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Relationship between Conflict and Labor Market in the Deep South of Thailand

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Abstract

This study investigated the dynamic relationship between the conflicts and the labor market using the district-level quarterly data from four border provinces (Pattani, Yala, Narathiwat, and four districts from Songkhla). Using the Panel VAR, we found that conflicts had a negative but statistically insignificant impact on the labor market regarding the number of injuries. However, the number of wounds in the preceding period was positively correlated with the unemployment rate based on the Social Security Office data. In contrast, neither formal nor overall labor market fluctuations had affected conflict incidents.

To ensure the robustness of our results, we used the synthetic control method to calculate the counterfactual unemployment rate and the counterfactual number of new establishments from annual provincial data. Our estimates of the effect of conflict on the unemployment rate and the number of new business openings were the difference between the reported values and their synthetic version during 2004 – 2017. We also used the two-way fixed effects model to analyze the correlation between the unemployment rate gap between the actual and synthetic provinces and the number of conflict incidences, government expenditure, and the defense budget share from the government expenditure. The unemployment rate in the deep South provinces was higher, and the number of new establishments was lower than in their comparable synthetic provinces. In addition, the number of incidences was positively correlated with the difference between the actual and the synthetic unemployment rate. The government expenditure was negatively correlated with the unemployment rate gap but statistically insignificant. Moreover, the defense budget share was positively correlated with the gap between the actual unemployment rate and its synthetic counterpart.

Keywords: Economic Impact of Conflicts, Labor Market, Deep South of Thailand

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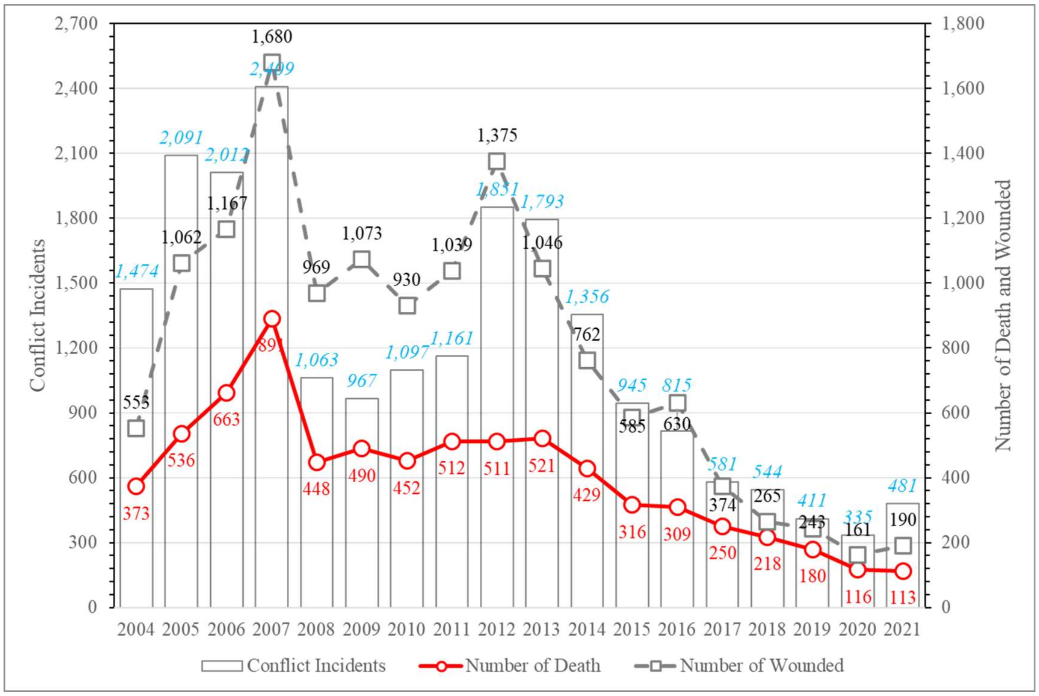
1. Introduction and Background

Conflicts[1] in Thailand's deep South (Pattani, Yala, Narathiwat, and specific parts of Songkhla provinces[2]) have continued, especially since 2004. Figure 1 depicts annual conflict incidents, deaths, and wounds from 2004-2021. It was clear that conflict incidents had risen during 2004-2007, then slowed down from 2007-2009 before another upturn during 2009-2012. The conflict incidents had a downward trend after 2012. During the period, there were 21,386 conflict incidents, with 7,328 death and 14,104 wounded. The characteristics of conflict incidents ordered by frequency were shooting 41%, bombing 20%, cordon and search 9%, arson 8%, and others 22%, such as harassment, attack, and sabotage.

There are various economic channels to pass through the consequence of conflicts such as physical capital and human capital loss, household, and business concerns, which could be followed by consumption and production drop, government budget shifting from raising productivity to national defense, and raising transaction costs and burdens from strict security measures (Chongwilaikasaem and Ingviya, 2020). The adverse economic impacts would lead to economic instability, such as higher unemployment rates, which could directly hit local people.

Firms might reduce their production or relocate plants to other safe zones. The consequence could directly hit local people through a higher unemployment rate. Worsened business sentiment could discourage firms from investing or, even worse, drive them to relocate plants to other safe zones. The employment would be further hurt thereafter.

[1] Deep South Watch, Prince of Songkla University, Pattani campus defined a conflict as a clash for values and claims on status and rights, power, resources and ruling authority and lands. The fiight's intention is to kill and hurt opponents, and neutraility enforcement.
[2] Consists of Jana, Na Tawee, Tepa and Saba Yoi districts.



Source: Authors' calculation based on Database of Deep South Watch, Prince of Songkla University, Pattani campus.

Figure 1: Annual conflict Incidents, number of death and wounded during 2004-2021

The causality between conflicts and the labor market might not be apparent. A high unemployment rate could worsen the economic situation and further stir up conflicts, as a high unemployment rate reduces conflict generators' opportunity costs relative to intended outcomes[3] from conflicts. They tend to make more attempts to generate more conflicts.

Most empirical literature on the effect of conflict on economic variables has used cross-country data or time series of a particular country. Using cross-country data, Blomberg et al. (2004) and Meierrieks and Gries (2012) found a negative relationship between terrorism and economic growth. In terms of foreign direct investment, Bandyopadhyay et al. (2014) found a negative relationship between conflicts and foreign direct investment, while Redic et al. (2019)'s results do not suggest the same conclusion. Using the time series of Afghanistan, Afzali (2019) found a positive association between terrorism and unemployment. Brodeur (2017) used US county-

[3] Conflict generators' intended outcomes are short-term social instability to push long-term reallocation of resources and/or balance of power shift.

level data and found a positive relationship between attacks and unemployment. Using synthetic control analysis for the Basque region, Abadie and Gradeazabal (2003) found that terrorism has a negative impact on GDP.

Given the issue's seriousness, there are few studies on the relationship between conflicts and economic stability in Thailand, however. Most studies focus only on the impact of conflicts on economic activities. Chongwilaikasaem and Ingviya (2020) constructed the Deep South Violence Index based on district-level data in deep South Thailand during 2012-2017 and used electricity usage data to proxy economic activities. They found that economic activities statistically decreased once conflicts got more intense. However, the paper might underestimate conflicts' impact on the back of data collecting constraints as the database was constructed during 2012-2017 with less severe incidents and rather long after the initiation of conflicts. Local people and firms would somehow be able to adjust themselves to live with conflicts. Besides, the paper had not considered the possibility that a conflict can also be an endogenous variable.

This study intended to estimate the impact of the conflicts in the southern provinces of Thailand on the area's labor market. We examined both district-level and province-level statistics for the four border provinces: Pattani, Yala, Narathiwat, and Songkhla[4]. On the conflicts' front, we utilized the University of Maryland's Global Terrorism Database to account for the number of events and victims wounded and killed from 2004 through 2020. The conflicts are measured by the number of combat incidents, the number of wounded, and the number of fatalities.

Gathering labor market datasets was rather complicated on the back of lacking a comprehensive labor database in Thailand. We, thus, compiled labor market and economic data from various sources. To begin with, we used economic data during 1985-2020 from the National Economic and Social Development Council's Gross Regional and Provincial Product and province-level government spending from 1990 and 2020 from provincial treasury offices. The number of unemployed people from 1985 and 2020 from the National Statistical Office's Labor Force Survey. Data of workers under the social security system 1994-2020 were drawn from Social Security Office. We also used firm registration dates as proxies of formal business openness

[4] Only Chana, Na Thawi, Thepha, and Saba Yoi districts in the district-level statistics.

between 1985 and 2020 from the Ministry of Commerce's Department of Business Development.

We examined the dynamic relationship between conflicts and economic conditions using dynamic panel data analysis with quarterly data. We expected that the unemployment rate would increase when conflict violence increased. Due to the ongoing conflict in the southern border provinces, business owners may reduce their investments or relocate their production bases to less dangerous regions. On the contrary, we did not expect rising unemployment to increase conflicts because the conflicts in the southern border provinces are mainly caused by different political ideologies, not economic difficulties.

In addition, the number of employed and the number of establishments reported by the Social Security Office at the district level served as economic indicators for the formal sector in this study.

For the NSO Labor force survey, we discovered that conflicts had a negative but statistically insignificant impact on the labor market regarding the number of injuries. Using the SSO's formal market data, however, the number of wounds in the preceding period was positively correlated with the unemployment rate. In contrast, neither formal nor overall labor market changes have any effect on conflict incidents.

We employed the synthetic control approach to estimate the counterfactual unemployment rate and the counterfactual number of new enterprises from annual province data to ensure the robustness of our results. Our estimates of the effect of conflict on the unemployment rate and the number of new company openings were the difference between the reported values and their synthetic version from 2004 and 2017. The two-way fixed effects model was also utilized in this study to examine the relationship between the unemployment rate disparity between actual and synthetic provinces, the number of conflict incidences, government expenditure, and the defense budget percentage of the total government expenditure. In the deep South provinces, the unemployment rate (accounting for both informal and formal employment) was higher, while the number of new enterprises was lower than in comparable synthetic provinces. In addition, the number of incidences was positively correlated with the difference between the actual and the synthetic unemployment rate, while increasing conflict incidents in the previous year would cause a statistically significant reduction in this year's gap between the actual new business opening and its synthetic counterpart.

As the labor market is an excellent indicator of economic activities in each area as well as reflects the long-term economic development, this study would contribute to the labor economics literature in a broad sense and provide more empirical evidence to estimate the impact of extreme shocks on the labor market in a more specific area.

The rest of the paper will be organized as follows. The next session is to discuss the labor market background in Thailand and the labor market structure in the deep South Thailand. Then, the third section review literature, while the fourth section goes through the research methodology. The last two sessions elaborate on the study's results and conclude the paper.

2. Labor Market Background in Thailand

Thailand's labor market has specific characteristics such as an excessively and continuously low unemployment rate and a structural trend break of the structural transformation. This section is to lay the background of Thailand's labor market, especially in the rural area, to prepare for the analysis of conflicts' implications on labor market.

2.1 Thailand's local labor market structure

Bank of Thailand (2019) discussed how structural issues in the Thai labor market had explained the unconventionally low unemployment rate in Thailand, namely, the large informal sector, e.g., the agricultural sector and self-employed, a large number of underemployed, discouraged, yet unidentified, out-of-labor force workers, and skill mismatch. To understand Thai labor market, therefore, requires us to assess the overall labor market in wider dimensions such as labor force participation, working hours, and income. Indeed, Thailand's formal and informal sectors are connected (Wasi et al., 2021). More than half of formal employees had left the formal sector before retirement, whereas almost half of the formal sector firms had less than five employees, similar to informal firms.

On the front of long-term development of the Thai labor market, the Bank of Thailand (2013) analyzed how Thailand's economic growth slowed down considerably on the back of lower employment and labor productivity growth since the Asian Financial Crisis in 1997. Klyuev (2015) argued that structural transformation to reallocate labor from low labor productivity, such as in agriculture, a large sector relative to other countries with a similar level of income, to a more productive sector, such as manufacturing, has stalled lately. The author claimed that possible explanations were skill gaps among rural and urban workers, the government's agricultural price support schemes, and the uniform minimum wage. Charoenloet (2015) showed that globalization and industrialization encouraged firms to subcontract work to informal homeworkers, which sustained a large share of workers in rural areas with low value-added economic activities. This evidence is also supportive of stalled structural transformation in Thailand.

Another severe structural problem in the Thai labor market is the rapidly aging population, which may cause higher underemployment, lower labor participation rate, and more inequality. Arayavechkit et al. (2015) found that younger cohorts are workers and older cohorts are entrepreneurs. Hence, a rapidly aging population could worsen the inequality problem as labor supply shortage would drive mediocre entrepreneurs to become self-employed without employees. Moreover, Wasi et al. (2019) examined the more significant wage gap between college and non-college workers, even with declining overall income inequality. The authors provided the changes in education-occupation composition, i.e., college workers less concentrated in high-skill jobs, while a larger share of secondary educated workers in low-skill jobs instead of the middle-skill ones, as a critical explanation. Employees with higher wages earn more since their market entry. The gap would get more comprehensive over time, then. This gap may explain the wage disparity between urban and rural areas, implying lower working hours and labor force participation in local economies.

2.2 The deep South provinces' labor market development

The rural or local labor market in Thailand, including our areas of interest, the Southern provinces with conflicts, also has the following characteristics: large agricultural and informal sector, stalled structural transformation, and high underemployed and low labor participation rate. This sub-section discusses some stylized facts about the correlation between conflicts and labor market development. In so doing, we compare the group of three Southern provinces labeled as Border with the group of other close provinces[5], called Nearby, and the overall country and regional labor markets. We found six stylized facts[6]:

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[5] Satun and Phatthalung provinces.

[6] The number of victims in figure 2-7 is made up of both the injured and dead due to the conflict according to University of Maryland's Global Terrorism Database.

1. The income per capita in Border provinces had similar development relative to those in the Nearby provinces, though they seem to be consistently lower than the country and regional levels (Figure 2)
2. Structural transformation, proxied by the Gross Provincial Product's share of the agriculture sector, in Border provinces had a similar pace relative to Nearby and regional provinces. (Figure 3)
3. The unemployment rate in Border provinces has increased significantly to be higher than those in the Nearby provinces since 2007, consistent with the period of more severe conflicts. (Figure 4)
4. Working hours per week in Border provinces had continually been lower than those in the Nearby provinces at the regional and country levels. (Figure 5)
5. Labor force participation in the Border provinces had been lower than in other areas. Nevertheless, this could somehow reflect the inherent problem of conflicts in the area. (Figure 6)
6. The formal sector, proxied by new business registration in the Border provinces, did not have different dynamics relative to other areas. (Figure 7)

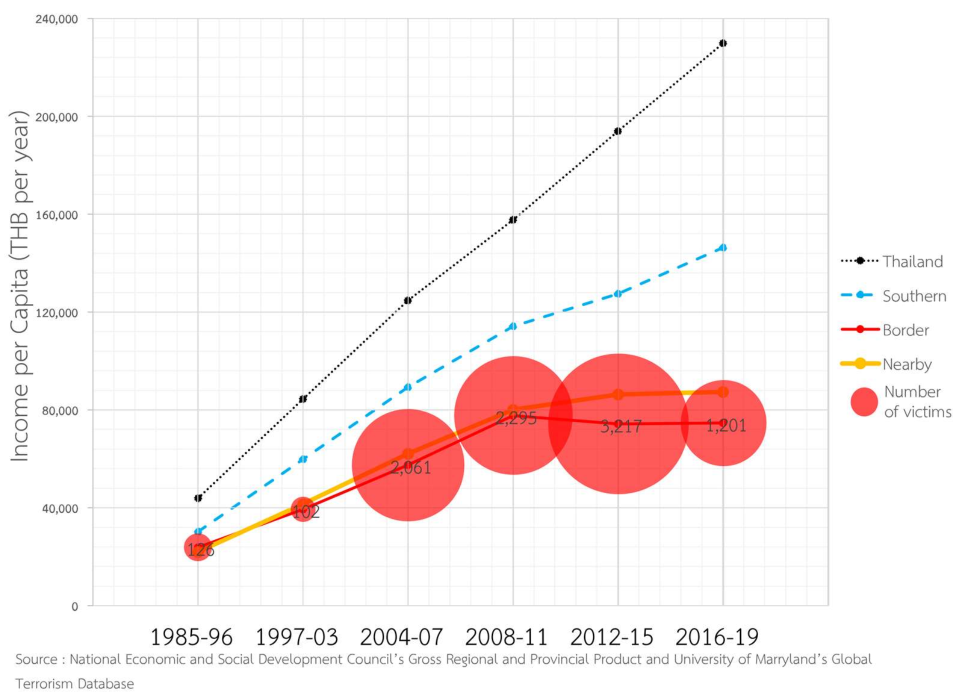
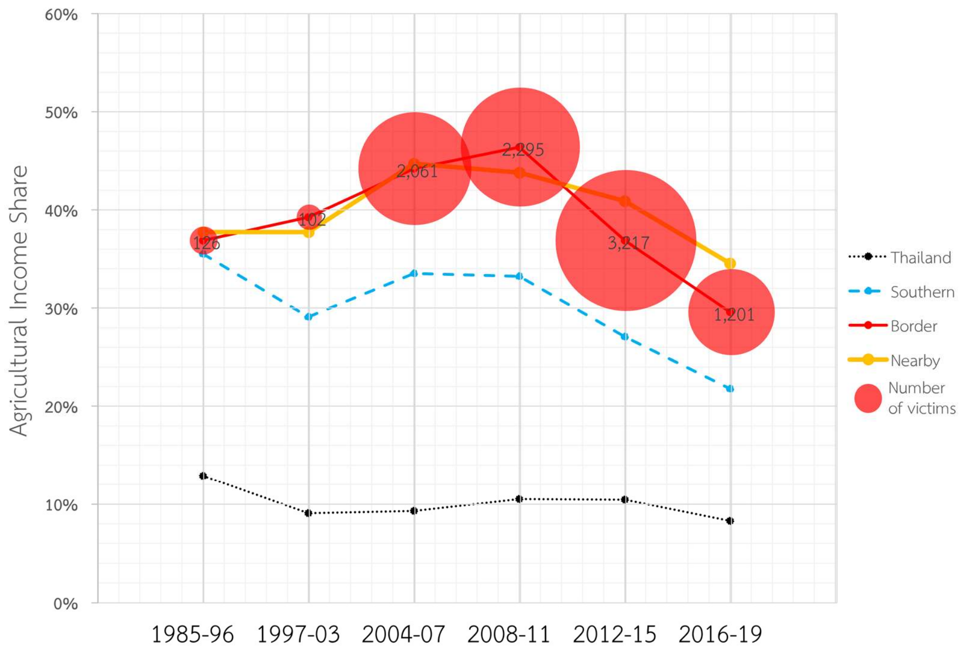
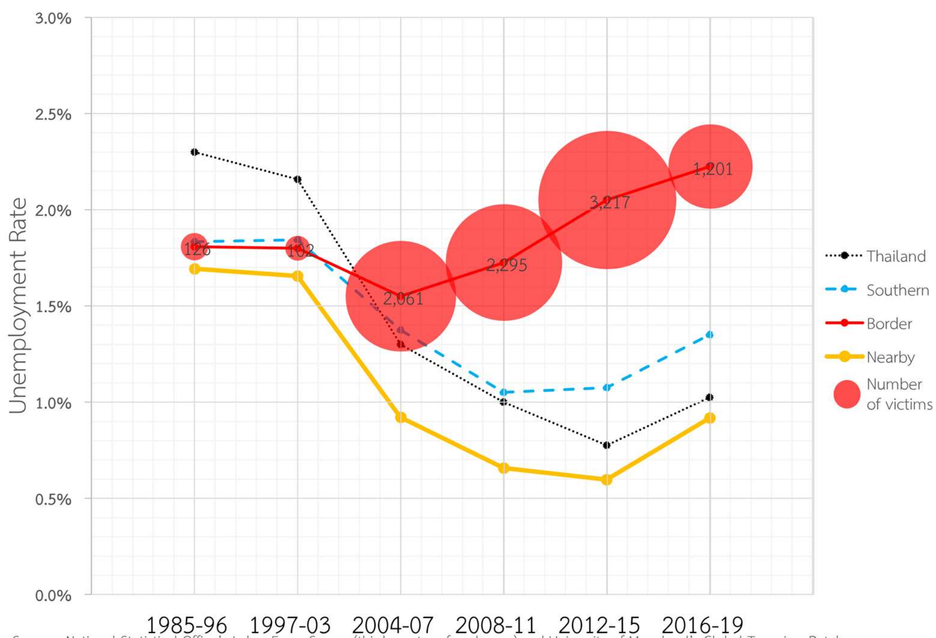


Figure 2 : Income per Capita in border provinces and other regions



Source : National Economic and Social Development Council's Gross Regional and Provincial Product and University of Marryland's Global Terrorism Database

Figure 3 : Agricultural income share in border provinces and other regions

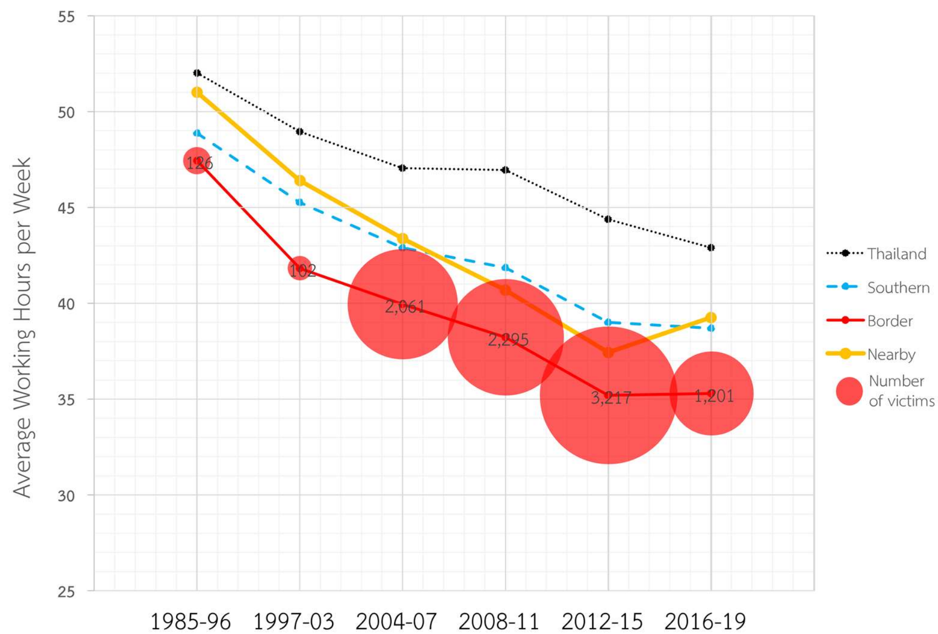


Source : National Statistical Office's Labor Force Survey (third quarter of each year) and University of Marryland's Global Terrorism Database

Remark : Labor Force was revised to cover persons with the age of 15 years, instead of 13 years, and over since 2001.

Since 2014, the survey has changed estimation to be based on the population census 2010.

Figure 4 : Unemployment rate in border provinces and other regions

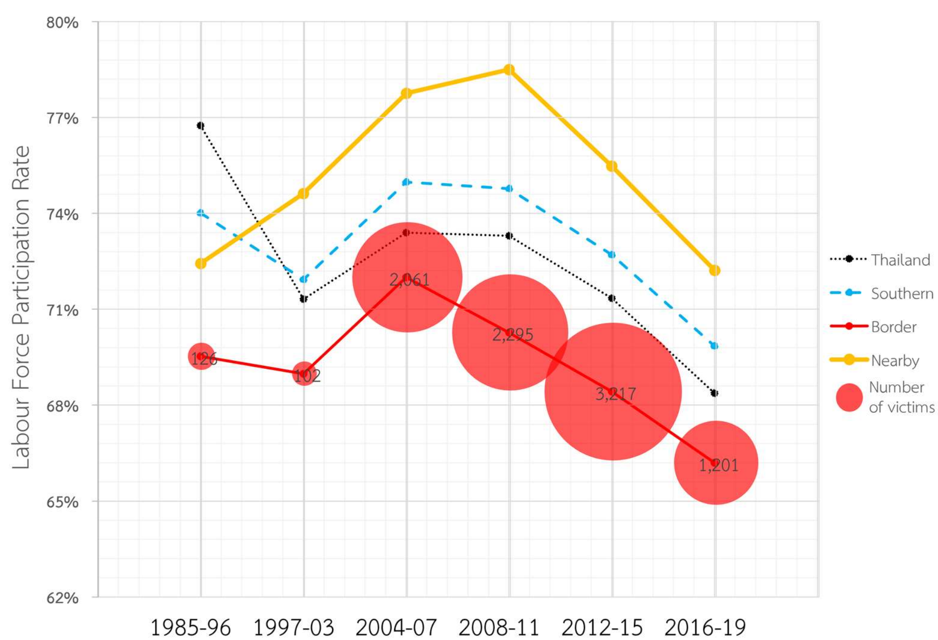


Source : National Statistical Office's Labor Force Survey (third quarter of each year) and University of Marryland's Global Terrorism Database

Remark : Labor Force was revised to cover persons with the age of 15 years, instead of 13 years, and over since 2001.

Since 2014, the survey has changed estimation to be based on the population census 2010.

Figure 5: Average working hours per week in border provinces and other regions



Source : National Statistical Office's Labor Force Survey (third quarter of each year) and University of Marryland's Global Terrorism Database

Remark : Labor Force was revised to cover persons with the age of 15 years, instead of 13 years, and over since 2001.

Since 2014, the survey has changed estimation to be based on the population census 2010.

Figure 6 : Labor force participation rate in border provinces and other regions

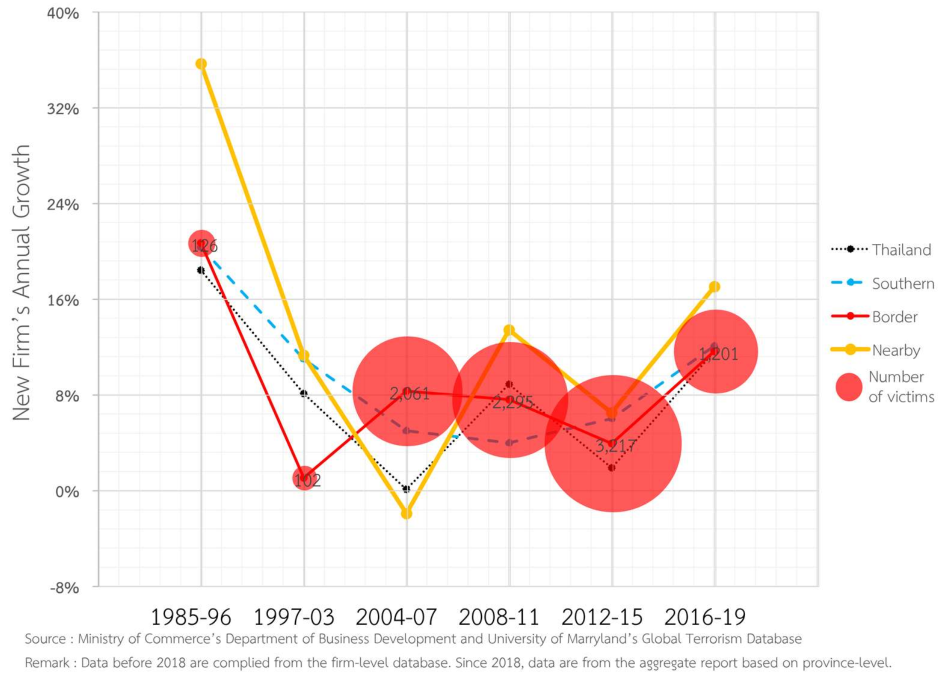


Figure 7 : New firm's annual growth in border provinces and other regions

In summary, the unemployment rate in the three provinces with conflicts seems to be significantly higher than in the other provinces with the same economic and geographic background. However, other indicators have not indicated such disparity. The unobvious uncontrolled stylized facts motivate us to estimate the causality of conflicts and labor market as well as ensure the robustness of the results with two models: Panel Vector Autoregressive and Synthetic Control methods.

3. Literature Review

After the September 11 attacks, the impact of terrorism on economic outcomes such as economic growth, investment, and employment has been empirically studied. The studies employ both individual country and cross-country data.

Blomberg et al. (2004) analyzed the association between terrorism, domestic conflicts, international war, and economic growth utilizing domestic and international conflicts. Using annual data from 177 nations from 1968 to 2000, they discovered a negative association between cross-country growth regression, panel data regression, and structural VAR models. Meierrieks and Gries (2012) utilized panel data on 160 countries between 1970 and 2007 to examine the association between civil disturbance and economic growth using the Granger Causality test described by Hurlin and Venet (2001). Before and after the end of the Cold War, they discovered the Granger Causality between variables of varying magnitude and directions.

Bandyopadhyay, Sandler and Younas (2014) examined the association between foreign direct investment (FDI) and terrorism in 78 developing countries between 1984 and 2008. Using the dynamic panel equation model, the researchers determined that terrorism had a detrimental effect on foreign direct investment (FDI). Redic, Dragicevic, and Sotosek (2019) focused on FDI in tourism and utilized a panel Vector Autoregressive (VAR) model with the Granger Causality test. According to the report, terrorism did not Granger cause foreign direct investment in the tourism sector.

Afzali (2019) examined the association between terrorism and unemployment using Afghan time-series data. It was discovered that terrorism negatively affected unemployment. Using successful and failed insurgency data, Brodeur (2017) determined the impact of terrorism on unemployment using county-level data from the United States. According to the study, success terrorism negatively impacted employment and wages. Adelaja and George (2020) examined the influence of unemployment on terrorism.

A small number of studies also use the synthetic control approach to identify the causal effects of conflict on economic results. Abadie and Gardeazabal (2003) analyzed the impact of disturbance on the GDP of Spain's Basque area by constructing a synthetic control group as a counterfactual against which to measure the actual GDP of the Basque region when the unrest broke out. This study indicated that instability contributed to a 10% decline in GDP. Bilgel and Karahasan (2017) investigates the economic costs of Kurdistan Workers' Party terrorism, which emerged in the mid-1980s in the Eastern and Southeastern provinces of Turkey using the synthetic control method. They find that from 1988 to 2001, after the emergence of terrorism, the per capita real GDP in Eastern and Southeastern Anatolia was lower than comparable synthetic Eastern and Southeastern Anatolia without terrorism by about 6.6 %.

There are still research gaps to be closed in the literature related to the relationship between conflicts and the Thai economy. In addition, most past studies used qualitative methods or relied on surveys to retrieve extended distant information to compare before and after the conflicts had risen (Boonsiri ,2016 ; Khawla-ead, 2008; Songsom, 2009). However, Chongwilaikasaem and Ingviya (2020) studied the district-level relationship during 2012-2017 with a panel data regression model and found that more intensive conflicts led to a statistically significant drop in economic activities proxied by electricity usage.

On the Thai labor market research literature, Arayavechkit et al. (2015) found that younger cohorts are workers and older cohorts are entrepreneurs. The rapidly aging population could worsen the inequality problem as labor supply shortage would drive mediocre entrepreneurs to become self-employed without employees.

Wasi et al.(2019) examined a more significant wage gap between college and non-college workers, even with declining overall income inequality. Changes in education-occupation composition, i.e., college workers less concentrated in high-skill jobs, while a larger share of secondary educated workers in low-skill jobs instead of middle-skill ones, is vital explanations. Employees with higher wages earn more since their market entry. The gap would get wider over time, then.

For the movement between the formal and informal labor market in Thailand, Wasi et al. (2021) explored employees under the social security system during 2002-2018. They found linkages between the formal and informal sectors, i.e., more than half of formal workers moved to work informally, either temporarily or permanently.

4. Methodology and Data

This section presents an analysis of the association between conflicts and employment. Section 4.1 investigates the Granger causality between conflicts and the labor market using the panel Vector Autoregression model. In section 4.2, the synthetic control approach is applied to ensure the robustness of our results.

4.1 Panel VAR study

In the first portion of this study, a panel Vector Autoregression (PVAR) is utilized (Holtz-Eakin, Newey, and Rosen, 1988). The panel VAR combines the VAR method, which investigates the dynamic relationship between endogenous variables, with the panel data method, which accounts for unobserved district-specific heteroskedasticity. Since there is no a priori theory regarding the causal relationship between conflict activities and labor markets, the VAR method is appropriate for achieving our goal. The panel VAR model is specified as follows:

$$y_{it} = \beta y_{it-1} + \gamma z_{it} + a_i + d_t + \varepsilon_{it}$$

where $y_{it} = (Labor_{it}, Conflict_{it})$ is a two-variable random vector composed of a measure of labor activity and conflict activity, z_{it} is controlled macroeconomic variable, a_i denotes unobserved district-specify heterogeneity, d_t denotes time-effects; and ε_{it} is an idiosyncratic error term. Our panel VAR estimation routine follows Abrigo and Love (2016).

We also perform the Panel Granger Causality test to investigate the relationship between conflicts and employment indicators. We used the sample of 37 districts from four Southern provinces between 2003 and 2019. The data are collected quarterly.

Conflicts involve using violence to achieve economic, political, religious, or social goals through the intimidation and fear of a larger population. We utilize three conflict indicators: the number of events, the number of wounded victims, and the number of fatalities. The GTD was developed by LaFree and Dugan (2007) and is maintained by the University of Maryland. Each district's conflict indicator is proportional to its population.

For the unemployment data, we utilize two data sources. The first set of data comprises the unemployment rate and worked hours derived from the National Statistical Office's (NSO) Labor Force Survey. The second set of Data is obtained from the Social Security Office (SSO), where businesses are required to submit employment data and unemployed individuals in the registration system are eligible for unemployment benefits. The SSO unemployment rate is derived from the number of employed and individuals receiving unemployment benefits. This indicator indicates a more formal labor market than the NSO survey indicators.

We included change in commercial bank deposits as the economic variable for a control variable. The banking data were taken from the Bank of Thailand.

4.2 Synthetic control approach

To ensure the robustness of our results, we also use the synthetic control method (Abadie and Gardeazabal, 2003; Abadie et al., 2010) to analyze the relationship between conflict and unemployment rate.

Since the labor market trends in Thailand's deep south provinces are unique. Thus, we cannot identify a suitable "control" group of provinces that is comparable to the deep south in terms of the unemployment rate prior to the conflict in the deep south. The synthetic control method allows us to create a synthetic control group that mimics various economic factors that has the potential to be unemployment determinants of the "treatment" group (provinces that are in the conflict area) before the conflict occurred in 2004 by using the convex combination of provinces that have not been exposed to conflict. We then use the difference in the post-conflict unemployment rate between the "treatment" and "synthetic control" groups as an indicator of the effect of conflict on the unemployment rate.

The synthetic control methodology is described below. Let j $(j = 1, \ldots, J+1)$ be provinces, province $j = 1$ be the province faced with economic impact from the conflict[7] or the "treatment group", and provinces $j = 2, \ldots, J+1$ be provinces that are not faced with the conflict or the "donor pool", the group of potential comparison units. Let t $(t = 1, \ldots, T)$ be years, years $t = 1, \ldots, T_0$ be the pre-conflict period and years $T_0 + 1, \ldots, T$ be the conflict period.

The synthetic control averages the units in the donor pool using the following method. Let $W = (w_2, \ldots, w_{J+1})'$ be a $J \times 1$ vector of weights, where $0 \leq w_j \leq 1$ for $J = 2, \ldots, J+1$ and $w_2 + \ldots + w_{J+1} = 1$. The synthetic control method chooses W^* that minimizes

$$\sum_{m=1}^{k} v_m (X_{1m} - X_{0m} W)^2$$

where v_m stands for the importance weight of characteristic m in the calculation of the difference between X_{1m} and $X_{0m}W$. The value of v_m is chosen to minimize the root mean square predictor error (RMSPE) in the pre-conflict period, where $RMSPE = \left(\frac{1}{T_0}\sum_{t=1}^{T_0}\left(Y_{1t} - \sum_{j=2}^{J+1} w_j Y_{jt}\right)^2\right)^{\frac{1}{2}}$, Y_{jt} is the outcome of unit j at time t,

X_{1m} is the explanatory variable of characteristic m for the treated unit, and

X_{0m} is the $1 \times J$ vector of the explanatory variable of characteristic m for the units in the donor pool.

After W^* is estimated, we can calculate the treatment effect in the conflict period $t > T_0$ from the equation $Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$.

[7] In the case of multiple treated units (i.e., many cities may be faced with conflict like the deep south provinces – Pattani, Yala, Narathiwat, and Songkhla), the synthetic control can be applied to each of the treated units.

In order to do synthetic control, we gathered annual provincial data from 1989 – 2019 from various sources as follows: (1) the labor force survey (LFS) collected by the National Statistics Office (NSO) provides the unemployment rate; (2) the Office of the National Economics and Social Development Council (NESDC) publishes Data on the Gross Provincial Product (GPP) per capita, the proportion of agricultural GPP, GPP deflator, and total population; and (3) the Ministry of Labor reports the minimum wage.

5. Results

5.1 Panel VAR

First, the dynamic relationship between three types of conflict variables and the unemployment rate from the labor force survey is investigated. Table 1 shows a negative relationship between the lag of conflict events per capita and the unemployment rate. This result contradicts the explanation offered by theory.

Table 1: NSO Unemployment and Conflicts: Panel VAR

	Model 1			Model 2	
	Unemployment Rate	Number of Events Per cap		Unemployment Rate	Number of wounds Per cap
Lag of Unemployment rate	0.130***	-0.015	Lag of Unemployment rate	0.131***	0.066
	[0.046]	[0.075]		[0.045]	[0.263]
Lag of Number of events per cap	-0.023**	0.309**	Lag of Number of wounds per cap	0.012	0.251
	[0.010]	[0.133]		[0.016]	[0.217]
Percentage change of deposit per cap	-0.339**	2.635*	Percentage change of deposit per cap	-0.247	5.153
	[0.148]	[1.401]		[0.145]	[3.767]
Year Dummies	Yes	Yes	Year Dummies	Yes	Yes
N	2073 [panel = 37]		N	2073 [panel = 37]	

Notes: Standard deviations are in square brackets. *,**,*** indicate significance at 10, 5, and 1% levels, respectively.

According to Table 1, the number of wounds per capita has a weakly positive correlation with the unemployment rate. This outcome is inconsistent with a theoretical explanation. The types of conflict intensity may have varying effects on the labor market. Moreover, considering the Granger causality. There is no Granger causality between the number of events, deaths, injuries, and unemployment. (Table 2)

Table 2: NSO Unemployment and Conflicts- Granger Casaulity

	Test Statistics	P-value
Number of Wounds per capita → Unemployment rate	0.579	0.447
Unemployment rate → Number of Wounds per capita	0.063	0.802
	Test Statistics	P-value
Number of Fatalities per capita → Unemployment rate	0.080	0.777
Unemployment rate → Number of Fatalities per capita	0.071	0.790

The average number of hours worked is also a gauge of the labor market. The correlation between an increase in events, injuries, or fatalities per capita and average work hours is statistically insignificant, as shown in Table 3. Even conflict activity has a negative impact on the labor market as measured by the labor force survey, but the effect is negligible and statistically insignificant. This result could be the consequence of a sampling error in which some districts were not selected. In addition, the unemployment rate is 0 in various districts and quarters. Additionally, we examine the formal labor market using Social Security Office data.

Table 3: NSO Hours Per Labor Force and Conflicts – Panel VAR

Model 1			Model 2			Model 3		
	Hours per LF	Number of Event Per cap		Hours per LF	Number of wounds Per cap		Hours per LF	Number of kills Per cap
Lag of Hours per LF	0.422***	2.209	Lag of Hours per LF	0.423***	6.955**	Lag of Hours per LF	0.422***	1.397
	[0.052]	[1.362]		[0.051]	[2.802]		[0.052]	[1.323]
Lag of Number of events per cap	-0.0003	0.305**	Lag of Number of wounds per cap	-0.0004	0.246	Lag of Number of kills per cap	-0.0003	0.177
	[0.001]	[0.133]		[0.0005]	[0.217]		[0.001]	[0.110]
Percentage change of deposit per cap	0.009	2.671*	Percentage change of deposit per cap	0.008	5.267	Percentage change of deposit per cap	0.009	1.681*
	[0.020]	[0.133]		[0.020]	[3.730]		[0.020]	[0.937]
Year Dummies	Yes	Yes	Year Dummies	Yes	Yes	Year Dummies	Yes	Yes
N	2073 [panel = 37]							

Notes: Standard deviations are in square brackets. *,**,*** indicate significance at 10, 5, and 1% levels, respectively.

The estimated parameters of the panel VAR(1) with SSO unemployment data are reported in Table 4. Our results show that the SSO unemployment rate responds statistically significantly positively to its lagged value and lag of the number of wounded victims. However, the other measures of conflicts – the number of events and number of killed victims – are not statistically associated with the SSO unemployment rate. On the other hand, conflict measures are not influenced by lagged of SSO unemployment rate. Therefore, when we consider the formal labor market, conflict activity adversely affects the labor market, not vice versa.

The impact of conflicts on the formal labor market has been substantiated by the dynamic relationship reported in Table 5. The number of firms is statistically negatively associated with the lag of wounded victims and fatalities. However, the number of conflict events is not statistically associated with the number of firms.

Table 4: SSO Unemployment Rate and Conflicts – Panel VAR

	Model 1			Model 2			Model 3	
	SSO Unemployment Rate	Number of Event Per cap		SSO Unemployment Rate	Number of wounds Per cap		SSO Unemployment Rate	Number of kills Per cap
Lag of SSO Unemployment rate	0.124*** [0.039]	-0.188 [0.371]	Lag of SSO Unemployment rate	0.125*** [0.039]	-1.041 [1.021]	Lag of SSO Unemployment rate	0.125*** [0.039]	-0.422 [0.403]
Lag of Number of events per cap	0.001 [0.001]	0.316** [0.142]	Lag of Number of wounds per cap	0.0004** [0.0002]	0.253 [0.221]	Lag of Number of kills per cap	0.0008 [0.0008]	0.198* [0.120]
Percentage change of deposit per cap	0.001 [0.009]	2.657* [1.430]	Percentage change of deposit per cap	0.001 [0.009]	5.259 [3.851]	Percentage change of deposit per cap	0.0003 [0.009]	1.775* [0.951]
Year Dummies	Yes	Yes	Year Dummies	Yes	Yes	Year Dummies	Yes	Yes
N	1911 [panel = 34]							

Notes: Standard deviations are in square brackets. *,**,*** indicate significance at 10, 5, and 1% levels, respectively.

Table 5: SSO Number of Firms and Conflicts – Panel VAR

	Model 1			Model 2			Model 3	
	SSO Number of Firms	Number of Event Per cap		SSO Number of Firms	Number of Wounds Per cap		SSO Number of Firms	Number of kills Per cap
Lag of SSO Number of Firms	1.073*** [0.022]	0.003 [0.010]	Lag of SSO Number of Firms	1.073*** [0.022]	-0.026 [0.034]	Lag of SSO Number of Firms	1.073*** [0.022]	0.006 [0.011]
Lag of Number of events per cap	-0.011 [0.009]	0.315** [0.142]	Lag of Number of wounds per cap	-0.006** [0.002]	0.254 [0.221]	Lag of Number of kills per cap	-0.020** [0.008]	0.197 [0.120]
Percentage change of deposit per cap	0.129 [0.170]	2.657 [1.429]	Percentage change of deposit per cap	0.119 [0.169]	5.243 [3.857]	Percentage change of deposit per cap	0.123 [0.170]	1.775 [0.950]
Year Dummies	Yes	Yes	Year Dummies	Yes	Yes	Year Dummies	Yes	Yes
N	1911 [panel = 34]							

Notes: Standard deviations are in square brackets. *,**,*** indicate significance at 10, 5, and 1% levels, respectively.

The result sheds light on the dynamic relationship between conflicts and the labor market using data from two sources. The conflicts have a more significant impact on the formal sector labor market and firms than on the entire labor market. The intensity of conflict events, such as the number of wounded and killed, also plays a substantial role in the decline of the formal labor market. On the contrary, labor market fluctuation do not affect the conflicts.

5.2 Synthetic control approach

We define Pattani, Yala, Narathiwat, and Songkhla provinces as the "*deep south conflict"* provinces in the "treatment" group, and the rest of the 69 provinces in Thailand belongs to the donor pool. We recognize the period 1989 – 2003 to be the pre-conflict period and 2004 – 2019 as the conflict period.

The synthetic control method builds comparison provinces for Pattani, Yala, Narathiwat, and Songkhla from a combination of other provinces in the donor pool. Those comparison provinces were similar to treatment provinces in the pre-conflict period in various economic dimensions that has the potential to be unemployment determinants. The economic characteristics we consider to synthetize our outcome variables, unemployment rate and the number of new establishments, are GPP per capita, the agricultural proportion of the GPP, GPP deflator, minimum wage, and population.

According to Figure 8, the difference between the reported unemployment rate and the counterfactual unemployment rate built for Pattani, Yala, Narathiwat, and Songkhla from the synthetic control method reflects that during the conflict period, the reported unemployment rates in the four deep south provinces (solid lines) are higher than their counterfactual unemployment rates (dashed lines). Figure 9 displays the box plot of the difference in the unemployment rate between each province in the "treatment group" and its synthetic version. During the deep south conflict (2004 – 2019), the median difference between the reported and counterfactual unemployment rates in Pattani, Yala, Narathiwat, and Songkhla are 0.95, 0.30, 1.51, and 0.89 percentage points, respectively.

The number of new establishments and their counterfactual values of the four deep south provinces are shown in Figure 10. After 2004, the reported numbers (solid lines) were lower than the counterfactual numbers (dashed lines). The median difference between the reported and counterfactual numbers of new establishments during 2004 - 2017[8] in Pattani, Yala, Narathiwat, and Songkhla are -32.25, -38.40, -44.87, and -54.39 establishments, respectively.

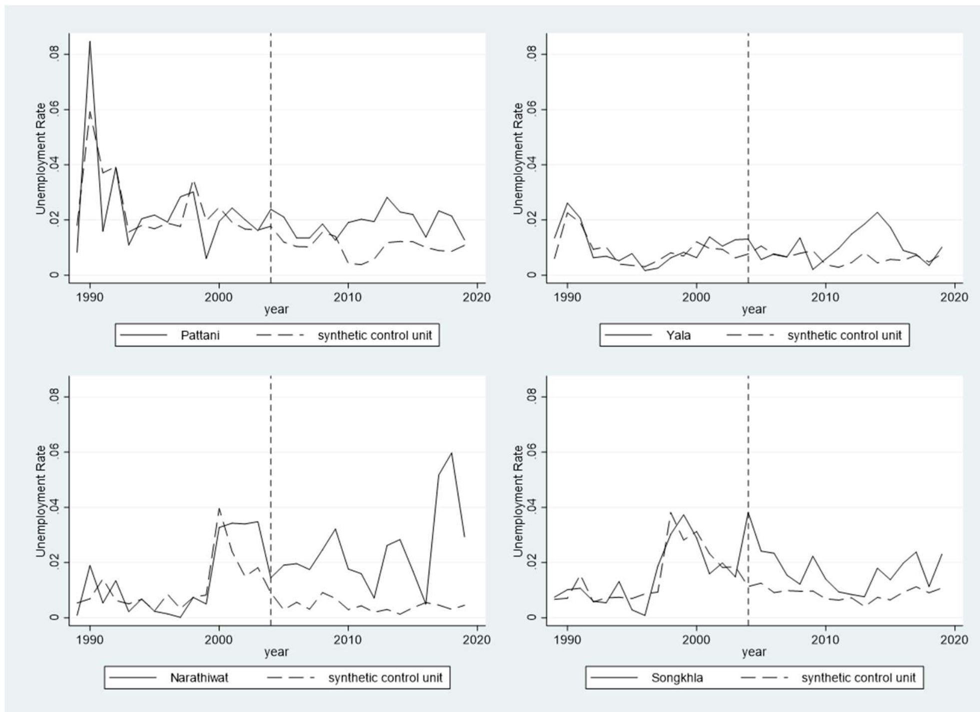


Figure 8: The difference between the reported (solid lines) and counterfactual unemployment rates (dashed lines) in Pattani, Yala, Narathiwat, and Songkhla.

[8] The provincial data on new establishments are publicly accessible until 2017.

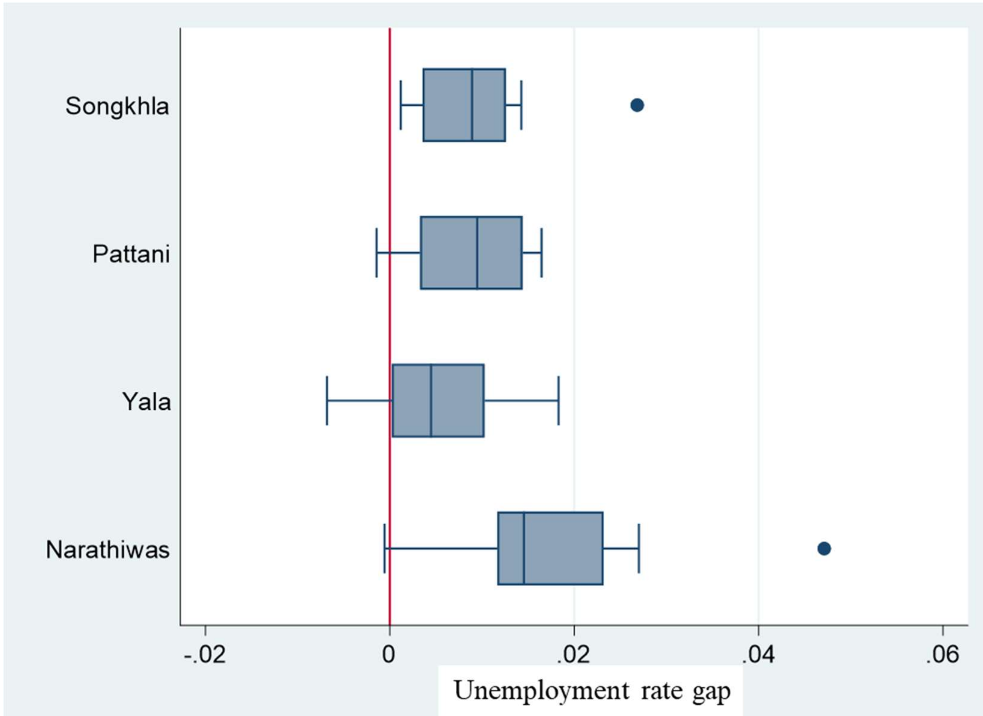


Figure 9: Box plot of the unemployment rate gap for each province
in the treatment group since 2004

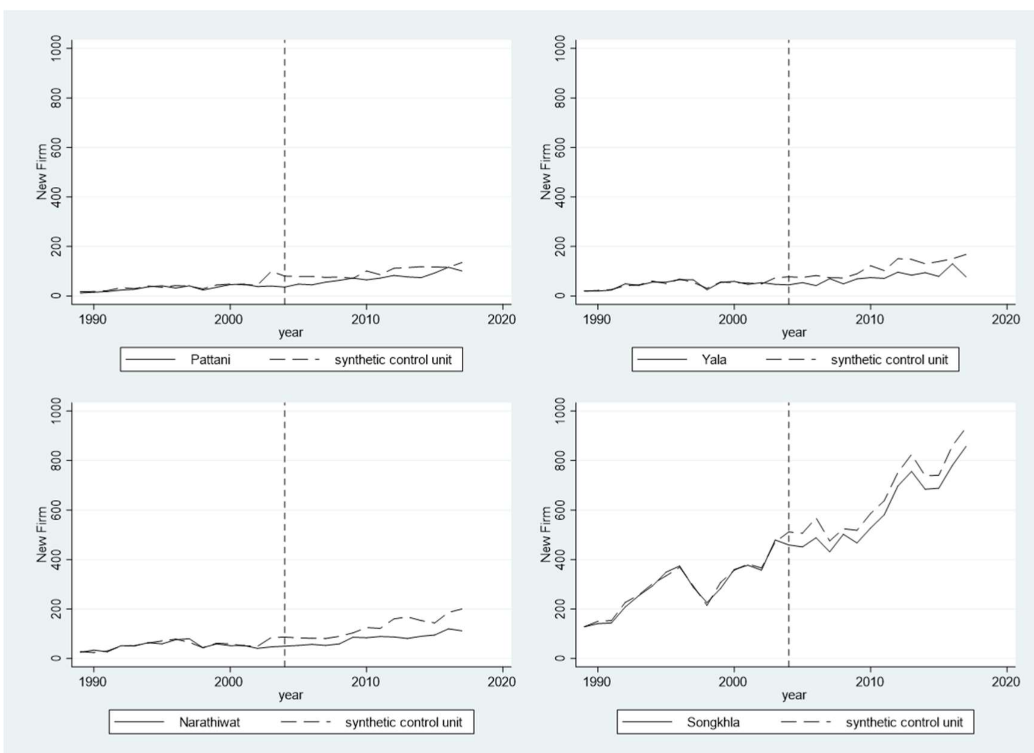


Figure 10: The difference between the reported (solid lines) and counterfactual new establishments (dashed lines) in Pattani, Yala, Narathiwat, and Songkhla.

Furthermore, this study conducted a placebo study to test the difference within the "control" group, no conflict area, between the reported and counterfactual unemployment rate since 2004. If the placebo study creates gaps of the same size as those estimated from conflict provinces in the deep south, then our analysis does not show that conflict positively affects the unemployment rate. If, on the other hand, the placebo test shows that the gaps estimated for the deep south conflict provinces are different compared to the gaps for the provinces that did not have conflict in the donor pool, then our analysis shows that conflict affects the unemployment rate.

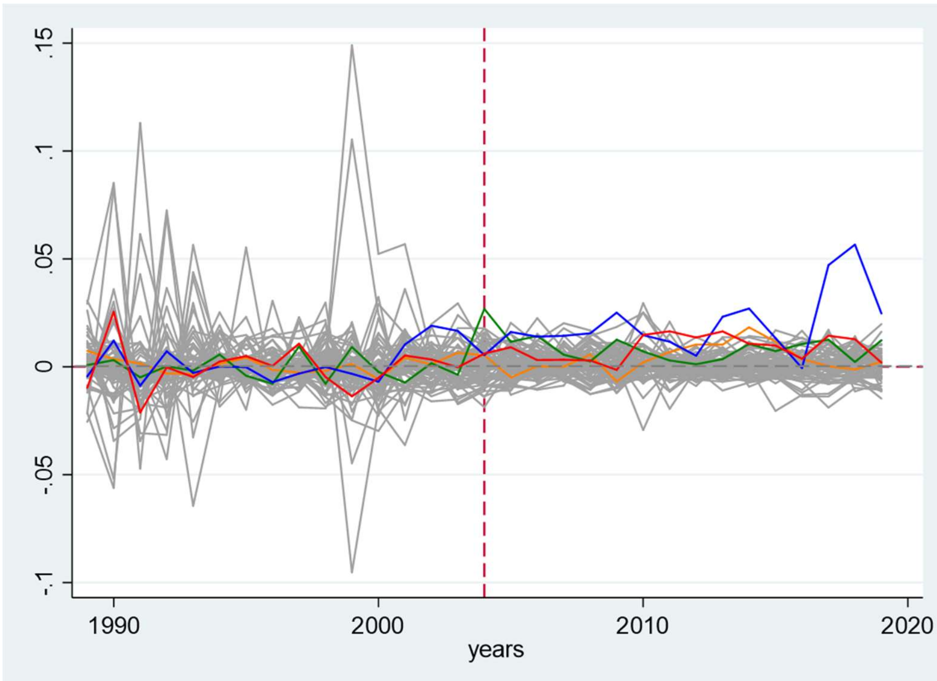
The placebo study result is shown in Figure 11. The vertical axis in Figure 11 represents the difference between reported and counterfactual unemployment rate. The gray lines show the differences in each of the 69 "control" provinces and the red, orange, blue, and green lines show the differences in Pattani, Yala, Narathiwat, and Songkhla, respectively.

Before the deep south conflict started (1989 – 2003), the average difference between the reported and counterfactual unemployment rates in the group of the 68 provinces outside the conflict area is indifferent from zero (mean = 0.0002954, s.d. =0.0010202) and similar to the average difference in the four provinces in the conflict area (mean =0.0004242, s.d. =0.0050089). The difference of this average is statistically insignificant between the two groups (p-value =0.9154).

However, after the conflict started (2004 – 2019), the average difference between the reported and counterfactual unemployment rates in the group of provinces outside the conflict area is near zero (mean = 0.0008562, s.d. =0.0006418), the average difference in the conflict area increases substantially (mean =0.0103006, s.d. =0.0042412). The average difference in the non-conflict area is significantly lower than the conflict area (p-value =0.0000).

Moreover, figure 12 displays the box plot of the difference in the unemployment rate between each province in the donor pool and its synthetic version. The figure shows that the median of the estimated gap for each province in the donor pool is around zero.

The placebo study to test the difference within the "control" group between the reported and counterfactual number of new establishments after 2004 is presented in Figure 13. We find that the average difference between the reported and counterfactual number of new establishments in the 68 provinces[9] outside of the deep south conflict boundary during 1989 – 2003 is not far from zero (mean = -0.0496974, s.d. =0.0308193). This effect is similar to the area of conflict (mean =-0.053885, s.d. =0.098677). The difference of this average is insignificantly different between both groups (p-value =0.8541).



Note: The red, orange, blue, and green lines show the differences in Pattani, Yala, Narathiwat, and Songkhla, respectively.

Figure 11. Placebo study of the effect of unemployment.

After the conflict began (2004 – 2017), the average difference between the reported and counterfactual number of new establishments is still not far from zero (mean = -0.0806966, s.d. =0.0307037) for the group outside of the deep south conflict boundary, but observably lower (mean =-0.2627855, s.d. =0.0766266) for the area of conflict. The average difference in the non-conflict area is significantly higher than the conflict area (p-value =0.0000).

[9] We excluded Bangkok from the group because the number of new establishments in Bangkok is considerably higher than other provinces which prevents us from using the synthetic control method to generate a counterfactual value for Bangkok.

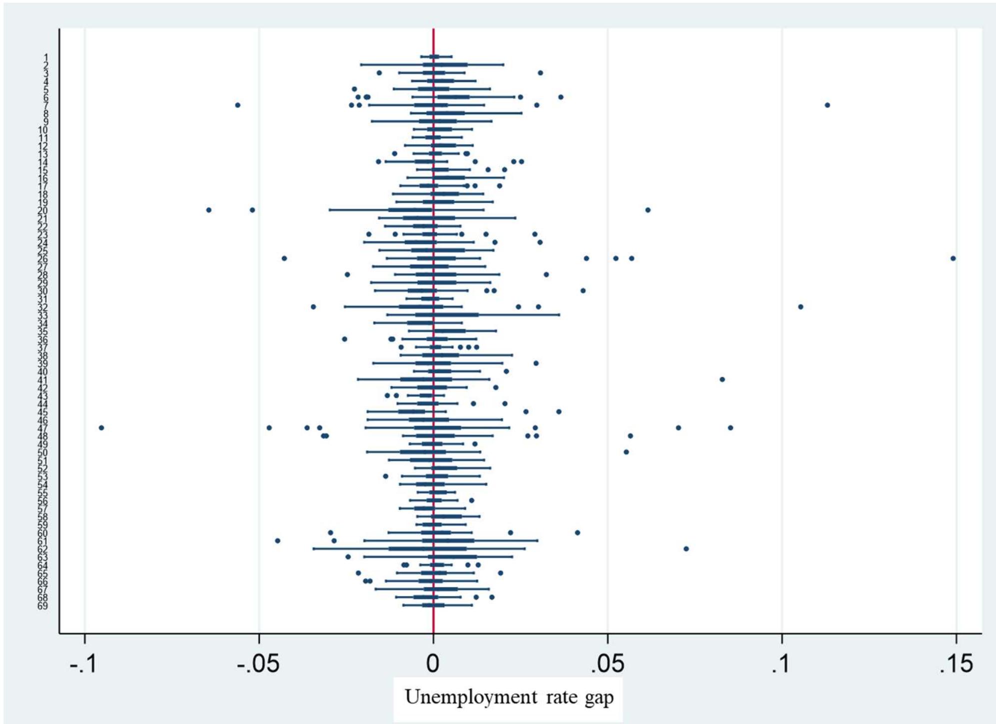
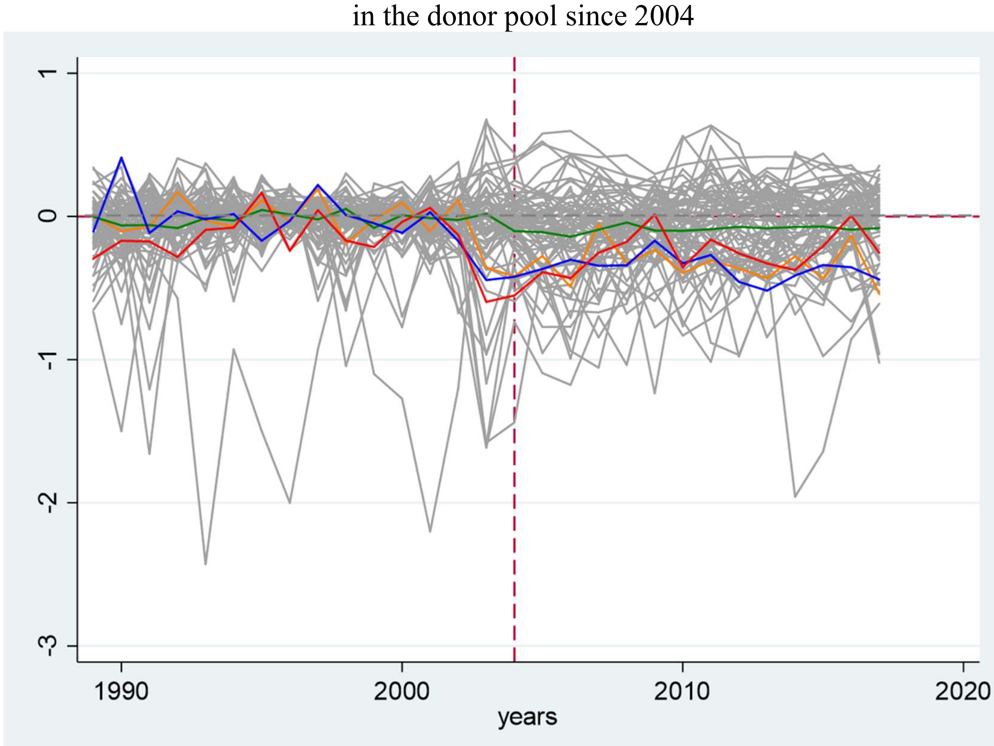


Figure 12: Box plot of the unemployment rate gap for each provinces in the donor pool since 2004



Note: The red, orange, blue, and green lines show the differences in Pattani, Yala, Narathiwat, and Songkhla, respectively.

Figure 13. Placebo study of the effect of new establishments.

We now utilize the effects of unemployment rate and number of establishments from the synthetic control method in Pattani, Yala, Narathiwat, and Songkhla to study the correlation between the diffenence between the actual and the synthetic unemployment rate and the number of incidences of conflict (per 100,000 population), government expenditure, and the proportion of defense budget with the two-way fixed effects model (Equation (1)).

$$Y_{\mathrm{it}} = \beta_1 \mathrm{event}_{\mathrm{it}} + \beta_2 \mathrm{govexp}_{\mathrm{it}} + \beta_3 \mathrm{share}_{\mathrm{it}} + \gamma_{\mathrm{i}} + \delta_{\mathrm{t}} + \mathrm{u}_{\mathrm{it}} \quad \text{\_\_\_\_\_\_}(1)$$

where Y_{it} is the diffence between the reported and counterfactual unemployment rate from the synthetic control[10] method in province i on year t,

$\mathrm{event}_{\mathrm{it}}$ is the number of incidences of conflict (per 100,000) in province i on year t,

$\mathrm{govexp}_{\mathrm{it}}$ is the government expenditure budget in province i on year t,

$\mathrm{share}_{\mathrm{it}}$ is the share of defense budget[11] in the government expenditure in province i on year t,

γ_{i} is the unobserved heterogeneity across provinces (constant across the study period),

δ_{t} is the time fixed effects (to control for other factors that may have an effect on annual unemployment rate, e.g., the different domestic economy-booster public policy packages that are launched each year), and

u_{it} is the idiosyncratic error term (independent and identical distribution: i.i.d.).

This study uses 56 observations across 4 deep south provinces during 2004 – 2017 to estimate equation (1). The provincial number of incidences is collected from the University of Maryland's Global Terrorism Database, and the government expenditure budget and the budget allocated for national defense are collected from the Bureau of the Budget of Thailand. We apply the robust standard error while estimating equation (1) to account for any possibility of serial correlation or heteroskedasticity.

[10] Larger positive Y values indicate a larger effect of the conflict on the unemployment rate.
[11] We calculate the "defense budget" by adding the provincial budgets of the Royal Thai Armed Forces Headquarters (Ministry of Defense), the Royal Thai Police office, and the Southern Border Provinces Administrative Center.

The results are reported in Table 6. When the incidence of conflict (per 100,000) increases one time, the unemployment rate gap (actual - synthetic) significantly (at the 0.05 confidence level) increases by 0.000482 percentage points. Interestingly, even though government expenditure was supposed to alleviate the effect of conflict on unemployment, the magnitude is relatively small and statistically insignificant (at the 0.1 confidence level). The share of the government budget for national defense may cause a crowding-out effect that leads to a reduction in private investments and other government expenditures that may positively boost the economy, which may result in more unemployment. If the proportion of the government budget allocated to national defense increases by one percent, then the unemployment rate gap (at the 0.01 confidence level) increases by 0.0219 percentage points. However, when substituting the number of incidences with the number of injuries or deaths, both indicators of conflict do not statistically significantly affect the unemployment rate gap.

Table 6 The effect on nemployment rate and the level of conflict.

VARIABLES	(1) Effect on unemployment rate
event	0.000482**
	(9.07e-05)
govexp	-9.13e-13
	(4.37e-13)
share	0.0219***
	(0.00362)
Constant	0.0117
	(0.00645)
Province FE	YES
Year FE	YES
Observations	56
Number of province	4
R-squared	0.379

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Moreover, we substituted the dependent variable (Y_{it}) in equation (1) with the effect on the new establishments[12] and use the lag of the explanatory variables in equation (1) as the new explanatory variables[13] to estimate another model. The findings are shown in Table 7. When the incidence of conflict (per 100,000) increases one time, the increase rate in new establishments (at the 0.05 confidence level) decreases by 0.06 percentage points compared to the counterfactual value. It is surprising to see that although government expenditure was designated to increase the number of new establishments, the magnitude is small and statistically insignificant (at the 0.1 confidence level). The crowding out effect may also relate here. If the proportion of the government budget allocated to national defense increases by one percent, then the number of new establishments decreases significantly (at the 0.01 confidence level) by 14.39 percent compared to the counterfactual value.

Table 7 The effect on new establishments and the level of conflict.

VARIABLES	(1) Effect on new establishments
L.event	-0.00315**
	(0.000856)
L.govexp	7.10e-12
	(1.41e-11)
L.share	-0.144*
	(0.0478)
Constant	-0.293***
	(0.0485)
Province FE	YES
Year FE	YES
Observations	52
Number of proid	4
R-squared	0.479

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[12] The effect on new establishments = $\frac{reported\ number\ of\ new\ establishments - counterfactua\ \ number\ of\ new\ establishmen}{counterfactual\ number\ of\ new\ establishmen}$

[13] We use lags of explanatory variables because there are time lags involved in the decision to start a business which is unlike the case of employment decisions.

6. Conclusion

We used the panel VAR model and quarterly provincial data during 2004 – 2019 to investigate the correlation between conflict and the labor market in the deep southern provinces of Thailand (Pattani, Yala, Narathiwat, and Songkhla). The findings of this study indicate that although the conflict caused the unemployment rate (under the social security system) in the conflict area to surge, the unemployment rate did not reversely cause further conflict. This finding confirmed our hypothesis that the conflict might affect human and physical capital in the production process and cause threats to citizens and entrepreneurs in the area of conflict. The conflict also generated defense-related transaction costs that reduced consumption and production and increased unemployment. The increase in unemployment did not affect the level of conflict since the deep south conflict was based on the divergence of political thoughts and not a problem of economic instability.

To ensure the robustness of our results, we used the synthetic control method to calculate the counterfactual unemployment rate and the counterfactual number of new establishments from annual provincial data. Our estimates of the effect of conflict on the unemployment rate and the number of the new business opening were the difference between the reported values and their synthetic version during 2004 – 2017. This study also used the two-way fixed effects model to analyze the correlation between the unemployment rate gap between the actual and synthetic provinces and the number of conflict incidences, government expenditure, and the defense budget share from the government expenditure.

We discovered that the unemployment rate (accounting for both informal and formal employment) in the deep south provinces was higher, and the number of new establishments was lower than their synthetic version. Furthermore, the number of incidences was found to be positively correlated with the gap between the actual and synthetic unemployment rates. Government spending was negatively correlated with the unemployment rate gap (although statistically insignificant). The defense budget share was positively correlated with the difference between the actual and synthetic unemployment rates (which may occur from the crowding out effect).

Three policy implications can be drawn from our study. First, the conflict caused economic instability. The government should issue unemployment relief packages for the conflict area and provide incentives for new establishments to enter the conflict area. Second, the benefit of unemployment reduction should be introduced in the cost-benefit analysis of conflict-resolution strategies. Lastly, the government should keep the defense budget under control so that public expenditure or investment is allocated to economic boosting policies such as research and development that can simultaneously benefit private investment.

This study is not without limitations. We conducted a non-structural model that did not allow us to provide exact explanations of how conflict could adversely affect unemployment. Also, we explored the effects of conflict on the labor market, specifically on only unemployment. Other aspects of the labor market, like the number of working hours and labor participation decisions, were not considered in our study and should be considered for further research.

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