Essays on the Thai Economy

by

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Declaration of Authorship

I, Peerapat Tandavanitj, declare that this thesis titled, "Essays on the Thai Economy" and the work presented in it are my own. I confirm that:

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- Where I have consulted the published work of others, this is always clearly attributed.
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General Introduction

This dissertation includes three essays on the Thai economy. The first two chapters focus on the impact of the insurgency in Southern Thailand, and the third paper analyses the effect of the government's rice pledging scheme.

The insurgency in the southern region of Thailand, including Yala, Pattani, and Narathiwat, and some parts of Songkhla province, began in 2004. As the end of 2017, the total number of deaths was 6,686 persons, including military, government officials, insurgents, and civilians. The conflict has run for more than a decade and is likely to continue in the near future. However, few studies focus on the effect of this insurgency. In particular, none of the economic literature has considered this issue yet, although the study of the economics of terrorism has been a very active field since the September 11 attack. Therefore, this research is among the first that analyses the economic effect of the insurgency in Southern Thailand.

In the first chapter, I employ a synthetic control analysis to examine the economic impact of this insurgency. I use the Thai Socio-Economic Survey to construct panel data at the provincial level. The result shows that households in the affected provinces had real expenditure per capita lower than its predicted level about by about an average 16.21 percent per annum. Furthermore, I divide households into subgroups based on their characteristics and estimate the treatment effects separately. First, I divide the observations by urban and rural areas. The results indicate evidence that the insurgency had an impact on urban households more than rural households. I next divide the sample by age of household head. The estimates exhibit that the most affected group was the youngest group, those 20 to 34 years old.

While the first chapter indicates the macroeconomic effect, and the affected area is treated as a single treatment unit, the second chapter examines the impact of the insurgency at the district level by exploiting the variation in violent incidents and deaths among districts from 2004 to 2017. The empirical results suggest that areas with a high insurgency intensity experienced migration outflows and hence negative net migration. Over the long-term, I also find that districts with high numbers of incidents and deaths had lower average growth in population and lights at night as compared to more peaceful districts. For the labour market, the results do not show any effect of the insurgency on monthly wages and working hours of local employees.

This research contributes to the literature on the economics of terrorism, and the results are consistent with most studies that indicate the negative impact of insurgency on the economy and outflow migration. However, my study is among the first to illustrate the heterogeneous effect of the insurgency. In fact, the results suggest that the magnitude of the impact depends on the characteristics of households and the local-level intensity of the insurgency.

In the third chapter, I examine the impact of the Thai rice pledging scheme. This policy aimed to resolve the rice over-supply problem during the harvest season. The program allowed farmers to use their products as collateral. Consequently, farmers could store their products during the low-price harvest season and redeem them back to sell when prices increased. Generally, the pledging price was set close to the market price, and a limited amount of rice was eligible for pledging for each household and each area. However, the rice pledging scheme during 2011 to 2014 allowed for an unlimited amount of rice to be pledged at a high price. Hence, rice farmers experienced temporary increases in sales prices during this period. This chapter aims to examine the impact of this program on revenues of rice farmers by using annual household panel data from 2009 to 2015. The results indicate that the policy did increase the nominal revenues of rice farmers by approximately 35 percent annually. Moreover, the heterogeneity analysis provides suggestive evidence that only the middle 50 percent rice farmers by income level benefited from the program, while the top and bottom 25 percent of rice farmers did not gain from the policy.

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Chapter 1

The Economic Cost of the Insurgency in Southern Thailand : A Synthetic Control Analysis

Abstract

In this chapter, I use a synthetic control analysis to examine the economic cost of the insurgency in Southern Thailand. I employ the Thai Socio-Economic Survey to construct panel data at the provincial level. The results show that households in the affected provinces had real expenditure per capita lower than its predicted level by about an average of 16.21 percent per year. For the heterogeneity analysis, the result indicates that the effect of the insurgency had a significant impact on urban households but not on rural households. Additionally, the insurgency effect was more intense for households with young household heads.

1.1 Introduction

The only region in Thailand with a Muslim majority and Malay cultural background is the far southern region, including Pattani, Yala, and Narathiwat, and part of Songkhla province (see Figure 1.1). Tensions have existed between local people and Bangkok's central cover for decades. Although a Pattani separatist group had been active since the 1940s, the movement faded away in the 1970s, and thus the overall situation was relatively peaceful until January 2004 when an armoury in Narathiwat province was assaulted and some 400 automatic rifles were stolen. By the end of the year, there were 1,471 violent incidents in which 373 people were killed. Hence, most of the literature considers 2004 as the beginning of the current insurgency. The total number of deaths as of the end of 2017 was 6,686 persons, including military, government officials insurgents, and civilians. A range of explanations have been provided as to the causes of this insurgency.[1]

Most research on this insurgency focuses on the causes of the conflict, for example McCargo (2015), Yusuf (2007), and Srisompob and Panyasak (2006). However, there is no study that concentrates on the long-term economic impact of the insurgency. This chapter aims to examine the impact of this insurgency on the well-being of local households. The main challenge of this research is to find a proper control area to compare with the affected area. Although the violent incidents have been limited only to three southern provinces and other provinces have not been directly affected by the insurgency, it is still difficult to choose a province from the unaffected pool to be a comparison unit. Therefore, I employ the synthetic control method that has been used by Abadie and Gardeazabal (2003) which studied the economic impact of the conflict in the Basque country in Spain.

I use the Thai socio-economic survey, which is a repeated cross-sectional household survey, to construct balanced panel data at the provincial level, which covers eight pre-treatment years, and six post-treatment years. The main outcome variable of interest is real expenditure per capita. The identification assumption is that in the absence of the insurgency, the real expenditure per capita of the treated unit would have performed like that of its synthetic control comparison. The estimates show that the real expenditure per capita of the treated area is lower than its predicted level by around an average of 16.21 percent or 8,008 baht per year. Furthermore, most synthetic control research has used macro-level data. This study is among the first to use household level data, and hence the first to examine the heterogeneity effect. I divide households into subgroups based on their characteristics and estimate their treatment effects separately. First, I divide the observations by urban and rural areas. The results indicate that the insurgency had a large impact on urban households but not on rural households. The real expenditure per capita of urban households was lower than its corresponding by an average of 14.87 percent per year while that of rural households was higher than its comparison unit by an average of 3.55 percent per year.

[1] I will discuss this in further detail in Section 1.2.

I next divide the sample by age of household head. The estimates exhibit that the most affected group was the youngest group, 20 to 34 years old, as its expenditure per capita were lower than their synthetic control unit by about an average of 30.26 percent per year. The households with head aged 35 to 49 years old were the second most affected group with their expenditure per capita an average of 13.53 percent per year lower than their comparison unit. The oldest group, older than 50 years old, were less affected, with their expenditure per capita lower than their control unit only by an average of 6.63 percent per year. Consequently, my results indicate that the younger generation has been more highly affected by the insurgency than the older one.

I next divide the sample by age of household head. The estimates exhibit that the most affected group was the youngest group, 20 to 34 years old, as its expenditure per capita were lower than their synthetic control unit by about an average of 30.26 percent per year. Among households aged 35 to 49 years old, expenditure per capita was an average of 13.53 percent per year lower than their comparison unit. However, this estimate is statistically insignificant. Finally, the oldest group, older than 50 years old, had expenditure per capita lower than their control unit only by an average of 6.63 percent per year. This result is also statistically insignificant. Consequently, my results indicate that the younger generation has been more highly affected by the insurgency than the older ones.

This research contributes to the literature on the economic effects of terrorism. In fact, my results are consistent with many studies that demonstrate the negative impact of terrorism incidents and internal violent conflict on the economy, for instance Collier et al. (2004) and Blomberg et al. (2004) which are based on cross-country data.[2] The rest of this chapter is organized as follows: in Section 1.2, I begin by providing background on the insurgency in Southern Thailand and discussing notable research on this conflict. In Section 1.3, I explain the dataset. I then present the methodology and the main results in Section 1.4. In Section 1.5, I examine the results of the heterogeneity analysis. Finally, Section 1.6 is the conclusion.

[2] See Abadie and Gardeazabal (2003) for a study of the Basque country in Spain, Blomberg et al. (2011) for the Sub-Saharan region, Miguel et al. (2004) for Columbia, and Justino and Verwimp (2013) for Rwanda. Moreover, Murdoch and Sandler (2004) illustrate the negative growth spillovers of terrorism, while Justino (2009) establishes an endogenous link between violence conflict and economic well-being.

1.2 Background of the Insurgency

Southern Thailand is the only part of the country that has a strong Malay sociocultural identity. Historically, this region belonged to the Pattani Kingdom. It was similar to other neighboring kingdoms that accepted Islamic beliefs and was governed under a Sultanate monarchical system. However, the Kingdom of Siam, later Thailand, always had influence over the Pattani Kingdom, until the British Empire established the British Malaya colony and aimed to include the Pattani Kingdom under its authority. After negotiation with Siam, they signed the Anglo-Siam Treaty in 1909. This agreement included a division of the Pattani Kingdom and abolished its monarchy. Since then, part of the former Pattani Kingdom has been controlled by the Thai central government in Bangkok, and the rest was under the British authority, then became part of Malaysia after its independence in 1963 (Winichakul (1994) and Baker and Phongpaichit (2014)).

A Pattani separatist movement had been active since the 1940s, but the movement faded away in the 1970s (Baker and Phongpaichit (2014)). However, in January 2004, an armoury in Narathiwat province was assaulted and some 400 automatic rifles were stolen. By the end of the year, there were 1,471 violent incidents in which 373 people were killed, including the Krue-se incident in April and Takbai incident in October that killed 107 and 78 people respectively.[3] Baker and Phongpaichit (2014) link this outbreak to the global escalation of Islamic extremism. Nonetheless, there was no strong evidence indicating that international terrorism networks supported this movement in Southern Thailand, and the violent situation remains comparatively small and has been limited to the region. There is no identifiable group claiming responsibility for violent incidents. Hence, the authors conclude that the political objective of the movement is complicated and difficult to interpret. Yusuf (2007) also explained the insurgency as a local conflict between the Malay-Muslim minority and Thai Buddhists, particularly representatives of the Thai state.

Srisompob and Panyasak (2006) discuss possible causes of the insurgency as follows: First, there is no clear evidence linking the insurgency to local poverty. Unlike many other violent conflicts, before the insurrection this area had satisfactory economic performance. In 2004, Narathiwat, the poorest province in this region, ranked fifty-fourth out of seventy-seven provinces in average household income. Nevertheless, the region was still relatively poor compared to its neighbors, particularly Hatyai district in Songkhla province, which is

[3]See McCargo (2015) for further detail on this

the trading center of Southern Thailand, and Malaysia, which shares the same historical roots. Moreover, the authors indicate that there was no correlation between the insurgency and the poverty of villages in the region. Second, this insurgency could be the outcome of long mishandling of the region by the government, especially ethic insensitivity. Perceived unjust treatment stimulated reactions from locals and led to domestic militant groups. The authors also mentioned other possible causes of the conflict: for example, that government officials, and the military have conspired to accelerate the insurgency for their own advantage, that local mafia gangs have benefited from the insurgency, and the existence of drugs and social problems, since government officials have regularly claimed that the insurgents have been acting under the influence of drugs. In the end, the causes of the conflicts remain unclear.[4]

1.3 Data

The main dataset used in this study is the Thai Socio-Economic Survey (SES), conducted by the National Statistics Office. This repeated cross-sectional dataset is surveyed annually at the household level and covers all provinces. It includes details on income, expenditure, debts, assets, as well as household characteristics. The main outcome variable of interest is real expenditure per capita as a proxy for household well-being. I include only data from years that have details on household income, since I use income structure as a key set of predictor variables, as further described in section 1.4. So the data in this study consists of eight years from the pre-treatment period (1988, 1990, 1992, 1994, 1996, 1998, 2000, 2002), and six years from the post-treatment period (2004, 2006, 2009, 2011, 2013, 2015).

I next construct a balanced panel at the provincial level by averaging all households in each province. For the treated unit, I combine all three southern provinces together to be a single treated unit, and the other 70 provinces that have not been affected by the insurgency are in the donor pool.[5] For Songkhla province, 4 out of 16 districts have also been affected by the insurgency, and this area neighbors the three southern provinces. However, the total number of incidents that have taken place in this area is only 640 incidents or about 3.2 percent of the total number of incidents, and the majority of Songkhla province

[4]Further discussion on cause and consequence of the insurgency can be found in McCargo (2015), Abuza (2009), and Croissant (2005).

[5]The current number of provinces in Thailand is 77 including Bangkok. However, in 1988, the first year of the data, there were 73 provinces. Therefore, in this study, households in the four newly established provinces are included in their original provinces.

did not have any violent incidents. Moreover, Songkhla province is the trading hub between Thailand and Malaysia, and the business area has rarely been affected by the insurgency. It also benefits from a free trade agreement which became effective in 2010.[6] This trade agreement would enhance the well-being of local households, and given its timing, affect the estimates. Finally, since the dataset does not include district level detail, it is not possible to identify households in Songkhla's affected districts. Therefore, I do not include Songkhla province into the treated unit.

Additionally, I deflate all financial variables by a provincial price index to account for changes in prices across provinces.[7] I also winsorize expenditure and income of households in each province if it was difference from the mean more than two standard deviations. Columns (1) and (3) of Table 1.1 exhibit the number of households and average real expenditure per capita in the data for the whole country, while columns (2) and (4) show figures for the treated area. The treatment households make up about 4 percent of the total observed households, and real expenditure per capita in the treated area was around 20 percent lower than the country average.

1.4 Empirical Strategy and Main Results

In this section, I first discuss the synthetic control method and then present the main results. After that, I describe inference. This study uses the synthetic control estimation technique introduced by Abadie and Gardeazabal (2003) and then developed further by Abadie et al. (2010, 2015). A standard difference-in-difference estimate requires the assumption that in the absence of treatment the average outcomes of treated and control units would follow a parallel tendency. In contrast, the synthetic control method has an advantage in the situation where there is no reliable control unit. Instead of using an average of all control units or one control unit, the synthetic control method uses optimal weights to generate an appropriate comparison unit that is close to the treated unit during the pre-treatment period. Therefore, the effect of the insurgency is estimated by comparing the affected area to the synthetic control unit during the post-treatment period.

[6]The Association of South East Asia Nations Free Trade Agreement became effective on 1 January 2010. Thailand, Malaysia, and Singapore were among the first countries to decrease tariff rates to 0 to 5 percent for other member countries. Thereafter, the cross-border trade through Songkhla province substantially increased.

[7]I use the Gross Provincial Product deflator as the price index because the Consumer Price Index is not available at the provincial level.

Suppose that there is a sample of $J + 1$ provinces indexed by j and a treated area denoted by $j = 1$. A collection of provinces $j = 2$ to $j = J + 1$ are potential comparison provinces, the so-called donor pool. The data is observed at the time periods $t = 1, ..., T$ with T_0 being the first year of the treatment period. Hence, the pre-treatment period is from $t = 1$ to $t = T_0 - 1$. A synthetic control is defined as weights for the units in the donor pool, denoted by a $J \times 1$ vector of weights, $W = (w_2, ..., w_{J+1})'$. Note that all elements in this weight vector must be non-negative and sum to one. We have to choose a set of predictor variables that can represent the treated area's characteristics and have predictive power for outcomes. Let k denote the number of predictor variables, and X_1 be a $k \times 1$ vector of pre-treatment values of predictor variables for the treated unit. The synthetic control process aims to match the vector X_1 to X_0W, where X_0 is a $k \times J$ matrix of the pre-treatment values of the predictor variables for the donor pool.

The difference between the treated unit and a synthetic control unit is given by the vector $X_1 - X_0W$. Therefore, the synthetic control is the optimal weight, W^*, that minimizes the magnitude of this difference. The optimization problem is such that:

$$\min_{\mathbf{W}} (X_1 - X_0W)'V(X_1 - X_0W) \tag{1.1}$$

where V is a non-negative diagonal matrix where each element in matrix V represents the predictive power of each predictor variable.[8] A high value means a predictor variable has more importance to a synthetic control unit. The synthetic control process will generate the best comparison unit that will minimize the difference between the treated unit and a synthetic control. This gap can be measured by the root mean squared prediction error (RMSPE) as

$$RMSPE_1 = \sqrt{\frac{1}{T_0 - 1}\left(Y_{1t} - \sum_{j=2}^{J+1} w_j^* \cdot Y_{jt}\right)^2} \tag{1.2}$$

where Y_{jt} is the outcome of interest for unit j at time t, and thus Y_{1t} is an outcome of the treated unit at time t. Hence, the synthetic control process will minimize the average of pre-treatment RMSPE. Moreover, a synthetic control estimator at time t for $t \geq T_0$ is the

[8] The matrix V is chosen among all positive definite and diagonal matrices to minimize the mean squared prediction error of the outcome variable during the pre-treatment period. Implicitly, the synthetic control procedure in this study is a data-driven process that jointly chooses V and W^* (for further discussion, see Abadie and Gardeazabal (2003) and Abadie et al. (2010)).

difference between Y_{1t} and the optimal weighted average of all Y_{jt} where $j > 1$:

$$Y_{1t} - \sum_{j=2}^{J+1} w_j^* \cdot Y_{jt}. \tag{1.3}$$

The treatment effect estimated by the synthetic control method is represented as a vector $(Y_{1T_0}, \ldots, Y_{1T})$.

A synthetic control result essentially depends on the set of predictor variables. I use the following criteria in the predictors' selection process. First, a predictor has to represent household or provincial characteristics. Then it must have predictive power in the synthetic control estimation, as represented by the diagonal matrix V. In fact, during a trial process, several variables were given zero weight in V, and thus I have excluded them from the set of predictors without any effect on the estimation. The variables which have predictive power and hence are used as the set of predictors in this study are exhibited in Table 1.2. The first predictor variable is the income of the household. I use a real income per capita, which is calculated at province level similar to the real expenditure per capita. Both variables indicate household economic conditions. The next predictors are the shares of household income from different income sources, which are the shares of income from agriculture and non-agriculture and the share of in-kind income.[9] These predictors represent the economic structure of household earning. Then, I use the age of household head, the number of household members, and the share of elderly people in the household, which is the number of a household members older than 60 years old divided by the total number of household members, in order to capture household characteristics. Moreover, I also include real expenditure per capita for some pre-treatment years. Note that Kaul et al. (2015) suggest that including all lagged outcome values as predictors can substantially distort the synthetic control estimator because other predictors will be insignificant in constructing the synthetic control unit. I include four lagged predictors, which are real expenditure per capita in the years 1988, 1990, 1994, and 2000.

In Table 1.2, columns (1) and (3) exhibit the average of predictors for the treated unit and the whole dataset during the pre-treatment period. Relative to the whole country, the affected area had lower real expenditure and real income per capita, but a larger family size. The average age of household head and elderly share were similar. Column (2) shows

[9]The financial income sources in this dataset include wage, income from agriculture, income from non-agriculture business, transfer, property income, and other income source.

the estimated predictors for the synthetic control unit which was produced to match the treated unit. The similar figures in column (1) and (2) indicate that this synthetic control unit has replicated the treated unit well. This synthetic control unit is a weighted combination of four provinces, which are Phetchabun (with a weight of 0.292), Lopburi (0.273), Roi-et (0.231), and Udonthani (0.205). Figure 1.1 shows the geographical location of these provinces. None of them is in the Southern region thus it was unlikely that they were subject to a negative spillover effect from the insurgency.

Figure 1.2 illustrates the trends in expenditure per capita for estimated synthetic control unit and a treated unit. The synthetic control process aims to minimize the gap between these two lines before treatment period, while a gap after the treatment represents the treatment effect. If the synthetic control line is above the actual treated unit, this indicates a negative impact of the treatment. From the figure, before the insurgency began in 2004, real expenditure per capita for the synthetic control unit closely matched that of the treated unit. However, a gap between the trends arises suddenly from 2004. The outcome of the synthetic control unit increases sharply from 2004 to 2009 but the treated unit only marginally grew during the same period. This gap clearly illustrates a negative impact of the insurgency on real expenditure per capita. I redraw this gap in Figure 1.3 to more vividly exhibit the estimates. The highest treatment effect was in 2009 when the real expenditure per capita of the treated unit was 32.77 percent or 14,847 baht lower than the synthetic control unit. Notice that this gap was decreased markedly in 2011, likely partly due to the severe flooding in most areas of Thailand, including Phetchabun and Lopburi, since the southern region was not affected by the flood. Although this gap slightly decreases after 2009, the average treatment effect from 2004 to 2015 remains sizeable. The affected area has an average real expenditure per capita lower than its predicted level by around an average of 16.21 percent or 8,008 Thai Baht per year.[10]

In their seminal papers Abadie and Gardeazabal (2003) and Abadie et al. (2010) also develop a statistical inference procedure to evaluate the significance of synthetic control estimates by applying placebo treatments to unaffected areas, the so-called in-place placebo. If the actual treatment is not a product of random chance, these placebo estimates should be small. On the other hand, if the gap between the synthetic control unit and the unit to which it is matched is large for several placebo tests, it is possible that the actual treatment effect has randomly occurred, and thus the synthetic control estimate is not likely

[10]I report the full estimates in Table 1.3.

significant. Consequently, the result will be validated if and only if it is significantly larger than the placebo results. I reproduce the synthetic control method for all provinces in the donor pool with the placebo treatment in 2004 as with the actual treatment. Note that I exclude the three southern provinces from the donor pool for these placebo studies.

Table 1.4 reports the provinces with the 10 most negative average impact estimates. Kalasin province was affected the most, followed by Maehongson and Kamphangphet, while the actual treatment unit is ranked tenth.[11] Nevertheless, for the synthetic control estimator, we have to consider not only the treatment effect but also how well the synthetic control process can replicate the treated unit during the pre-treatment period, which is measured by RMSPE as stated in equation 1.2. As suggested by Abadie et al. (2010, 2015), I estimate the ratio R_i as

$$R_i = \frac{\sqrt{\frac{1}{T-T_0}\sum_{t=T_0}^{T}\left(Y_{it} - \sum_{j=2}^{J+1} w_j^* \cdot Y_{jt}\right)^2}}{\sqrt{\frac{1}{T_0-1}\sum_{t=1}^{T_0-1}\left(Y_{it} - \sum_{j=2}^{J+1} w_j^* \cdot Y_{jt}\right)^2}} \tag{1.4}$$

where Y_{it} is the outcome of province i is year t, and $i \neq j$. As noted earlier, the treatment effect begins from the year T_0. Then, the numerator of the ratio R_i is an approximation of the average estimated effect of treatment, and the denominator is the average of pre-treatment RMSPE, which illustrates how well the synthetic control unit can replicate the treated unit. Therefore, a high ratio R_i indicates that the treatment has a large impact on a treated unit, and the synthetic control approach also generates a well-fitted comparison unit. To support the significance of the synthetic control estimate, the ratio for actual treatment (R_1) has to be relatively large compared with the ratios of all placebo treatments. Recall that a case where a province has a high treatment effect but a low ratio R_i indicates that the province's synthetic control unit cannot closely match its outcomes during the pre-treatment period, and hence the estimated treatment effect can be overestimated. The ratio for the actual treatment is 7.22, which is the eighth largest ratio among all 71 provinces. A p-value as proposed by Abadie et al. (2010) is $\frac{8}{71} = 0.112$, which is the probability of obtaining a ratio R_i as high as that of the actual treatment if the treatment randomly occurred.

I next estimate an in-time placebo, which assumes that the treatment began in another

[11]Similar to Figure 1.3, I also graphically report placebo estimates and actual estimate in Figure A1.1 where a thick line represents the actual treatment, and others are the placebos.

year, but remains in the actual treated area (Abadie et al. (2010)). Instead of 2004, I replicate the synthetic control analysis for the three southern provinces with the treatment year fixed at 2002, and then 2006. The estimates are graphically reported in Figure 1.4. For the placebo 2002 calculation, the gap between the synthetic control unit and the treated unit rises in 2004 although the placebo treatment period is from 2002. Similarly, the gap in the placebo 2006 estimation appears in 2004 before the placebo treatment period. Moreover, the ratio R_i for the placebos 2002 and 2006 are 6.19 and 5.98 respectively, which are lower than a ratio of 7.22 for the actual treatment effect. Hence, the in-place and in-time placebo estimates support the validity of my main result.

Furthermore, instead of using real expenditure per capita, I also take family structure into the account by employing an equivalence scale with adult scale equal to 1, and 0.5 for the elderly and children. The estimated effect on the real expenditure equivalence scale is presented in Figure A1.3, which also indicates a negative impact of the insurgency. The result is similar to the previous estimate for real expenditure per capita. In conclusion, the results indicated the insurgency has had a sizeable negative impact on household well-being.

1.5 Heterogeneity Analysis

Most synthetic control studies are based on macroeconomic indicators, particularly in the literature in terrorism economics, for example Abadie and Gardeazabal (2003), Bilgel and Karahasan (2017), and Singhal and Nilakantan (2016).[12] In this paper, I take advantage of micro-level data to scrutinize the heterogeneity effect among households that have different characteristics. As I mentioned earlier, my study is among the first to examine this heterogeneous impact using a synthetic control method. Understanding this heterogeneity is very important if we want to clarify who was most affected by the insurgency. Hence, I separate households by their characteristics and then use averages of these subgroups at the province level to re-estimate the synthetic control unit with the same set of predictors as the main estimation procedure. The outcome variable of interest remains real expenditure per capita. Nonetheless, the weights of provinces in each synthetic control unit are different due to the data generating process that aims to find the most similar comparison

[12] Bilgel and Karahasan (2017) investigate the impact of separatist terrorism in Turkey on provincial GDP, while Singhal and Nilakantan (2016) examine the effect of counter-terrorism policy against the Naxalite insurgency in India on state domestic product per capita.

unit.

Firstly, I divide households by urban and rural areas, which are defined by the nature of the local administration. If the local administration is smaller than the municipality level, the the location is considered as a rural area. Table 1.5 shows the average of the predictor variables during the pre-treatment period for these subgroups. The two areas have different socio-economic structures as shown in columns (1) and (2). In the rural area, most households work in the agricultural sector with 27 percent of their incomes from agriculture. On the other hand, the majority of urban households are in the industry and service sectors. Only 8 percent of their revenues were from agriculture while 25 percent were from non-agriculture. Moreover, urban households also had higher income and expenditure levels than rural households. Table 1.6 exhibits the weights of provinces in each synthetic control unit, where each subgroup has a different combination of control provinces.

The main estimates for both subgroups are shown in Figure 1.5 and Table 1.7. The estimated treatment effect on urban households is large and negative. The real expenditure per capita from 2004 to 2015 was lower than the predicted level by an average of 14.87 percent or 8,950 Thai baht per year with a p-value of 0.070. This maybe because violent incidents could have affected business in urban area, as a law which has been enforced in the region since 2004 decrease business hours for shops and restaurants. In contrast, the estimates show that rural households were not substantially affected by the insurgency. Real expenditure per capita was higher than the control unit by an average of 3.55 percent or 1,504 baht per year with a p-value of 0.314 indicating a statistically insignificant effect. Note, however, that during 2004 to 2011, the price of rubber which is the main crop in this area, notably increased. Figure A1.2 shows the real expenditure per capita of rural households in the treated area alongside the rubber producer price index. From this graph, we can observe the rapid increase in price of rubber. Although the rubber price declined after 2011, the overall price level remained higher than in the pre-treatment period. This high price of rubber presumably increased the wealth of rural households in treated area, which may be why the estimates do not show a negative impact of the insurgency.

Note that when we compare the results from the heterogeneity evaluation to Section 1.4, the treatment effect for all households is observed to be larger than both estimated impacts for urban and rural groups. In a difference-in-difference analysis, the weighted average of estimates for sub-groups will be close to the full sample estimate. However, in this study, each analysis calculates the synthetic control unit separately in order to have the best comparable unit for a different subgroup. Therefore, these synthetic control units are constructed based on different weights for control provinces, making such deviations between full-sample and subgroup estimates possible.

I next divide observations into three subgroups based on the age of the household head. The first group is from 20 to 34 years old, the next group is from 35 to 49 years old, and the last group is older than 50 years. The youngest group presumably represents junior employees who have just started their careers or young entrepreneurs with a relatively small business. The family size for this group is also smaller than in other groups, and many of them live alone, as shown in Table 1.5. This groups had the highest expenditure and income per capita. In contrast, a households with a head that was older than 50 years old were presumably generally working as a senior level employee or operating a larger business. Moreover, the oldest group has a higher income share from agriculture compare to younger groups. Notably, the youngest group has the lowest income shares from agriculture, and hence usually work in the industry and services sectors.

The heterogeneity estimates are exhibited in Table 1.8, and Figure 1.6. The impact was highest on the youngest groups, whose average real expenditure per capita was an average of 30.3 percent or 16,607 baht per year lower than the predicted level with a p-value of 0.085. For the households with household head age 35 to 49 years old, average real expenditure per capita decreased by an average of 13.53 percent or 6,855 baht per year comparing with the control unit, with a p-value of 0.464. Meanwhile, the oldest group was also less affected by the insurgency. Their average real expenditure per capita declined by only an average of 6.5 percent or 2,961 baht per year relative to the predicted level with a p-value of 0.225.[13]

[13]In addition, I separate households into two groups by birth year of the household head. The first group includes households with a household head born from 1954 to 1968 and another group includes heads born from 1938 to 1953. I do not include households whose head was born after 1968 because the number of observations is very small during the pre-treatment period. The results are consistent with the heterogeneity analysis by age of household head finding, that the insurgency has a greater impact on the younger cohort.

1.6 Conclusion

This study shows that the insurgency in Southern Thailand has had a significant impact on local household well-being. However, the effect on each household has differed depending on the characteristics of a household. One of the important findings of this study is that the younger generation was more affected as compared to older groups. Several studies of the economics of terrorism have found a correlation between poor economic conditions and conflict, for example Samaranayake (1999), Testas (2001), and Feridun and Sezgin (2008). The lack of economic opportunity can induce further civil violence and becomes a root cause of a prolonged insurgency. For Southern Thailand, my result, which indicates the severe effect on a young generation, implies a further negative impact on household well-being in the future. In the long-term, the underperforming economy can further intensify the insurgency. Therefore, government policy should not focus only on security and military operations but also on enhancing the local economy.

Figure 1.1: Map of Thailand, the Treatment Area, and
Provinces in Synthetic Control Unit

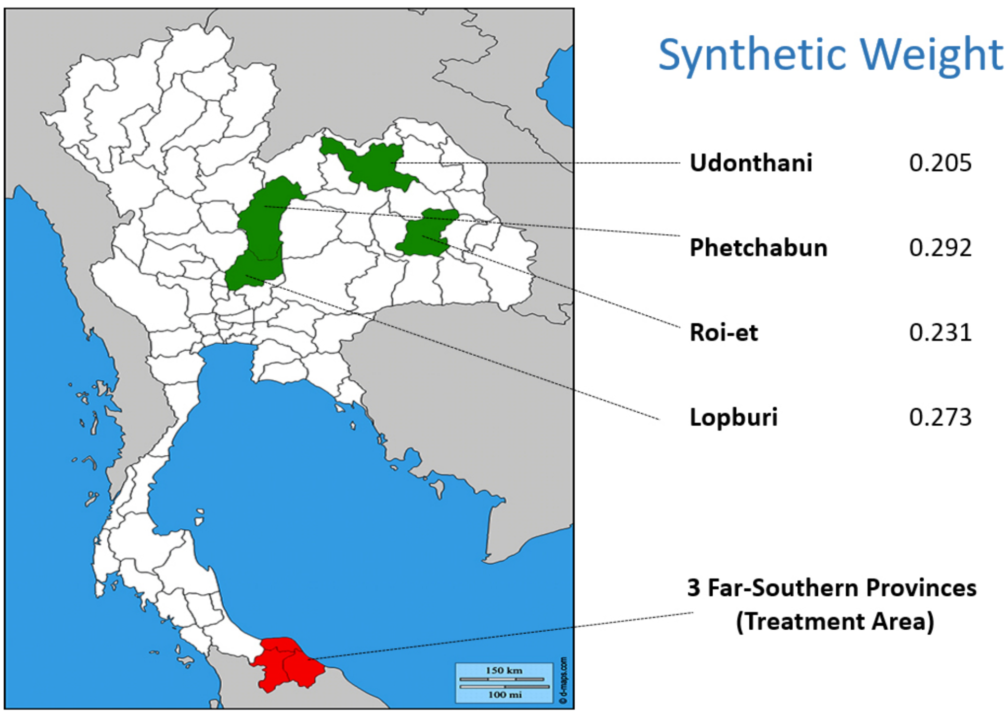


Figure 1.2: Main Result

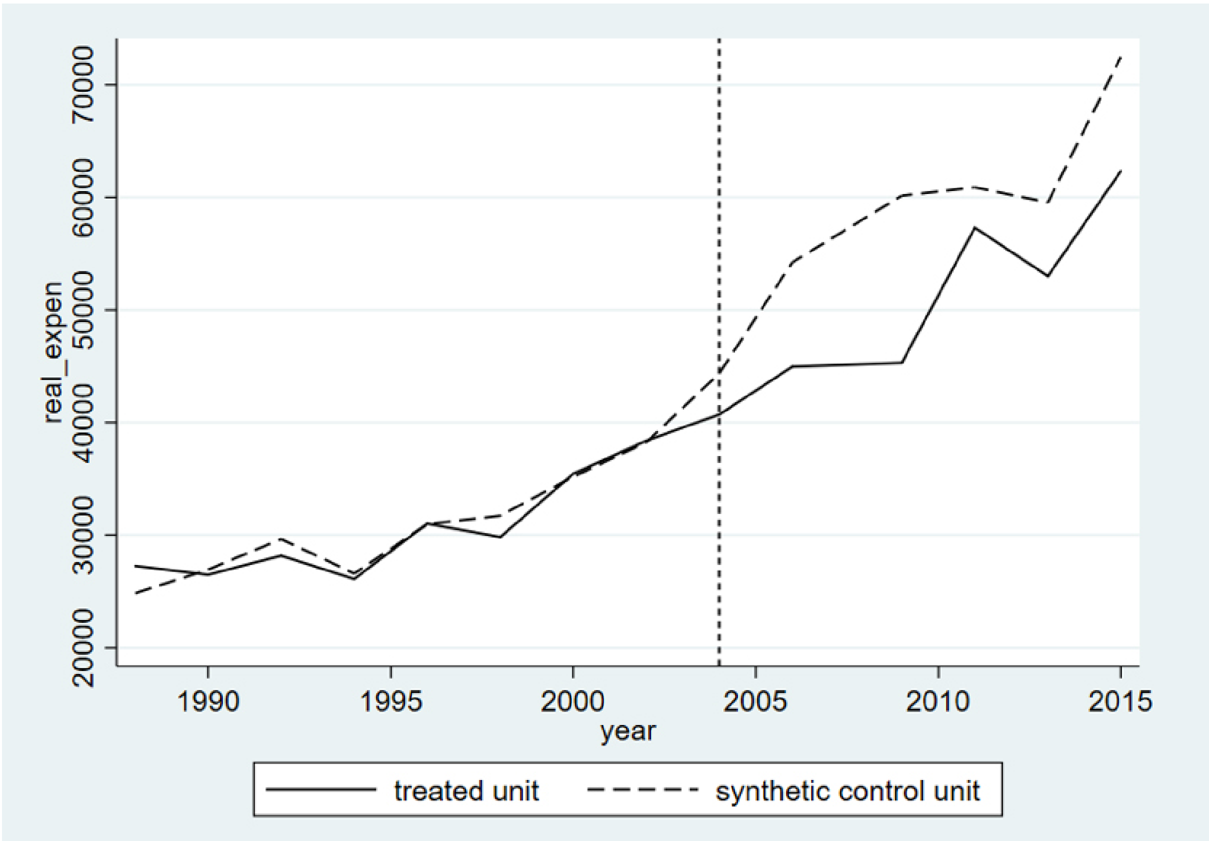


Figure 1.3: Treatment Effect

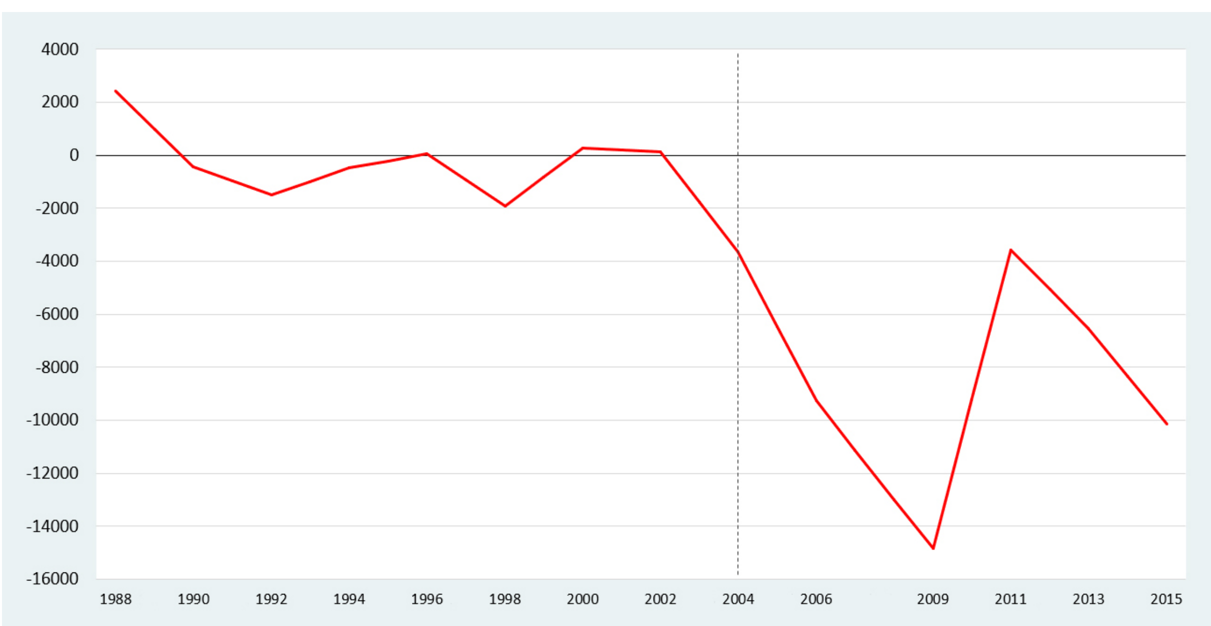


Figure 1.4: In-time Placebo Estimation

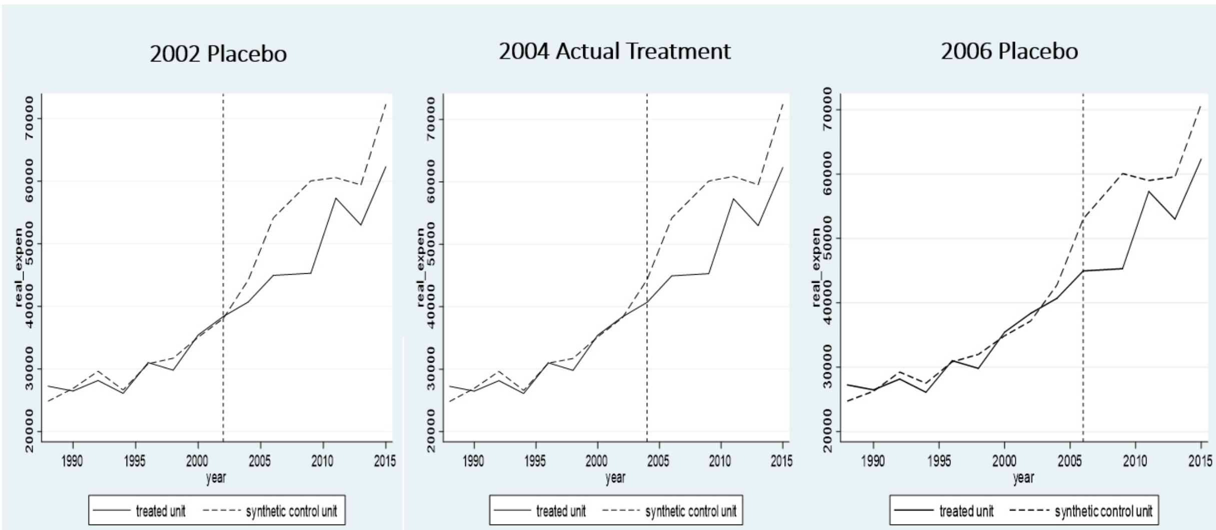


Figure 1.5: Synthetic Control Estimates by Area

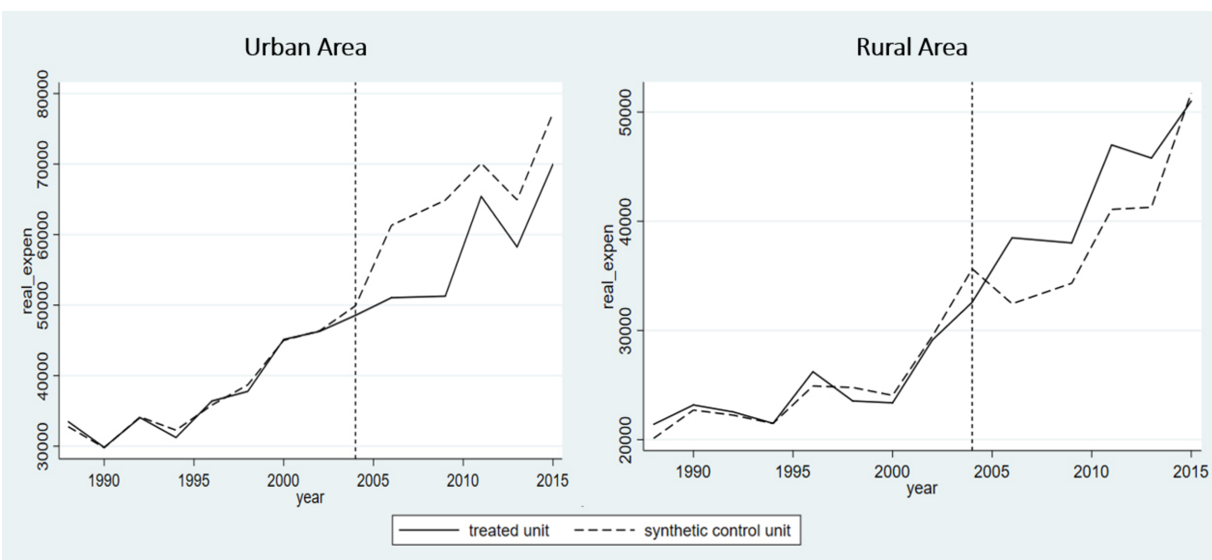


Figure 1.6: Synthetic Control Estimates by Age of Household Head

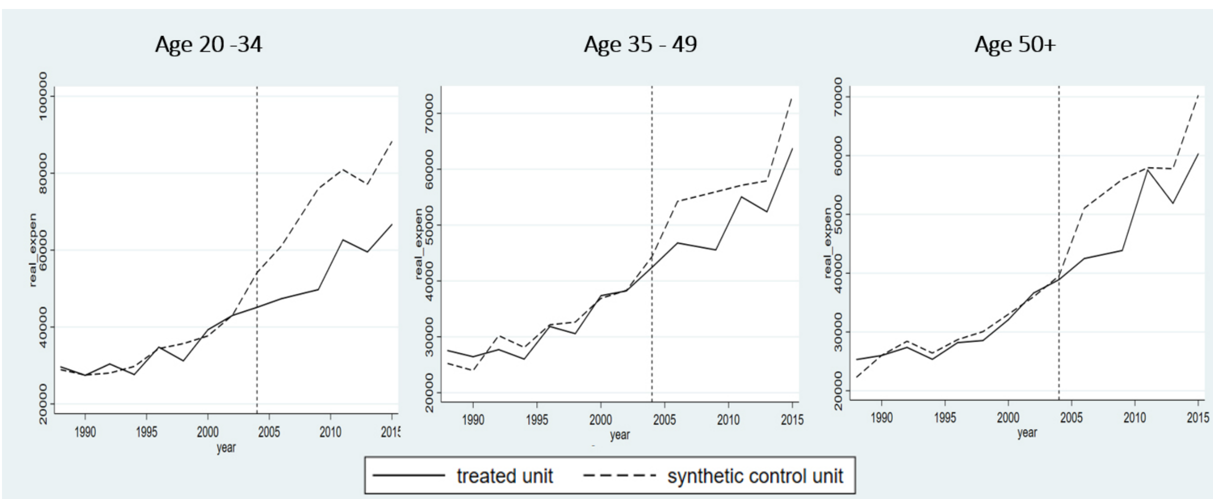


Table 1.1: Number of Households and Real Expenditure per Capita

	Number of Household		**Real Expenditure per Capita**	
	Total (1)	**Treated Area (2)**	**Total (3)**	**Treated Area (4)**
1988	11,704	566	32,504	27,251
1990	12,694	668	36,432	26,484
1992	14,859	674	44,528	28,162
1994	14,947	849	41,377	26,102
1996	19,887	846	45,937	31,015
1998	21,802	778	45,153	29,816
2000	26,405	835	46,030	35,440
2002	29,260	1,230	48,627	38,379
2004	32,802	1,208	53,746	41,124
2006	36,881	1,302	63,365	44,922
2009	39,752	1,396	66,622	45,305
2011	53,910	1,363	69,144	57,304
2013	52,486	1,354	73,053	53,000
2015	62,335	1,448	78,288	62,335

Source: National Statistic Office and author's estimate

Table 1.2: Predictor Variables in the Main Analysis

Average Pre-treatment Period (1988 - 2002)	**Treated Unit (1)**	**Synthetic Unit (2)**	**Total (3)**
Real Income per Capita	29,748	31,452	43,716
Number of Household Members	4.21	3.82	3.72
Age of Household Head	47.65	48.79	47.41
Share of Farm Income	0.145	0.149	0.128
Share of Non-farm Income	0.15	0.142	0.19
Share of In-kind Income	0.187	0.127	0.269
Share of Elderly	0.109	0.118	0.111
Real Expenditure per Capita (1988)	27,251	24,822	32,504
Real Expenditure per Capita (1990)	26,484	26,932	36,432
Real Expenditure per Capita (1994)	26,102	26,589	41,377
Real Expenditure per Capita (2000)	35,440	35,176	46,030

Table 1.3: The Economic Impact of the Insurgency

	Treat Unit	Synthetic Unit	Gap	(%)
Pretreatment Period				
1988	27,251	24,822	2,429	(8.91)
1990	26,484	26,932	-448	(-1.69)
1992	28,162	29,644	-1,482	(-5.26)
1994	26,102	26,589	-487	(-1.86)
1996	31,015	30,968	47	(0.15)
1998	29,816	31,717	-1,902	(-6.38)
2000	35,440	35,176	264	(0.75)
2002	38,379	38,241	138	(0.36)
Posttreatment Period				
2004	40,712	44,370	-3,658	(-8.99)
2006	44,958	54,225	-9,266	(-20.61)
2009	45,305	60,153	-14,847	(-32.77)
2011	57,304	60,886	-3,582	(-6.25)
2013	53,000	59,554	-6,555	(-12.37)
2015	62,335	72,477	-10,142	(-16.27)
Average Treatment Effect			**-8,008**	**(-16.21)**

Table 1.4: Provinces with Largest Negative Estimates

	Province	Region	Avg. Treatment Effect (%)	Ratio R_i
1	Kalasin	Northeast	-39.57	5.56
2	Maehongson	North	-26.36	5.13
3	Kamphangphet	North	-21.77	2.14
4	Trat	Central	-19.06	2.39
5	Yasothon	Northeast	-18.44	6.40
6	Loei	Northeast	-17.15	1.78
7	Khonkaen	Northeast	-17.11	6.09
8	Nakhonsawan	North	-17.01	4.83
9	Chainat	Central	-16.80	5.73
10	**Actual Treated Unit**	**South**	**-16.21**	**7.22**

Table 1.5: Pre-treatment Household Characteristics

	Area		**Age of Household Head**		
	Urban (1)	**Rural** (2)	**20 - 34** (3)	**35 - 49** (4)	**50+** (5)
Real Expenditure per Capita	28,658	14,768	20,616	19,225	17,882
Real Income per Capita	23,178	14,016	32,925	18,780	17,877
Number of Household Members	3.93	4.48	3.46	4.60	4.24
Age of Household Head	46.44	48.85	29.04	41.47	62.41
Share of Elderly	0.099	0.119	0.011	0.016	0.240
Share of Farm Income	0.08	0.27	0.10	0.16	0.22
Share of Non-farm Income	0.25	0.11	0.15	0.21	0.17
Share of in-kind income	0.20	0.25	0.19	0.20	0.26

Table 1.6: Provincial Weights for Synthetic Control Units

Main Result		**Area**				**Age of Household Head**					
		Urban		**Rural**		**20 - 34**		**35 - 49**		**50+**	
Province	**Weight**	**Province**	**Weight**	**Province**	**Weight**	**Province**	**Weight**	**Province**	**Weight**	**Province**	**Weight**
Lopburi	0.273	Lopburi	0.241	Nakhonnayok	0.115	Lopburi	0.337	Lopburi	0.17	Lopburi	0.079
Phetchabun	0.292	Phetchabun	0.285	Maehongson	0.563	Phrae	0.114	Maehongson	0.082	Maehongson	0.23
Udonthani	0.205	Udonthani	0.111	Udonthani	0.289	Udonthani	0.236	Phetchabun	0.387	Phetchabun	0.352
Roi-et	0.231	Mahasarakham	0.243	Nakhon Si Thammarat	0.033	Roi-et	0.28	Sisaket	0.208	Udonthani	0.274
		Roi-et	0.064			Satun	0.034	Roi-et	0.153	Phangnga	0.031
		Satun	0.057							Satun	0.034

Table 1.7: Impact of the Insurgency on Urban and Rural Households

	Urban Households				Rural Households			
	Treat Unit	**Synthetic Unit**	**Gap**	(%)	**Treat Unit**	**Synthetic Unit**	**Gap**	(%)
1988	33,483	32,846	636	(1.90)	21,403	20,172	1,231	(5.75)
1990	29,831	29,857	-26	(-0.09)	23,176	22,440	736	(3.17)
1992	34,061	34,161	-99	(-0.29)	22,537	22,825	-289	(-1.28)
1994	31,229	32,026	-797	(-2.55)	21,492	21,008	484	(2.25)
1996	36,410	35,866	544	(1.49)	26,223	25,504	719	(2.74)
1998	37,776	39,149	-1,373	(-3.63)	23,539	25,184	-1,645	(-6.99)
2000	45,137	45,180	-43	(-0.09)	23,371	24,116	-745	(-3.19)
2002	46,290	46,449	-160	(-0.34)	29,128	29,118	10	(0.04)
2004	47,764	50,113	-2,349	(-4.92)	32,605	35,024	-2,419	(-7.42)
2006	51,108	61,617	-10,509	(-20.56)	38,489	33,297	5,192	(13.49)
2009	51,264	66,219	-14,955	(-29.17)	38,018	35,416	2,601	(6.84)
2011	65,415	70,052	-4,637	(-7.09)	46,989	42,046	4,942	(10.52)
2013	58,247	66,813	-8,566	(-14.71)	45,783	43,963	1,820	(3.98)
2015	69,990	78,940	-8,950	(-12.79)	51,009	54,122	-3,113	(-6.10)
Average Treatment Effect			**-8,328**	**(-14.87)**			**1,504**	**(3.55)**

Table 1.8: Impact of the Insurgency by Age of Household Head

	Age: 20 - 34				Age: 35 - 49				Age: 50+			
	Treat Unit	**Synthetic Unit**	**Gap**	(%)	**Treat Unit**	**Synthetic Unit**	**Gap**	(%)	**Treat Unit**	**Synthetic Unit**	**Gap**	(%)
1988	29,641	28,411	1,230	(4.15)	27,543	25,617	1,927	(7.00)	25,305	22,704	2,601	(10.28)
1990	27,442	27,682	-241	(-0.88)	26,442	24,811	1,631	(6.17)	25,996	25,393	602	(2.32)
1992	30,394	28,862	1,532	(5.04)	27,717	30,345	-2,627	(-9.48)	27,371	26,870	501	(1.83)
1994	27,644	29,620	-1,976	(-7.15)	26,019	28,078	-2,059	(-7.91)	25,350	26,265	-915	(-3.61)
1996	34,764	32,382	2,381	(6.85)	31,853	32,297	-444	(-1.39)	28,190	29,606	-1,416	(-5.02)
1998	31,204	33,633	-2,428	(-7.78)	30,571	32,807	-2,236	(-7.31)	28,538	28,428	111	(0.39)
2000	39,292	39,342	-49	(-0.13)	37,368	37,121	247	(0.66)	32,077	32,943	-866	(-2.70)
2002	43,015	42,433	582	(1.35)	38,233	38,893	-659	(-1.72)	36,629	34,708	1,920	(5.24)
2004	43,840	53,283	-9,443	(-21.54)	41,953	45,092	-3,139	(-7.48)	38,800	41,170	-2,369	(-6.11)
2006	46,862	61,512	-14,650	(-31.26)	46,920	54,325	-7,405	(-15.78)	42,622	49,603	-6,981	(-16.38)
2009	49,729	72,323	-22,593	(-45.43)	45,557	56,876	-11,319	(-24.85)	43,851	49,131	-5,280	(-12.04)
2011	62,658	81,087	-18,429	(-29.41)	55,059	57,273	-2,214	(-4.02)	57,558	52,994	4,564	(7.93)
2013	59,508	71,298	-11,790	(-19.81)	52,380	59,024	-6,644	(-12.68)	51,875	53,312	-1,437	(-2.77)
2015	66,668	89,406	-22,738	(-34.11)	63,692	74,102	-10,410	(-16.35)	60,301	66,564	-6,263	(-10.39)
Average Treatment Effect			**-16,607**	**(-30.26)**			**-6,855**	**(-13.53)**			**-2,961**	**(-6.63)**

Chapter 2

The Migration and Economic Impact of the Insurgency in Southern Thailand

Abstract

This chapter studies how the insurgency in Southern Thailand has affected migration and the local economy. I exploit the variation in violent incidents and deaths among Thai districts from 2004 to 2017 to clarify the heterogeneous local effects of this insurgency. Empirical evidence supports the view that the insurgency has induced migration outflows. It also reduced population growth and economic activity over the long term. For the labour market, the results do not show any effect of the insurgency on monthly wages and working hours of local employees.

2.1 Introduction

The insurgency in Southern Thailand, including Yala, Pattani, and Narathiwat, and some parts of Songkhla province, began in 2004 as discussed in the previous chapter. Although the study of the economics of terrorism has been a very active field since the September 11 attack in the United States, none of the economic literature has considered this context yet. Therefore, this research is among the first that analyses the economic effect of the insurgency in Southern Thailand. In this chapter, I exploit the variation in violent incidents and deaths among districts from 2004 to 2017 to clarify the effect of this insurgency on migration and the local economy. The empirical results suggest that areas with a high insurgency intensity experienced migration outflows and hence negative net migration. Over the long-term, I also find that districts with high numbers of incidents and deaths had lower population growth and average lights at night as compared to more peaceful districts. I then use the Labour Force Survey to examine the insurgency's impact on employment. However, the result does not show any effect of the insurgency on monthly wages and working hours of local employees.

This research contributes to the literature on the economic effect of terrorism, particularly migration and the labour market. Many studies on the economics of terrorism such as Collier et al. (2004), and Blomberg et al. (2011) show that regions which experience a long term conflict or insurgency tend to see declining economic prospects.[1] My results indicate that insurgency is a push force that induces people to migrate out. This force for migration is also illustrated in both cross-country analyses, for instance Moore and Shellman (2004), and Dreher et al. (2011), and sub-national conflict studies, including Engel and Ibáñez (2007) and Ibáñez and Vélez (2008) for Columbia, Czaika and Kis-Katos (2009) for the Aceh region in Indonesia, Adhikari (2013) for Nepal, and Morrison (1993) for Guatemala. However, most of the literature investigates the total impact on migration for the whole conflict area. This study is among the first to examine the impact on migration within the conflict area using heterogeneity in the intensity of the insurgency.

I also consider the impact on the labour market, where most research has found that insurgencies and terrorist attacks have a significant impact on employment. For instance, Kondylis (2010) concludes that displacements after the civil conflict in Bosnia led to higher unemployment rates, Berrebi and Ostwald (2016) show that terrorist attacks decrease female labour force participation and increase the gender gap, and Brodeur (2018) finds that successful attacks in the United States decrease the number of jobs and total earnings. In contrast, Ahern (2018) finds that terrorist attacks have a negative impact on economic growth, but decrease the unemployment rate and increase employee compensation. Eckstein and Tsiddon (2004) provide a theoretical model that suggests similar consequences due to increases in government spending. Furthermore, Sayre (2009) studies Palestinian suicide bombs in Israel and suggests that high unemployment rates caused high rates of suicide bombs, but not vice-versa. Enders et al. (2016) also suggest that poor labour mar-

[1] See the further discussion of the literature in Chapter 1.

kets can accelerate conflict.

Furthermore, Brück et al. (2017) conclude that research on the economics of terrorism and conflict has recently shifted from a macro perspective to more micro-level studies in order to understand the responses and roles of individuals as well as microeconomic institutions. My research also employs micro-level data to uncover the impact of insurgency and contributes to this growing literature. The central contribution of this study is to examine the intra-regional impact due to variation in insurgency intensity within a small area. The remainder of this paper is structured as follows. In Section 2.2, I present an overview of the data. I next present the estimation strategy and empirical evidence in Section 2.3. Lastly, the conclusion is in Section 2.4.

2.2 Data

My empirical analysis relies on variation in the insurgency across districts and time. In this study, the main explanatory variables are the numbers of incidents and deaths, based on data from the Deep South Watch organization.[2] The data was collected at the district level on a yearly basis from 2004 to 2017, and covers 37 districts in four provinces. Data on violent incidents includes shootings, bombs, and assassinations, but it will not be possible to separate incidents by the type of event. For the number of deaths, this data set counts civilians, military officers, civil servants, and insurgents, but again the data cannot be broken down by group.

Figure 2.1 provides a map of the affected districts, exhibiting the variation in insurgency among districts. Dark shaded areas represent districts with a high average number of incidents across 2004-2017, and the light shaded areas indicate districts with fewer incidents. I also report descriptive statistics in Table 2.1. The district where the insurgency has been most intense is Mueang-Yala with an average of 123.9 incidents per year, followed by Ra-ngae (86.1 incidents), Raman (78.9), Rueso (76.7), and Bannagsata (75.0). Similarly, these five districts are also among the highest average number of deaths. On the other hand, Nathawi has the lowest average number of incidents, with only 2.8 incidents per year, followed by Chana (6.5), Maelan (7.3), Maikaen (7.5), and Kabang (8.6). For Nathawi and Chana, in particular, there have been some years in which no violent incident

[2]The Deep South Watch Organization was established in 2006 as a non-governmental organization based in Prince Songkhla University at Pattani campus.

took place. Figure 2.2 exhibits the time variation in insurgency intensity, the other key dimension of variation, by plotting the average numbers of incidents and deaths across all districts from 2004 to 2017. Moreover, Figure A2.1 exhibits the positive correlation between the numbers of incidents and deaths by district and year.

For migration, I use administrative data from the Thai Ministry of Interior. This official data set includes the population in each district at the end of each year. It also records the number of people moving out of and moving into the district. However, this data set cannot track their destinations or original locations. I report descriptive statistics in Table 2.2.

This study also aims to examine the insurgency's effect on economic activity. Unfortunately, there are no indicators of aggregate economic activity available at the district level. Thus, I use night light data as a proxy for local economic activity (Henderson et al. (2012)). I use the average visible, stable lights, and cloud-free coverage data from the National Centers for Environmental Information of the National Oceanic and Atmospheric Administration. The latitude range covered in this study is very small, and so all pixels represent the same land surface area. Each pixel is given a number between 0 to 63, which indicates the darkest and the brightest areas respectively. I calculate the average level of lights at night across all pixels in each district and year.

To investigate the insurgency's impact on the labour market, I use the Labour Force Survey conducted by the National Statistical Office of Thailand. This survey employs two-stage stratified sampling at the provincial level. First, each province is divided into units by type of local administration, which are municipal and non-municipal areas. The first strata is blocks for municipalities and villages for non-municipalities, which are selected independently and separately. Then households are randomly selected from these blocks and villages. The survey is conducted on a monthly basis. However, in this study I use only third quarter data because it is the harvesting season that has less seasonal migration from agriculture to other sectors (Paweenawat and Mcnown (2018)). A potential source of concern arises from the fact that households in large districts are included in the sample every year, but small districts are not surveyed in some years, so that in terms of the districts, my data set is not balanced. However, the choice of districts excluded in each survey is not related to the insurgency. This survey contains individual-level information, including age, sex, educational attainment, marital status, occupation, industry, work status, work hours, income and other benefits. For the labour market analysis, the main outcome variables are monthly wages and working hours.

2.3 Empirical Strategy and Results

2.3.1 Effect on Migration

In this subsection, my goal is to estimate the effect of the insurgency on migration. The main source of variation in my identification strategy is the numbers of incidents and deaths across districts and years. I use two different approaches. The first model is a parametric ordinary least squares regression, and the second method is a semiparametric partially linear model. This aims to investigate the possibility of both linear and nonlinear effects of the insurgency on migration.

Firstly, I estimate a linear panel data fixed effects model as a following equation:

$$LnY_{dt} = \beta \cdot Ln\ X_{d,t} + \alpha_d + \gamma_t + \varepsilon_{dt} \tag{2.1}$$

where Y_{dt} denotes the migration outcome variables, including migration inflow, migration outflow, or the ratio of net migration to total population of the district d in year t. The regressor $Ln\ X_{d,t}$ denotes the log of the number of violent incidents or deaths.[3] However, the migration decision might not only have been determined by the insurgency in the current year, but also influenced by events in the past. Furthermore, some migration did occur early in the year, while many incidents would have happened later and presumably did not affect these earlier migration decisions. Therefore, I also estimate equations 2.2 and 2.3, which include the number of incidents and deaths from the previous year ($X_{d,t-1}$), or the two years earlier ($X_{d,t-2}$), as treatment variables, respectively:

$$LnY_{dt} = \beta \cdot Ln\ X_{d,t-1} + \alpha_d + \gamma_t + \varepsilon_{dt} \tag{2.2}$$

$$LnY_{dt} = \beta \cdot Ln\ X_{d,t-2} + \alpha_d + \gamma_t + \varepsilon_{dt} \tag{2.3}$$

In all regressions, I include district and year fixed effects, denoted as α_d and γ_t respectively. Hence, the parameter of interest, β, captures the effect of incidents and deaths

[3] I add one to the actual data for all log transformations in this study, so that $Ln\ X_{d,t}$ is $Ln\ (1 + Incidents_{d,t})$ or $Ln\ (1 + Deaths_{d,t})$

on migration outcome in the absence of district-year-varying omitted factors. I employ a multi-way clustering method (MacKinnon et al. (2017), and Roodman et al. (2018)) to cluster standard errors at the district and year levels, with 37 districts and 12 to 14 years depending on the specifications. This procedure allows me to account for correlation in the error terms in both dimensions.

Table 2.3 reports the estimates for the number of violent incidents. In the first three columns, we observe positive estimated coefficients for migration outflow. However, only the result for current-period incidents in column (1) is statistically significant with p-value 0.062. For migration inflows, presented in column (4) to (6), the estimates are close to zero and not significant. The last three columns show results from regressions with net migration as a share of the population. The estimates with the number of incidents in the current year and previous year in columns (7) and (8) are negative with p-value 0.051, and 0.108 respectively, while the estimate in the last column is not statistically significant. Results from regressions with the number of deaths are reported in Table 2.4. Similar to the previous estimates, the migration outflow effects are positive and statistically significant for the current year. Again, the estimates for migration inflow are not significantly different from zero. The effects on net migration relative to population are negative and statistically significant for the current year and the previous year. Consequently, these results suggest that high insurgency intensity induces migration outflows and thus negative net migration.

I next estimate the effect of insurgency on migration using the semi-parametric panel data model with fixed-effects, developed by Baltagi et al. (2002). This estimation method is more flexible and allows me to capture an effect of insurgency on migration that is possibly nonlinear. The main advantage of this particular approach is to include fixed effects in the model since in my data set there is a possibility of unobservable factors on both these dimension which might cause an omitted variable bias. The nonlinear relationship between insurgency and migration can be specified as follows

$$LnY_{dt} = f\left(Ln\ X_{d,t}\right) + \alpha_d + \gamma_t + \varepsilon_{dt} \tag{2.4}$$

where $f(\cdot)$ is the unspecified functional form. In fact, this specification is comparable to Equation 2.1 except that the main independent variable ($Ln\ X_{d,t}$) enters the model nonlinearly. Baltagi et al. (2002) shows that the district fixed effects (α_d) can be eliminated by taking a first difference. Then, the first difference model is given by:

$$LnY_{dt} - LnY_{dt-1} = \Big[f\left(Ln\ X_{d,t}\right) - f\left(Ln\ X_{d,t-1}\right)\Big] + \left(\gamma_t - \gamma_{t-1}\right) + \varepsilon_{dt} - \varepsilon_{dt-1}. \tag{2.5}$$

Baltagi et al. (2002) also suggest that $\left[f\left(Ln\ X_{d,t}\right) - f\left(Ln\ X_{d,t-1}\right)\right]$ can be estimated by the series differences $\left[p^k\left(Ln\ X_{d,t}\right) - p^k\left(Ln\ X_{d,t-1}\right)\right]$ where $p^k\left(Ln\ X_{d,t}\right)$ is the first k terms of a sequence of functions $\big(p_1\left(Ln\ X_{d,t}\right), p_2\left(Ln\ X_{d,t}\right), \ldots\big)$. Desbordes and Verardi (2012) propose a typical example in which p^k series could be a spline, and thus in this study, I use a B-spline regression model of order $k = 4$.[4]

Similar to the linear model, the treatment variables considered here are contemporaneous the log of the number of incidents, and log of the number of deaths, and the outcomes of interest are log of migration outflow, log of migration inflow, and net migration. Firstly, I estimate the effect of the insurgency on the migration outflow. Figure 2.3 exhibits the semiparametric estimates of the function $f(\cdot)$. The points in the graphs are partial residuals for the log of migration outflow adjusted for estimated fixed effects, and centered on the mean.[5] The shaded areas correspond to a 95% confidence interval. For both regressors, the graphs illustrate a gradual positive slope. High intensity in incidents or deaths is associated with a high migration outflow, with a similar magnitude to the 0.03 estimated with the linear model. The semiparametric estimates for migration inflow are illustrated in Figure 2.4. These partial fit graphs show that the estimates of the slope of the semiparametric function are close to zero and relatively flat. For net migration, the semiparametric estimates are exhibited in Figure 2.5. Similar to the linear estimates, net migration shows a negative relationship with the number of incidents and number of deaths. Note that in all semiparametric estimates, the estimates of fixed effects are close to those of the linear parametric regression. These semiparametric results show that the effects of the treatment variables on the migration outcomes are roughly linear. Hence, the results from the previous linear models are sufficient to explain the effects of the insurgency.[6]

These linear parametric and nonlinear semiparametric models cannot capture a discontinuous effect where the insurgency might affect migration at some threshold intensity

[4]This procedure can be executed by the *xtsemipar* command in Stata, developed by Libois and Verardi (2013).

[5]A partial residual can be represented as $\hat{u}_{it} = LnY_{dt} - \hat{\alpha}_d - \hat{\gamma}_t = f\left(Ln\ X_{d,t}\right) + \hat{\varepsilon}_{dt}$.

[6]I also use log of the number of incidents and deaths from the previous year as treatment variables. The estimated nonlinear functions are illustrated in Figure A2.2 to A2.4. The results remain similar to the linear estimates.

level. Therefore, my next empirical strategy focuses only on the impact of a high intensity of the insurgency by using a step function as an alternative model to investigate the effect on the top decile. Accordingly, I estimate the following equation:

$$LnY_{dct} = \beta_T Topdecile_{dct} + \alpha_d + \gamma_t + \varepsilon_{dct}. \tag{2.6}$$

where $Topdecile_{dct}$ equals one if the district d in year t is in the top 57 districts and years that had the highest number of incidents (or deaths) and zero otherwise. Hence, the coefficient β_T measures the migration effect on the top decile as compared with the other 461 districts and years. Results are reported in Table 2.5. The only statistically significant estimate is in column (5), which indicates negative net migration due to the high intensity of violent incidents. However, other coefficients are not significant, suggesting that the top decile does not have a different migration pattern to other deciles. Consequently, this empirical evidence suggests that the insurgency effect on migration can be best explained by the continuous estimation.

The previous results indicate the short-term effect of insurgency: that a higher intensity of violent incidents or deaths induces greater migration outflows. I now aim to assess the long-term effect of insurgency on local population. Hence, I estimate equation 2.7, where the regressor is the log sum of the number of incidents or deaths in district d from 2004 to 2017, and the dependent variable is the change in the log of population of district d over the same period.

$$LnPopulation_{d,2017} - LnPopulation_{d,2004} = \beta \cdot Ln(\sum_{t=2004}^{2017} X_{d,t}) + \varepsilon_d \tag{2.7}$$

The results are shown in columns (1) and (2) of Table 2.6. Both long-difference coefficients are negative, approximately 0.03, and statistically significant at the 5% level.

I also construct a placebo estimate using the change in population from 1996 to 2003 as a dependent variable ($LnPopulation_{d,2003} - LnPopulation_{d,1996}$) since the total number of incidents and deaths should not have any effect on migration prior to the insurgency. The placebo results are reported in column (3) and (4): these are not significant, but the magnitudes are close to the estimates in columns (1) and (2). This might reflect some existing trend in population change. To correct for this possible pre-existing trend, in equation 2.8 I add the population change from 2003 to 1996 as a lag of the dependent variable to account for district specific trends:

$$\begin{aligned}\triangle\ LnPopulation_{d,2017-2004} &= \beta \cdot Ln(\sum_{t=2004}^{2017} Incident_{d,t}) \\ &+ \delta \triangle\ LnPopulation_{d,2003-1996} + \varepsilon_d \end{aligned} \tag{2.8}$$

Results from OLS estimation with the pre-trend control are reported in column (5) and (6) of Table 2.6. Even though the coefficients are significant and still negative, the magnitudes noticeably decrease as compared with the results in column (1) and (2). For the total number of incidents, the coefficient decreases in magnitude from -0.0295 to -0.0155, while the coefficient on the total number of deaths also falls in magnitude to -0.0142 from -0.0273. This empirical evidence suggests that the decline in population during the insurgency is partly due to a pre-trend effect. Additionally, the lagged control variable is likely to be correlated with the residual. Therefore, I instrument for this lagged variable by the 1996 level, as suggested by Anderson and Hsiao (1981). Results from IV estimates in column (7) and (8) display similar coefficients in the OLS regressions. All in all, the results from long-difference regressions are consistent with the findings from the previous short-run estimates, confirming that the insurgency induces migration outflows and leads to a decline in population growth.

2.3.2 Effect on Economic Activity

In this sub-section, I aim to investigate the effect of the insurgency on economic activity. As explained in Section 2.2, I use lights at night as a proxy for economic activity. I apply a similar strategy as I did for population change to investigate the long-term effect of insurgency on economic activity. The change in log average lights at night between 2013 and 2004 is the dependent variable, and the regressor is the log of the total number of incidents or deaths in the district during the same period. The results are presented in columns (1) and (2) of Table 2.7. Similar to population, the estimated coefficients for both total incidents and deaths are significant and negative, -0.123 and -0.0876 respectively. For placebo regressions, I use the change in lights at night between 2003 and 2000 as the dependent variable. The results, which are reported in columns (3) and (4), are not statistically significant and the values are not close to the estimates in columns (1) and (2).[7] In

[7] I also follow the same estimation strategy used for long-term population change by adding changes in lights at night between 2003 and 2000 as a pre-trend control variable, and then instrumenting it with the

conclusion, the districts with higher insurgency intensity experience declines in the growth of lights at night.[8] This is consistent with results in sub-section 2.3.1, consistent with the possibility that due to the insurgency, lower growth in economic activity is caused by the net migration outflow, and vice-versa.

2.3.3 Effect on the Labour Market

In this sub-section, I aim to investigate the effect of the insurgency on the local labour market. The two main outcomes of interest are the monthly wage and working hours. Specifically, I estimate:

$$\ln Wage_{idt} = \beta \ln X_{dt} + \alpha_d + \gamma_t + \varepsilon_{idt} \tag{2.9}$$

$$\ln WorkHour_{idt} = \beta \ln X_{dt} + \alpha_d + \gamma_t + \varepsilon_{idt} \tag{2.10}$$

where $Wage_{idt}$ and $WorkHour_{idt}$ are the monthly wage and working hours of individual i who was in district d during year t. The explanatory variable X_{dt} is the number of incidents or deaths in district d in year t, and standard errors are clustered using a multi-way clustering method by district and year. Tables 2.8 and 2.9 exhibit estimates with number of incidents and number of deaths respectively. The coefficients in the odd columns are estimated without individual controls, and the estimates in the even columns control for gender, working in the private or public sector, working in the agricultural or non-agricultural sector, and university degree. In Table 2.8, only the estimates in columns (4) and (8) are statistically significant. The result in column (4) indicates that a higher number of violent incidents in the previous year is associated with a higher monthly wage. The estimate in column (8) exhibits relationship between the number of incidents in a given year and working hours. Although it is statistically significant, the sign of this estimate is not consistent with the estimate without controls in column (7). Moreover, all of the estimates in Table 2.9 are insignificant. Overall, we cannot conclude that there has been an impact of the insurgency on monthly wages and working hours based on these results.

night light level in 2000. However, the first stages indicate very weak instruments. (F-statistics of 2.87 and 2.98 for columns (7) and (8), respectively.) Nonetheless, I report the results in Table 2.7 column (5) to (8).

[8] I estimate the short-term effect of the insurgency on lights at night by using the same empirical strategy as in the previous subsection. However, the results do not show a substantial effect.

2.4 Conclusion

This paper studies how the insurgency in Southern Thailand has affected migration and the local economy. Empirical evidence that I present supports the view that the insurgency has induced migration outflows, reducing population growth and economic activity in the long term. Nonetheless, the data does not allow me to precisely identify the people who migrated and track their destinations. Further research employing micro-level data sets is therefore necessary to better understand the impact of the insurgency. Even though my results do not show the impact of the insurgency on the labour market, further research on the socio-economic status of local people remains necessary, ideally with a more comprehensive dataset. Moreover, it would be valuable to investigate effects of displacement on the economic and labour market conditions at migrants' destinations (see for instance Kondylis (2010)).

In addition, one issue that has yet to be explored in this study is the role of the government. Since the violent situation began, the Thai government has set up several military stations and patrols in the area, particularly in risky zones. These actions could have had an indirect effect on insurgent attacks and civilian decisions, as suggested by Di Tella and Schargrodsky (2004), and Draca et al. (2011). On the other hand, greater government spending could also have affected economic and labour market outcomes as discussed in Blomberg et al. (2004) and Eckstein and Tsiddon (2004). Research on these possibilities could help shed additional light on the situation in southern Thailand.

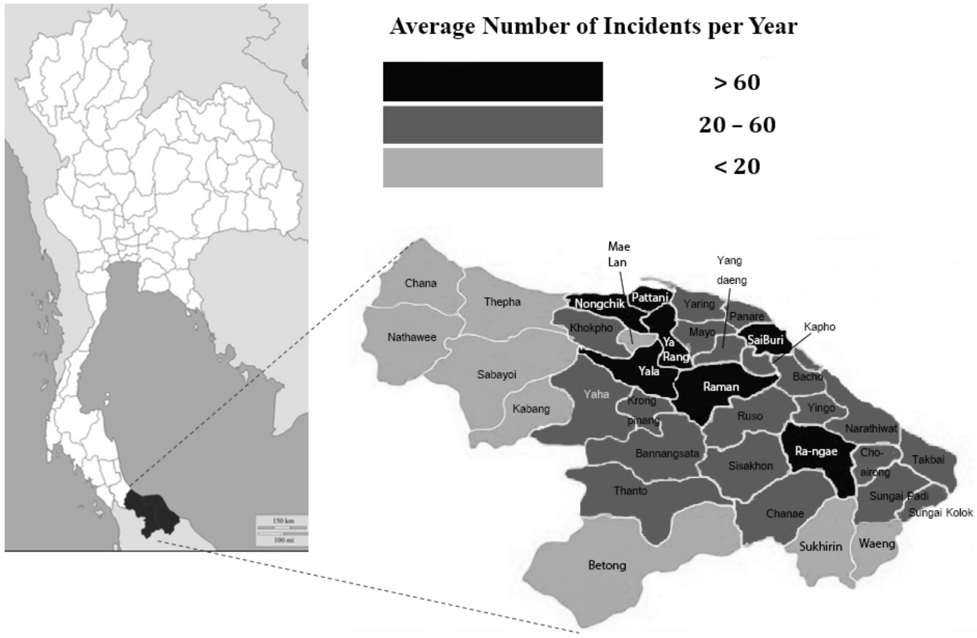


Figure 2.1: Map of Thailand and Conflict Area in Southern Region

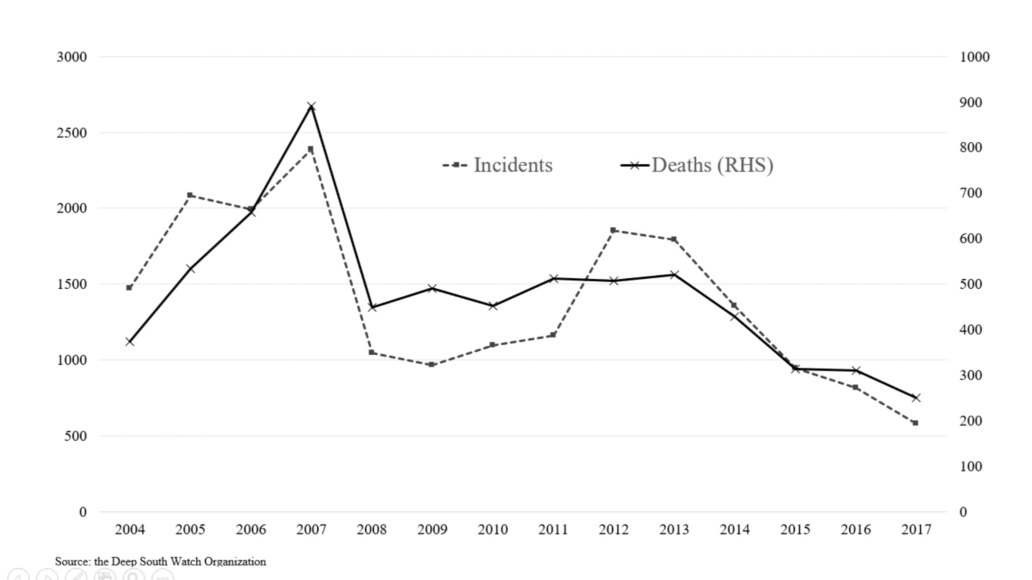
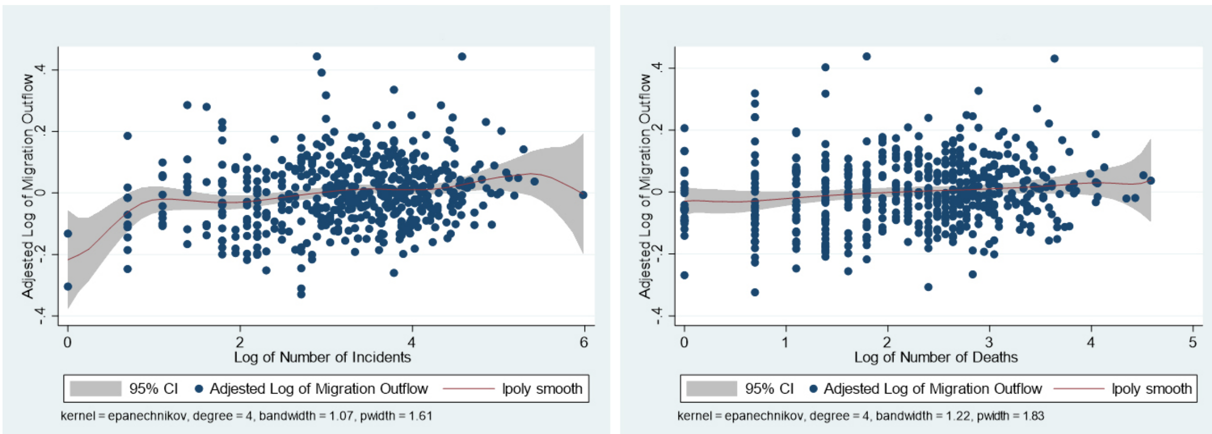


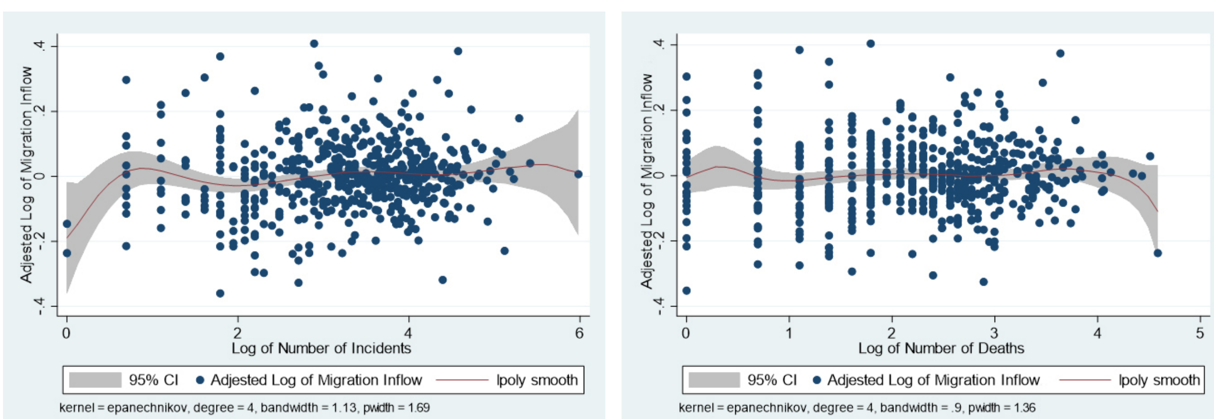
Figure 2.2: Average Numbers of Violent Incidents and Deaths

Figure 2.3: Partial Fits of Adjusted Log Migration Outflow and Treatment Variables



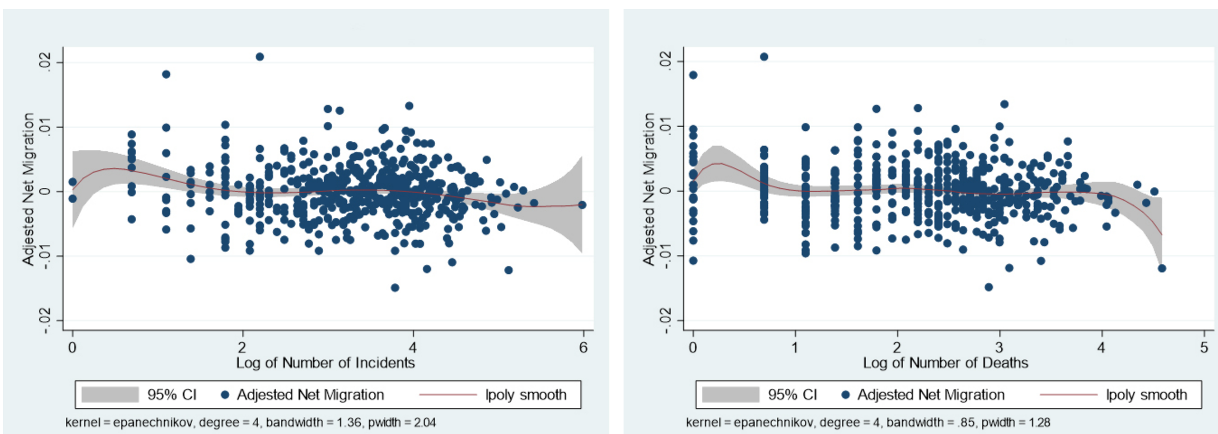
Note: The log of the number of migrants flowing out has been adjusted for the fixed effects. The points in each graph are partial residuals for log migration outflow, and the shaded area represents 95% confidence intervals.

Figure 2.4: Partial Fits of Adjusted Log Migration Inflow and Treatment Variables



Note: The log of the number of migrants flowing in has been adjusted for the fixed effects. The points in each graph are partial residuals for log migration inflow, and the shaded area represents 95% confidence intervals.

Figure 2.5: Partial Fits of Adjusted Net Migration and Treatment Variables



Note: The share of net migrants in the population has been adjusted for the fixed effects. The points in each graph are partial residuals for net migration, and the shaded area represents 95% confidence intervals.

Table 2.1: Statistics on Violent Incidents and Deaths by District

District	Province	Area	Population	Incidents			Deaths		
		(sq.km.)	Avg.	Avg.	Min	Max	Avg.	Min	Max
Muang Narathiwat	Narathiwat	305	116,047	41.6	17	63	11.9	5	20
Takbai	Narathiwat	253	67,949	35.4	16	62	9.9	3	16
Bacho	Narathiwat	172	50,300	46.2	15	73	11.8	5	21
Yi-ngo	Narathiwat	201	43,111	22.9	11	44	5.1	1	10
Ra-ngae	Narathiwat	435	87,635	86.1	29	161	34.9	12	90
Rueso	Narathiwat	468	67,096	76.7	29	177	30.0	12	76
Sisakhon	Narathiwat	503	35,631	28.8	11	54	10.6	5	27
Waeng	Narathiwat	374	50,543	15.7	4	41	3.1	0	12
Sukhirin	Narathiwat	517	24,200	8.8	1	27	2.9	0	10
Su-ngai Kolok	Narathiwat	139	74,278	31.5	9	55	10.8	5	18
Su-ngai Padi	Narathiwat	373	54,495	45.2	16	152	14.8	2	56
Chanae	Narathiwat	550	34,660	32.4	11	62	12.4	7	19
Cho-ai-rong	Narathiwat	163	37,831	34.9	6	80	11.4	2	20
Mueang Pattani	Pattani	97	124,153	60.6	16	123	21.7	7	38
Khokpho	Pattani	339	65,644	40.5	5	71	14.1	0	24
Nongchik	Pattani	232	72,713	63.4	33	128	18.1	10	35
Panare	Pattani	144	44,340	30.6	9	86	13.1	2	30
Mayo	Pattani	216	55,889	33.8	21	50	13.2	4	20
Thungyangdaeng	Pattani	115	21,749	21.4	5	45	10.6	1	20
Saiburi	Pattani	178	65,651	57.8	27	89	23.9	12	45
Maikaen	Pattani	55	11,807	7.5	2	15	2.1	0	6
Yaring	Pattani	197	81,889	38.7	13	89	13.3	8	26
Yarang	Pattani	184	89,443	73.2	26	127	23.8	5	40
Kapho	Pattani	94	16,877	21.6	2	83	8.6	0	22
Maelan	Pattani	89	15,641	7.3	1	24	2.9	0	9
Mueang Yala	Yala	258	162,708	123.9	41	395	33.6	14	83
Betong	Yala	1,328	59,021	12.6	5	37	3.2	1	8
Bannangsata	Yala	629	56,188	75.0	23	166	27.8	7	97
Thanto	Yala	648	22,919	30.6	11	55	5.6	2	11
Yaha	Yala	500	56,625	36.4	11	81	16.8	5	53
Raman	Yala	516	88,140	78.9	11	185	26.4	6	57
Kabang	Yala	451	21,004	8.6	1	22	2.7	0	11
Krongpinang	Yala	191	25,290	21.4	5	43	8.9	3	23
Chana	Songkhla	503	100,038	6.5	0	14	3.1	0	10
Nathawi	Songkhla	747	63,982	2.8	0	8	1.5	0	4
Thepha	Songkhla	978	71,942	18.1	2	47	5.8	0	15
Sabayoi	Songkhla	866	70,703	18.4	2	61	7.2	0	36
Total		**14,008**	**2,208,131**						

Source: Ministry of the Interior, and the Deep South Watch Organization

Table 2.2: Statistics on Population and Migration by District

	Population		**Migration Outflow**			**Migration Inflow**			**Net Migration**		
District	**2004**	**2017**	**Avg.**	**Max**	**Min**	**Avg.**	**Max**	**Min**	**Avg.**	**Max**	**Min**
Muang Narathiwat	108,145	125,232	8,445	10,088	6,700	7,017	8,571	5,999	-1,429	196	-2,786
Takbai	63,530	72,407	2,509	4,024	1,896	2,814	4,555	2,218	306	531	104
Bacho	47,090	54,269	2,130	3,543	1,791	2,384	3,509	1,998	254	527	-34
Yi-ngo	40,416	46,016	1,470	2,285	1,145	1,931	2,538	1,563	461	717	249
Ra-ngae	83,580	92,366	3,916	5,228	3,076	4,178	5,334	3,306	262	843	-241
Rueso	62,064	72,116	3,211	4,377	2,678	3,456	4,310	2,870	245	583	-67
Sisakhon	30,547	39,827	1,740	2,335	1,497	2,131	3,003	1,652	391	668	121
Waeng	46,676	53,843	1,774	2,554	1,268	2,126	3,004	1,558	352	549	190
Sukhirin	21,756	26,258	1,436	2,014	1,117	1,642	2,232	1,240	206	825	-74
Su-ngai Kolok	69,419	78,576	5,323	6,760	4,808	4,414	5,793	3,791	-909	-556	-1,427
Su-ngai Padi	53,919	56,692	2,402	3,614	1,710	2,573	3,585	1,954	171	321	-119
Chanae	30,829	38,342	1,331	1,808	1,053	1,527	1,991	1,132	196	425	20
Cho-ai-rong	35,804	40,295	1,518	2,710	1,156	1,590	2,215	1,049	71	387	-546
Mueang Pattani	117,957	132,628	9,629	12,102	8,676	7,552	9,381	6,248	-2,077	-773	-3,734
Khokpho	64,031	68,180	2,542	3,795	1,906	2,656	3,294	2,110	114	469	-501
Nongchik	68,144	79,856	3,723	4,513	3,086	4,264	4,993	3,432	541	1,516	-222
Panare	42,850	46,336	1,779	2,603	1,173	1,807	2,408	1,210	28	236	-236
Mayo	52,707	60,333	2,541	3,397	2,022	2,789	3,415	2,263	248	499	-209
Thungyangdaeng	19,920	23,983	1,006	1,301	816	963	1,244	698	-43	100	-187
Saiburi	62,633	69,844	2,792	3,557	2,151	2,931	3,864	2,435	138	592	-387
Maikaen	11,168	12,637	479	693	349	439	606	314	-40	42	-127
Yaring	77,113	87,540	3,094	4,510	2,327	3,298	4,013	2,685	205	543	-497
Yarang	83,073	93,131	3,456	4,505	2,526	3,661	4,412	3,059	205	689	-666
Kapho	15,613	18,452	670	789	449	739	880	523	69	168	-6
Maelan	14,652	16,876	641	908	498	679	883	471	38	191	-119
Mueang Yala	161,621	169,003	13,506	19,037	12,160	9,682	14,591	8,041	-3,824	-2,478	-4,635
Betong	53,451	62,523	3,939	5,418	3,084	3,879	5,790	2,678	-61	372	-565
Bannangsata	52,357	61,109	2,429	3,025	2,054	2,555	3,420	1,977	126	500	-667
Thanto	20,750	24,857	1,165	1,669	877	1,334	1,977	962	169	364	-64
Yaha	50,466	62,259	2,222	3,168	1,619	2,476	3,448	1,916	254	476	59
Raman	82,364	94,785	3,548	4,766	2,714	4,080	4,812	3,464	532	867	46
Kabang	16,988	24,282	829	1,052	719	1,119	1,565	867	290	513	98
Krongpinang	21,871	28,477	826	1,151	662	1,275	1,711	1,031	450	656	266
Chana	93,283	106,635	3,992	5,433	3,338	5,194	7,021	4,429	1,202	1,821	885
Nathawi	57,640	68,962	3,712	4,891	3,291	4,087	5,514	3,212	376	999	-273
Thepha	66,103	77,892	2,758	3,705	2,374	3,345	4,482	2,784	588	1,110	34
Sabayoi	61,894	77,780	2,581	3,053	2,079	3,290	3,951	2,502	709	905	379

Source: Ministry of the Interior

Table 2.3: Effect of Violent Incidents on Migration

	Ln Migration Outflow			Ln Migration Inflow			Net Migration/Population		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log of Number of Incidents	0.0298			0.000341			-0.00172		
	(0.0620)			(0.9850)			(0.0510)		
Log of Number of Incidents in Previous Year		0.0294			0.00232			-0.00138	
		(0.1040)			(0.9220)			(0.1080)	
Log of Number of Incidents 2 Years Earlier			0.000116			-0.0144			-0.000807
			(0.9980)			(0.4140)			(0.2560)
Observations	518	481	444	518	481	444	518	481	444

Note: Standard errors are clustered by multi-way clustering method at the district level and year with 37 districts and 12-14 years respectively. The respective p-values are reported in the parentheses using post-estimation command *boottest* (Roodman (2018)) with 1,000 replications.

Table 2.4: Effect of Number of Deaths on Migration

	Ln Migration Outflow			Ln Migration Inflow			Net Migration/Population		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log of Number of Deaths	0.0281			-0.000741			-0.00151		
	(0.0610)			(0.9590)			(0.0040)		
Log of Number of Deaths in Previous Year		0.0287			-0.00389			-0.00141	
		(0.0940)			(0.8220)			(0.0000)	
Log of Number of Deaths 2 Years Earlier			0.0243			0.0149			-0.000463
			(0.1447)			(0.4390)			(0.2470)
Observations	518	481	444	518	481	444	518	481	444

Note: Standard errors are clustered by multi-way clustering method at the district level and year with 37 districts and 12-14 years respectively. The respective p-values are reported in the parentheses using post-estimation command *boottest* (Roodman (2018)) with 1,000 replications.

Table 2.5: Top Decile: Number of Incidents and Deaths

	Migration Outflow		Migration Inflow		Net Migration/Population	
	(1)	(2)	(3)	(4)	(5)	(6)
Log of Incidents	0.0400		0.00883		-0.00211	
	(0.2220)		(0.7720)		(0.0460)	
Log of Deaths		0.0304		0.0123		-0.00112
		(0.4890)		(0.6840)		(0.4420)
Observations	518	518	518	518	518	518

Note: Standard errors are clustered by multi-way clustering method at the district level and year with 37 districts and 14 years respectively. The respective p-values are reported in the parentheses using post-estimation command *boottest* (Roodman (2018)) with 1,000 replications.

Table 2.6: Long-term Effect on Population

	$LnPopulation_{i,2017}$ $-LnPopulation_{i,2004}$		$LnPopulation_{i,2003}$ $-LnPopulation_{i,1996}$		$LnPopulation_{i,2017}$ $-LnPopulation_{i,2004}$			
	OLS		Placebo		OLS		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ln(\sum_{t=2004}^{2017} Incidents_{i,t})$	-0.0295		-0.0248		-0.0155		-0.0161	
	(0.0120)		(0.0186)		(0.00558)		(0.00464)	
$Ln(\sum_{t=2004}^{2017} Deaths_{i,t})$		-0.0273		-0.0229		-0.0142		-0.0146
		(0.0120)		(0.0185)		(0.00570)		(0.00495)
$(LnPopulation_{i,2003}$ $-LnPopulation_{i,1996})$					0.563	0.569	0.541	0.555
					(0.0479)	(0.0493)	(0.0856)	(0.0915)
Observations	37	37	37	37	37	37	37	37

Note: Robust standard errors are reported in parentheses. In columns (5) and (6), log of population in 1996 was used as an instrument for change in log of population from 1996 to 2003.

Table 2.7: Long-term Effect on Night Lights

	$LnAvgLight_{i,2013}$ $-LnAvgLight_{i,2004}$		$LnAvgLight_{i,2003}$ $-LnAvgLight_{i,2000}$		$LnAvgLight_{i,2013}$ $-LnAvgLight_{i,2004}$			
	OLS		Placebo		OLS		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ln(\sum_{t=2004}^{2013} Incidents_{i,t})$	-0.123		-0.0658		-0.114		0.025	
	(0.0424)		(0.0883)		(0.0413)		(0.167)	
$Ln(\sum_{t=2004}^{2013} Deaths_{i,t})$		-0.0876		-0.0758		-0.0766		0.096
		(0.0490)		(0.0855)		(0.0502)		(0.172)
$(LnAvgLight_{i,2003}$ $-LnAvgLight_{i,2000}$					0.136	0.146	2.255	2.419
					(0.0952)	(0.103)	(1.352)	(1.450)
Observations	37	37	37	37	37	37	37	37

Note: Robust standard errors are reported in parentheses. In columns (5) and (6), log of night lights in 2000 was used as an instrument for change in log of night lights from 2000 to 2003.

Table 2.8: Effect of Violent Incidents on Monthly Wages and Working Hours

	Log of Wage						Log of Total Working Hours					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Ln\ Incident_{i,t}$	0.102	0.00799					0.0208	-0.0177				
	(0.4500)	(0.6750)					(0.2000)	(0.0040)				
$Ln\ Incident_{i,t-1}$			0.104	0.0253					0.0224	-0.00309		
			(0.3710)	(0.0268)					(0.1500)	(0.7730)		
$Ln\ Incident_{i,t-2}$					0.0910	0.0111					0.0238	0.00898
					(0.4330)	(0.3642)					(0.1040)	(0.4010)
Observations	26,545	26,545	24,647	24,647	22,512	22,512	26,545	26,545	24,647	24,647	22,512	22,512

Note: Standard errors are clustered by multi-way clustering method at the district level and year with 37 districts and 12-14 years depending on the specifications. The respective p-values are reported in the parentheses using post-estimation command *boottest* (Roodman (2018)) with 1,000 replications.

Table 2.9: Effect of Death on Monthly Wages and Working Hours

	Log of Wage						Log of Total Working Hours					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Ln\ Death_{i,t}$	0.0858	0.00387					0.0209	-0.00935				
	(0.4340)	(0.7718)					(0.2800)	(0.3590)				
$Ln\ Death_{i,t-1}$			0.0875	-0.00478					0.0195	-0.0161		
			(0.3670)	(0.5662)					(0.3250)	(0.1550)		
$Ln\ Death_{i,t-2}$					0.0865	0.0113					0.0248	0.00123
					(0.3270)	(0.4440)					(0.1820)	(0.9020)
Observations	26,545	26,545	24,647	24,647	22,512	22,512	26,545	26,545	24,647	24,647	22,512	22,512

Note: Standard errors are clustered by multi-way clustering method at the district level and year with 37 districts and 12-14 years depending on the specifications. The respective p-values are reported in the parentheses using post-estimation command *boottest* (Roodman (2018)) with 1,000 replications.

Chapter 3

The Effects of Rice Policy in Thailand: Evidence from Microdata 2009 - 2015

Abstract

The Thai government implemented a rice pledging scheme during 2011-2014 allowing for an unlimited amount of rice to be pledged at a high price. Hence, rice farmers experienced temporary increases in sales prices during this period. This chapter examines the impact of this program on revenues of rice farmers by using annual household panel data from 2009 to 2015. The results indicate that the policy did increase the nominal revenues of rice farmers by approximately 35 percent annually. Finally, a heterogeneity analysis provides suggestive evidence that only the middle 50 percent of rice farmers by income level benefited from the program, while the top and bottom 25 percent of rice farmers did not gain from the policy.

3.1 Introduction

Thailand's rice pledging policy was first introduced in 1981 to resolve the rice over-supply problem during the harvest season. The program allowed farmers to use their products as collateral at the Bank of Agriculture and Agricultural Cooperatives. Consequently, farmers could store their products during the low-price harvest season and redeem them back to sell when prices increased. Generally, the pledging price was set close to the market price, and a limited amount of rice was eligible for pledging for each household and each area. Hence, government spending on the program remained low (Poapongsakorn and Jarupong (2010), Isvilanonda (2010)). Most subsequent governments continued this rice pledging scheme with small adjustments in price and quota per area. However, in 2011, there was an important change in the program when the government under Prime Minister Yingluck Shinnawatra allowed for an unlimited amount of rice to be pledged at a high price. This had been a prominent part of the election campaign that led to a land-slide victory in the July 2011 general election. With a higher than market price and offers of unlimited purchases, the government became the largest rice buyer in the domestic market. While the government gained more popularity from farmers who experienced a high sales price, this policy generated an enormous fiscal burden and hence people in urban areas were against the program. This controversy was one of the key reasons for the political protests against the government in Bangkok that started from October 2013 and led to the coup d'etat in May 2014. The following military government immediately terminated the rice pledging policy.

Consequently, this high-price rice-pledging scheme was implemented for only about three years from October 2011 to May 2014. Total government spending for this program was 718,966 million baht (20 billion US dollars), which was around 10 percent of the government budget and 2 percent of GDP. Rice pledged to the program was about 72 percent of total production. This policy can be considered as a natural experiment that was imposed for 3 years, allowing for a study of the benefits to households of a temporary positive shock to the rice price.[1] Accordingly, the main objective of this study is to examine the impact of the 2011-2014 rice pledging program on farmers' revenue by employing household level data.

The dataset used in this study consist of annual panel data at the household level from the Townsend Thai project. This survey was conducted in six provinces with different socio-economic backgrounds and geography. For this research, I use data from 2009 to 2015. Although the policy was implemented from October 2011 to May 2014, the treatment period in this study is 2012 to 2014, which corresponds to the time that participating farmers actually received money through the program. The variable of interest in this study is household agricultural revenue. This data is separated into three types of revenue

[1] In fact, the objectives of this policy were not only to increase farmers' incomes and improve their living standards, but also to raise the export price of Thai rice due to the government's monopoly power. This research focuses only on the first objective, which is the impact on farmers.

sources: rice, tree crop and field crop. Hence, I divide households into those three categories based on their main revenue sources during the pre-treatment period (2009-2010) and define households as rice farmers if the shares of nominal revenue from rice in their total nominal revenue was higher than the share for the other two crop types. Furthermore, to take into account the facts that changes in farmers' income were not only influenced by government policy but also by world prices of agricultural products, I construct provincial price deflators based on export prices of agricultural commodities and provincial production shares to deflate nominal revenue to revenue net of world price changes. Consequently, the dependent variables in this research are total nominal revenue of households, total real revenue of households (i.e. net of world price changes), and real revenue from the main crop of households. Moreover, only permanent farmers who had income from agriculture every year are included in the sample, which consists of 440 households with 272 rice farmers and 168 non-rice farmers.

The first set of estimates aim to examine the impact of the policy only on rice farmers, under the identification assumption that rice farmers' income in 2012 to 2014 increased due to the policy while their revenues in other years remained unchanged, including in 2015 after the policy was terminated. The results show a significant increase in nominal revenue, real revenue, and revenue from main crop during the treatment period. However, rice farmers' revenue increases could have been induced not only by this policy, but also by other factors that took place during the treatment period. Accordingly, I also apply a difference-in-difference approach in order to exclude the impact of these other factors, by including non-rice farmers as a comparison group. For this specification, the key assumption is that the rice pledging program affected only the revenue of rice farmers while other factors affected revenues of rice farmers and non-rice farmers equally. The estimates show positive and significant difference-in-difference coefficients for all dependent variables, supporting the conclusion of the benefit of the policy to rice farmers.

In a set of alternative specifications, this study also uses farmers' share of revenue from rice in 2009 and 2010 as the regressor instead of categorizing households into rice and non-rice farmers, using their initial shares of income from rice as a measure of their degree of exposure to the policy. Hence, this specification expects that a farmer with a higher initial share of revenue from rice was treated more intensely, and hence their income would increase by more due to the policy. The results show that the total nominal revenue and total real revenue of households during policy implementation increased by 23.7 percent and 19.8 percent of their initial share of revenue from rice respectively. These results again indicate a positive impact of the policy which is consistent with the previous estimates.

Finally, this policy aimed to support poor farmers. However, all farmers could pledge their production to the government, including wealthy farmers, and thus they may also have benefited from the program. Consequently, the last empirical strategy aims to examine the heterogeneous effects of the policy. I first define rich and poor farmers as the top and bottom 25 percent of revenue earners in 2009 and 2010. The results indicate that only the middle 50 percent of rice farmer households benefited from the program.

This study contributes to the agricultural policy literature, particularly the literature on the effects of government purchasing programs. One related work is Chen et al. (2014) which models the impact of government agricultural goods purchasing policy during a collapse in agricultural prices due to a good harvest. This study also shows that government intervention can stabilize wholesale prices and farmers' nominal incomes. However, most frontier research on agricultural policy in developing countries focuses on the effects of input subsidies and determinants of households' technology adoption. Those studies include Duflo et al. (2011) on fertilizer use in Kenya, Carter et al. (2013) on improvement in seeds and fertilizer in Mozambique, and Ricker-Gilbert et al. (2011) on fertilizer subsidies in Malawi. Insurance policy is also an active topic of study, particularly as a risk-management tool for households. The works of Gin et al. (2007) on rainfall insurance in India, Karlan et al. (2014) on liquidity constraints and rainfall insurance in Ghana, and Reyes et al. (2017) on revenue insurance for farmers and fishermen in the Philippines show the possible positive contribution of insurance policy in the agricultural sector.

The empirical results of this study point to benefits of the rice pledging policy for rice-growing households since the revenue of these farmers increased during the treatment period. However, further research is needed to understand how this program affected farmers in dimensions other than revenue, particularly expenditure, saving, and investment decisions. Moreover, this study does not identify effects on macroeconomic variables such as inflation, non-farm income, and employment. The heterogeneity analysis suggests that poor farmers did not benefit from the program, which was not entirely in line with the policy objective of improving the revenue of the poor. Moreover, the policy increased incomes of farmers only in the short run, since the study showed that farmers' revenue declined after the policy was terminated. Finally, a crucial limitation of the 2011-2014 rice pledging policy was its enormous fiscal burden, suggesting that the program would not have been able to continue in the long term although its goal could be achieved in the short term. Alternatively, the policy could be adjusted to target only poor farmers in order to reduce the budget required.

The remainder of this chapter is organized as follows: Section 3.2 provides information about rice policy in Thailand, including the 2011-2014 rice pledging scheme. The related literature for this study is also discussed in this part. Section 3.3 explains the dataset used as well as the definition of the main variables, Section 3.4 examines empirical strategies and results, and Section 3.5 draws conclusions and implications from the results.

3.2 Background

3.2.1 Agricultural Policy in Thailand

The agricultural policy in Thailand from the 1950s to the 1970s was unfavourable to the agricultural sector, particularly the export tax that government imposed on rice from the end of World War II in order to control domestic inflation and increase government revenue. Because rice was the most valuable export at that time, the export tax on rice yielded significant revenue, which was used to support the industrialization process. Nonetheless, the government policy became more pro-agriculture in the 1980s due to several factors. Firstly, Thailand signed the GATT agreement in 1982 which forced it to liberalize the rice sector. As a result, the rice export tax was gradually phased out. Secondly, Thai technocrats began to realize the widening gap between urban and rural areas, which was a result of the imbalance in development between the industrial and agricultural sectors. Hence, the government policy turned to support the agricultural sector and particularly rice, together with industrial policy. Moreover, the democratic parliament became the crucial institution for policy formation after the collapse of the military dictatorship in 1973. Therefore, rice policy became a politically important issue (Siamwalla and Setboonsarng (1991), Warr (2001), and Isvilanonda (2010)).

The rice support policy was first introduced in 1965. The government intervened in the market when there was excess supply by buying rice at a slightly below-market price in order to absorb excess production and increase the market price. However, there was no effect on the overall rice market since the proportion of government buying was about 1 to 2 percent of total production. In 1981, the rice support policy was significantly changed when the rice-pledging program was introduced. Farmers could use their rice as collateral at the Bank of Agriculture and Agricultural Cooperatives (BAAC), a government-owned financial institution. Initially, they could borrow as much as 80 percent of the product's value, up to 100,000 baht or about 4,000 US dollars per farmer. Consequently, farmers were able to store their products in registered storehouses during the low-price harvest season and redeem them to sell in the high-price off-season. This measure also relieved farmers' liquidity constraints since their production inputs were regularly bought from local suppliers with the credit provided by the program. Nonetheless, farmers had to pay an interest rate and storage fee to the BAAC of around 13 percent per year when they redeemed their products. Hence, they redeemed their rice back only if the market price was particularly high. However, in practice they seldom redeemed rice back in order to avoid high interest payments, and thus the BAAC had to sell it at the market price instead. Prior to 1986, less than 1 percent of the production was pledged to the program. Therefore, the government sharply cut their lending rate to 3 percent per year and allowed farmers to keep their products in their own storehouses to avoid an extra storage fee and other transaction costs. After this adjustment, the number of farmers who participated in this program increased significantly. The proportion of rice that was pledged under the program increased to an average of 6.8 percent of total production during 1987 to 2001. Also, the pledging price was set close to the market price, so government expenditure on this policy remained low (Poapongsakorn and Jarupong (2010), and Isvilanonda (2010)).

During this period, other major crops such as rubber, cassava and sugar cane were also supported by government policy. Generally, price guarantee schemes were used to counter situations where prices were particularly low. However, the scale of these policies were smaller than that of the rice policy in term of the budget required and farmer participation (Chomchan et al. (2014)).

3.2.2 Contemporary Rice Policy

Rice policy is politically important in Thailand since it has direct consequences for rural voters. Hence it has always been actively debated in every election. Nonetheless, a series of governments continued the rice pledging program as described above with little adjustment in price and quota per area. The first major change came in 2001 when the government notably increased the pledging price to 30 percent, higher than the market price, but limited the amount of pledgeable rice for each area and farmer. This was also the first time that the policy was implemented at the national level (Duangbootsee (2014)). Rice pledged under this program immediately increased to around 20 percent of total production. Government expenditure also increased: the government spent 6.9 billion baht (200 million US dollars) on this policy in 2000, which ascended to 49 billion baht (1.5 billion US dollars) and 56 billion baht (1.75 billion US dollars) in 2001 and 2002 respectively, as shown in table A3.1. Because the pledging price was higher than the market price, few farmers withdrew their rice, so the government's rice stock gradually accumulated due to the lack of ability to sell rice to the market (Poapongsakorn and Jarupong (2010)).

However, the rice pledging program was significantly affected by high global commodity prices during 2004-2007. Since farmers could sell at high market prices, very few farmers pledged rice to the government. In 2008, the government replaced the rice pledging policy with an income guarantee scheme. Under this program, farmers were guaranteed a minimum income based on the amount of rice they normally produced, even if their crop turned out badly due to external causes such as flood, drought and diseases. Moreover, there was no direct government intervention in the rice market since farmers sold their rice to markets. Farmers received compensation from government only if the market price was lower than the government's reference price, which was set close to the market price. This program required the BAAC to survey participants' farms in order to estimate the expected product and farmers were compensated based on their land. Implicitly, this policy worked similar to the rice pledging policy with a limited quota per farmer. This policy was criticized for being favourable to huge land owners rather than small-scale farmers who regularly cultivated on rented land. Furthermore, this scheme required high operating costs since the BAAC had to survey the land and crop each participant. Moreover, even participants who did not allocate all their land area to growing rice could to receive benefits based on their land area (Poapongsakorn and Jarupong (2010)).

The most controversial rice policy was the change to the rice pledging scheme during the tenure of former Prime Minister Yingluck Shinawatra, who came to the office in October 2011. The new government terminated the income guarantee scheme and brought the rice pledging policy back with a very high pledged price and an unlimited amount of rice for each farmer. This policy was first announced in May 2011 as a prominent part of the election campaign that led to a land-slide victory in the July 2011 general election. While the government gained more popularity from farmers due to this policy, people in urban areas were against the program since it led to uncontrollable contingent liability. Moody's credit rating agency downgraded Thai sovereign debt in June 2013 as a result of the huge fiscal burden of this policy, leading to frustration from the business sector. This policy was one of the reasons for the political protests against the government in Bangkok starting from October 2013, which led to the coup d'etat in May 2014. The following military government immediately terminated this rice-pledging scheme (Sawasdipakdi (2014)).

According to the National Rice Policy Committee (2013), the objectives of this policy were to increase farmers' incomes and improve their living standards. Moreover, it also aimed to raise the export price of Thai rice due to the government's monopoly power since Thailand was the largest rice exporter during that time. Unfortunately, the latter objective failed to be achieved since the international price did not increase while the Thai government held its large stock of rice.[2] This study focuses only on the first objective, that is the impact on farmers, which is expected to be positive.

The high-price rice-pledging scheme was implemented for about three years from October 2011 to May 2014. The total budget for this program was 718,966 million baht which was around 10 percent of the government budget and 2 percent of GDP. Rice pledged to the program was about 72 percent of total production (detail in Table A3.2). Although the rice sector had been subject to government interventions for decades, the rice pledging scheme during 2011 to 2014 was clearly different in terms of its budget, as illustrated in Table A3.1. Hence, this study aims to examine the impact of this exceptional program during 2011 to 2014 while the periods when other programs were in place are defined as untreated. Further information on the treatment and control periods in this study will be provided in Section 3.3.

The effect of the policy has been the subject of debate. From the macroeconomic perspective, most studies have pointed to the negative effect of this policy. Chulaphan et al. (2012) argued that this rice pledging scheme lessened the Thai competitive advantage in the global rice market. Permani and Vanzetti (2016) applied a 10-region dynamic stochastic partial equilibrium model of global rice trade to evaluate the impact of the scheme, and found that the policy supported producer incomes, but generated a burden on taxpayers and consumers.

[2] This was consistent with the argument of Mahanaseth and Tauer (2014) that even though Thailand was the largest rice exporter, there were other competitors, especially India and Vietnam. They suggested that when Thailand reduced its export level, those countries would increase production and take over Thailand's market share instead. Hence, the Thai government did not have sufficient influence in the international rice market to determine the global price. This result is consistent with Dawe (2008) and Ghoshray (2011) which also illustrate that the Thai domestic rice price followed the global price.

Microeconomic studies focusing on the policy's impact on farmers have found a positive effect. For example, Attavanich (2016) used farm-level data to examine the effect of this 2011-2014 rice pledging program. The results showed that the policy increased small farms' revenue more than that of medium and large farms. However, the program had no significant effect on farm investment. Kobayashi et al. (2016) evaluated the effect of the rice pledging program on the distribution of income by production factor. The results showed that family labour received the highest benefit during main crop production, but for the second crop, hired labour and suppliers of purchased inputs gained most from the policy. Moreover, this study also simulated the effect of an input purchase price support scheme as an alternative policy. The results indicated that suppliers of purchased inputs would benefit most from this alternative policy, but the effect on other factors' owners was limited. Furthermore, Poapongsakorn et al. (2014) focused on the program's implementation and corruption. The results showed high transaction costs and rent seeking that led to higher government spending than expected. They also found delays of payments in several areas. However, overall farmers were found to be satisfied with this policy.

This study aims to understand the effect of the policy at the micro level, and the main difference from other research is the dataset. While other studies have relied on cross-sectional data, this study uses panel data. This allows me to estimate the impact of the policy across time, comparing farmers between pre-treatment and treatment years. Moreover, it is possible to investigate the responses of particular household types to this policy. The details of the dataset will be described below.

3.3 Data

The dataset used in this research is annual panel data at the household level from the Townsend Thai project. The dataset includes six provinces from four regions, which are Chachoengsao and Lopburi from the Central region, Buriram and Sisaket from the North-Eastern region, Prae from the Northern region, and Satun in the Southern region, as illustrated in Figure A3.1 (Townsend (2011), Townsend et al. (2013)). These six provinces have different socio-economic backgrounds and geographical locations as shown in Table A3.4. This variation across the sample provinces well represents the regional heterogeneity in the Thai agricultural sector.

The dataset is separated into two categories, rural and urban areas. Since this study focuses on the agricultural sector, I use only rural households' data. Through stratified random sampling, the dataset is based on four districts per province from Chachoengsao, Lopburi, Buriram, and Sisaket, and two districts per province from Satun and Phrae (which have a smaller population than the other four provinces). Subsequently, four villages from each district and then 15 households in each village have been randomly selected. Hence, this dataset includes 1,200 households each year, with an attrition rate of around 1.3 percent (Townsend et al. (2013)). This dataset is based on surveys at the household level, including details on income, consumption, borrowing, lending, saving, assets, agricultural assets, household composition, and business activity.[3]

For this research, I use data from 2009 to 2015, which covers pre-treatment, treatment and post-treatment years. Although the policy was implemented from October 2011 to May 2014, the treatment period in this study is defined as 2012 to 2014. Rice production in Thailand consists of two crops per annum. The main crop is cultivated in the latter half of the year during the rainy season and harvested around November and December. The second crop is planted in areas with good water management systems or sufficient rainfall level, and is harvested around May to June. For participants in the program, the expected time of receipt of money was around 1-2 months after harvest (Poapongsakorn et al. (2014)). Hence, farmers who participated in the program for the main crop in 2011 would have received money in early 2012. Consequently, the effective treatment period for this study is 2012 to 2014 as illustrated in Table A3.3. The table shows a timeline of the rice pledging policy, including the time that farmers received money.

The dependent variable in this study is the agricultural revenue of a household. It includes revenue from three types of sources: rice, tree crops and field crops. Tree crops mainly include rubber and cassava, while sugar cane and maize are classified as field crops. Hence, I divide households into those three categories, defined based on their main revenue sources during the pre-treatment period, including 2009 and 2010 but not 2011. I exclude 2011 from this calculation because this policy was first publicly introduced in June 2011 as part of the election campaign in advance of the July 2011 election. Farmers may have adjusted their planting behaviours after they knew the election result, and I therefore use only 2009 and 2010 to define the farmer's type in order to exclude the endogenous effect of

[3]This dataset is the only long period panel dataset in Thailand, and thus it has been widely used in several studies focusing on the Thai micro-level economy. The notable works examining the impact of policy or external shocks on the households are Gruber et al. (2014), focusing on the impact of universal health care reform, and Kaboski and Townsend (2012), investigating the effect of the government village fund.

the policy. Consequently, a household is defined as a rice farmer only if their initial share of nominal revenue from rice in total nominal revenue was highest among all three crop types. Moreover, I drop households that do not have data in all seven years (2009-2015) since most of these households are exclusively observed early or late in the sample period. This is because the latter households were selected to replace the former in the data set. This survey has a low attrition rate so this issue is associated with a small number of observations.

Presumably, the policy directly affected only revenue from rice and did not affect the other two crops. Rice farmers are considered as the treated group while other crops' farmer are a control group. Nevertheless, some tree crop and field crop farmers also had revenue from rice as a secondary or third crop. Figure 3.1 shows the proportion of nominal revenue from rice in total nominal revenue in the pre-treatment (2009-2010) and treatment (2012-2014) periods. The scatter plot illustrates that many non-rice households had revenue from rice during the initial period and vice versa. Moreover, many households changed their crop revenue distribution between those two periods. The households above the 45 degree line increased their shares of rice revenue, including some non-rice households that had rice as their major revenue source during the treatment period. On the other hand, many rice farmers also decreased their rice revenue share as represented below the 45 degree line. Considered jointly, these issues might lead to either underestimation or overestimation of the effect of interest.

In fact, there are some households that did not have revenue from agriculture in every year of the data set but had non-agricultural income such as remittances and wages. These non-permanent farmers also tended to have extreme switches in crop type reflected in their revenue structures. For example, they might switch from 100 percent rice to 80 percent tree crops in the following period. Presumably, these farmers did not rely only on agriculture so could abandon their land during bad years or when other sectors provided better earning opportunities. Their behaviours may have been different from permanent farmers who had to grow crops to cover their living costs. Accordingly, these non-permanent farmers were excluded from this study. Figure 3.2 illustrates the evolution in share of nominal revenue from rice without the non-permanent agricultural households. Compared with Figure 3.1, the latter plot illustrates fewer extreme switching households.

After these adjustments, the data set for this study includes 440 households from 73 villages, with 272 rice farmers and 168 non-rice farmers. Table 3.1 exhibits the number of households by province and crop type, and the second part of the table shows the actual provincial crop structure estimated from the 2009 agricultural production report by the Office of Agricultural Economics. The data illustrates the variety in production structure across provinces. The Central and Northern regions (Chachoengsao, Lopburi, and Phrae) had rice production of around 60 to 75 percent of total agricultural production. For the North-Eastern region (Buriram and Sisaket), rice contributed around 80 percent. Satun in the Southern region had rubber as its main crop, while rice only contributed 7.7 percent of total revenue. Importantly, the number of households by crop type in each province has a similar pattern to the actual provincial agricultural structure, reflecting the representativeness of this data set.

One factor that can influence farmers' revenue is the export price. If the policy's impact is evaluated based only on nominal revenue, the result will also include the effect of world price fluctuations. Most agricultural production in Thailand is for export. Hence domestic prices of such commodities are highly influenced by global prices. Table A3.5 shows the export price indices of five main crops, namely rice, rubber, cassava, sugar cane, and maize, estimated from customs data. In fact, the global prices of rubber, maize, and sugar cane were very unstable and increased sharply during 2010 to 2012. While, the rice price was relatively stable. I use these export price indices, along with provincial production structures, to construct provincial price indices for field crops and tree crops as presented in Table A3.6. I then deflate revenue from rice by the export price index and revenue from field crops and tree crops by these provincial price indices to derive a measure of real revenue net of world price fluctuations. Figure A3.4 illustrates the average household's nominal revenue only from their main crop, showing that the average household's revenue from tree crops and field crops sharply increased during the pre-treatment period. In contrast, Figure A3.5 shows the average household's real revenue from main crop after deflating by the export price indices. The graph displays a more parallel tendency among the three types of households during the pre-treatment period. Consequently, by removing the effect of export prices, I can estimate the policy impact accurately.[4]

Table 3.2 presents the average revenue of households for the whole period (2009-2015), the pre-treatment period (2009-2010), and the treatment period (2012-2014). The first three columns show all households in the sample, while the following columns separate

[4]Figures 3.1 and 3.2 are reproduced using real revenue in Figures A3.2 and A3.3.

households by income into rich (top 25%) and non-rich (bottom 25%) which will be further discussed in section 3.4.2. This table includes both nominal and real (net of world price changes) revenue data.

One important limitation of this dataset is that there is no information on program participation of households. Hence, the results of this study will exhibit the impact on all rice farmers, not only farmers who directly participated in the program. However, Poapongsakorn and Jarupong (2010) study the rice pledging scheme in 2005-2006, and find that farmers who did not participate also received a benefit from the program via an increase in the rice price.

3.4 Empirical Strategy and Results

3.4.1 Main Results

In the first specification, only rice farmers are taken into account. Hence, the identification strategy for the first estimates is that rice farmers' income in 2012 to 2014 increased only due to the policy while their revenues in other years remained unchanged, including in 2015 after the policy was terminated. I estimate equation 3.1 where Y_{it} is the outcome variable of household i in year t, the fixed effect for household i is denoted by α_i, and the $TREAT_t$ dummy indicates the treatment period, and equals one for the years 2012 to 2014 when the policy was in effect and zero otherwise.

$$\ln(Y_{it}) = \beta \cdot TREAT_t + \alpha_i + \varepsilon_{it} \tag{3.1}$$

The results are illustrated in the first three columns of Table 3.3. Standard errors are clustered at the village level (with 51 villages), and p-values are reported in parentheses. The estimated coefficients show a significant increase in the revenue of rice farmers during the policy period. Total nominal revenue and total real revenue increased by an annual average of 35.5 and 29.7 percent respectively. Real revenue from rice increased by 23.7 percent. The number of observations when the dependent variable is revenue from rice is 1,877, which is lower than 1,904 for the other two dependent variables, because some rice farmers did not have income from rice in some years but still had revenue from other crops in that year.

I next separate out annual changes using year fixed effects. This specification does not separate treatment and control years. However, it can show farmer's revenue movement in each year, which is represented by the coefficients β_t in equation 3.2 as follows:

$$\ln(Y_{it}) = \beta_t + \alpha_i + \varepsilon_{it} \tag{3.2}$$

The results are presented in the last three columns of Table 3.3 which indicate that revenue of rice farmers increased since 2010 before the policy was introduced. When the program was terminated, farmers' revenues declined in 2015. The revenue difference between 2014 and 2015 is statistically significant in each specification. Moreover, I also cluster standard errors at the district level (with 16 districts). To address the small number of clusters, I use a wild bootstrap approach based on Cameron et al. (2008) and report the p-values in square brackets in Table 3.3. For this specification, the results are still robust to this different level of clustering.

The revenue increases of rice farmers could have been induced not only by the policy but also by other factors that took place during the treatment period. Accordingly, non-rice farmers are included in the next specification as a comparison group. Specifically, I use a difference-in-difference approach in order to exclude other effects that impacted the agricultural sector as a whole, as represented in equation 3.3. Henceforth, the identification assumption is that the rice pledging scheme impacted only rice farmers but not non-rice farmers, and that both rice and non-rice farmers were equally affected by all other factors.

$$\ln(Y_{it}) = \beta \cdot TREATRICE_{it} + \delta_t + \alpha_i + \varepsilon_{it}. \tag{3.3}$$

Here, $TREATRICE_{it}$ is a dummy indicating that household i at year t is a treated farmer and equals one for rice farmers from 2012 to 2014. Thus, the difference-in-difference estimator (β) captures the policy effect. Standard errors are clustered at the village level (with 73 villages).

The results are reported in columns (1) to (3) of Table 3.4, which are positive and significant when standard errors are clustered at the village level. These results indicate that rice farmers' revenue rose during the treatment period. The magnitude of the estimated effect is now somewhat smaller. Similarly to equation 3.2, I also separately estimate treatment coefficients by year so that β_t now reflects the difference between rice farmers and other crops' farmers in the year t. Column (4), with total nominal revenue as the dependent variable, reports an insignificant difference in 2010 to 2012, which became positive and significant in 2013 and thereafter. On the contrary, the real revenue estimates are positive and significant since 2010, though the estimated coefficients again peak during the treatment period and decline after the program was abolished. This is because of the high world prices of other crops during 2010-2011, particularly rubber and sugar cane, in contrast with the stable rice price (see Table A3.5). These results further support the positive impact of the policy on the incomes of rice farmers. When standard errors are instead clustered at the district level, p-values (shown in square brackets) substantially increase, and the coefficients are not statistically significant.

In fact, some non-rice farmers also allocated land for planting rice, although their main revenue was from other sources. Hence, the rice pledging policy presumably also benefited those farmers even though they might not have gained as much as pure rice farmers. Thus, in my next specification I do not categorize households into rice and non-rice farmers but allow households to be treated depending upon their dependence on rice production. Consequently, I use share of revenue from rice in the year 2009 and 2010 as a proxy for the degree of exposure to the policy of each household. The shares are illustrated on the horizontal axis of Figure 3.2, exhibiting the variation among households in this measure.[5]

In this section, I estimate equation 3.4 with total nominal revenue and total real revenue as dependent variables. I first define the initial share of nominal revenue from rice in 2009 and 2010 of household i, denoted as $SHARERICE_i$, which varies from zero to one and is constant over time. The regressor $SHARERICE_i \times TREATMENT_t$ equals to this share in 2012 to 2014 and is zero otherwise. In addition, year and household fixed effects are included as δ_t and α_i respectively.

$$\ln(Y_{it}) = \beta \cdot SHARERICE_i \times TREATMENT_t + \delta_t + \alpha_i + \varepsilon_{it} \tag{3.4}$$

The estimated coefficients are reported in Table 3.5 which shows positive and significant effects for both nominal and real revenues. The results can be interpreted as suggesting that the total nominal revenue and total real revenue of households during the policy period increased by 23.7 percent and 19.8 percent of their initial share of revenue from rice respectively. This implies that the benefit from the program of each household was determined by its initial share of rice revenue. This conclusion is consistent with the estimates of equations 3.1 and 3.3, not only in its positive direction but also in its similar magnitude.

[5] Table A3.7 displays the evolution of the share of revenue from rice for farmers in the three income categories discussed below.

In columns (3) and (4), the equation instead includes a set of interaction terms of initial share of revenue from rice with each year. Consequently, the coefficients β_t represent the impact of the initial share of revenue from rice on total revenue of household i in year t. For total nominal revenue, the coefficients are negative in 2010 and 2011, which is again the result of high prices for non-rice crops. However, these become positive after 2012 and statistically significant from 2013. For total real revenue, the coefficients are positive and significant from 2010 to 2015. This pattern is similar to the results in Tables 3.3 and 3.4.

3.4.2 Heterogeneity by Income Level

The previous results indicate that the rice pledging policy did enhance farmers' income, which achieved one of the policy's objectives as discussed in section 3.2. However, another crucial goal of the program was to decrease poverty or to support poor farmers. Unfortunately, this dataset does not include any poor households according to the national poverty line which was at 31,764 baht (as shown in Table A3.4). The average revenue of households in this study is 205,208 baht, as illustrated in Table 3.2, and therefore, households in this dataset are likely to represent middle class and rich farmers.

Instead of estimating the policy's effect on the poor which is not allowed by the dataset, it is possible to examine the heterogeneous impact by different income levels of households. I use total revenue of households in 2009 and 2010 to identify the economic status of farmers. For this study, poor farmers are defined as the bottom 25 percent of total revenue for 2009 and 2010, which are the households that had income lower than 92,650 baht per year. The top 25 percent is defined as rich farmers, which are the households that had income higher than 392,068 baht per year. The remaining households are considered as the middle 50 percent of farmers.

Accordingly, 110 of 440 households are marked as poor farmers, which includes 101 rice farmers and 9 non-rice farmers. For rich households, 46 of 110 are rice farmers and 64 of 110 are non-rice farmers. It is noteworthy that the number of rice households in the poor group is much higher than in the rich group, which reflects the poverty status of rice farmers in Thailand. From Table 3.2, the average nominal revenue of rich rice farmers from 2009 to 2015 was around 436,498 baht per year, which was seven times higher than the 59,556 baht per year of poor rice farmers.[6]

In order to clarify the heterogeneity of the policy's impact, I estimate equation 3.5 where $POOR_i$, $RICH_i$ and $MID50_i$ indicate the poor, rich and middle 50 percent household dummies respectively. $TREATRICE_{it}$ denotes the policy dummy which equals one for rice farmer i in treatment period t. The coefficients γ^P and γ^R capture the impact of the policy on poor and rich rice farmers respectively. Likewise, the coefficient γ^M represents the effect of the policy on the middle 50 percent of rice farmers.

$$\begin{aligned} \ln(Y_{it}) = & \gamma^P \cdot TREATRICE_{it} \cdot POOR_i + \gamma^R \cdot TREATRICE_{it} \cdot RICH_i \\ & + \gamma^M \cdot TREATRICE_{it} \cdot MID50_i + \theta_t^P \cdot POOR_i + \theta_t^R \cdot RICH_i \\ & + \delta_t + \alpha_i + \varepsilon_{it} \end{aligned} \tag{3.5}$$

From the results in Table 3.6, the estimated coefficients in the first three columns indicate a positive effect of the policy on the middle 50 percent of rice farmers' revenue. For rich rice farmers, the estimated coefficient is positive and significant only for the log of real revenue from main crop. However, the results suggest that the poor rice farmers did not benefit from the program, in contrast to the policy's objective. However, there were only 9 poor non-rice farmers as compared with 101 poor rice farmers. This small sample of poor non-rice households might have an impact on the estimates, so this evidence should be interpreted as suggestive.

Again, I separate the regressors by year using year dummies, and the results are reported in columns (4) to (6) of Table 3.6. For the middle 50 percent of rice farmers, revenues increased more quickly than revenues of other crops' farmers, particularly during the treatment period. Meanwhile, the overall revenue change of poor households (θ_t^P) compared to the middle 50 percent of households is positive and for rich households (θ_t^R) this is negative.[7] This result can be explained as regression to the mean, since the rich and poor households are defined based on their revenue in 2009 and 2010. In the following years, even though these rich farmers' income gradually increased, the bottom 75 percent caught up, and this catchup occurred more quickly for poor farmers. However, the estimated treatment interactions for rich and poor rice farmers are negative, indicating revenue of rich and poor rice farmers increased more slowly than the comparison groups of non-rice

[6] Figure A3.6 plots the density of total revenue across farmers in 2009-2010.

[7] Table A3.8 reports the full results of estimation of equation 3.5 and table A3.9 shows the results when standard errors are clustered at the district level.

farmers.

3.5 Conclusions and Policy Implications

The results provide suggestive evidence of benefits of the 2011-2014 Thai rice pledging policy for rice-growing households, by suggesting that revenue of farmers did increase due to the program. However, further research is needed to understand how this program affected farmers in other dimensions than revenue, particularly their expenditure, saving, and investment decisions. Moreover, this study does not include effects on macroeconomic variables such as inflation, wages, and employment. Further research to uncover these effects will allow us to better understand the full impact of this program.

Since agriculture remains an important sector in the Thai economy, good policy to enhance the agricultural sector is still necessary. However, the crucial limitation of the 2011-2014 rice pledging policy was its enormous fiscal burden, and hence such a program would not have been able to continue in the long term. From the heterogeneity analysis, relatively poor farmers did not benefit from the program, which was not in line with the policy objectives, which aimed to improve only the revenue of the poor, and led to unnecessary spending. Moreover, the policy did not permanently increase the incomes of farmers since the study shows farmers' revenue declined after the policy was terminated.

Appropriate policies to support agriculture should be able to be maintained in the long term with rational contingent liability. One alternative adjustment to reduce the budget implications could be a targeted benefit program in which only poor households can participate in the policy. If the government also aims to relieve the impact of price fluctuations for the overall agricultural sector, an income guarantee scheme or production insurance could be better options in terms of budget requirements. However, the income guarantee policy that was implemented from 2009 to 2011 had to be adjusted due to problems in the implementation process and cooperation from stakeholders, as explained in Section 3.2.2. Nonetheless, Duangbootsee and Myers (2015) compared the welfare impacts of a rice pledging program and an income guarantee program given the same targeted selling price for farmers, and found that the income guarantee program would have led to a higher increase in producer surplus, while the rice pledging scheme generated a higher deadweight loss. Alternatively, an insurance policy could be an option to allow farmers to cope with extremely harmful incidents such as drought or flood. Indeed, several studies have shown a possible positive contribution of insurance policy for the agricultural sector, for example Gin et al. (2007) on rainfall insurance in India, Karlan et al. (2014) on liquidity constraints and rainfall insurance in Ghana, and Reyes et al. (2017) on revenue insurance for farmers and fishermen in the Philippines.

Ideally, good policy should have a persistent positive impact even after the policy is removed, which means an increase in farm productivity. A popular suggestion is an input subsidy. However, the long-term effect of such a policy is still ambiguous. Carter et al. (2014) show that a temporary subsidy to fertilizer in Mozambique had a persistent impact as well as a technology adaptation spillover. However, Duflo et al. (2011) found the opposite result in an experiment in Kenya. Alternatively, some research focuses on the liquidity constraints of farmers, which could provide a tipping point to enhance outcomes in the agricultural sector (e.g. Brune et al. (2016)). The Thai government has implemented village funds as countrywide micro-finance since 2001, which have been somewhat successful in relieving liquidity constraints in rural areas (see Kaboski and Townsend (2012)). The search for better agricultural policy remains challenging for both policymakers and economists.

Figure 3.1: Share of Revenue from Rice (Nominal)

Figure 3.2: Share of Revenue from Rice excluding Non-permanent Agricultural Households (Nominal)

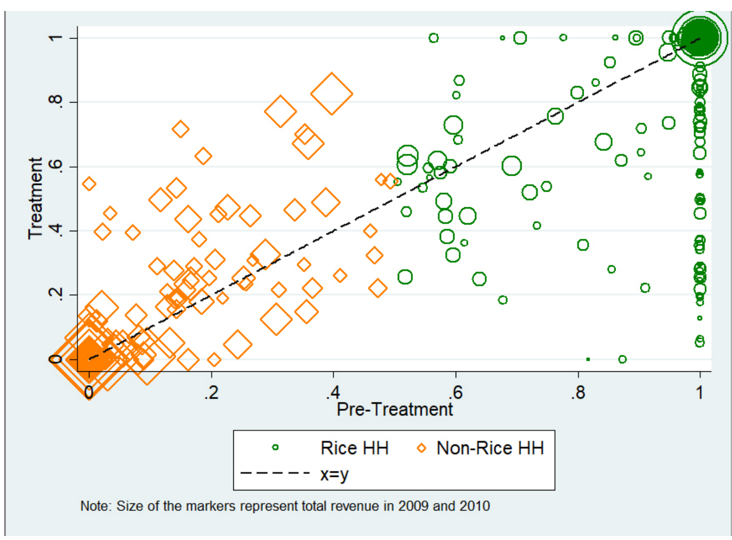


Table 3.1: Number of Households by Main Source of Revenue and Province

	Chachoengsao	**Buriram**	**Lopburi**	**Sisaket**	**Phrae**	**Satun**	**Total**
Number of Households by Main Source of Revenue							
Rice	56	93	10	108	5	0	272
Tree crop	39	8	1	12	0	49	109
Field Crop	5	1	37	1	15	0	59
Total	100	102	48	121	20	49	440
Percentage of Households by Main Source of Revenue							
Rice	56.0	91.2	20.8	89.3	25.0	0.0	62.2
Tree crop	39.0	7.8	2.1	9.9	0.0	100.0	25.5
Field Crop	5.0	1.0	77.1	0.8	75.0	0.0	12.3
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Share of Agricultural Production Value in 2009							
Rice	**71.3**	**76.7**	**62.8**	**86.9**	**73.7**	**7.7**	
Tree Crop	**26.1**	**18.0**	**7.4**	**11.3**	**0.4**	**92.3**	
Rubber	12.5	10.2	0.0	8.1	0.1	92.3	
Cassava	13.6	7.8	7.4	3.2	0.2	0.0	
Field Crop	**2.7**	**5.3**	**29.7**	**1.8**	**25.9**	**0.0**	
Sugarcane	2.5	5.3	19.9	0.3	0.6	0.0	
Maize	0.2	0.0	9.9	1.5	25.3	0.0	
Total	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	

Note: The numbers of households by main source of revenue are based on the dataset used in this study. Share of agricultural production value is estimated by the author from the provincial agricultural production data by the Office of Agricultural Economics.

Table 3.2: Summary Statistics

	All Households			Top 25%			Bottom 25%		
	All (1)	**Rice** (2)	**Non-Rice** (3)	**All** (4)	**Rice** (5)	**Non-Rice** (6)	**All** (7)	**Rice** (8)	**Non-Rice** (9)
Whole Period (2009 - 2015)									
Nominal Revenue	205,108.7	154,079.4	287,727.6	481,717.2	436,497.7	514,218.6	58,832.7	59,556.6	50,708.6
	(5,302.9)	(4,691.6)	(11,219.6)	(16,438.4)	(17,877.9)	(25,067.7)	(1,746.9)	(1,822.7)	(6,077.4)
Rice	90,158.9	133,104.6	20,627.9	191,798.0	421,316.8	26,831.4	42,436.8	45,878.3	3,815.1
	(3,057.7)	(4,582.2)	(1,567.3)	(10,518.6)	(18,083.0)	(3,575.6)	(1,145.6)	(1,158.7)	(1,098.8)
Other Crops	114,949.8	20,974.8	267,099.7	289,919.1	15,180.9	487,387.3	1,6395.9	13,678.3	46,893.5
	(4,869.5)	(1,368.3)	(11,222.9)	(17,022.4)	(3,361.6)	(25,344.6)	(1,478.1)	(1,487.7)	(5,659.6)
Real Revenue	183,470.1	159,223.1	222,727.3	423,848.9	461,154.9	397,035.1	58,656.7	60,329.9	39,879.7
	(4,439.8)	(4,871.3)	(8,422.7)	(13,412.7)	(18,561.0)	(18,715.7)	(1,623.9)	(1,699.9)	(4,926.8)
Rice	97,280.9	143,471.3	22,496.6	205,336.8	450,266.9	29,293.2	46,319.3	50,076.4	4,156.4
	(3,234.6)	(4,826.5)	(1,738.3)	(11,100.5)	(18,812.9)	(3,984.2)	(1,292.2)	(1,313.6)	(1,181.2)
Other Crops	86,189.2	15,751.8	200,230.7	218,512.1	10,888.1	367,741.9	12,337.4	10,253.5	35,723.3
	(3,637.6)	(1,045.5)	(8,369.0)	(12,719.4)	(2,295.7)	(18,881.6)	(1,142.1)	(1,147.8)	(4,449.7)
Pre-Treatment Period (2009 - 2010)									
Nominal Revenue	166,061.7	124,756.9	232,936.1	434,559.9	437,672.0	432,323.0	30,201.7	30,932.6	21,999.4
	(8,093.8)	(8,348.7)	(15,674.1)	(23,868.5)	(32,563.8)	(33,797.9)	(1,003.2)	(1,013.8)	(4,216.3)
Rice	78,842.8	119,112.0	13,645.0	19,0176.7	426,726.4	20,156.7	27,558.3	29,811.1	2,277.8
	(5,472.0)	(8,333.8)	(1,725.5)	(19,560.4)	(33,359.3)	(4,071.5)	(1,042.9)	(983.1)	(1,436.7)
Other Crops	87,218.9	5,644.9	219,291.1	244,383.2	10,945.7	412,166.4	2,643.4	1,121.5	19,721.7
	(6,906.9)	(877.8)	(15,543.0)	(23,837.3)	(3,858.9)	(33,857.9)	(511.0)	(287.3)	(3,386.7)
Real Revenue	152,968.2	127,085.5	194,873.5	397,977.6	446,293.8	363,250.4	30,522.5	31,666.9	17,679.5
	(7,433.1)	(8,508.2)	(13,462.5)	(22,142.0)	(33,172.4)	(29,387.7)	(1,024.1)	(1,042.1)	(3,237.7)
Rice	81,205.5	122,665.7	14,079.5	195,307.2	438,106.1	20,795.4	28,515.4	30,842.1	2,404.8
	(5,592.0)	(8,508.1)	(1,778.9)	(19,955.9)	(33,826.1)	(4,195.4)	(1,091.9)	(1,033.5)	(1,524.6)
Other Crops	71,762.7	4,419.8	180,794.0	202,670.5	8,187.7	342,455.0	2,007.0	824.8	15,274.7
	(5,860.8)	(678.5)	(13,320.6)	(20,441.6)	(2,821.0)	(29,435.6)	(382.2)	(210.8)	(2,412.7)
Treatment Period(2012 - 2014)									
Nominal Revenue	233,239.0	180,446.3	318,713.0	531,283.7	478,923.3	568,917.8	76,142.4	77,076.8	65,657.4
	(9,100.0)	(7,742.2)	(19,697.5)	(28,321.5)	(27,172.2)	(44,455.9)	(3,253.0)	(3,417.1)	(10,483.3)
Rice	103,941.2	152,684.1	25,024.1	213,244.9	466,806.9	30,997.2	51,972.4	56,158.3	4,998.1
	(5,120.7)	(7,616.7)	(2,804.9)	(16,947.1)	(27,642.4)	(6,365.4)	(2,061.5)	(2,073.6)	(2,085.5)
Other Crops	129,297.8	27,762.1	293,688.9	318,038.8	12,116.4	537,920.6	24,170	20,918.5	60,659.3
	(8,478.5)	(2,436.3)	(19,779.1)	(29,925.5)	(3,582.5)	(45,159.4)	(2,894.9)	(2,971.2)	(9,462.9)
Real Revenue	205,403.9	181,771.2	243,666.3	459,670.5	498,528.8	431,741.1	73,201.3	75,029.9	52,679.7
	(7,498.8)	(7,915.8)	(14,734.6)	(22,647.8)	(27,864.9)	(33,293.8)	(2,924.6)	(3,070.0)	(8,753.2)
Rice	109,715.4	161,048.1	26,605.3	223,870.8	489,159.7	33,194.4	55,253.8	59,710.2	5,243.5
	(5,321.6)	(7,881.3)	(3,055.2)	(17,606.5)	(28,311.0)	(7,024.1)	(2,287.5)	(2,317.1)	(2,151.2)
Other Crops	95,688.5	20,723.1	217,061.0	235,799.7	9,369.1	398,546.7	17,947.5	15,319.8	47,436.2
	(6,300.8)	(1,857.7)	(14,704.5)	(22,310.1)	(2,762.4)	(33,735.0)	(2,179.7)	(2,216.3)	(7,620.6)
Number of HH	440	272	168	110	46	64	110	101	9

Source: Author's estimates
Note: Standard deviations are represented in parentheses.

Table 3.3: Only Rice Farmer Households

	Log of Total Nominal Revenue (1)	Log of Total Real Revenue (2)	Log of Real Revenue from Main Crop (3)	Log of Total Nominal Revenue (4)	Log of Total Real Revenue (5)	Log of Real Revenue from Main Crop (6)
Treatment Year	0.355 (0.000) [0.000]	0.297 (0.000) [0.000]	0.237 (0.000) [0.000]	-	-	-
2010	-	-	-	0.222 (0.000) [0.076]	0.258 (0.000) [0.060]	0.257 (0.000) [0.057]
2011	-	-	-	0.431 (0.000) [0.018]	0.456 (0.000) [0.007]	0.423 (0.000) [0.005]
2012	-	-	-	0.557 (0.000) [0.001]	0.449 (0.000) [0.005]	0.381 (0.000) [0.003]
2013	-	-	-	0.686 (0.000) [0.000]	0.624 (0.000) [0.000]	0.464 (0.000) [0.001]
2014	-	-	-	0.672 (0.000) [0.009]	0.839 (0.000) [0.000]	0.702 (0.000) [0.000]
2015	-	-	-	0.480 (0.000) [0.069]	0.646 (0.000) [0.039]	0.434 (0.000) [0.084]
Observations	1,904	1,904	1,877	1,904	1,904	1,877

Note: Numbers in parentheses are p-values when standard errors are clustered at the village level. Numbers in square brackets are p-values when standard errors are clustered at the district level with wild bootstrap procedure.

Table 3.4: Difference-in-Difference Results

	Log of Total Nominal Revenue (1)	Log of Total Real Revenue (2)	Log of Real Revenue from Main Crop (3)	Log of Total Nominal Revenue (4)	Log of Total Real Revenue (5)	Log of Real Revenue from Main Crop (6)
Treatment Rice	0.208 (0.000) [0.088]	0.172 (0.000) [0.345]	0.195 (0.000) [0.321]	-	-	-
Treated Rice 2010	-	-	-	-0.0656 (0.485) [0.026]	0.313 (0.000) [0.167]	0.298 (0.000) [0.289]
Treated Rice 2011	-	-	-	-0.126 (0.226) [0.019]	0.465 (0.000) [0.325]	0.580 (0.000) [0.825]
Treated Rice 2012	-	-	-	0.0816 (0.414) [0.047]	0.397 (0.000) [0.239]	0.465 (0.000) [0.357]
Treated Rice 2013	-	-	-	0.203 (0.011) [0.087]	0.390 (0.000) [0.233]	0.329 (0.001) [0.210]
Treated Rice 2014	-	-	-	0.412 (0.000) [0.206]	0.648 (0.000) [0.701]	0.667 (0.000) [0.492]
Treated Rice 2015	-	-	-	0.290 (0.025) [0.073]	0.449 (0.000) [0.231]	0.286 (0.032) [0.138]
Observations	3,080	3,080	2,853	3,080	3,080	2,853
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Numbers in parentheses are p-values when standard errors are clustered at the village level. Numbers in square brackets are p-values when standard errors are clustered at the district level with wild bootstrap procedure.

Table 3.5: Share of Rice : All Households

	Log of Total Nominal Revenue (1)	Log of Total Real Revenue (2)	Log of Total Nominal Revenue (3)	Log of Total Real Revenue (4)
TREATMENT*SHARERICE	0.237	0.198	-	-
	(0.000)	(0.000)		
	[0.108]	[0.372]		
2010*SHARERICE	-	-	-0.118	0.342
			(0.234)	(0.000)
			[0.038]	[0.186]
2011*SHARERICE	-	-	-0.223	0.491
			(0.049)	(0.000)
			[0.023]	[0.322]
2012*SHARERICE	-	-	0.0534	0.436
			(0.635)	(0.000)
			[0.067]	[0.268]
2013*SHARERICE	-	-	0.208	0.439
			(0.027)	(0.000)
			[0.112]	[0.269]
2014*SHARERICE	-	-	0.406	0.704
			(0.001)	(0.000)
			[0.201]	[0.685]
2015*SHARERICE	-	-	0.284	0.481
			(0.057)	(0.001)
			[0.076]	[0.224]
Observations	3,080	3,080	3,080	3,080
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: Numbers in parentheses are p-values when standard errors are clustered at the village level. Numbers in square brackets are p-values when standard errors are clustered at the district level with wild bootstrap procedure.

Table 3.6: Heterogeneity by Income Level

	Log of Total Nominal Revenue (1)	Log of Total Real Revenue (2)	Log of Real Revenue from Main Crop (3)	Log of Total Nominal Revenue (4)	Log of Total Real Revenue (5)	Log of Real Revenue from Main Crop (6)
Treatment Middle-50	0.189	0.147	0.169	-	-	-
	(0.000)	(0.003)	(0.022)			
Treatment Rich	0.070	0.065	0.117	-	-	-
	(0.286)	(0.322)	(0.080)			
Treatment Poor	-0.134	-0.193	-0.239	-	-	-
	(0.534)	(0.345)	(0.634)			
Treatment Middle-50 2010	-	-	-	0.0910	0.452	0.469
				(0.418)	(0.000)	(0.000)
Treatment Middle-50 2011	-	-	-	-0.164	0.401	0.610
				(0.197)	(0.000)	(0.000)
Treatment Middle-50 2012	-	-	-	0.0842	0.387	0.520
				(0.469)	(0.001)	(0.001)
Treatment Middle-50 2013	-	-	-	0.128	0.298	0.292
				(0.204)	(0.003)	(0.043)
Treatment Middle-50 2014	-	-	-	0.545	0.745	0.762
				(0.000)	(0.000)	(0.000)
Treatment Middle-50 2015	-	-	-	0.326	0.467	0.341
				(0.014)	(0.000)	(0.035)
Treatment Rich 2010	-	-	-	-0.639	-0.609	-0.667
				(0.000)	(0.000)	(0.000)
Treatment Rich 2011	-	-	-	-0.388	-0.315	-0.496
				(0.028)	(0.044)	(0.025)
Treatment Rich 2012	-	-	-	-0.486	-0.426	-0.524
				(0.006)	(0.013)	(0.015)
Treatment Rich 2013	-	-	-	-0.387	-0.311	-0.357
				(0.025)	(0.066)	(0.087)
Treatment Rich 2014	-	-	-	-0.955	-0.845	-0.785
				(0.000)	(0.000)	(0.000)
Treatment Rich 2015	-	-	-	-0.933	-0.858	-0.857
				(0.000)	(0.000)	(0.000)
Treatment Poor 2010	-	-	-	-0.582	-0.539	-0.562
				(0.122)	(0.141)	(0.175)
Treatment Poor 2011	-	-	-	-0.534	-0.469	-0.720
				(0.124)	(0.158)	(0.072)
Treatment Poor 2012	-	-	-	-0.641	-0.658	-0.901
				(0.005)	(0.003)	(0.095)
Treatment Poor 2013	-	-	-	-0.531	-0.556	-0.566
				(0.195)	(0.171)	(0.226)
Treatment Poor 2014	-	-	-	-1.093	-1.013	-1.969
				(0.008)	(0.013)	(0.000)
Treatment Poor 2015	-	-	-	-0.611	-0.602	-1.778
				(0.095)	(0.102)	(0.000)
Observations	3,080	3,080	2,853	3,080	3,080	2,853
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Numbers in parentheses are p-values when standard errors are clustered at the village level.

Appendices

Appendix 1

Figure A1.1: Actual Treatment and Placebo Estimates

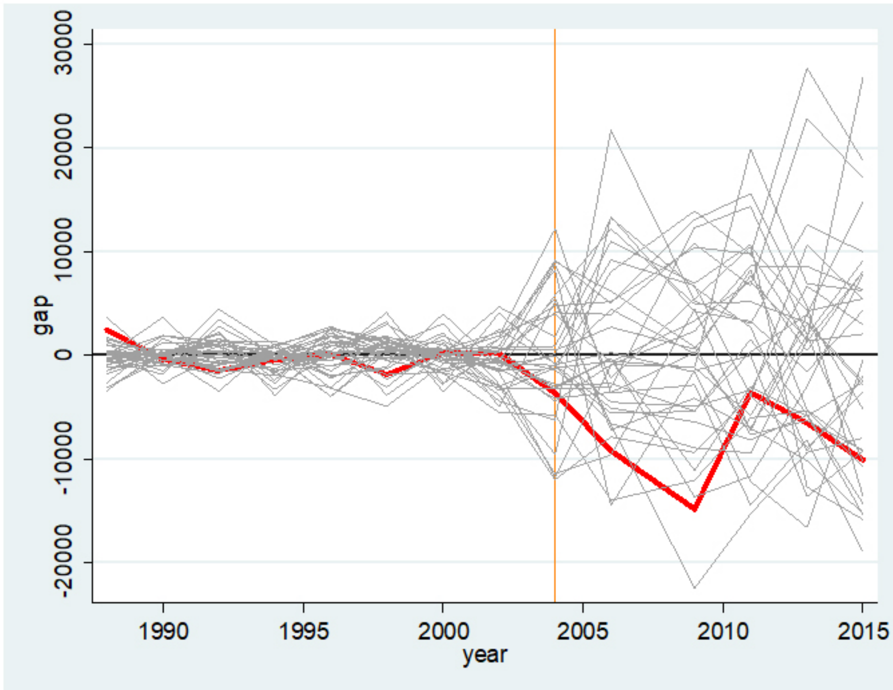
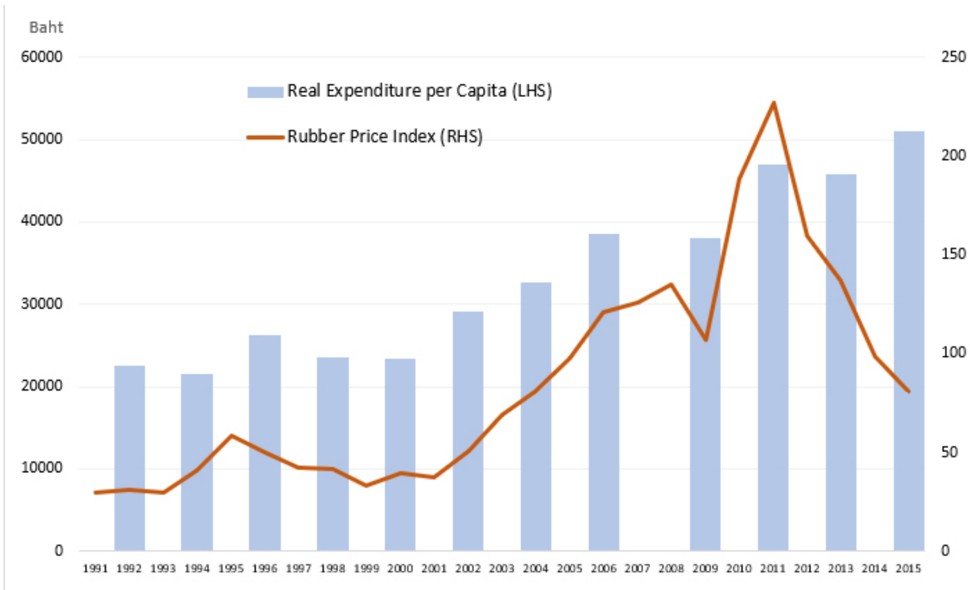
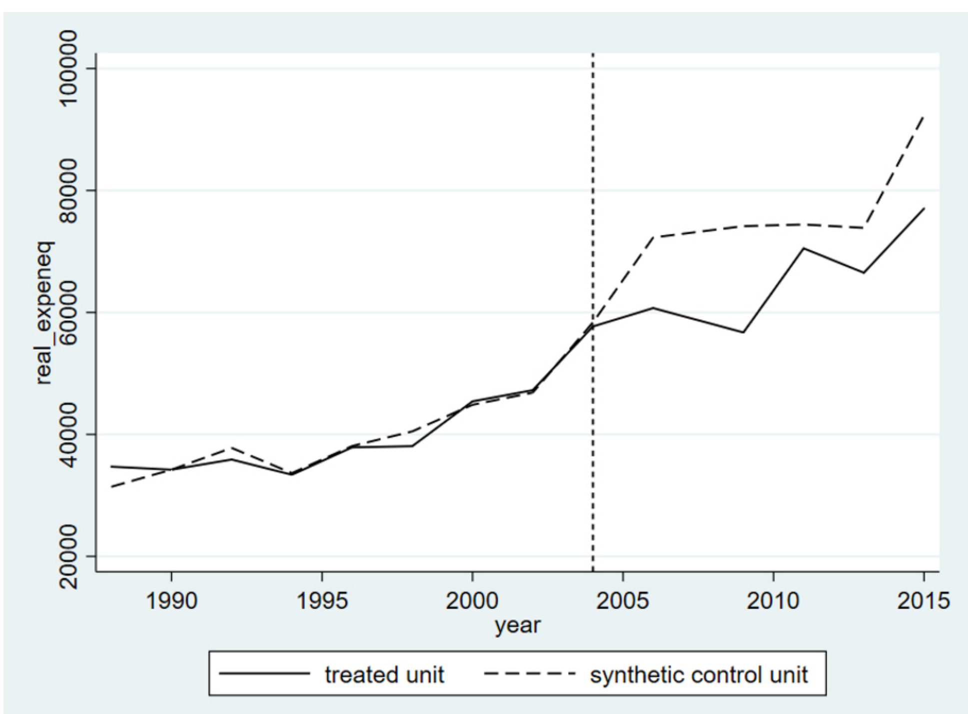


Figure A1.2: Rubber Price Index and Rural Households Real Expenditure per Capita in the Treated Area



Note: Rubber Price Index is Producer Price Index (2004-2006) = 100
Source: FAO and Author's estimation

Figure A1.3: Effects of the Insurgency on Real Expenditure Equivalence Scale



Appendix 2

Figure A2.1: Log Number of Incidents and Log Number of Deaths

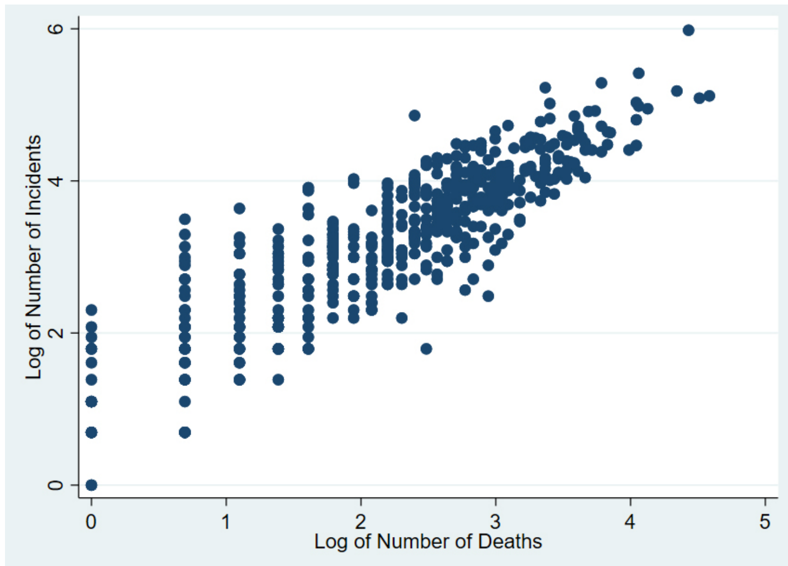
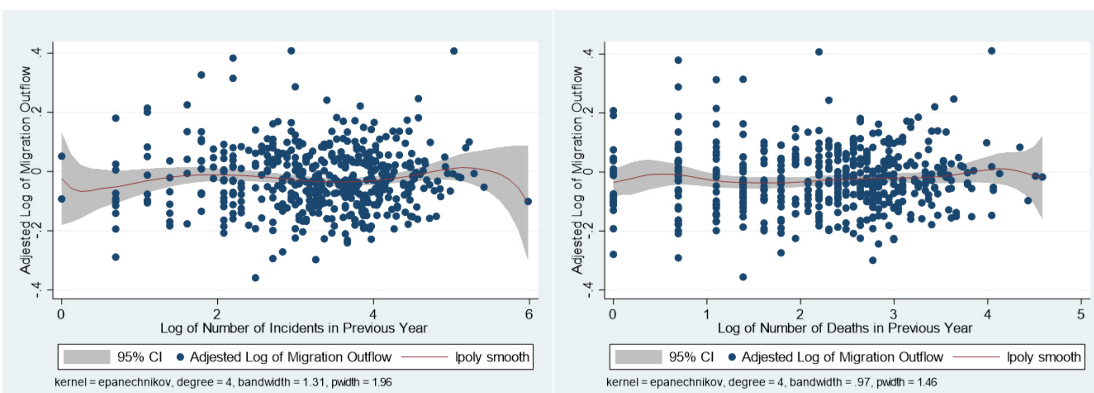
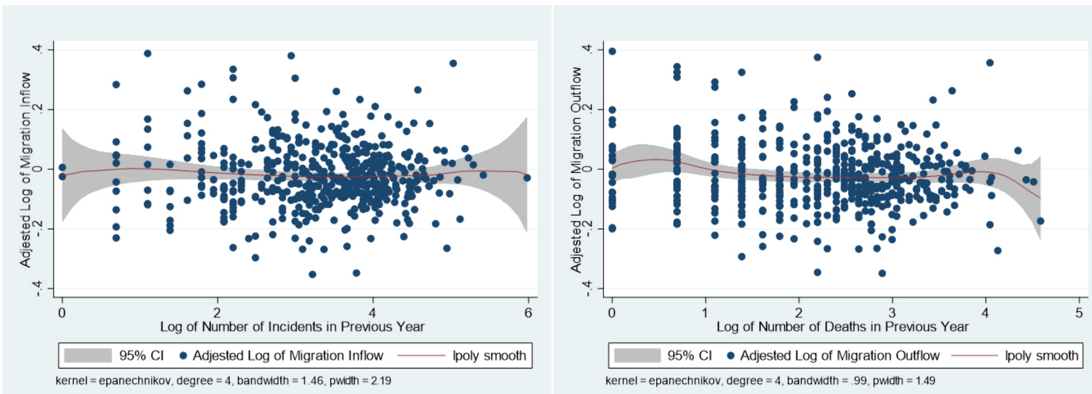


Figure A2.2: Partial Fits of Adjusted Log Migration Outflow and Treatment Variables



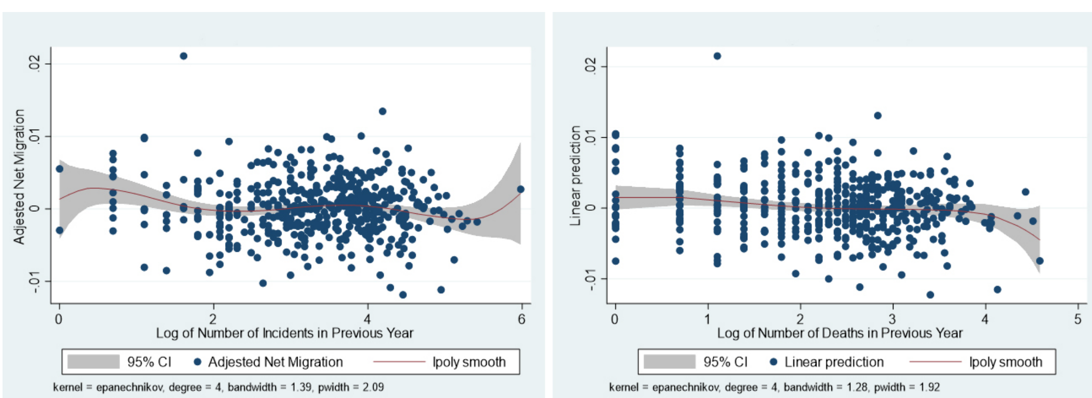
Note: The log of the number of migrants flowing out has been adjusted for the fixed effects. The points in each graph are partial residuals for log migration outflow, and the shaded area represents 95% confidence intervals.

Figure A2.3: Partial Fits of Adjusted Log Migration Inflow
and Treatment Variables



Note: The log of the number of migrant flowing in has been adjusted for the fixed effects. The points in each graph are partial residuals for log migration inflow, and the shaded area represents 95% confidence intervals.

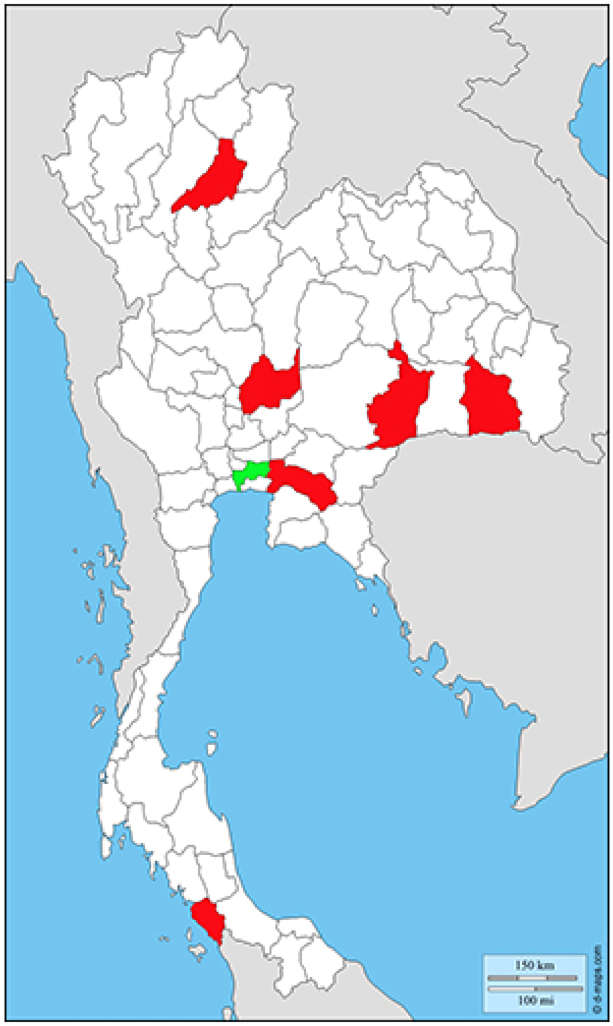
Figure A2.4: Partial Fits of Adjusted Net Migration and Treatment Variables



Note: The share of net migrants in the population has been adjusted for the fixed effects. The points in each graph are partial residuals for net migration, and the shaded area represents 95% confidence intervals.

Appendix 3

Figure A3.1: Map of Thailand



Note: Red areas represent the provinces in the dataset and Bangkok is represented in green.

Figure A3.2: Share of Revenue from Rice(Real)

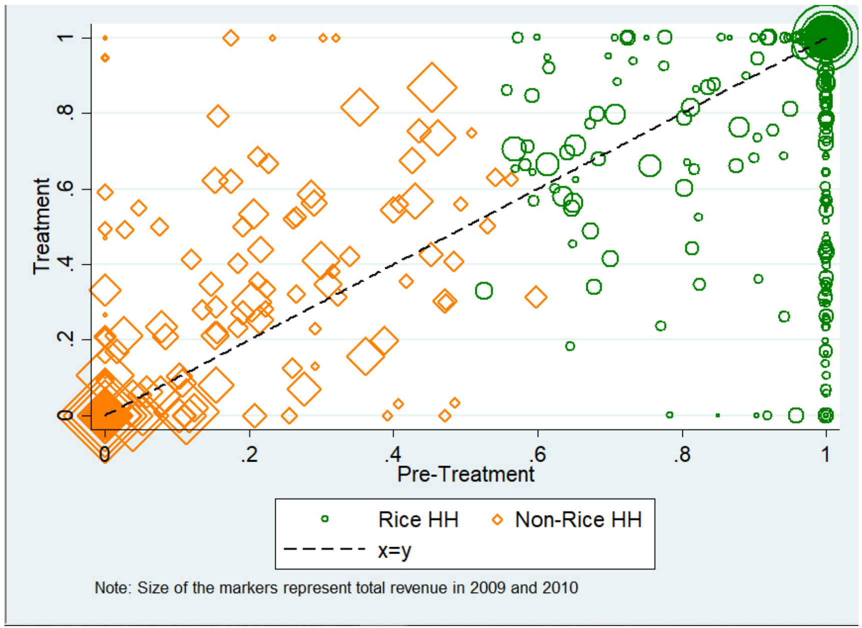


Figure A3.3: Share of Revenue from Rice excluding Non-permanent Agricultural Households (Real)

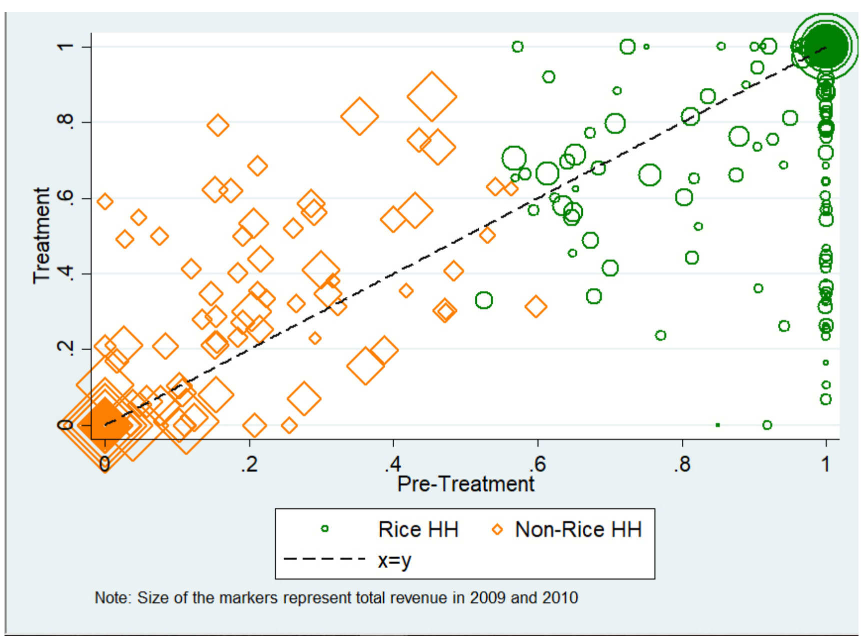


Figure A3.4: Average Household's Nominal Revenue from Main Crop

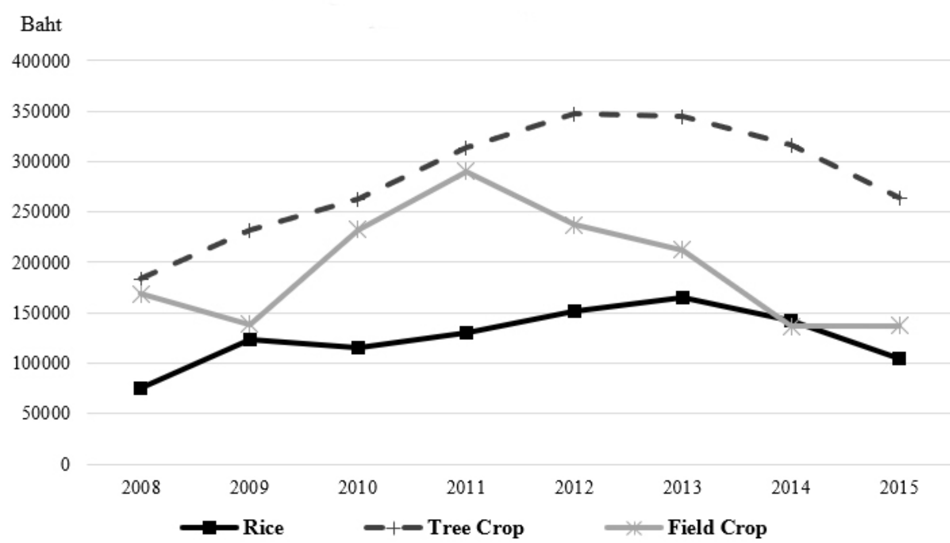


Figure A3.5: Average Household's Real Revenue from Main Crop

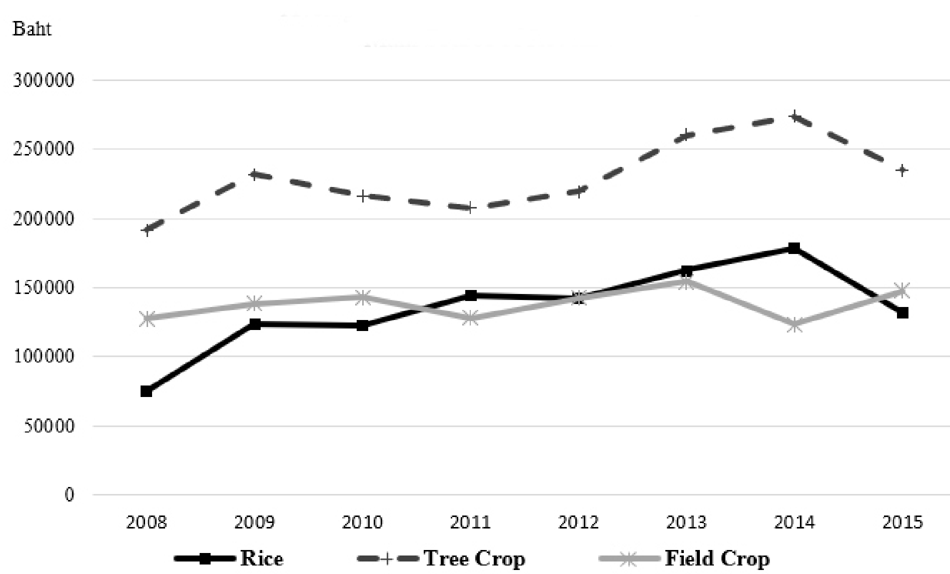


Figure A3.6: Kernel Density Estimate of Log of Total Revenue in 2009-2010

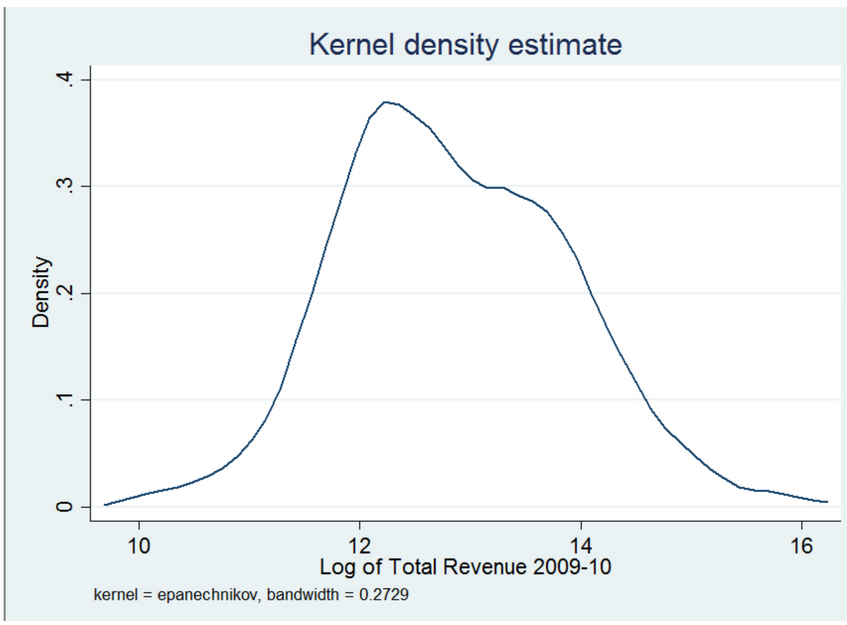


Table A3.1: Government Budget for Rice Policy 2001 - 2014

Budgetary Year	Total Budget (Mil. Baht)
1999/00	3,300
2000/01	6,900
2001/02	49,026
2002/03	56,427
2003/04	57,920
2004/05	72,525
2005/06	80,650
2006/07	66,200
2007/08	70,100
2008/09	126,000
2009/10	60,000
2010/11	60,000
2011/12	288,420
2012/13	356,560
2013/14	191,573

Source: Poapongsakorn and Jarupong (2010), The Center for International Trade Studies (2013) and Attavanich (2015). *Note:* Government budget year is from October to September. Hence the 2011/12 budget covered the 2011/12 main crop and the 2012 second crop.

Table A3.2: Rice Pledging Scheme 2011-2014

	No. of Participants	Pledged Rice		
	Mil. Persons	**Mil. Baht**	**Mil. Tons**	**% of Production**
Main Crop 2011/12	1.06	118,343	8.3	45.7
Main Crop 2012/13	1.78	239,003	15.07	75.6
Main Crop 2013/14	1.66	191,573	11.66	58.6
Second Crop 2012	0.92	170,047	14.54	124.7
Second Crop 2013	0.77	117,557	7.93	76.3
Total		**718,966**	**57.5**	**71.8**

Source: Attavanich (2015)

Table A3.3: Timeline of Rice Pledging Scheme

Year	First Crop (Rainy Season)	Second Crop (Dry Season)	Received Money
2009	Pre-Treatment	Pre-Treatment	**Pre-Treatment**
2010	Pre-Treatment	Pre-Treatment	**Pre-Treatment**
2011	Pre-Treatment	Treatment	**Pre-Treatment**
2012	Treatment	Treatment	**Treatment**
2013	Treatment	Treatment	**Treatment**
2014	Treatment	Post-Treatment	**Treatment**
2015	Post-Treatment	Post-Treatment	**Post-Treatment**

Note: The treatment period in this study depends on the timing of the receipt of money.

Table A3.4: Provincial Descriptive Statistics

	Chachoengsao	**Buriram**	**Lopburi**	**Sisaket**	**Phrae**	**Satun**	**Thailand**
Region	Central	North-East	Central	North-East	North	South	
Nominal GDP (mil. Baht)	281,518	67,715	81,433	56,722	23,184	30,624	11,689,941
GDP per Capita (Baht)	382,127	53,282	105,455	53,779	54,201	111,550	176,135
Agricultural % of GDP	6.8	27.1	18.1	30.7	20.1	47.9	10.9
Area (sq.km.)	5,334.4	10,321.6	6,198.4	8,838.4	6,537.6	2,478.4	513,115
Agricultural Area (sq.km.)	2,225.2	5,600.4	3,093.8	5,445.8	1,164.9	678.8	186,597.9
% of Total Area	41.7	54.3	49.9	61.6	17.8	27.4	36.4
Number of Districts	11	23	11	22	8	7	878
Number of Villages	892	2,544	1,129	2,633	708	279	74,965
Population	749,000	1,248,400	764,900	1,029,800	422,500	272,000	66,300,000
Labor Force	432,170	578,542	449,048	577,532	254,051	147,490	38,576,200
in Agriculture	119,727	308,714	158,721	380,703	114,909	77,377	12,732,700
% of Labour Force	27.7	53.4	35.3	65.9	45.2	52.5	33.0
Unemployment	1.1	0.4	0.6	1.5	0.4	0.7	0.8
Poverty Headcount Ratio	6.5	35	16.8	36.5	17.8	9.2	13.6
Poverty Line (baht/year)	30,264	25,224	30,876	24,852	26,280	28,452	31,764

Source: National Economic and Social Development Board, National Statistics Office, and Ministry of Labour.
Note: GDP and poverty indices are averaged over 2009 to 2014. Administration, population and labour statistics are as of 2014.

Table A3.5: Export Price Index (2009 = 100)

	2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Rice	100.00	94.18	90.58	106.27	101.31	79.79	79.7
Rubber	100.00	170.82	239.34	168.76	135.88	106.46	87.4
Cassava	100.00	139.35	170.81	154.81	150.47	152.56	151.6
Sugar	100.00	126.31	137.41	145.95	117.19	114.98	98.1
Maize	100.00	112.36	176.26	180.26	156.43	116.51	135.0

Note: The estimates are based on annual value and quantity of export data in local currency from the Bank of Thailand database.

Table A3.6: Provincial Price Indices (2009 = 100)

	2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Tree Crop Price Index							
Chachoengsao	100	154.4	203.6	161.5	143.5	130.5	120.9
Buriram	100	157.1	209.5	162.7	142.2	126.5	115.3
Lopburi	100	139.4	171.0	154.8	150.4	152.4	151.5
Sisaket	100	162.0	220.1	164.8	140.0	119.4	105.4
Phrae	100	151.1	196.5	160.0	145.0	135.3	127.5
Satun	100	170.8	239.3	168.8	135.9	106.5	87.4
Field Crop Price Index							
Chachoengsao	100	125.2	140.5	148.7	120.4	115.1	101.0
Buriram	100	126.3	137.5	146.0	117.2	115.0	98.1
Lopburi	100	121.7	150.3	157.3	130.2	115.5	110.3
Sisaket	100	114.5	170.2	174.9	150.3	116.3	129.2
Phrae	100	112.7	175.3	179.4	155.5	116.5	134.1
Satun	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

Source: Author's estimates; see text for details.

Table A3.7: Average Share of Revenue from Rice

	Top 25%			Middle 50%			Bottom 25%		
	All (1)	**Rice** (2)	**Non-Rice** (3)	**All** (4)	**Rice** (5)	**Non-Rice** (6)	**All** (7)	**Rice** (8)	**Non-Rice** (9)
Nominal Revenue									
Whole Period	0.441	0.954	0.0719	0.547	0.856	0.142	0.807	0.873	0.0591
	(0.0168)	(0.00822)	(0.00854)	(0.0110)	(0.00859)	(0.00903)	(0.0124)	(0.0102)	(0.0169)
Pre-Treatment Period	0.432	0.954	0.0573	0.569	0.928	0.0975	0.889	0.964	0.0541
	(0.0165)	(0.00736)	(0.00513)	(0.0111)	(0.00486)	(0.00543)	(0.00968)	(0.00373)	(0.0129)
Treatment Period	0.447	0.959	0.0784	0.522	0.810	0.143	0.760	0.822	0.0552
	(0.0167)	(0.00635)	(0.00885)	(0.0103)	(0.00888)	(0.00759)	(0.0128)	(0.0111)	(0.0136)
Real Revenue									
Whole Period	0.452	0.962	0.0849	0.572	0.879	0.169	0.823	0.890	0.0727
	(0.0168)	(0.00696)	(0.00940)	(0.0109)	(0.00761)	(0.0101)	(0.0119)	(0.00934)	(0.0201)
Pre-Treatment Period	0.442	0.962	0.0679	0.582	0.939	0.113	0.898	0.972	0.0673
	(0.0165)	(0.00603)	(0.00599)	(0.0110)	(0.00421)	(0.00629)	(0.00944)	(0.00297)	(0.0160)
Treatment Period	0.458	0.967	0.0926	0.554	0.839	0.178	0.781	0.844	0.0680
	(0.0167)	(0.00514)	(0.00988)	(0.0102)	(0.00788)	(0.00898)	(0.0122)	(0.0102)	(0.0168)
Number of HH	110	46	64	220	125	95	110	101	9

Source: Author's estimates.

Table A3.8: Heterogeneity by Income Level

	Log of Total Nominal Revenue (1)	Log of Total Real Revenue (2)	Log of Real Revenue from Main Crop (3)	Log of Total Nominal Revenue (4)	Log of Total Real Revenue (5)	Log of Real Revenue from Main Crop (6)
Treatment Middle-50	0.189	0.147	0.169	-	-	-
	(0.000)	(0.003)	(0.022)			
Treatment Rich	0.070	0.065	0.117	-	-	-
	(0.286)	(0.322)	(0.080)			
Treatment Poor	-0.134	-0.193	-0.239	-	-	-
	(0.534)	(0.345)	(0.634)			
Treatment Middle-50 2010	-	-	-	0.0910	0.452	0.469
				(0.418)	(0.000)	(0.000)
Treatment Middle-50 2011	-	-	-	-0.164	0.401	0.610
				(0.197)	(0.000)	(0.000)
Treatment Middle-50 2012	-	-	-	0.0842	0.387	0.520
				(0.469)	(0.001)	(0.001)
Treatment Middle-50 2013	-	-	-	0.128	0.298	0.292
				(0.204)	(0.003)	(0.043)
Treatment Middle-50 2014	-	-	-	0.545	0.745	0.762
				(0.000)	(0.000)	(0.000)
Treatment Middle-50 2015	-	-	-	0.326	0.467	0.341
				(0.014)	(0.000)	(0.035)
Treatment Rich 2010	-	-	-	-0.639	-0.609	-0.667
				(0.000)	(0.000)	(0.000)
Treatment Rich 2011	-	-	-	-0.388	-0.315	-0.496
				(0.028)	(0.044)	(0.025)
Treatment Rich 2012	-	-	-	-0.486	-0.426	-0.524
				(0.006)	(0.013)	(0.015)
Treatment Rich 2013	-	-	-	-0.387	-0.311	-0.357
				(0.025)	(0.066)	(0.087)
Treatment Rich 2014	-	-	-	-0.955	-0.845	-0.785
				(0.000)	(0.000)	(0.000)
Treatment Rich 2015	-	-	-	-0.933	-0.858	-0.857
				(0.000)	(0.000)	(0.000)
Treatment Poor 2010	-	-	-	-0.582	-0.539	-0.562
				(0.122)	(0.141)	(0.175)
Treatment Poor 2011	-	-	-	-0.534	-0.469	-0.720
				(0.124)	(0.158)	(0.072)
Treatment Poor 2012	-	-	-	-0.641	-0.658	-0.901
				(0.005)	(0.003)	(0.095)
Treatment Poor 2013	-	-	-	-0.531	-0.556	-0.566
				(0.195)	(0.171)	(0.226)
Treatment Poor 2014	-	-	-	-1.093	-1.013	-1.969
				(0.008)	(0.013)	(0.000)
Treatment Poor 2015	-	-	-	-0.611	-0.602	-1.778
				(0.095)	(0.102)	(0.000)
Rich 2010	-0.132	-0.196	-0.204	0.149	0.126	0.152
	(0.240)	(0.033)	(0.034)	(0.256)	(0.306)	(0.251)
Rich 2011	-0.174	-0.261	-0.209	-0.0361	-0.0694	0.0969
	(0.125)	(0.002)	(0.067)	(0.788)	(0.562)	(0.613)
Rich 2012	-0.137	-0.204	-0.0916	0.000623	-0.0235	0.165
	(0.253)	(0.042)	(0.483)	(0.996)	(0.848)	(0.343)
Rich 2013	-0.289	-0.331	-0.139	-0.186	-0.213	-0.00474
	(0.012)	(0.001)	(0.285)	(0.120)	(0.070)	(0.976)
Rich 2014	-0.353	-0.407	-0.321	0.0497	0.00246	0.103
	(0.006)	(0.000)	(0.012)	(0.736)	(0.986)	(0.555)
Rich 2015	-0.573	-0.580	-0.381	-0.134	-0.151	0.0488
	(0.000)	(0.000)	(0.003)	(0.346)	(0.261)	(0.766)
Poor 2010	0.124	0.262	0.223	0.626	0.598	0.578
	(0.199)	(0.007)	(0.018)	(0.091)	(0.097)	(0.160)
Poor 2011	0.378	0.580	0.621	0.926	0.871	1.077
	(0.000)	(0.000)	(0.000)	(0.007)	(0.009)	(0.007)
Poor 2012	0.671	0.803	0.885	1.000	1.011	1.221
	(0.003)	(0.000)	(0.070)	(0.000)	(0.000)	(0.023)
Poor 2013	0.727	0.818	0.831	0.939	0.964	0.914
	(0.003)	(0.001)	(0.085)	(0.021)	(0.017)	(0.047)
Poor 2014	0.817	0.922	0.950	1.399	1.330	2.265
	(0.001)	(0.000)	(0.054)	(0.001)	(0.001)	(0.000)
Poor 2015	0.559	0.611	0.563	1.006	1.000	2.176
	(0.000)	(0.000)	(0.000)	(0.006)	(0.006)	(0.000)
Observations	3,080	3,080	2,853	3,080	3,080	2,853
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Numbers in parentheses are p-values when standard errors are clustered at the village level.

Table A3.9: Heterogeneity by Income Level

	Log of Total Nominal Revenue (1)	Log of Total Real Revenue (2)	Log of Real Revenue from Main Crop (3)	Log of Total Nominal Revenue (4)	Log of Total Real Revenue (5)	Log of Real Revenue from Main Crop (6)
Treatment Middle-50	0.189	0.147	0.169	-	-	-
	[0.4861]	[0.3993]	[0.7160]			
Treatment Rich	0.070	0.065	0.117	-	-	-
	[0.9836]	[0.5407]	[0.4817]			
Treatment Poor	-0.134	-0.193	-0.239	-	-	-
	[0.3442]	[0.3047]	[0.6130]			
Treatment Middle-50 2010	-	-	-	0.0910	0.452	0.469
				[0.1197]	[0.3706]	[0.2579]
Treatment Middle-50 2011	-	-	-	-0.164	0.401	0.610
				[0.0397]	[0.773]	[0.3592]
Treatment Middle-50 2012	-	-	-	0.0842	0.387	0.520
				[0.1141]	[0.8561]	[0.7044]
Treatment Middle-50 2013	-	-	-	0.128	0.298	0.292
				[0.1663]	[0.6154]	[0.7369]
Treatment Middle-50 2014	-	-	-	0.545	0.745	0.762
				[0.3163]	[0.0395]	[0.3306]
Treatment Middle-50 2015	-	-	-	0.326	0.467	0.341
				[0.7683]	[0.4781]	[0.8403]
Treatment Rich 2010	-	-	-	-0.639	-0.609	-0.667
				[0.7668]	[0.7120]	[0.8268]
Treatment Rich 2011	-	-	-	-0.388	-0.315	-0.496
				[0.4583]	[0.3786]	[0.5881]
Treatment Rich 2012	-	-	-	-0.486	-0.426	-0.524
				[0.4661]	[0.4082]	[0.4214]
Treatment Rich 2013	-	-	-	-0.387	-0.311	-0.357
				[0.3835]	[0.3130]	[0.4108]
Treatment Rich 2014	-	-	-	-0.955	-0.845	-0.785
				[0.5351]	[0.7248]	[0.9433]
Treatment Rich 2015	-	-	-	-0.933	-0.858	-0.857
				[0.3568]	[0.5015]	[0.9056]
Treatment Poor 2010	-	-	-	-0.582	-0.539	-0.562
				[0.0519]	[0.0168]	[0.0391]
Treatment Poor 2011	-	-	-	-0.534	-0.469	-0.720
				[0.0947]	[0.0588]	[0.1036]
Treatment Poor 2012	-	-	-	-0.641	-0.658	-0.901
				[0.3451]	[0.3419]	[0.5852]
Treatment Poor 2013	-	-	-	-0.531	-0.556	-0.566
				[0.15191]	[0.1726]	[0.3264]
Treatment Poor 2014	-	-	-	-1.093	-1.013	-1.969
				[0.8402]	[0.5785]	[0.7012]
Treatment Poor 2015	-	-	-	-0.611	-0.602	-1.778
				[0.3171]	[0.3235]	[0.6829]
Observations	3,080	3,080	2,853	3,080	3,080	2,853
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Numbers in square brackets are p-values when standard errors are clustered at the district level with wild bootstrap procedure.

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