(0.2129)	(0.0508)	(0.1971)

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Table 3.6 – continued from previous page

VARIABLES	Whole sample		Young		Middle-age		Old	
	NBREG	Inflate	NBREG	Inflate	NBREG	Inflate	NBREG	Inflate
Marital status	0.0039	-0.1774**	0.2254***	-0.1901	-0.1762**	-0.0664	-0.0517	0.4796
	(0.0381)	(0.0866)	(0.0813)	(0.1407)	(0.0871)	(0.2652)	(0.0595)	(0.3102)
Age	0.0291***	0.0039	0.1293*	0.3641***	-0.0295	-0.2714	0.3245***	0.2664
	(0.0069)	(0.0191)	(0.0691)	(0.1319)	(0.1209)	(0.3479)	(0.0780)	(0.3340)
Age squared	-0.0001*	-0.0007***	-0.0026*	-0.0080***	0.0006	0.0025	-0.0027***	-0.0028
	(0.0001)	(0.0002)	(0.0013)	(0.0026)	(0.0014)	(0.0042)	(0.0007)	(0.0029)
Female	0.1132***	-0.6523***	0.2199***	-0.4937***	0.0027	-0.9841***	0.1401***	-0.6378***
	(0.0291)	(0.0657)	(0.0639)	(0.1142)	(0.0503)	(0.1542)	(0.0470)	(0.1513)
Year of schooling	-0.0418***	0.0724***	-0.0419***	0.0719***	-0.0608***	0.0580***	-0.0318***	0.0671***
	(0.0039)	(0.0095)	(0.0078)	(0.0143)	(0.0071)	(0.0206)	(0.0060)	(0.0213)
Alcohol spending	-0.0084	-0.0269	-0.6738**	-2.8804***	0.4736*	1.6372***	0.0079	0.2382
	(0.1571)	(0.4605)	(0.3022)	(1.0304)	(0.2483)	(0.5528)	(0.2436)	(0.6877)
Tobacco spending	0.4271***	-0.2266	0.3236	-0.4340	0.3389**	-0.2924	0.5572***	-1.1181
	(0.1088)	(0.2674)	(0.2091)	(0.5150)	(0.1651)	(0.4071)	(0.1815)	(0.8690)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.1819	-0.1759	-1.3431	-4.7401***	1.1904	5.3846	-8.6919***	-8.7462
	(0.1397)	(0.3435)	(0.8852)	(1.6922)	(2.5362)	(7.1888)	(2.2948)	(9.5344)
Log of dispersion parameter	0.8086***		0.8991***		1.0141***		0.6606***	
	(0.0310)		(0.0827)		(0.0453)		(0.0402)	
Vuong Test	13.65***		7.70***		6.11***		7.46***	
Observations	30,364	30,364	11,640	11,640	10,599	10,599	8,125	8,125

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Compare to table 3.4, the pesticide used for rice crop and non-rice food crop show consistent effects on the number of hospital visits. In the pooled sample, the number of hospital visits increases by 3.31% for every million VND spent on pesticide for rice crop. The figure is 4.42% and 4.84% in the middle-age and old group. The inflate parts also show that pesticide for rice crop increases the chance of visiting hospital in a year. Meanwhile, the pesticide used for non-rice food only affects the young group, that the value of the coefficient is about 15%.

Additionally, tobacco consumption also increases the number of hospital visits. In the pooled sample, the number of hospital visits raises by 43-44% for every million VND of tobacco spending per adults. Meanwhile, it is about 35%, 35% and 57% in the young, middle-age and old groups. However, alcohol consumption, on average, does not affect the number of hospital visits. Because alcohol consumption reduces the frequency of hospital visits in the young group, but increases it in the middle-age group.

3.4 Conclusion

Pesticide has a negative impact on farmers and their families' health. In this study, we examine this effect by considering the number of hospital visits and health care expenditure. The results showing that higher pesticide consumption leads to more frequent hospital visits and higher health care cost. The effect of pesticide consumption do not only affect farmers but also their family members who is not necessary to involve in farm work.

Our study contributes to the current literature in several folds. First of all, to the best of our knowledge, this is one of the first studies addressing the effect of pesticide use on health status of farmers in Vietnam. Second, we found that pesticide use associates with the poorer health status of Vietnamese farmers. Third, our results may suggest Vietnamese policymakers should promote the use of organic pesticide, which might reduce the adverse health effect on farmers. Given our estimation results, the effect of pesticide use is strong but probably modest. However, in the sense that the adverse health effect from pesticide use accumulates as time goes by, the effects would be huge after years of exposing to pesticide from farming.

Also, there are still many questions that we have not answered yet. Particularly, we are curious about the effect of living next to the rice field to people's health conditions. With an evidence from Lamers et al. (2011) that pesticide was abusively used, households living next the to rice field must bear a higher level of pesticide pollution than households living away from it through groundwater and air. This includes not only farm households but also non-farm ones who do not consume pesticide. With the current available data, answering this question is impossible and it requires field trips to collect original data.

CHAPTER 4
CONCLUSION

As the first chapter provides a brief introduction, the second chapter analyzes the effect of weather on labor allocation decision and household total income in Vietnam. Theoretically, agricultural household facing higher risk in the farm production would allocate more time on off-farm sector. By using data from Vietnam Household Living Standard Surveys, we are able to confirm that weather conditions affect the labor allocation decision of agricultural households. Particularly, climate patterns observed over a longer period generally have a stronger effect on the off-farm participation. The econometric models also show the positive correlation between off-farm participation and household total income, in which off-farm participation increases total income by 81%. Additionally, the results also suggest that agricultural households resilient with natural disasters, particularly storm, by participating off-farm sector.

Meanwhile, the third chapter assesses the relationship between pesticide use and health burden of farmers in Vietnam. By using the number of hospital visits for treatment and total health expenditure as the proxy for health status of farmers, we found that higher amount of pesticide use associates with higher health burden. Even though the causal relationship has not been confirmed yet, the results may suggest Vietnamese policymakers to promote the use of organic pesticide which might reduce the adverse health effect on farmers.

Overall, the thesis has contributed to the literature by investigating the topics that are not been fully studied in Vietnam before. Additionally, the studies also provides important insights for Vietnamese policymakers to reduce the uncertainty causing by weather in agricultural sector and reduce the adverse effect of pesticide. In these studies, there are still many limitations as well as many questions that we have not answered yet, but we hope to be able to solve those puzzles in the near future.

REFERENCES

Ahad, K., A. Mohammad, F. Mehboob, A. Sattar, and I. Ahmad, "Pesticide Residues in Rawal Lake, Islamabad, Pakistan," *Bulletin of Environmental Contamination and Toxicology*, March 2006, *76* (3), 463–470.

Alesina, A., P. Giuliano, and N. Nunn, "On the Origins of Gender Roles: Woman and the Plough," *Quaterly Journal of Economics*, 2013, *128* (2), 469–530.

Antle, John M. and Prabhu L. Pingali, "Pesticides, Productivity, and Farmer Health: A Philippine Case Study," *American Journal of Agricultural Economics*, August 1994, *76* (3), 418–430.

_ , Donald C. Cole, and Charles C. Crissman, "Further Evidence on Pesticides, Productivity and Farmer Health: Potato Production in Ecuador," *Agricultural Economics*, March 1998, *18* (2), 199–207.

Arouri, M., C. Nguyen, and A. B. Youssef, "Natural Disasters, Household Welfare, and Resilience: Evidence from Rural Vietnam," *World Development*, 2015, *70*, 59–77.

Awondo, S. N., O. A. Ramirez, G. J. Colson, E. G. Fonsah, and G. Kostandini, "Self-Protection from Weather Risk using Improved Maize Varieties or Off-Farm Income and the Propensity for Insurance," *Agricultural Economics*, 2017, *48* (1), 61–76.

Bai, Yanhong, Ling Zhou, and Jiang Wang, "Organophosphorus Pesticide Residues in the Market Foods in Shaanxi Area, China," *Food Chemistry*, 2006, *98*, 240–242.

Benjamin, D. and L. Brandt, "Agriculture and Income Distribution in Rural Vietnam under Economic Reforms: A Tale of Two Regions," William Davidson Working Paper 519, University of Toronto, Department of Economics March 2002.

Buchmueller, T. C., R. G. Valletta, and S. Mohanty, "The Effect of Health Insurance on Married Female Labor Supply," *The Journal of Human Resources*, Winter 1999, *30* (1), 42–70.

Bui, A. T., M. Dungey, C. V. Nguyen, and T. P. Pham, "The impact of natural disasters on household income, expenditure, poverty and inequality: evidence from Vietnam," *Applied Economics*, 2014, *46* (15), 1751–1766.

Central Intelligence Agency, *The CIA World Factbook*, New York, NY: Skyhorse Publishing, Inc., 2015.

Crissman, Charles C., Donald C. Cole, and Fernando Carpio, "Pesticide Use and Farm Worker Health in Ecuadorian Potato Production," *American Journal of Agricultural Economics*, August 1994, *76* (3), 593–597.

Currie, J. and B. C. Madrian, "Health, Health Insurance and the Labor Market," in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*, Vol. 3, Amsterdam: North Holland, 1999, chapter 50, pp. 3309–3416.

Dang, Duc Nhan, Manh Am Nguyen, F.P. Carvalho, J.-P. Villeneuve, and C. Cattini, "Organochlorine Pesticides and PCBs along the Coast of North Vietnam," *Science of The Total Environment*, September 1999, *237–238*, 363–374.

Dasgupta, Susmita, Craig Meisner, David Wheeler, Khuc Xuyen, and Thi Tam Nhan, "Pesticide Poisoning of Farm Workers – Implication of Blood Test Results from Vietnam," *International Journal of Hygiene and Environmental Health*, 2007, *210*, 121–132.

Davis, B., P. Winter, G. Carletto, K. Covarrubias, E. J. Quinores, A. Zezza, K. Stamoulis, C. Azzarri, and S. DiGiuseppe, "A Cross-Country Comparison of Rural Income Generating Activities," *World Development*, 2010, *38* (1), 48–63.

Demeke, A. B. and M. Zeller, "Weather Risk and Household Participation in Off-farm Activities in Rural Ethiopia," *Quarterly Journal of International Agriculture*, 2012, *51* (1), 1–20.

Fan, C. C., "Rural-Urban Migration and Gender Division of Labor in Transitional China," *International Journal of Urban and Regional Research*, March 2003, *27* (1), 24–47.

Fay, M., R. Bierbaum, A. Kopp, A. Liverani, A. Lotsch, A. Agrawal, H. Patel, I. Noble, J. Racine, J. Strand, J. Bucknall, K. Hamilton, M. Rosegrant, N. Engle, N. Cenacchi, M. Westphal, R. Block, R. Fuentes, S. Fankhauser, S. Chang, X. Wang, and X. Wang, "Development and Climate Change," World Development Report 2010, The World Bank, Washington, DC 2010.

Ferreira, F. H. G., "Rural Nonfarm Activities and Poverty in the Brazilian Northeast," *World Development*, 2001, *29* (3), 509–528.

Garthwaite, C., T. Gross, and M. J. Notowidigdo, "Public Health Insurance, Labor Supply, and Employment Lock," *The Quarterly Journal of Economics*, March 2014, *129* (2), 653–âĂŞ696.

Global Facility for Disaster Reduction and Recovery, "Building Resilient Communities in Vietnam," Project Highlights, The World Bank, Washington, D.C 2013.

Hansen, C. W., P. S. Jensen, and C. V. Skovsgaard, "Modern Gender Roles and Agricultural History: The Neolithic Inheritance," *Journal of Economic Growth*, 2015, *20* (4), 365–404.

Hill, R.H., S.L. Head, S. Bake, M. Gregg, D.B. Shealy, S.L Bailey, C.C. William, E.J. Sampson, and L.L. Needham, "Pesticide Residues in Urine of Adults Living in the United States: Reference Range Concentrations," *Environmental Research*, November 1995, *71* (2), 99–108.

Hoang, T. X., C. S. Pham, and M. A. Ulubasoglu, “Non-Farm Activity, Household Expenditure, and Poverty Reduction in Rural Vietnam: 2002–2008,” *World Development*, December 2014, *64*, 554–568.

Hoang, Van Minh, Thi Kim Phuong Nguyen, Priyanka Saksena, Chris D. James, and Ke Xu, “Financial Burden of Household Out-of-Pocket Health Expenditure in Vietnam: Findings from the National Living Standard Survey 2002-2010,” *Social Science & Medicine*, November 2013, *96*, 258–263.

Hong, S.H., U.H. Yim, W.J. Shim, J.R. Oh, P.H. Viet, and P.S. Park, “Persistent Organochlorine Residues in Estuarine and Marine Sediments from Ha Long Bay, Hai Phong Bay and Ba Lat Estuary, Vietnam,” *Chemosphere*, July 2008, *72* (8), 1193–1202.

Ito, T. and T. Kurosaki, “Weather Risk, Wage in Kind, and the Off-Farm Labor Supply of Agricultural Households in a Developing Country,” *American Journal of Agricultural Economics*, 2009, *91* (3), 697–710.

Ivrin, G., “Vietnam: Adjustment, Growth and Poverty,” *Journal of International Development*, September 1997, *9* (6), 783–801.

Jia, L. and M. Petrick, “How Does land Fragmentation Affect Off-Farm Labor Supply: Panel Data Evidence from China,” *Agricultural Economics*, May 2014, *45* (3), 369–380.

Jiang, Yu-Feng, Xue-Tong Wang, Ying Jia, Fei Wang, Ming-Hong Wu, Guo Ying Sheng, and Jia-Mo Fu, “Occurrence, Distribution and Possible Sources of Organochlorine Pesticides in Agricultural Soil of Shanghai, China,” *Journal of Hazardous Materials*, 2009, *170*, 989–997.

Jowett, M., P. Contoyannis, and N.D. Vinh, “The Impact of Public Voluntary Health Insurance on Private Health Expenditure in Vietnam,” *Social Science & Medicine*, January 2003, *56* (2), 333–342.

Kolpin, Dana W., Jack E. Barbash, and Robert J. Gilliom, “Occurrence of Pesticides in Shallow Groundwater of the United States: Initial Results from the National Water-Quality Assessment Program,” *Environmental Science and Technology*, 1998, *32* (5), 558–566.

Lamers, Marc, Maria Anyusheva, Nguyen La, Van Vien Nguyen, and Thilo Streck, “Pesticide Pollution in Surface- and Groundwater by Paddy Rice Cultivation: A Case Study from Northern Vietnam,” *Clean–Soil, Air, Water*, 2011, *39* (4), 356–361.

Le, D. T., “Economic and Welfare Impacts of Disasters in East Asia and Policy Responses: The Case of Vietnamese Communities,” in D.P. Aldrich, S. Oum, and Y. Sawada, eds., *Resilience and Recovery in Asian Disasters*, Vol. 18 of *Risk, Governance and Society*, Springer Japan, 2015, pp. 51–73.

Lohmann, Steffen and Tobias Lechtenfeld, “The Effect of Drought on Health Outcomes and Health Expenditures in Rural Vietnam,” *World Development*, August 2015, *72*, 432–448.

Maumbe, Blessing M. and Scott M. Swinton, "Hidden Health Costs of Pesticide Use in Zimbabwe's Smallholder Cotton Growers," *Social Science and Health*, November 2003, *57* (9), 1559–1571.

Mendelsohn, R., W. D. Nordhaus, and D. Shaw, "The Impact of Global Warming on Agriculture: A Ricardian Analysis," *The American Economic Review*, 1994, *84* (4), 753–771.

_ , W. Nordhaus, and D. Shaw, "Climate Impacts on Aggregate Farm Value: Accounting for Adaptation," *Agricultural and Forest Meteorology*, 1996, *80* (1), 55–66.

Mendola, M. and C. Carletto, "Migration and Gender Differences in the Home Labour Market: Evidence from Albania," *Labor Economics*, 2012, *19*, 870–880.

Mishra, A., K. A. Mottaleb, and S. Mohanty, "Impact of Off-Farm Income on Food Expenditures in Rural Bangladesh: An Unconditional Quantile Regression Approach," *Agricultural Economics*, March 2016, *46* (2), 139–148.

Mishra, A. K. and B. K. Goodwin, "Farm Income Variability and the Supply of Off-Farm Labor," *American Journal of Agricultural Economics*, 1997, *79*, 880–887.

_ and D. M. Holthausen, "Effect of Farm Income and Off-Farm Wage Variability on Off-Farm Labor Supply," *Agricultural and Resource Economics Review*, 2002, *31* (2), 187–199.

Mitra, Sophie, Michael Palmer, Daniel Mont, and Nora Groce, "Can Households Cope with Health Shocks in Vietnam?," *Health Economics*, July 2016, *25* (47), 888–907.

Nguyen, Hung Minh, Masayuki Someya, Binh Minh Tu, Tatsuya Kunisue, Hisato Iwata, Mafumi Watanabe, Shinsuke Tanake, Hung Viet Pham, and Cach Tuyen Bui, "Persistent Organochlorine Residues in Human Breast Milk from Hanoi and Hochiminh City, Vietnam: Contamination, Accumulation Kinetics and Risk Assessment for Infants," *Environmental Pollution*, June 2004, *129* (3), 431–441.

Nguyen, Huu Dung and Thi Thanh Dung Tran, "Economic and Health Consequences of Pesticide Use in Paddy Production in the Mekong Delta, Vietnam," Research Reports, EEPSEA 2003.

Noy, I. and T. B. Vu, "The Economics of Natural Disasters in a Developing Country: The Case of Vietnam," *Journal of Asian Economics*, 2010, *21*, 345–354.

Oseni, G. and P. Winters, "Rural Nonfarm Activities and Agricultural Crop Production in Nigeria," *Agricultural Economics*, 2009, *40*, 189–201.

Parveen, Z., M.I. Khuhro, and N. Rafiq, "Monitoring of Pesticides Residues in Vegetables (2000-2003) in Karachi, Pakistan," *Bulletin of Environmental Contamination and Toxicology*, January 2005, *74* (1), 170–176.

Pham, Manh Hoai, Thuy Ngoc Nguyen, Hung Minh Nguyen, Hung Viet Pham, Micheal Berg, Afredo C. Alder, and Walter Giger, "Recent Level of Organochlorine Pesticides and Polychlorinated Biphenyls in Sediments of the Sewer System in Hanoi, Vietnam," *Environmental Pollution*, 2010, *150*, 913–320.

_ , Zita Sebesvari, Binh Minh Tu, Hung Viet Pham, and Fabrice G. Renaud, "Pesticide Pollution in Agricultural Areas of Northern Vietnam: Case Study in Hoang Liet and Minh Dai Communes," *Environmental Pollution*, December 2011, *159* (12), 3344–3350.

Pham, V. H., T. G. MacAulay, and S. P. Marsh, "The Economics of Land Fragmentation in the North of Vietnam," *The Australian Journal of Agricultural and Resource Economics*, 2007, *51* (2), 195âĂŞ–211.

Pimentel, David, "Environmental and Economic Costs of the Application of Pesticides Primarily in the United States," *Environment, Development and Sustainability*, June 2005, *7* (2), 229–252.

Pingali, Prabhu L., Cynthia B. Marquez, and Florencia G. Palis, "Pesticides and Philippine Rice Farmer Health: A Medical and Economic Analysis," *American Journal of Agricultural Economics*, August 1994, *76* (3), 587–592.

PPD (Plant Protection Department), *Report on Results of Nation-wide Inspection of Pesticide Regulation Enforcement in 2000* October 2000. Large-scale Inspection Meeting in Hanoi.

Saqib, T.A., S.N. Naqvi, P.A. Siddiqui, and M.A. Azmi, "Detection of Pesticide Residues in Muscles, Liver and Fat of 3 Species of Labeo Found in Kalri and Haleji Lakes," *Journal of Environmental Biology*, June 2005, *26* (2), 433–439.

Sepehri, Ardeshir, Sisira Sarma, and Wayne Simpson, "Does Non-Profit Health Insurance Reduce Financial Burden? Evidence from the Vietnam Living Standards Survey Panel," *Health Economics*, June 2006, *15* (6), 603–616.

_ , Wayne Simpson, and Sisira Sarma, "The Influence of Health Insurance on Hospital Admission and Length of Stay – The Case of Vietnam," *Social Science & Medicine*, October 2006, *63* (7), 1757–1770.

Sheahan, Megan, Christopher B. Barrett, and Casey Goldvale, "Human Health and Pesticide Use in Sub-Saharan Africa," *Agricultural Economics*, November 2017, *48* (51), 27–41.

Stampini, M. and B. Davis, "Does Nonagricultural Labor Relax Farmers' Credit Constraints? Evidence from Longitudinal Data for Vietnam," *Agricultural Economics*, March 2009, *40* (2), 177–188.

Su, W., T. Eriksson, L. Zhang, and Y. Bai, "Off-farm Employment and Time Allocation in On-farm Work in Rural China from Gender Perspective," *China Economics Review*, 2016, *41*, 34–45.

Tariq, Muhammad Ilyas, Shahzah Afzal, and Ishtiaq Hussain, "Pesticides in Shallow Groundwater of Bahawalnagar, Muzafargarh, D.G. Khan and Rajan Pur Districts of Punjab, Pakistan," *Environmental International*, June 2004, *30* (4), 471–479.

Thomas, T., L. Christiaensen, Q. T. Do, and D. T. Le, "Natural Disasters and Household Welfare: Evidence from Vietnam," Policy Research Working Paper 5491, The World Bank December 2010.

Tu, T. A., N. T. Dao, and X. T. Hoang, "Migration to Competing Destinations and Off-Farm Employment in Rural Vietnam: A Conditional Logit Analysis," DEPOCEN Working Paper Series 2008/22, Development and Policies Research Center, Hanoi 2008.

van de Walle, D. and D. Cratty, "Is the Emerging Non-Farm Market Economy the Route out of Poverty in Vietnam," *Economics of Transition*, June 2004, *12* (2), 237–274.

Wagstaff, Adam, "The Economic Consequences of Health Shocks: Evidence from Vietnam," *Journal of Health Economics*, January 2007, *26* (1), 82–100.

Widawsky, David, Scott Rozelle, Songqing Jin, and Jikun Huang, "Pesticide Productivity, Host-Plant Resistance and Productivity in China," *Agricultural Economics*, 1998, *19*, 203–217.

Zhou, Xueguang, "Economic Transformation and Income Inequality in Urban China: Evidence from Panel Data," *American Journal of Sociology*, January 2000, *105* (4), 1135–1174.

Zhu, Youfeng, Hui Liu, Zhiqun Xi, Hangxing Cheng, and Xiaobai Xu, "Organochlorine Pesticides (DDTs and HCHs) in Soils from the Outskirts of Beijing, China," *Chemosphere*, 2005, *60*, 770–778.

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