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I am submitting herewith a thesis written by Ming-Jou Tsai entitled "Assessing the Economic Impact of a Devastating Natural Disaster." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Agricultural and Resource Economics.

T. Edward Yu, Major Professor

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Assessing the Economic Impact of a Devastating Natural Disaster

A Thesis Presented for the
Master of Science
Degree
The University of Tennessee, Knoxville

Ming-Jou Tsai
August 2019

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ABSTRACT

Natural disasters can result in serious damage and losses on people, infrastructure, and economic activities in the affected region. According to Loayza et al. (2012), among all kinds of natural disasters, earthquake has the largest average economic damage on a per-event base and per-affected person. The 2008 Wenchuan earthquake was the most devastating earthquake in China since 1980's, and was the top one earthquake by displaced population and the top seven one by the number of people killed in history (Daniell, 2013). Given its massive damage to human life and regional economic activities, it is important to better understand the impact of the 2008 Wenchuan earthquake on the economy in the affected area.

Existing studies related to the economic impact of the Wenchuan earthquake primarily focused on the immediate damage to the economy with only few exceptions related to the long-term impact or a particular sector or service. This study thus includes two specific objectives. First, we determine the long-term impact of the 2008 Wenchuan earthquake on the aggregate economy, the output of various industries, and different income-level groups in the severely damaged area. Second, we further identify the earthquake's impact on the agriculture sector in the affected counties of Sichuan province.

Results of the first study show that the Gross Domestic Product (GDP) in the severely damaged area could not recover even eight years after the earthquake. Also, the earthquake lowered the value-added of three categories of industry, with the secondary industry encountering the most losses followed by the tertiary and primary industries. Moreover, the counties with high-income level experienced more disruptions from the earthquake compared to low-income and medium-income counties, likely due to the different industrial structures among three income groups. In terms of the agricultural sector, results in the second study suggest that agricultural outputs in the extremely seriously-affected area and seriously-affected area were

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26% and 11% lower than the remaining counties as a result of the earthquake. The results also imply that the change of marginal productivity of agricultural inputs after the earthquake reduce agricultural outputs in both affected areas.

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CHAPTER I
INTRODUCTION

Natural disasters such as droughts, floods, storms, hurricane, and earthquake can cause devastating damage on human, infrastructure, and economic activities. According to the Emergency Events Database (EM-DAT), the natural disasters that occurred in 2018 resulted in around USD 108 billion economic loss and 10,809 deaths. The total economic damage that caused by natural disasters in 2018 was way larger than the average amount in the 18th century due to the rapid development of the economy in these decades. Among the economics sectors, agricultural sector is particularly sensitive to these events that cause sudden production losses and commodity prices perturbation. Loayza et al. (2012) analyzed a 1961-2005 cross-country panel dataset and found that the adverse growth effect of a severe natural disaster in agricultural sector was much higher than industrial and service sectors. Moreover, the FAO indicated that, on average, the agricultural sector in developing countries accounted for around 22 percent of total damage and losses from natural disasters between 2003 and 2013, which was higher than the other economic sectors (FAO, 2015).

According to a survey of Geller (1997), predicting an earthquake and notifying the society in advance is much more difficult than the alerts of other natural disasters. Also, earthquake occurred the most and caused the largest average economic damage per event and per person affected (Loayza et al. 2012). In addition, the impact of the earthquake is likely different between various economic sectors and remains over time if the affected region is not resilience enough to absorb the damage (duPont and Noy 2015; Bulte et al. 2018). Therefore, analyzing the earthquake impact across the economic sectors has important policy implications.

The 2008 Wenchuan earthquake with the 7.9 Richter scale magnitude hit the northeast of the Sichuan province on May 12th, 2008 and caused huge damages to the economy and human

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life. This earthquake was the most devastating earthquake in China since 1980's, the direct loss in the whole economy was nearly US$ 124 billion, and the indirect loss of production and housing sectors was equivalent to around 40% of the direct loss (Wu et al. 2012). In addition, the agricultural sector endured an estimated loss of US$6 billion as a result of the earthquake (Northoff and de Vleeschauwer 2008). In terms of human impacts from the disaster, 69,185 of people died, 374,147 of people got injured, and 18,457 of people missing (Li et al. 2009). The large number of casualties and missing people made the Wenchuan earthquake the top one earthquake by displayed people and the top seven by people killed (Daniell, 2013).

Most of the existing literature have only focused on the short-term and aggregated impact of the 2008 Wenchuan earthquake. For example, evaluating the direct and indirect losses from the Wenchuan earthquake right after the disaster (Yuan 2008, Northoff and de Vleeschauwer, 2008, Ye et al. 2011). Moreover, majority of the literature tend to investigate the climate-related disasters' impact on agriculture as this type of disaster is the most threatening event to the agricultural sector (Mendelsohn et al. 1994, Horridge et al. 2005, Norouzi and Taslimi 2012, Haque and Jahan 2015). The earthquake's impact on agriculture received little attention in the existing literature (Loayza et al. 2012, Parwanto and Oyama 2015).

To fill this gap in related literature, the objectives of Chapter 2 in this study are to (1) examine if the long-term negative impact of the earthquake exist on GDP in the severely damaged area; (2) determine if the earthquake's impact on three economic sectors vary; and (3) assess whether the counties with different economic status in the severely damaged area were affected differently by the earthquake. The objectives of Chapter 3 are to (1) determine if the earthquake has negative impact on the agricultural output in the affected areas; and (2) examine whether the earthquake's impact varied by the affected areas associated with the damage level.

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CHAPTER II
LONG-TERM IMPACT OF THE 2008 WENCHUAN EARTHQUAKE ON ECONOMIC OUTPUT BY INDUSTRY SECTOR AND INCOME LEVEL IN SICHUAN

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Abstract

The study estimated the 2008 Wenchuan earthquake's impact on overall GDP, value-added of three different types of industry, and GDP per capita across different income levels in Sichuan province. The synthetic control method was applied to a panel data of 128 counties over the period 1997-2016 to assess the earthquake's impact in the severely damaged area. Results suggest that the 2008 Wenchuan earthquake had a persistent and significant negative impact on overall GDP in the severely damaged area of Sichuan province. In addition, the earthquake's adverse impact varied across industries, with the secondary industry experienced the most losses. Finally, contrast to the previous studies, our findings suggest that the economy of the most affluent county group experienced the most hit from the earthquake, likely due to its heavy dependence on the damaged secondary industry.

Keywords: 2008 Wenchuan earthquake, synthetic control method, panel data, economic impact

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Introduction

With the rapid economic growth around the world over the past decades, the devastating impact of natural disasters on human life and economic activities has become an increasingly important issue. Among all of the natural disasters, earthquake could be the most devastating to people, infrastructure, and industries and is one of the most difficult to accurately predict (Bishop, 2017). Moreover, earthquake could result in tsunamis that cause casualties, and have a potential long-term impact on economic activities. Among the three major seismic belts on earth, the Alpine-Himalayan seismic belt encounters approximately 17% of the largest earthquake around the world and has caused many economic and social destructions in the Eurasian region, such as the 2015 Nepal earthquake, the 2008 Wenchuan earthquake in China, and the 2003 Bam earthquake in Iran (U.S. Geological Survey, 2019).

The Wenchuan earthquake on May 12, 2008, which occurred in the southwest of China, was China's most devastating earthquake since the 1980's. The 7.9 Richter scale earthquake resulted in 69,185 deaths, 374,174 injuries, and 18,457 people missing, this number making the Wenchuan earthquake the top seven and top one earthquake by people killed and displaced population, respectively, over the period 1990-2013 (Li et al., 2009; Daniell, 2013). In addition, the estimated direct economic loss from the earthquake was nearly US$ 124 billion and the indirect cost in production and housing sectors was equivalent to nearly 40% of direct cost (Wu et al., 2012). Almost four-fifth of the building was flattened out by the earthquake; the number of destroyed buildings from the Wenchuan earthquake was more than the total number of houses in Australia (Pletcher and Rafferty, 2019; Daniell, 2013).

Given this massive damage and losses, the duration of the earthquake's impact on economic output and the recovery pace of the economy have become a focus of policy and

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research (Yuan, 2008; Ye et al. 2011; Huang et al. 2015). Those related studies primarily focused on the immediate or short-term economic or societal effect of the Wenchuan earthquake as the post-quake period was not sufficient to examine the long-term effect in the past until recently. Also, the difficulty of isolating the sole impact of a natural disaster, such as earthquake, from other events has hindered the estimation of its long-term impact (Lynham et al. 2017). However, the impact of a catastrophic earthquake could extend over a long period. For example, duPont and Noy (2015) found that the Kobe earthquake in 1995 hit Japan's economy so bad that its GDP per capita could not regain its pre-quake status even 13 years after the earthquake. Best and Burke (2017) also suggested the 2010 Haiti earthquake caused long-term negative impact on GDP and the output of the service sector. In terms of the 2008 Wenchuan earthquake, Zhu et al (2018) suggested that the disaster caused a long-term negative economic impact; while Luo and Kinugasa (2018) could not identify an extended impact of the earthquake on household savings. Thus, it is legitimate to further evaluate if the Wenchuan earthquake influenced the economy in the affected area over a long period.

In addition to identifying the long-term impact of the 2008 Wenchuan earthquake on aggregate GDP, its impact on the output of various industry groups in the affected area warrants further attention. The impact of earthquake on each industry could differ since the industrial structure varies among the affected counties. Through simulation, Lin et al. (2012) found earthquake can cause different impacts on the production by industry sector given the repercussion effect differing across industry sector based on their features. Wu et al. (2012) claimed that large amount of house collapses and the long duration of reconstruction period together in the 2008 Wenchuan earthquake causes the most adverse impact on the housing and production sectors. Identifying which industry group is sensitive to the earthquake over time

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provides important information for damage prevention and related insurance policy development. However, related analysis is still lacking for the 2008 Wenchuan earthquake.

Previous studies have also shown that economic development or income level in the affected area by natural disasters is linked to the related damage caused by the natural disasters. In general, the poorer regions are likely to suffer more from a disaster than the prosperous area because people in the poorer region may not be able to afford to repair and reconstruction from the disaster. Masozera et al. (2007) found that the households with lower income in New Orleans are more vulnerable to Hurricane Katrina than the higher income level group. Barone and Mocetti (2014) even indicated that, in the long-run, earthquake may have a positive impact on GDP in those highly developed economies and a negative impact in those lower developed countries. Related studies currently compared the impacts of natural disasters on various income groups using diverse disasters in different regions. However, those disasters varied by scale, timing, and geographic characteristics thus the comparison could be misleading. Evaluating the impact of a specific natural disaster on different income groups in a region is still few.

The objectives of this study thus is three-fold: 1) identifying the potential long-term economic impact of the 2008 Wenchuan earthquake; 2) assessing the output impacts of the earthquake on different industry groups; and 3) determining the impacts of the earthquake on the economics associated with various income groups in the affected area. We hypothesize that the 2008 Wenchuan earthquake had a long-term negative impact on GDP in the affected counties (referred as hypothesis 1). In addition, it is hypothesized that the output impact of the Wenchaun earthquake varied by industry group (referred as hypothesis 2). Finally, we hypothesize that, under the 2008 Wenchuan earthquake, the speed of recovery of the GDP per capita for those affected counties with higher income level is faster than those affected countries with lower

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income level (referred as hypothesis 3).

Literature Review

Existing literature have adopted various approaches and aspects when evaluating the economic impact of a natural disaster, such as earthquake. A number of studies aimed to capture the immediate or short-run impact of the exogenous event on economy activities (Wu and Lindell, 2004; Masozera et al. 2007; Goda et al. 2015); while recent research started to focus on the long-term impact of a disaster (Barone and Mocetti, 2014; duPont and Noy, 2015; Lynham et al. 2017; Best and Burke; 2017; Luo and Kinugasa, 2018). In addition, several scholars have focused on the impacts of a natural disaster on various sectors to capture the heterogeneous effect across sectors (Lin et al. 2012; Wu et al. 2012), or compared disasters' impacts between different development statuses or economic conditions (Masozera et al. 2007; Barone and Mocetti, 2014).

Survey or interview data collected immediately after the disaster has been commonly used to capture the short-term effect of a natural disaster. Wu and Lindell (2004) compared the housing reconstruction between the 1999 Chi-Chi earthquake in Taiwan and the 1994 Northridge earthquake in the United States through a survey. The authors found that having a pre-impact recovery plan increased the efficiency of task management immediately after the earthquake and enhanced the speed of housing restoration. Goda et al. (2015) conducted a survey 6-11 days after the 2015 Gorkha Nepal earthquake to analyze the resulting damage and loss. They found that the structural design of building was crucial to prevent the damage of earthquake in Nepal. Although interviewing affected individuals right after a disaster can capture the instant impact, collecting such data sometimes can be too costly, time-consuming, and subjective. In addition, the data

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collected by survey method may not be precise if the questionnaires are not well defined or designed (Mathiyazhagan and Nandan, 2010).

In term of investigating the long-term impacts of natural disaster, various methods such as autoregressive integrated moving average (ARIMA), vector autoregressions (VAR), difference-in-difference (DID), and synthetic control methodology (SCM) have been used to examine the long-term impact of natural disaster in previous studies. Zhu et al. (2018) applied an ARIMA model to examine the GDP recovery in the severely damaged counties in the Sichuan province, China after the 2008 Wenchuan earthquake. Their results suggested that nine out of ten severely affected counties could not fully recovered even six years after the earthquake. Fomby et al. (2009) employed the VAR method to identify the relationship between four different types of natural disasters (e.g. droughts, floods, earthquakes, and storms.) and economic growth. Also, they analyzed the impacts of natural disaster on agricultural and non-agricultural sectors to precisely interpret the disaster impact on economic activities. They found that earthquakes have slightly positive impact on output growth in the non-agricultural sector in the first year after the disasters and make no significant impact on the agricultural sector in the developing countries.

Belasen and Polachek (2009) applied a generalized-DID model to examine the impact of hurricanes during 1988 to 2005 on the labor markets in Florida. The mainly finding of their study is that the working earning in those Florida counties that were directly hit by the hurricanes increased nearly 4% while the employment in those stricken counties decreased. In addition, the working earning in those neighboring counties decreased and the employment unchanged. They also found that hurricane had a positive impact on working earning and a negative impact on employment in those directly hit countries. In addition, those impacts increased along with the destructive power of the hurricane. Tanaka (2015) used a DID approach but along with the

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matching method that matched the manufacturing plants in affected areas with those in unaffected area, to evaluate the pure effect of the 1995 Great Hanshin-Awaji earthquake on plant's growth in Japan. The author found that the employment and value-added growth of plants in the affected area severely reduced in the following three year after the earthquake.

One of the assumptions in the DID method is that the trend of treated group and control group before the intervention of interest must be parallel (Mora and Reggio, 2012), however, this assumption is hard to maintain in the real world. The other assumption is that it requires the unobserved factors to remain constant over time, so the factors can be eliminated by taking the time difference between the treated group and control group. The SCM developed by Abadie et al. (2010) extents the framework of DID by relaxing those two assumptions. duPont and Noy (2015) used the SCM to compare the deviation of the actual and the synthetic counterfactual to analyze whether the 1995 Great Hanshin-Awaji earthquake in Japan has the long-term impact on the economic activities. Using a 20 years pre-disaster and post-disaster panel data at the prefectural level, they found that the negative impact on GDP per capita was persistent as it did not reach to where it would be without been hit by the earthquake. Lynham et al. (2017) used SCM to examine what would have been in the Hawaii Island without been affected by the 1960 tsunami. They found that population, number of employers, unemployment rate, and sugar production experienced the negative and long-term impact after the tsunami. Applying the SCM approach, Luo and Kinugasa (2018) found that the saving rate of the affected people after the 2008 Wenchuan earthquake decreased largely in the short-run. However, the impact of the earthquake on household saving rate was temporary and the household saving rate returned to its pre-quake level shortly after the earthquake.

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To evaluate the impacts of the natural disaster among different sectors, the input-output model analysis has been a commonly adopted tool. While input-output models are useful to estimate the overall economic impact of the disasters, the derived multipliers could be biased and overestimate (or underestimate) the actual impacts on the economy (Grady and Muller, 1988). Lin et al. (2012) simulated two earthquakes in northern Taiwan to see the impact of each earthquake on the economic activities in different industrial sectors. The input-output analysis showed that the economic output of the manufacturing sector was damaged the most and its repercussion effects will amplify. They suggested the government should focus on encouraging the manufacturing sector to implement the earthquake mitigation strategies. Wu et al. (2012) used an adaptive regional input-output model to access the indirect economic loss and the ripple effects on different sectors (e.g. agriculture, mining, manufacturing sectors, etc.) in the Sichuan province, China after the 2008 Wenchuan earthquake. They found that the indirect economic losses cannot be overlooked as the indirect losses in production and housing sectors were nearly 40% of the direct economic losses, which were about 300 billion yuan.

Okuyama (2004) employed input-output approach to examine the impact of the Great Hanshin earthquake in Japan on income formation and gross output in two regions (Kinki and the rest of Japan) under two situations: with reconstruction activities and without reconstruction activities. The author found that the negative impact of the earthquake on the income formation in the rest of Japan were greater than the negative impact in Kinki. The impact on income formation was still negative even if with the reconstruction. Best and Burke (2017) identified the macroeconomic impacts of the 2010 Haiti earthquake on different economic sectors (e.g. the agricultural sector, services sector, energy sector, production sector, manufacturing sector, among others) by using the SCM to simulate the synthetic counterfactual for each sector. They

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found that the earthquake brought large and permeant effect on GDP and the output of the service sector. For the manufacturing sector, although the negative impact of earthquake was considerable, the recovery time of the manufacturing sector was faster than other sectors

A number of studies compared the economic impact of natural disasters between various economies or income groups. For example, Barone and Mocetti (2014) analyzed the earthquake impact on GDP per capita from two different earthquakes, 1976 Friuli earthquake and 1980 Irpinia earthquake, in Italy by using the SCM. They found that in the long-run, the earthquake had a positive impact on GDP per capita in Friuli but had a negative impact in Irpinia, where the development of economy and society was high in Friuli, and was low in Irpinia. They suggested that the affected region with lower development of economy may be more vulnerable than the one with higher development of economy when facing the impact form a disaster. Masozera et al. (2007) also found that the impact of Hurricane Katrina on households in New Orleans were differently, specifically, the household with lower income were more vulnerable to Hurricane Katrina than the higher income level group. Fomby et al. (2009) estimated the impact of natural disasters on the growth of agricultural and non-agricultural sectors in developing and developed countries over the period 1960-2007. They found that the impact of natural disasters in developing countries were stronger than in developed counties.

Conceptual Framework

Suppose there are *J*+1 units, let unit one be the treated unit, the unit that be affected by the natural disaster, and the remaining *J* units be the control units, which are not affected by the natural disaster. Assuming Y_{1t}, the orange solid line in Figure 1, represents the observed outcome for treated unit one at time *t*, where $t = 1, \dots T_0 \dots, T$. ($T_0$ refers to the time of the natural disaster occurred). Y_{1t}^N, the orange dashed line in the Figure 1, is the unobserved economic variable of

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interest for treated unit one at time *t* without been affected by the natural disaster. Let Y_{jt}, the green solid line in the Figure 1, be the observed outcome for the control unit *j* at time *t*, where $j = 2, \dots, J + 1$. The relationship between observed outcome and unobserved outcome of treated unit can be written as:

$$Y_{1t} = Y_{1t}^N + \alpha_{1t} \qquad (1)$$

where α_{1t} represents the effect of the natural disaster for treated unit one at time *t*.

Y_{1t}^N can be estimated by assigning different weights that minimize the deviation between Y_{1t} and Y_{1t}^N in pre-intervention period to different Y_{jt}, and summing up each product of assigning weight and Y_{jt}, plug it into equation (1) and rearrange equation (1) as:

$$\widehat{\alpha_{\iota t}} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \qquad (2)$$

where $t = T_0 + 1, \dots T$.

[Place Figure 1 here.]

Method

The SCM enables us to construct a synthetic counterfactual that represents what would have been in the absence of the natural disaster based on the information of the control group. It constructs the counterfactual by assigning different weights that can minimize the deviation between treated group and control group before the occurrence of the exogenous event to corresponding control units. By doing so, the trend of treated group and the estimated counterfactual will be similar. Also, the unobserved factors in the SCM are allowed to vary across time.

Following Abadie et al. (2010), suppose there are $J + 1$ regions and the first region is the treated unit, the remaining *J* regions are control units. Let Y_{it} represents the observed outcome

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for treated unit *i* at time *t*. Next, let Y_{it}^{N}, which can be specified using a factor model, represents the outcome for treated unit *i* at the time *t* that without being affected by the natural disaster, where $i = 1, \ldots. J + 1$, and $t = 1, \ldots., T$. The observed outcome can be written as:

$$Y_{it} = Y_{it}^{N} + \alpha_{it} D_{it}$$

$$Y_{it} = (\delta_t + \theta_t Z_i + \lambda_t \mu_i + \varepsilon_{it}) + \alpha_{it} D_{it} \qquad (1)$$

where α_{it} is the variable of interest which represents the effect of the natural disaster for treated unit *i* at time *t*, D_{it} equals to 1 if the treated unit *i* experienced the intervention at time *t*, and 0 otherwise, δ_t is an unknown common factor, θ_t is a $(1 \times r)$ vector of unknown parameters, Z_i is a $(r \times 1)$ vector of observed covariates (i.e. predictors) that did not affect by the event, λ_t is a $(1 \times F)$ vector of unobserved factors, μ_i is a $(F \times 1)$ vector of unknown parameters, and the error term ε_{it} refers to the unobserved temporary shocks with zero mean.

The treatment effect α_{it} can be estimated by substituting the unobserved Y_{it}^{N} with the weighted average of the control units, $\sum_{j=2}^{J+1} w_j^* Y_{jt}$, and then calculate the difference between the observed outcome and the weighted average of the control units (Abadie et al. 2010). w is a $(J \times 1)$ vector of weights, where $w_j \geq 0$ for $j = 2, \ldots\ldots, J + 1$ and $\sum_{j=2}^{J+1} w_j = 1$. Thus, the equation (1) can be rearrange as:

$$\widehat{\alpha_{it}} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \qquad (2)$$

The study area (i.e. treated counties) of this paper focuses on the 18 severely damaged counties in the Sichuan province defined in the study of Bulte et al. (2018). Bulte et al. (2018) classified the 18 severely damaged counties into a paired disaster countries group based on the pairwise aid policy that established right after the earthquake. Counties in the paired disaster counties group encountered the most severe damage from the earthquake, thus receiving the aid

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from both the central government and a matched prospective province. The matched province had a responsibility to provide at least 1% of its revenue from the previous year to the paired county for three consecutive years (i.e. from 2008 to 2010). For the control counties, we excluded the counties that less affected by the earthquake, and we also removed the seven non-disaster counties that adjacent to a paired disaster county to prevent the spill-over effect.

The SCM was initially designed for the case with one given treated unit in Abadie et al. (2010). However, multiple treated units may exist in some cases when the number of treated observations are more than one. In our study, we followed Krief et al. (2016) to calculate the weighted average for the aggregate outcome variables by using employed person as the weight. The equation of the weighted average for multiple treated units is as follow:

$$\overline{Y_{it}} = \frac{\sum_{i=1}^{\gamma} Y_{it}\beta_{it}}{\sum_{i=1}^{\gamma} \beta_{it}} \qquad (3)$$

where β_{it} represent the employed person for treated unit *i* at time *t* in this study; and γ refers to the number of the treated unit in each treated group.

When examining the earthquake's impact on different income group, we further disaggregated the study area into three different tiers based on their corresponding GDP per capita in 2007 (the year prior to the earthquake). The GDP per capita of the treated unit in 2007 below 25 percentile, between 25 and 75 percentile, and over 75 percentile is categorized into the low-income group, medium-income group, and high-income group, respectively. For each income group, we also used equation (3) to calculate the weighted average of the outcome variable. The corresponding control groups for different income level are the unaffected counties in Sichuan that match the same income threshold with the affected counties. For instance, if the 2007 GDP per capita of the unaffected county is under 25 percentile of 2007 GDP per capita in severely damaged area, then the unaffected county will be classified into the control group for

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the low-income group. Similarity, if the 2007 GDP per capita of the unaffected county is over 75 percentile of 2007 GDP per capita in severely damaged area, then the unaffected county will be classified into the control group for the high-income group. Finally, the remaining unaffected counties were classified into the control group for the medium-income group.

To test the significance of the 2008 Wenchuan earthquake on the economic output in the affected area in the post-quake period, we followed the study of Abadie et al. (2010) to generate the figure from the placebo test. The placebo test applied the synthetic control model to those counties that did not affect by the 2008 Wenchuan earthquake to get the placebo studies, which are the gaps between actual and corresponding counterfactual for each control unit. More specifically, the synthetic control method was separately applied to each control unit while remained the remaining control units and shifted the original treated unit into the control group to get the placebo studies. Following Abadie et al. (2010), if the gap between actual and corresponding counterfactual in the severely damaged area is similar to the gap of placebo studies, then the impact of earthquake is not significant on the variable of interest in the severely damaged area. On the other hand, if the gap between actual and corresponding counterfactual in severely damaged area is much larger than the gap of placebo studies, then the negative impact of the earthquake is significant on the variable of interest in the severely damaged area.

We also followed Cavallo et al. (2010) to calculate the lead-specific significant level (e.g. p-value) for each post-quake year which is from 2009 to 2016 in our study. This method can provide the information of the significance level of every year after the earthquake. We computed the p-value as:

$$p - value_l = \Pr\left(\hat{\alpha}_l^j < \bar{\alpha}_l\right) = \frac{\sum_j I(\hat{\alpha}_l^j < \bar{\alpha}_l)}{\#\ of\ control\ counties} = \frac{\sum_j I(\hat{\alpha}_l^j < \bar{\alpha}_l)}{J}$$

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where $\hat{\alpha}_l^j$ is the estimated earthquake effect for control unit j after l years of the earthquake when assuming control unit j suffers the same event as treated unit; $\bar{\alpha}_l$ is the average earthquake impact after l years of the earthquake for all treated units; and $I(\cdot)$ is the indicator function with the value one if the condition in the parentheses is met, and zero otherwise.

Data

The annual county-level data for the period from 1997 to 2016 from the Sichuan Statistical Yearbooks (1998-2017) was used in this study. The data covers 11 years before the 2008 Wenchuan earthquake, and eight years after the earthquake. The impact of the 2008 Wenchuan earthquake on aggregate GDP, the value-added of industry by category (including the primary, secondary and tertiary industry)[1], and GDP per capita by income group was examined to examine our three hypotheses. Table 1 displays the descriptive statistics for outcome variables in treated group. The classification of the county under severely damaged area is displayed in Table 2.

[Place Table 1 here.]

[Place Table 2 here.]

The predictors that constructing the synthetic counterfactual of overall GDP in the severely damaged area and the predictors' mean are displayed in Table 3. Table 4, 5, and 6 showed the predictors for constructing the synthetic counterfactual of value-added of primary, secondary, and tertiary industries in the severely damaged area and the predictors' mean, respectively.

[1] According to the Sichuan Provincial Bureau of Statistics, primary industry consists of crops, forestry, fishery, and livestock. Secondary industry includes mining, manufacturing, electricity, gas and, water production, supply industry, and construction industry, whereas tertiary industry refers to other industries with a main focus on service business.

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Finally, the predictors and its means for low-income, medium-income, and high-income groups are listed in Table 7.

[Place Table 3 here.]

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[Place Table 5 here.]

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[Place Table 7 here.]

Results

Figure 2 shows the trend in GDP from 1997 to 2016 for the severely damaged area and its corresponding synthetic counterfactual. In this study, the estimation of the earthquake impact is the difference between actual scenario and its synthetic counterfactual in the post-quake period, which is the gap between the solid line and the dashed line after 2008. The vertical dashed line refers to the year that the earthquake happened. The pre-intervention Root Mean Squared Prediction Error (RMSPE) for the severely damaged area is 2.64. The small pre-RMSPE suggests the predictors for estimating the synthetic counterfactual of the severely damaged areas provide an appropriate forecast of what would have been in the absence of the earthquake. Also, the synthetic GDP trend in Figure 2 is very close to the actual GDP trend in the pre-intervention period. This strongly indicates that the accuracy of the model and the prediction of the model can be believed.

[Place Figure 2 here]

Figure 2 suggests that the growth rate of GDP in the severely damaged area after the 2008 earthquake is slower compared to the growth rate of its synthetic counterfactual, that is, the gaps between the GDP in the severely damaged area and its synthetic counterfactual are

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increasing over time. Figure 2 also indicates that the negative impact on GDP in severely damaged area is persistent as the two lines do not converge even eight years after the earthquake. The two lines in Figure 2 diverged right after the earthquake, and the gap between two lines expanded over time. The deviations between the actual and synthetic counterfactual of GDP in 2008 started about 2,908 million yuan and amplified to 7,814 million yuan in 2016. Over the eight years post the quake, the average deviation of GDP in the severely damaged area was about 5,638 million yuan per year. Figure 2 supports hypothesis 1, indicating the 2008 Wenchuan earthquake had long-term impact on GDP in the severely damaged area of Sichuan province.

Figure 3(a), 3(b), and 3(c) represent value-added of primary, secondary, and tertiary industries trends and their corresponding synthetic counterfactuals in the severely damaged area during the period 1997-2016. As Figure 3 suggests, the predictors in the three different scenarios provide good prediction since the actual trend and its corresponding synthetic counterfactual in each scenario are close to each other in the pre-intervention period. The pre-intervention RMSPEs are 0.36, 1.29, and 0.76 for value-added of primary, secondary, and tertiary respectively. The small pre-intervention RMSPEs of three scenarios also indicate the proper prediction of the predictors.

[Place Figure 3 here]

In Figure 3, the secondary industry endures the largest negative impact of the earthquake compared to the primary and tertiary industries. Figure 3(a) shows that the primary industry was influenced by the earthquake initially but had returned to the level of what would have been without the earthquake in 2016. For the secondary and tertiary industries, the results suggest that the adverse impacts of the earthquake are long-term as the two lines in Figure 3(b) and 3(c) do not converge eight years after the earthquake. Also, as the Figures shown, the magnitude of the

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negative earthquake impacts in both secondary and tertiary industries are increasing over time. The deviations between actual and synthetic counterfactual of output value in the secondary industry right after quake was 2,056 million yuan in 2008 and reached to 5,335 million yuan in 2016. In terms of the tertiary industry, the deviations increased from 884 million yuan in 2008 to 3,231 million yuan in 2016. The average adverse earthquake impacts over the eight years were 4,273 and 2,174 million yuan per year for the secondary and tertiary industries, respectively. Figure 3 suggests that the impacts of the earthquake are different across the industrial sectors, confirming hypothesis 2 in our study.

The composition of the GDP of Sichuan province may explain the diverse impacts of the earthquake on the three types of industry. According to the Sichuan Statistical Yearbooks, the secondary industry dominated the GDP composition in the severely damaged area, accounting for 43% of its GDP from 1997 to 2016, followed by the tertiary industry (33%) and primary industry (24%). The dominance of the secondary industry in the economy of the damaged area may explain why it was affected by the devastating earthquake the most, followed by the tertiary industry and primary industry.

Figure 4(a), 4(b), and 4(c) represent GDP per capita trends for low-income, medium-income, and high-income groups and their corresponding synthetic counterfactuals in the severely damaged area during the period 1997-2016. As Figure 4 shows, the synthetic counterfactual for each income level group provides well predict in the post-intervention period as the pre-intervention RMSPEs are 0.01, 0.21, and 0.12 for low-income, medium-income, and high-income group, respectively. In addition, the gap between GDP per capita and its synthetic counterfactual in each income level group is close to zero in the pre-intervention period, this also suggests the accuracy of the model.

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[Place Figure 4 here]

In general, a place with higher income level or higher development level is more resilience when facing an unexpected shock (Barone and Mocetti, 2014). However, in our study, the economic output in the high-income group encountered the highest negative impact from the 2008 Wenchuan earthquake among the three income groups. As Figure 4(c) suggests, the two lines in the high-income group notably diverged after 2008 and the gap between two lines keeps increasing until 2014. This implies that the impact of the earthquake on the high-income group was long-term and persistent. The peak of the gap between synthetic counterfactual and actual data reached 23,395 yuan in 2014. In terms of the medium-income group, Figure 4(b) shows that a smaller gap existed between the two lines during the post-quake period. For the low-income group, Figure 4(a) shows that the divergence of the two lines is the smallest one among three income groups, thus we suspect that the earthquake caused the smallest impact in the low-income group.

Results in Figure 4 rejects hypothesis 3 in this study. The structure of GDP composition in each income group may explain why high-income group faces more serious impact from the earthquake. Table 8 displayed the average GDP composition in three income level groups in the severely damaged area. The average value-added of the primary, secondary, and tertiary industries in the high-income group accounts for 15%, 54%, and 31% from 1997 to 2007. The respective share of each industry in GDP composition is 31%, 35%, and 34% for medium-income group, and 41%, 22%, and 36% for low-income group over the same period. Our earlier results show that the secondary industry endured notably larger impact from the earthquake compared to tertiary and primary industries. Moreover, in the high-income group, the share of secondary industry in GDP is the highest one not only among three industries but also among

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three income groups. Thus, the impact of the earthquake on high-income group are relatively large than other income groups.

[Place Table 8 here.]

We adopted the placebo test in Abadie et al. (2010) to identify whether the earthquake impact is statistically significant in the severely damaged area. If the placebo test result shows that the estimated gap of the treated group is larger than the gaps for the control units in an unusually way, then we conclude that the earthquake has the significant effect in the affected area. Following Abaide et al. (2010), the unaffected counties with the pre-RMSPE two times higher than the treated group's RMSPE were discarded for each placebo tests in order to enhance the accuracy of the model.

Figure 5 presents the result of the placebo test for overall GDP in the severely damaged areas. The vertical axis in the Figure 5 represents the difference between the actual trend and the synthetic counterfactual trend while the horizontal axis refers the years from 1997 to 2016. The estimated gaps of GDP for the severely damaged area are highlighted as orange lines in the Figure 5. As Figure 5 shown, the negative impact of the earthquake is significant on overall GDP in the severely damaged area as the estimated gap of the treated group is unusually larger than others. The result of placebo test supports the hypothesis 1 in our study, the earthquake made the significant negative and long-term impact on GDP in the severely damaged area.

[Place Figure 5 here.]

Figure 6(a), 6(b), and 6(c) display the placebo tests for primary, secondary and tertiary industries, respectively. Figure 6(a) suggests that the 2008 Wenchuan earthquake does not result in significant negative impact on the primary industry as the gap of treated group is not unusually different compared to the placebo gaps in control countries. However, in Figure 6(b) and 6(c),

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the GDP gaps of treated group in medium-income and high-income groups are relatively unusual than the placebo gaps in control counties. This implies the earthquake affected the secondary and tertiary industries significantly. The results further confirm hypothesis 2 in our study, the earthquake causes different impacts across industry sectors.

[Place Figure 6 here.]

Figure 7(a), 7(b), and 7(c) show the placebo tests for low-income, medium-income, and high-income groups respectively. Figure 7(a) suggests that the 2008 Wenchuan earthquake does not make significant negative impact on low-income as the gaps of treated group in low-income group are similar to the placebo gaps in control countries. However, Figure 7(b) shows that the earthquake significantly affects the medium-income group from 2009 to 2011, since the gaps of treaded group in the medium-income group are the lowest one compared to the gaps in the control counties over this period. Also, in Figure 7(c), the GDP gaps of the treated group in high-income group are relatively unusual and larger than the placebo gaps in control counties before 2013. This implies the earthquake has the significant negative impact on the GDP per capita in the high-income group in the post-quake period from 2009 to 2013. The results again reject hypothesis 3 in our study, the affected area with higher income suffer more than the affected area with lower income.

[Place Figure 7 here.]

We also followed Cavallo et al. (2013) to further calculate the p-value for each outcome variable in every post-quake period and summarized the results in Table 9. As Table 9 suggests, the 2008 Wenchuan earthquake causes negative impact on the overall GDP in the severely damaged area for every post-quake period, the impacts of the earthquake from 2009 to 2016 are statistically significant at 1% level. For the primary industry, Table 9 shows that the earthquake

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carries the adverse impact from 2019 to 2013 at the 10% significant level. The secondary and tertiary industries in the severely damaged area are also significantly affected by the earthquake. For tertiary industry, the negative earthquake impacts are statistically significant at 1% level for every post-quake period. In terms of secondary industry, most of the post-quake periods are affected by the adverse earthquake impact at the 1% significant level, only 2014 and 2015 are at the 5% significant level. Finally, the earthquake has the significant and negative impact on the low-income group only for the first year right after the earthquake, the impact is significant at the 5% level. For the medium-income group, the earthquake's adverse impact is significant at the 5% level from 2009 to 2011. The high-income group in the severely damaged area receives the significant negative impact of earthquake on GDP per capita from 2009 to 2013 at the 1% level. After 2013, the negative impact is not significant which suggests the GDP per capita in the high-income group starts recovering from the devastating event.

[Place Table 9 here.]

Conclusion

On May 12, 2008, the 7.9 Richter scale Wenchuan earthquake hit the Sichuan province in China and caused a large amount of deaths, injuries and economic losses. Applying the SCM approach to the annual data for 125 counties over 2000-2017 and, this study examined the duration of the 2008 Wenchuan earthquake impact on GDP, value-added of primary, secondary, and tertiary industries, and GDP per capita by income groups in the affected counties. Also, the different impacts of the earthquake on economic output across industrial sectors and income levels are further analyzed.

Results from our analysis support hypothesis 1 in our study. The impact of the 2008 Wenchuan earthquake has significant long-term negative effect on GDP in the severely damaged

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area, the affected counties cannot recover even eight years after the earthquake. The result is consistent with the result in the study of Zhu et al. (2018), in their study, they also found that under the fully recover standard, the 2008 Wenchuan earthquake caused the long-term adverse impact on GDP in the affected counties.

Among the severely damaged area, the secondary industry suffers the most on the economic output from the 2008 Wenchuan earthquake followed by tertiary and primary industries. The earthquake brings the long-term and statistically significant influence in all of the industries but with different duration and magnitude. This result confirms the hypothesis 2 in our study, the earthquake impacts are different across industrial sectors. We suspect that the industrial structure of Sichuan province could be the main reason causing the different impacts for the three industries. In line with the study of Wu et al. (2012), Lin et al. (2012), and Best and Burke (2017), we also found the different earthquake impacts exist across industrial sectors. Our finding of the earthquake's damage on the primary industry also confirms the FAO's report (FAO 2015), which suggest that the recovery process of the primary industry is about five years.

Previous studies typically show that an area or a region with higher economic development is more resilient when strikes by an exogenous event due to the ability of affording the insurance and the reconstruction cost. However, in our study, the results suggest that in the severely damaged area, the high-income group experiences more serious damage from the earthquake than the low-income and medium-income groups. The industrial structure of the high-income group could be the main reason of having this surprising result. In high-income group, the secondary industry contributes more than half of the total GDP, while our results show that the secondary industry suffers largest effect from the earthquake among all industry types. The result does not support hypothesis 3 in the study. Results in our study reaches

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different conclusion from Masozera et al. (2007), Barone and Mocetti (2014), and Toya and Skidmore (2007) as those studies compared the impacts of different disasters on various regions or countries, while we focused on the comparison of a given disaster on the income group within the same damaged area.

To prevent and mitigate the adverse impact of earthquake in the certain region, the government should first consider the composition of industrial structure of the affected area to establish an appropriate mitigation policy in response to the catastrophe. Also, the government should encourage all of the industries to have the insurance in order to reduce the disaster risk. Further research on designing the earthquake mitigation plan and the insurance system for the industries is required to alleviate the earthquake impact.

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Appendix A Tables and Figures

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Table 1. Descriptive Statistics for Outcome Variables in Treated Group

	Overall GDP	Value-added of industry in the severely damaged area			GDP per capita in the severely damaged area		
	Severely damaged area	Primary industry	Secondary industry	Tertiary industry	Low-income group	Medium-income group	High-income group
No. of Obs.	360	360	360	360	80	180	100
Mean	55.66	9.59	27.25	18.81	0.70	1.28	2.32
Median	25.84	6.99	12.87	7.46	0.48	0.94	1.94
Variance	5016.32	94.60	1406.03	713.40	0.29	1.08	2.14
Std. Dev.	70.83	9.73	37.50	26.71	0.54	1.04	1.46
Min.	1.06	0.40	0.16	0.38	0.17	0.18	0.60
Max.	360.73	48.15	204.85	169.44	2.17	4.79	5.99

Note: Overall GDP and value-added of industry are measured in 100 million yuan, GDP per capita is measured in ten thousand yuan.

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Table 2. Classification of the Affected Counties under the Severely Damaged Area

Income threshold	Included county
Low-income group GDP per capita under 25 percentile in 2007	Hanyuan County Xiaojin County Qingchuan County Jiange County
Medium-income group GDP per capita between 25 and 75 percentile in 2007	Songpan County Heishui County Pingwu County Beichuan County Mao County Li County Jiangyou City An County Pengzhou City Chongzhou City
High-income group GDP per capita over 75 percentile in 2007	Wenchuan County Mianzhu City Dujiangyan City Shifang City

Table 3. Overall GDP Predictor Means

	Severely Damaged area		Average of
Variables	Real	Synthetic	control counties
Employed person	34.29	34.36	35.97
Land area	0.21	0.21	0.28
Government expenditure	3.33	3.33	3.45
GDP 2003	54.22	54.29	22.50
GDP 2005	60.50	60.57	29.15
GDP 2007	84.96	85.06	42.47

Note: All variables except lagged terms of GDP are averaged from 1997 to 2008. Employed persons are measured in 10,000 persons, land area is measured in 10,000 square kilometer, and government expenditure and GDP are measured in 100 million yuan.

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Table 4. Value-added of Primary Industry Predictor Means

Variables	Severely Damaged area Real	Severely Damaged area Synthetic	Average of control counties
Employed persons in primary industry	17.19	17.47	15.66
Electricity consumed in rural areas	11562.4	11417.82	4613.63
Total power of agricultural machinery	19.65	19.63	11.38
Irrigated land areas	23491.15	23459.64	13453.74
Government expenditure	3.33	3.37	2.91
Value-added of primary industry 2003	9.52	9.53	6.16
Value-added of primary industry 2005	12.27	12.28	8.21
Value-added of primary industry 2007	15.82	15.83	10.98

Note: All variables except lagged terms of value-added of primary industry are averaged from 1997 to 2008. Employed persons in primary industry are measured in 10,000 persons, electricity consumed in rural areas are measured in 10,000 kilowatt hours, total power of agricultural machinery is measured in 10,000 kilowatt, irrigated land areas are measures in hectare, and government expenditure and value-added of primary industry is measured in 100 million yuan.

Table 5. Value-added of Secondary Industry Predictor Means

Variables	Severely Damaged area Real	Severely Damaged area Synthetic	Average of control counties
Employed persons in secondary industry	7.99	7.96	4.65
Land area	0.21	0.21	0.26
Total assets	546165.4	546070.8	212682.8
Total Liability	370115.5	370338.7	138352.9
Government expenditure	3.33	3.31	3.19
Value-added of secondary industry 2001	18.07	18.04	7.35
Value-added of secondary industry 2003	23.84	23.79	8.42
Value-added of secondary industry 2007	41.04	40.93	20.86

Note: All variables except lagged terms of value-added of secondary industry are averaged from 1997 to 2008. Employed persons in secondary industry are measured in 10,000 persons, land areas are measured in 10,000 square kilometer, total assets and total liability are measured in 10,000 yuan, and government expenditure and value-added of secondary industry is measured in 100 million yuan.

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Table 6. Value-added of Tertiary Industry Predictor Means

Variables	Severely Damaged area		Average of control counties
	Real	Synthetic	
Employed persons in tertiary industry	9.13	10.53	10.14
Land area	0.21	0.17	0.18
Investment in fixed assets	158332.6	165162.4	145596.7
Real estate development	23079.51	23168.56	24447.29
Government expenditure	3.33	3.39	3.86
Value-added of tertiary industry 2003	20.86	20.85	11.56
Value-added of tertiary industry 2006	24.33	24.33	16.58
Value-added of tertiary industry 2007	28.10	28.11	19.27

Note: All variables except lagged terms of value-added of tertiary industry are averaged from 1997 to 2008 (real estate development is averaged 1999-2008). Employed persons in tertiary industry are measured in 10,000 persons, land areas are measured in 10,000 square kilometer, investment in fixed assets and real estate are measured in 10,000 yuan, and government expenditure and value-added of tertiary industry is measured in 100 million yuan.

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Table 7. Predictor Means: Low-income, Medium-income, High-income Groups

	Low-income			Medium-income			High-income		
	Severely Damaged area		Average of control counties	Severely Damaged area		Average of control counties	Severely Damaged area		Average of control counties
Variables	Real	Synthetic		Real	Synthetic		Real	Synthetic	
Employed person	22.82	22.89	27.07	34.63	29.34	25.97	39.02	29.16	23.86
Land area	0.31	0.31	0.41	0.20	0.14	0.20	0.18	0.09	0.20
Government expenditure	2.20	2.21	2.72	2.78	2.73	2.87	4.37	3.74	4.58
GDP per capita 2003	0.23	0.30	0.32	0.90	0.90	0.58	1.23	1.17	1.21
GDP per capita 2005	0.36	0.37	0.42	0.89	0.89	0.76	1.44	1.46	1.66
GDP per capita 2007	0.53	0.54	0.60	1.23	1.23	1.07	1.98	2.09	2.33

Note: All variables except lagged terms of GDP per capita are averaged from 1997 to 2008. Employed persons are measured in 10,000 persons, land area is measured in 10,000 square kilometer, government expenditure is measured in 100 million yuan, and GDP per capita is measured in 10,000 yuan.

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Table 8. Average GDP Composition in Three Income Groups in the Severely Damaged Area from 1997 to 2007

	Primary industry	Secondary industry	Tertiary industry
Low- income group	41%	22%	36%
Medium-income group	31%	35%	34%
High-income group	15%	54%	31%

Table 9. Deviation Between Actual and Synthetic Estimations for each Outcome Variables by Post-earthquake Period

	Overall GDP	Value-added of industry in the severely damaged area			GDP per capita in the severely damaged area		
Year	Severely damaged area	Primary industry	Secondary industry	Tertiary industry	Low-income group	Medium-income group	High-income group
2009	-31.998***	-1.710*	-23.514***	-15.359***	-0.601**	-0.301**	-1.187***
	(0.000)	(0.080)	(0.000)	(0.000)	(0.04)	(0.043)	(0.000)
2010	-40.632***	-1.423*	-34.572***	-17.252***	-0.045	-0.365**	-1.557***
	(0.000)	(0.080)	(0.000)	(0.000)	(0.44)	(0.043)	(0.000)
2011	-49.506***	-1.968*	-42.087***	-19.521***	-0.081	-0.431**	-1.930***
	(0.000)	(0.093)	(0.000)	(0.000)	(0.2)	(0.043)	(0.000)
2012	-62.944***	-2.706*	-50.540***	-23.710***	-0.09	-0.520	-2.184***
	(0.000)	(0.080)	(0.000)	(0.000)	(0.4)	(0.130)	(0.000)
2013	-69.910***	-2.888*	-55.078***	-24.386***	-0.104	-0.550	-2.300***
	(0.000)	(0.093)	(0.000)	(0.000)	(0.4)	(0.174)	(0.000)
2014	-70.366***	-2.315	-51.884**	-29.123***	-0.106	-0.273	-2.340
	(0.011)	(0.120)	(0.014)	(0.000)	(0.52)	(0.435)	(0.167)
2015	-74.809***	-1.990	-52.979**	-32.339***	0.055	-0.429	-1.506
	(0.000)	(0.133)	(0.014)	(0.000)	(0.84)	(0.478)	(0.167)
2016	-78.137***	-0.758	-53.351***	-31.830***	0.079	-0.454	-1.523
	(0.000)	(0.267)	(0.000)	(0.000)	(0.72)	(0.349)	(0.167)

Note: Numbers in parentheses are p-values. ***, **,* indicate significant at 1%, 5%, and 10% level, respectively.

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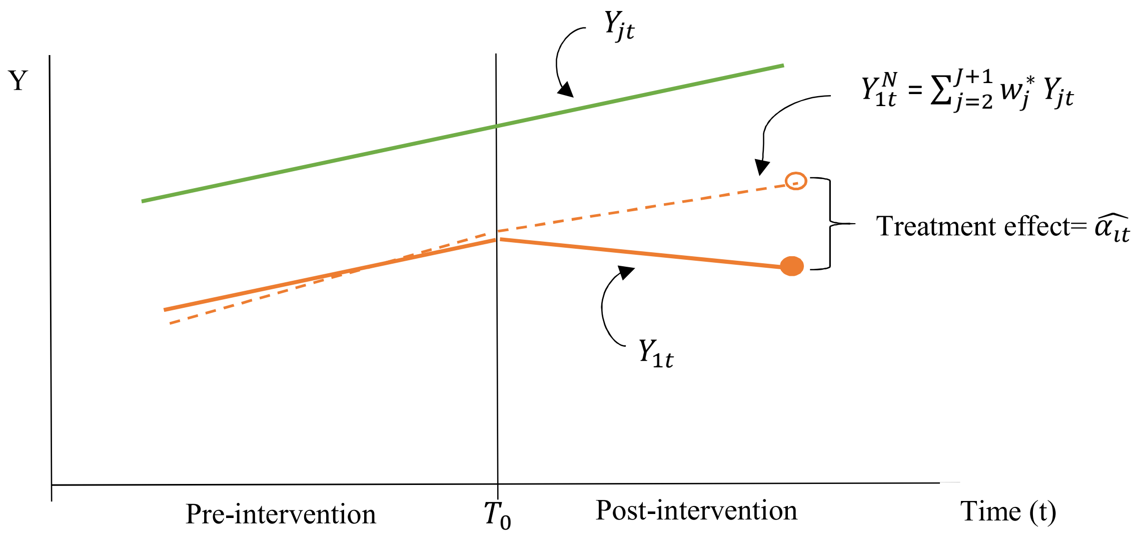

Figure 1. Synthetic Control Method Estimation

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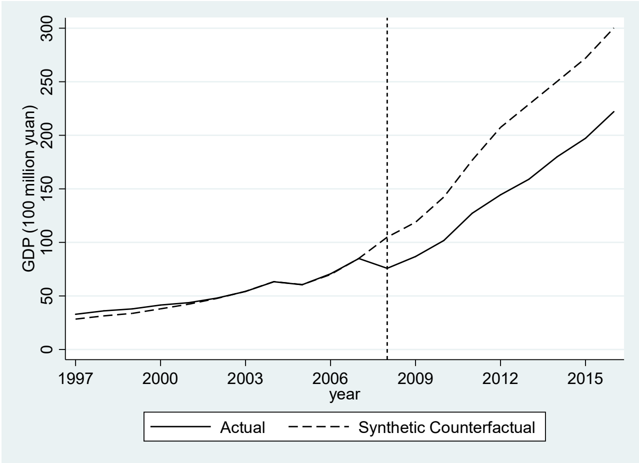

Trends in GDP in severely damaged area

Figure 2. Trends in GDP during 1997-2016: Severely Damaged Area versus its Corresponding Synthetic Counterfactual

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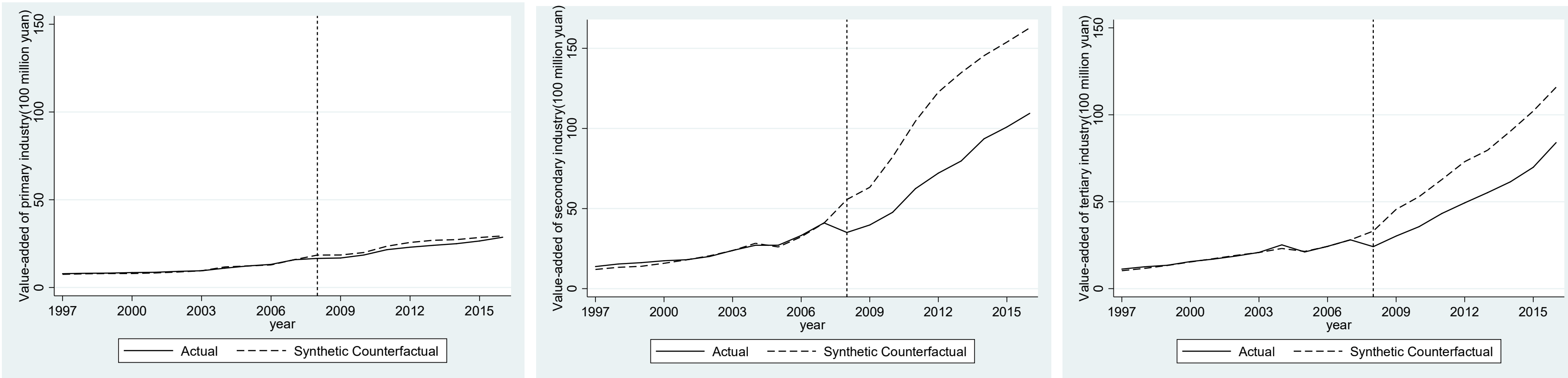

(a) Trends in value-added of primary industry (b) Trends in value-added of secondary industry (c) Trends in value-added of tertiary industry

Figure 3. Trends in Value-added of Primary, Secondary, and Tertiary Industries in the Severely Damaged Area during 1997-2016

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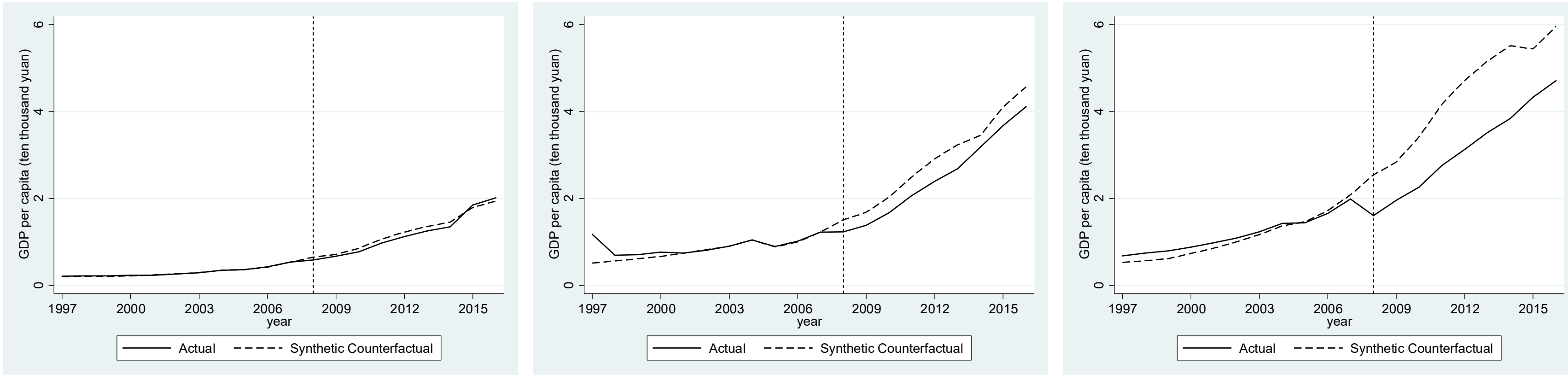

(a) Trends in GDP per capita: Low-income group vs. synthetic low income

(b) Trends in GDP per capita: Medium-income group vs. synthetic medium income group

(c) Trends in GDP per capita: high-income group vs. synthetic high income group

Figure 4. GDP Trends for Low-Income, Medium-Income, and High-Income Groups in the Severely Damaged Area during 1997-2016

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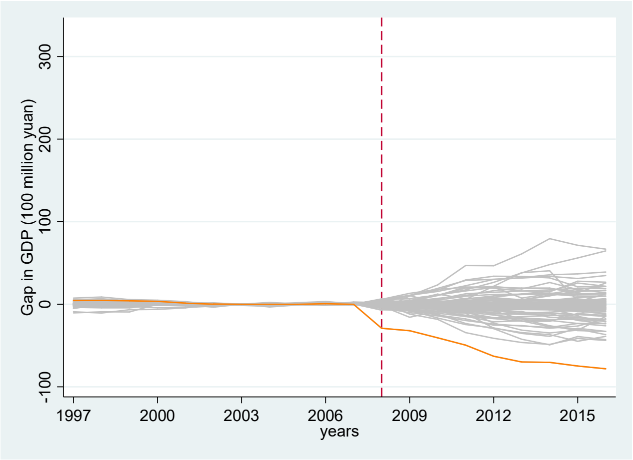

GDP gaps in the severely damaged area and
placebo gaps in control counties

Figure 5. Placebo Tests for Overall GDP in the Severely Damaged Area during 1997-2016 (Discarding Control Counties with Pre-RMSPE Two Times Higher than the Severely Damaged Area's.)

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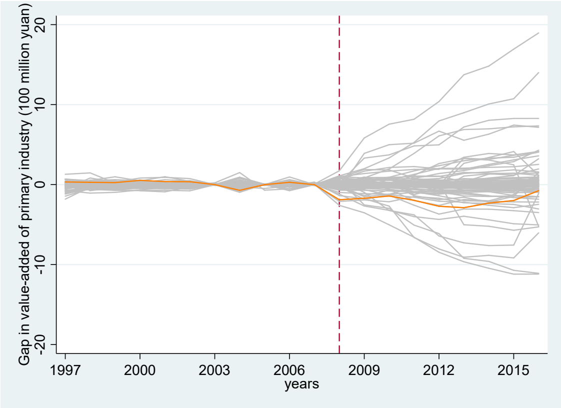
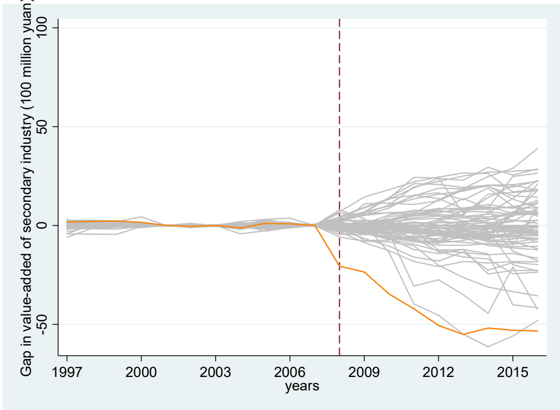
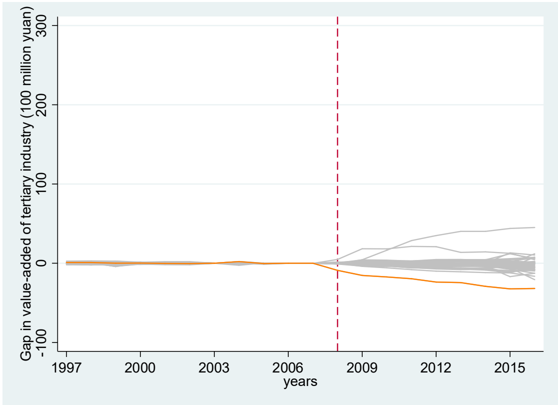


(a) Value-added of primary industry gaps in severely damaged area and placebo gaps in control counties



(b) Value-added of secondary industry gaps in severely damaged area and placebo gaps in control counties



(c) Value-added of tertiary industry gaps in severely damaged area and placebo gaps in control counties

Figure 6. Placebo Tests for Value-added of Primary, Secondary, and Tertiary Industries in Severely Damaged Area during 1997-2016(Discarding Control Counties with Pre-RMSPE Two Times Higher than the Severely Damaged Area's.)

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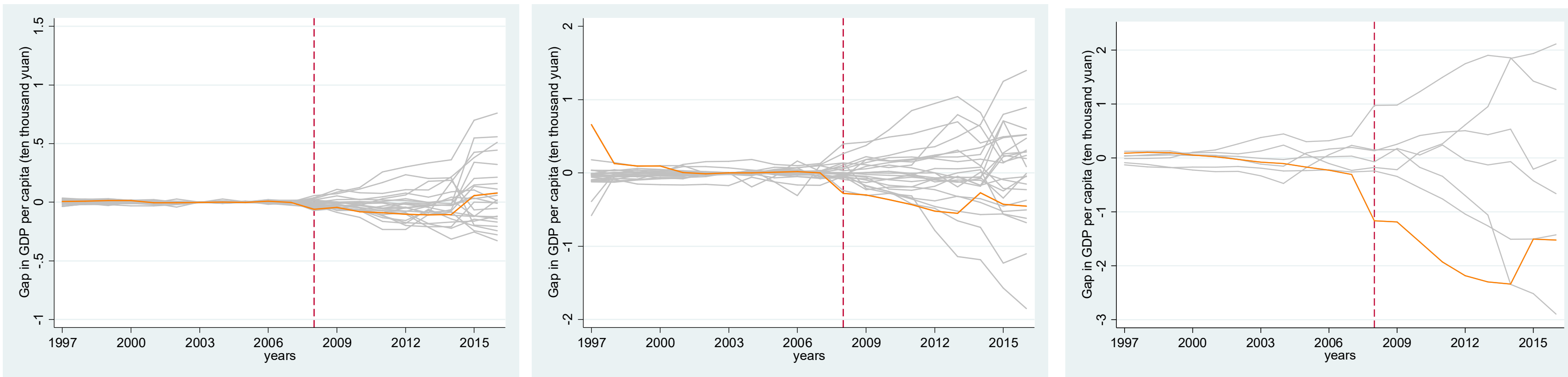

(a) GDP per capita gaps in low-income group and placebo gaps in control countries

(b) GDP per capita gaps in medium-income group and placebo gaps in control countries

(c) GDP per capita gaps in high-income group and placebo gaps in control countries

Figure 7. Placebo Tests for Low-, Medium-, and High-per Capita income Groups (Discarding Control Counties with Pre-RMSPE Two Times Higher than the Severely Damaged Area's.)

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CHAPTER III
THE IMPACT OF A NATURAL DISASTER ON THE AGRICULTURAL SECTOR: A CASE STUDY OF THE 2008 WENCHUAN EARTHQUAHE

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Abstract

This study estimated the impact of the 2008 Wenchaun earthquake on agricultural output in the extremely seriously-affected area and seriously-affected area. A panel regression model with correction of cross-sectional dependence, serial correlation, and heteroscedasticity was applied to an annual data over 133 counties from 1997 to 2016 to capture the earthquake's impact in the damaged areas. Our findings suggested that the 2008 Wenchuan earthquake caused significant and negative impact on the agricultural output in both damage areas with different magnitude. More severe area suffered larger negative impact from the earthquake. The change of the marginal productivity of the agricultural inputs in the damage areas after the earthquake was found to lower agricultural outputs compared to the output in other areas.

Keywords: earthquake, agricultural output, panel data, marginal productivity

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Introduction

According to the report form Food and Agriculture Organization (FAO) of the United Nations (FAO, 2015), a total of 78 natural disasters occurred between 2003 and 2013 and caused approximately 14% direct losses and about 30% indirect losses on the agricultural sector in developing countries. The total damages and losses of agricultural sector accounted for an average of 22% on total losses over this period while the remaining damage was on the other sectors such as social and infrastructure sectors. The report also suggested that natural disasters' impact on the agricultural sector can directly lower incomes and cause food insecurity. As the population as well as the frequency of the natural disasters increase over the past decade, understanding the disasters' impact on agriculture is getting more important.

When evaluating the impact of natural disasters on the agricultural sector, the majority of the previous studies focused on examining the impact of extreme climate-related disasters such as storm, flood, and drought on agriculture as this kind of disasters brought large portion of impact on agricultural production (e.g. Mendelsohn et al. 1994, Mainville 2003, Goyari 2005, Posthumus et al 2009, Norouzi and Taslimi 2012, Chau et al. 2015). The damage of geophysical disasters such as earthquake on the agricultural sector had only received little attention although a severe earthquake could still bring significant damage to the agricultural sector (Loayza et al., 2012).

On May 12th, 2008 at 14:28 CST, a devastating earthquake with 7.9 Richter scale struck the northeast part of the Sichuan province in China and resulted in enormous amount of deaths, injuries, and missing people. The 2008 Wenchuan earthquake was the most damaging disaster in China since 1980's. The 2008 Wenchuan earthquake not only caused a huge amount of causalities, but also triggered the significant impact on economic activities in the affected

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counties. Based on a post-quake report from FAO (Northoff and de Vleeschauwer, 2008), the agricultural sector of Sichuan province experienced the estimated $6 billion US dollar damage as the result of the 2008 Wenchuan earthquake. More than 30 million rural population have been affected by the disaster, lots of farmland and agricultural machinery were destroyed, millions of livestock also died from this event, a large number of houses and the storage place of crops collapsed due to the devastating earthquake. As the severe damage on the rural population, farmland, agricultural tools, and facilities, the farmers in the affected area were then lost the means to grow the agricultural products and earn the income. The estimated recovery process will take five to six years based on FAO's evaluation.

The objective of this study is to identify the potential impact of the 2008 Wenchuan earthquake on the output of the agricultural sector in the affected area of Sichuan province. Applying a panel regression model to a county-level annual data from 1997 to 2016, an agricultural production model that includes regular inputs and the dummy variables of earthquake time and area was formulated to capture the impact of the earthquake on agricultural output. To further understand the earthquake impact across the area with different damage scales, we followed the study of Dunford and Li (2011) to allocate the affected counties into the *extremely seriously-affected area* and *seriously-affected area*. As Loayza et al. (2012) suggested that a severe earthquake is likely to cause the significant and negative impact on agricultural sector, we hypothesized that the 2008 Wenchuan earthquake had significant and adverse impact on agricultural output in both affected areas. In addition, we hypothesize that the impacts varied by the affected areas associated with the damage level. That is, the extremely seriously-affected area encountered a larger negative impact from the earthquake than the seriously-affected area.

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Literature Review

Other studies have compared the impacts of natural disasters during this same period and region on agricultural production, growth of economic sectors, or trade flows of agricultural commodity (Israel and Briones 2012, Loayza et al. 2012, and Du et al. 2014). These studies provide general suggestions to help decision makers establish the disaster mitigation policy, but with less detailed information on each disaster's impact. Also, this type of study requires more systematic and coherent data of disasters to make a reasonable comparison between the impacts of natural disasters, but the data of disasters is not systematically reported around the world (FAO, 2015).

Israel and Briones (2012) examined the impact of the typhoons, floods, and droughts on the agricultural production in Philippine from 2000 to 2011. Agricultural multi-market Model for policy evaluation was used to forecast the quantity of supply, imports, exports, consumption, and prices of 18 agricultural products. They found that agricultural production was insignificantly affected by typhoons, floods, and droughts at the country level, while typhoons had significantly affected the agricultural production at the province level in the adverse way.

Loayza et al. (2012) estimated the impact of four main natural disasters (i.e., drought, flood, storm, and earthquake) on the growth of economic sectors. The country level data that consists of 68 developing and 26 developed countries from 1961 to 2005 was used to apply on the adopted generalized method of moments. They found that a severe drought, storm, and earthquake can bring significant negative impact on the agricultural growth in a developing country, whereas a severe flood carry positive impact on the agricultural growth though not significant.

Du et al. (2014) examined the aggregate impact of natural disasters on the grain production in China from 1990 to 2011. They focused on the five natural disasters: drought,

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flood, hail, frost, and typhoon. The linear regression model was used to investigate the disasters impact on the per unit area grain yield in each province in China. Grain production was significantly affected by the natural disaster during their study period, and the major grain producing provinces suffered more serious disaster effect compared to other provinces.

FAO (2015) investigated the impact of several types of natural disasters on agricultural sector in developing countries. Their finding showed that the agricultural sector in developing countries accounted for about 22% of total damage and losses caused by natural disasters. They suggested that drought is the most threatening natural disaster on agricultural followed by storms, floods, tsunamis, and earthquakes. Around 58% damage of crops came from floods, 85% damage of livestock came from drought, 69% damage of fisheries came from tsunami, and 89% damage of forestry came from earthquakes.

Several studies focused on examining impacts of a particular type of natural disaster on the agricultural sector in the affected region. The majority of these studies focus on the impact of climate-related disasters on agriculture, giving little attention to geophysical disasters on agriculture. However, as Loayza et al. (2012) suggested, a severe earthquake has the possibility to negatively impact the agricultural sector. FAO (2019) further suggested that earthquake could adversely affect agriculture by damaging the workforce, crop yields, livestock, irrigation system, and other agricultural facilities. Understanding the earthquakes' impact on agriculture is important issue, but little is known about this issue.

Mendelsohn et al. (1994) measured the climate change on the agricultural sector for almost 3,000 counties of the United States. Using Ricardian approach instead of traditional production-function technique, the value of farmland was estimated and replaced the yield of crop as the dependent variable. They suggested that for all seasons expect autumn, the higher

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temperature decreased the farm value due to the damage to crops. They also claimed that the higher precipitation in spring, summer, and winter increased the farm values.

Horridge et al. (2005) employed the Enormous Regional Model to stimulate the short-term impact of drought from 2002 to 2003 on several regions in Australia. They found that six out of the eight regions suffered the negative impact on the agricultural sector from the drought. Although agriculture's share of GDP was less than 4% in Australia, the drought damage reduced overall GDP by 1% on average, significantly damaging Australia's economy.

Norouzi and Taslimi (2012) examined the damage of flood on Iran's agricultural production using a vector autoregressive model. The annual nation-level data from 1971 to 2009 was used in their study. While the flood caused significant damage to Iran's agricultural sector in the short-term, the damage in the medium-term was greater and the damage of flood gradually dissipated in the long term.

Haque and Jahan (2015) estimated the flood of 2004 and 2007 impacts on the various economic sectors in the six regions of Bangladesh. The input-output model was used to obtain the flood impacts on the regional and national level. They suggested that the nation recover from the flood impact whereas three out of the six regions suffered the severe impact on either output, income, or employment from the floods. For all of the six regions, they suggested the agricultural sector is the most affected one compared to other sectors due to large loss of output and employment.

Chau et al. (2015) analyzed the impacts of three different classes of floods on the aggregated output value of four major crops in the Quan Nam province, which located in the central Vietnam. They used 2004, 2009, and 2007 flood that occurred in the Quan Nam province to simulate the three floods with different frequency, which is 1:10-, 1:20-, and 1:100- years

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flood, respectively. Two scenarios are considered in their study, one is with extreme flood scenario, the other on is without flood scenario. After comparing these two scenarios, they found that in the inundated areas of the Quan Nam province, the percentage losses on the aggregated output value of the four major crops are 12%, 56%, and 62% under the 1:10-, 1:20-, and 1:100-years flood, respectively.

Parwanto and Oyama (2015) analyzed 12 years prefecture-level data to investigate the impact of 2011 Great East Japan Earthquake across the economic sectors. They found that the manufacturing and agricultural sectors were negatively affected caused by the earthquake, of which the growth of agricultural sector had twice damage more than the growth of manufacturing sector on average. In addition, the damages suffered by the most affected area on both manufacturing and agricultural sectors were three times more than the less affected area.

Method

This study applied a fixed-effect model to estimate the earthquake's impact on the output of primary industry in the extremely seriously-affected and seriously-affected areas of Sichuan province. The estimated equation can be written as:

$$y_{it} = \propto + X_{it}'\beta + u_{it} \qquad \forall i = 1, \ldots, N \;\; t = 1, \ldots, T \tag{1}$$

where y_{it} is the natural logarithm of value-added of primary industry in county *i* at time *t*; $\propto$ is a constant term that will be estimated; X_{it}' is a $1 \times K$ vector of explanatory variables; β is a $K \times 1$ vector of coefficients to be estimated; and u_{it} is an error term that could possibly be correlated over i (or cross-sectional dependence) and serially correlated over t. Therefore, the error term is decompose to the following equation:

$$u_{it} = \tau_i + \partial_t + \varepsilon_{it} \tag{2}$$

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where τ_i and ∂_t capture the county and time fixed effects, respectively; and ε_{it} is an error term with some unobservable issues such as cross-sectional dependence and serial correlation.

Research has suggested that cross-sectional dependence could be an issue in the panel data as the common factors across the units (Robertson and Symons 2000; Pesaran 2004; and De Hoyos and Sarafidis 2006). In our study, all of the observations are from the same province and sharing the similar geographic characteristics and policies. Thus, this issue of cross-sectional dependence, that is $cov(\varepsilon_{jt}, \varepsilon_{kt}) \neq 0$ for $j \neq k$, is possible. The Pesaran's cross-sectional dependence (CD) test was used to determine if cross-sectional dependence was present, assuming under the null hypothesis of cross-sectional independence. Moreover, several studies have found serial correlation to be an issue in the panel data (Drukker 2003, Baltagi 2008, and Wooldridge 2010). The serial correlation, i.e. $cov(\varepsilon_{it}, \varepsilon_{it-j}) \neq 0$ for $j \neq 0$, in the error term can cause the biased standard error for the estimation. The Wooldridge test for autocorrelation that assuming under the null hypothesis of no serial correlation was applied to check if the serial correlation issue exists.

Assuming we identified those issues in our panel dataset, we used the ordinary least squares (OLS) regression with panel-corrected standard errors and first-order autocorrelation to address it[2]. The model corrected the error terms that are heteroskedastic, correlated over the observations and time. Besides, the earthquake time dummy variable E has the value of one for the year after 2008 (i.e. the year of the Wenchuan earthquake), and zero otherwise. The damage area dummy variables D_1 and D_2 have the value of one if the county is in the extremely

[2] We analyze the model using the command `xtpcse` in Stata along with the option command `correlation (ar1)`.

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seriously-affected area and seriously-affected area, respectively, and zero otherwise. Table 10 displays the classification of the affected county based on the study of Dunford and Li (2011).

[Place Table 10 here.]

Following Bin and Polasky (2004), Bin and Landry (2013), and Yu et al. (2012), the interaction term of earthquake time dummy E and damage area dummy D_1 was included to analyze the earthquake's effect in the extremely seriously-affected area. Similarly, the interaction term of earthquake time dummy E and damage area dummy D_2 was used to capture the earthquake's effect in the seriously-affected area. The model (referred as model 1) is written as:

$$y_{it} = \alpha + X_{it}'\beta + \gamma E + \theta(E \cdot D_1) + \delta(E \cdot D_2) + u_{it}$$
$$\forall i = 1, \dots, N \;\; t = 1, \dots, T \tag{3}$$

where β is a $K \times 1$ vector of agricultural inputs coefficients to be estimated; γ refers the change in the agricultural output in all counties during the post-quake period; and θ and δ are the estimated coefficients that represent the earthquake's effect specifically on the extremely seriously-affected and seriously-affected areas, respectively.

Other than model 1 that captures the post-quake change in all counties through the dummy variable E, model 2 included the interaction terms of earthquake time dummy E and explanatory variables to examine if the marginal productivity of inputs in all counties of Sichuan province changed after 2008. Model 2 is presented as follows:

$$y_{it} = \propto + X_{it}'\beta_1 + (E \cdot X_{it})'\beta_2 + \theta(E \cdot D_1) + \delta(E \cdot D_2) + u_{it}$$
$$\forall i = 1, \dots, N \;\; t = 1, \dots, T \tag{4}$$

where β_1^* is a $K \times 1$ vector of shift coefficients that captured the marginal productivity of agricultural inputs after 2008.

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Models 1 and 2 examine the earthquake's impact on agricultural output in those damage areas. To further investigate if the reduction of agricultural output in the damaged areas was due to the earthquake's influence on the marginal productivity of agricultural inputs, model 3 included two more interaction terms: $E \cdot X_{it} \cdot D_1$ and $E \cdot X_{it} \cdot D_2$. The interaction term $E \cdot X_{it} \cdot D_1$ examined the impact of the 2008 Wenchuan earthquake on the marginal productivity of agricultural inputs in the extremely seriously-affected area. Similarly, the other interaction term $E \cdot X_{it} \cdot D_2$ evaluated the impact of the 2008 Wenchuan earthquake on the marginal productivity of agricultural inputs in the seriously-affected area. Model 3 is thus written as:

$$y_{it} = \propto + X_{it}'\beta_1 + (E \cdot X_{it})'\beta_2 + (E \cdot X_{it} \cdot D_1)'\beta_3 + (E \cdot X_{it} \cdot D_2)'\beta_4 + \theta(E \cdot D_1) + \delta(E \cdot D_2) + u_{it}$$

$$\forall i = 1, \ldots, N \quad t = 1, \ldots, T \tag{5}$$

where β_3 and β_4 are the $K \times 1$ vector of estimated coefficients represent the earthquake impact on the marginal productivity of agricultural inputs in the extremely seriously-affected area and seriously-affected area, respectively.

The panel data will be applied into three different models to obtain more detailed analysis of the 2008 Wenchuan earthquake's impact on the agricultural sector. The results of Model 1 could provide the average change of the agricultural output in the counties of Sichuan province, extremely seriously-affected area, and seriously-affected area after 2008. Model 2 further examines the change of the marginal productivity of four agricultural inputs in the counties of Sichuan province after 2008. In terms of model 3, the earthquake's impact on the marginal productivity of agricultural inputs in the affected areas, extremely seriously-affected area and seriously-affected area, will be further identified. The results could help us understand if the

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earthquake affects the agricultural output through the change of the marginal productivity of agricultural inputs in both affected areas.

Data

The annual data of 133 counties from 1997 to 2016 in Sichuan province, China was used in this study. All of the data were collected and compiled from the Sichuan Statistical Yearbooks (1998-2017). The definition and unit of the variables in the study are displayed in Table 11, while the descriptive statistics of the variables are summarized in Table 12. On average, the real value-added of primary industry was around 63,076 yuan per acre for a county in a year but with large standard deviation[3]. Also, the counties in Sichuan province had an average of six agricultural employed person per acre, about 2,800 kilowatt hours (kwh) of electricity were consumed per acre, around 0.43 ton of fertilizer were used per acre, and night kilowatt (kw) of agricultural machinery power were adopted per acre within a year. About 8% of counties were located at the extremely seriously-affected area, and about 13% of counties were located at the seriously-affected area. The number of the observations of the variables are not identical due to the missing values.

[Place Table 11 here.]

[Place Table 12 here.]

Results

Table 13 displays the specification test results of our panel data. The results of Pesaran's CD test for all three models show that the null hypothesis of cross-sectional independence is rejected as the p-value is 0.000 which is less than the 5% significance level, that is $cov(\varepsilon_{jt}, \varepsilon_{kt}) \neq 0$ for $j \neq$

[3] The value-added of primary industry was deflated by dividing the nominal value by the GDP deflator of China. The based year is 2015.

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k. In addition, the results of the Wooldridge test for autocorrelation for all three models in Table 13 strongly rejects the null hypothesis of no first-order autocorrelation as the p-value is smaller compare to the 5% significance level, that is $cov(\varepsilon_{it}, \varepsilon_{it-j}) \neq 0$ for $j \neq 0$. Finally, the results of the Wald statistic for groupwise heteroscedasticity for all three models in Table 13 also reject the null hypothesis of homoscedasticity as the relatively small p-value compare to the 5% significant level, that is $cov(u_{it}, u_{kt}) \neq 0$ for $i \neq k$. These results indicate that the issues of cross-sectional dependence, serial correlation, and heteroskedastic disturbance need to be addressed before analyzing the model with our panel data in order to obtain more accurate estimation.

[Place Table 13 here.]

The results of model 1 in Table 14 suggest that four agricultural inputs (i.e., employed person in primary industry, electricity consumed in rural areas, consumption of chemical fertilizers, and total power of agricultural machinery) has a positive relationship with agricultural output, of which the employed person in primary industry had the most influential effect followed by fertilizer, agricultural machinery power, and electricity. A 1% increase in agricultural employed person leads to 0.41% of increase on the value-added of the primary industry, holding all else constant. In general, the agricultural outputs significantly increased in the counties of Sichuan province after 2008. In fact, the agricultural outputs in the extremely seriously-affected area and seriously-affected area were about 26% and 11% lower than other counties that are not in either extremely seriously-affected or seriously-affected areas.

[Place Table 14 here.]

Model 2 displays the estimation result of agricultural inputs variables, the interaction terms of earthquake time dummy and input factors, and interaction terms of earthquake time dummy and damage area dummy variables. Four coefficients for agricultural inputs were

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positive and significant. The results also suggest that after 2008, the marginal productivities of the agricultural employed person and fertilizer consumption dropped while the marginal productivities of agricultural machinery power and electricity consumption increased. The coefficient on the interaction term with agricultural employed person and earthquake time dummy variable (*E*) is negative and significant, this implies that the output elasticity of agricultural employed person significantly decreased to 0.37% (=0.44%-0.07%) after 2008. That is, the performance of employed person was relatively 0.07% lower compared to the pre-quake period. On the other hand, the marginal productivity of agricultural machinery power was 0.06% higher compared to the pre-quake period. The results of model 2 also indicated that the agricultural outputs in the extremely seriously-affected area and seriously-affected area were relatively 27% and 14% lower than the remaining counties, respectively.

Model 3 in Table 14 shows all of the agricultural inputs variables have the expected positive signs and are statistically significant. On average, the marginal productivity of the agricultural employed person and consumption of fertilizer were 0.05% and 0.01% lower after 2008, respectively; while the marginal productivity of the agricultural machinery power was 0.08% higher after 2008. The other agricultural input, consumption of electricity have no significant change after 2008.

Table 15 displays the marginal productivity of each agricultural inputs in the extremely seriously-affected and seriously-affected areas after the earthquake. The marginal productivity of agricultural employed person in the extremely seriously-affected area and seriously-affected area further decreased by 0.16% and 0.14% after the earthquake compared to the remaining counties. That is, after the earthquake, every 1% increases in agricultural employed person in the extremely seriously-affected area leads to 0.23% (=0.44%-0.05%-0.16%) increase on the

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agricultural output, holding others constant. Similarly, every 1% increases in employed person in the seriously-affected area leads to 0.25% (=0.44%-0.05%-0.14%) increase on the agricultural output, ceteris paribus. This can be due to the shift of the labor supply from agricultural sector to construction sector. As the construction industry needed more workers for infrastructure reconstruction after the destructive damage from the earthquake, the labor force from the agricultural sector may shift to the construction sector to accelerate the recovery process, hence lowers the marginal productivity of agricultural labors. Also, the extremely seriously-affected area suffered more than the seriously-affected area, the labor transfer situation in the extremely seriously-affected area is likely more than the seriously-affected area, making it has the lower performance on the employed person.

The marginal productivity of fertilizer in both damage areas were higher than the less affected area after hit by the earthquake. Specifically, the marginal productivity of fertilizer in the extremely seriously-affected area and seriously-affected area increased by about 0.28% and 0.11% compared to the less affected area. In other word, every 1% increases in fertilizer in the extremely seriously-affected area leads to 0.33% (=0.06%-0.01%+0.28%) increases on the agricultural output, holding other condition unchanged. Similarly, every 1% increases in fertilizer in the seriously-affected area leads to 0.18% (=0.06%-0.01%+0.11%) increases on the agricultural output, holding all else constant. The increasing productivity of fertilizer in the damage areas could be related to its contribution to the recovery of soil damage from the earthquake. As the damage in the extremely seriously-affected area was larger than the seriously-affected area, the performance of the fertilizer in the extremely seriously-affected area was likely more effective than in the seriously-affected area.

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The marginal productivity of agricultural machinery power in the seriously-affected area was significantly lower than the less affected area. To be more specific, the marginal productivity of the machinery power in the seriously-affected area decreased by 0.14% compared to the less affected area. That is, every 1% increase in the agricultural machinery power in the seriously-affected area lowered 0.01% (0.05%+0.08%-0.14%) in agricultural output, holding all else constant. However, there was no significant change on the performance of the machinery power in the extremely seriously-affected area. This could be explained as the counties in the extremely seriously-affected area received financial aids from both federal funds and a matching province, hence they had more financial capacity to purchase new machinery to replace the damaged equipment. Thus, the productivity of machinery power did not change in the extremely seriously-affected area but decrease in the seriously-affected area after the earthquake.

FAO reported that on average, earthquakes only accounted for 4% of total damage on the agricultural sector, which is a pretty small number compared to the damage caused by the other natural disasters such as drought (84%), storms (18%), floods (15%), and tsunamis (14%). However, in line with the study of Loayza et al. (2012), our findings suggested that a severe earthquake could make significant damage to the agricultural sector. We also found that the agricultural output decreased through the reduction of marginal productivity of agricultural inputs. To prevent and mitigate the earthquake impact on the agricultural sector, enhance the resilience of the agricultural sector and establish the pre-quake recovery plan is necessary.

Conclusion

The 2008 Wenchuan earthquake that hit Sichuan province, China was the most powerful earthquake since 1980s. Based on the report from FAO, this natural disaster caused the estimated $6 billion economic loss on the agricultural sector of Sichuan province, with huge damage on

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farmland, livestock, houses, and agricultural machinery, etc. FAO also suggested that the recovery process would take five to six year given the huge damage on the agricultural sector. In this study, we adopt the panel regression model with correction of cross-sectional dependence, serial correlation, and heteroscedasticity and used the annual data over 133 counties from 1997 to 2016 to further analyze the earthquake impact on the agricultural inputs in the affected areas with differing damaged scale.

Our findings suggested that on average, the agricultural output in the counties of Sichuan province were significantly higher than the pre-2008 period. However, the agricultural outputs in the extremely seriously-affected area and seriously-affected area were relatively and significantly lower than pre-2008 period. In line with the finding in Loayza et al. (2012), we also found that a severe earthquake is negatively affect the agricultural sector. We observed that the change of marginal productivity of the agricultural inputs could be a reason of causing the damage areas had the relatively low agricultural output than the less affected area.

The marginal productivity of employed person in the extremely seriously-affected and seriously-affected area were significantly lower than the less affected area after hit by the earthquake but with different extent. More severe affected area had the lower performance of employed person, this could be due to the young labor force of the agricultural sector transferred to the construction sector to help accelerate the recovery process of physical assets, and left the old labor force in the agricultural sector. Our result contrasts with the result in the study of Kirchberger (2017), they suggested the marginal productivity of rural workers increased after the earthquake as the workers in the agricultural sector shift out to the other sector after sector, thus, the rural workers stayed in the agricultural sector shared not only their contribution but also the contribution from the rural workers that shifted out to the other sectors.

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The marginal productivity of fertilizer in the extremely seriously-affected area and seriously-affected area were higher than the less affected area after the earthquake. The fertilizer was more effective in the extremely seriously-affected area, followed by the seriously-affected area and then less affected area. The marginal productivity of agricultural machinery power in the seriously-affected area was lower than the extremely seriously-affected area and less affected area after the earthquake. Finally, the performance of electricity in both damage area were similar to the less affected area even after hitting by the earthquake.

As the results in our study, we suggest that the government should send more capable labor from other unaffected provinces to help the reconstruction process and prevent the shift of the labor in the affected counties of Sichuan province. The marginal productivity of employed person could maintain at the pre-quake level and mitigate the reduction of agricultural output from the earthquake if the labor in the construction sector were enough to cover the reconstruction process. Our findings also suggest that the government could raise the amount of fertilizer in the post-quake period to efficiently increase the agricultural output in the affected areas.

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Appendix B Tables

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Table 10. Classification of the Affected Counties Based on Dunford and Li (2011)

Area	County
Extremely seriously-affected area	Wenchuan, Shifang, Qingchuan, Pingwu, Pengzhou, Mianzhu, Maoxian, Dujiangyan, Beichuan, Anxian
Seriously-affected area	Zitong, Yanting, Xiaojin, Wangcang, Songpan, Santai, Lushan, Luojiang, Lixian, Jiuzhaigou, Jiangyou, Jiange, Heishui, Guanghan, Dayi, Chongzhou, Baoxing

Table 11. Description and Unit of the Variables

Variable	Description
V_1	Value-added of primary industry
EP_1	Employed person in primary industry
Electricity	Electricity consumed in rural areas
Fertilizer	Consumption of chemical fertilizers
Mpower	Total power of agricultural machinery
E	Dummy variable for years after 2008 (1 if year ≥2008, 0 otherwise)
D_1	Dummy variable for the extremely seriously-affected area (1 if the affected county is in the extremely seriously-affected area, 0 otherwise)
D_2	Dummy variable for the seriously-affected area (1 if the affected county is in the seriously-affected area, 0 otherwise)

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Table 12. Descriptive Statistics of the Variables

	Unit	Obs.	Mean	Median	Std. Dev.	Min.	Max.
V_1	$/acre	2601	63076.32	49822.01	128249.6	5496.17	2834989
EP_1	Person/acre	2334	6.38	5.61	8.24	0.97	153.57
Electircity	Kwh/acre	2604	2799.26	1803.58	4029.93	13.98	101859.5
Fertilizer	Ton/acre	2598	0.43	0.42	0.31	0.00	2.91
Mpower	Kw/acre	1930	8.08	6.27	7.05	0.47	89.29
E		2660	0.45	0.00	0.50	0.00	1.00
D_1		2660	0.08	0.00	0.26	0.00	1.00
D_2		2660	0.13	0.00	0.33	0.00	1.00

Note: Definition of variables is in Table 2.

Table 13. Results of Testing Cross-sectional Dependence, Serial Correlation, and Heteroskedastic Disturbance for All Three Models

	Null hypothesis	Model	Test Statistics	P-value
Pasaran's CD test	Cross-sectional independence	Model 1	126.88	0.0000
		Model 2	127.20	0.0000
		Model 3	131.41	0.0000
Wooldridge test for autocorrelation	No first-order autocorrelation	Model 1	562.82	0.0000
		Model 2	588.34	0.0000
		Model 3	640.11	0.0000
Wald statistic for groupwise heteroscedasticity	Homoscedasticity	Model 1	4700.47	0.0000
		Model 2	3563.44	0.0000
		Model 3	4600.38	0.0000

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Table 14. Estimated Models

	Model 1		Model 2		Model 3	
ln(EP_1)	0.41***	(19.38)	0.44***	(18.20)	0.44***	(16.99)
ln(Electricity)	0.03***	(2.89)	0.03**	(2.85)	0.03**	(2.86)
ln(Fertilizer)	0.07***	(7.13)	0.07***	(7.23)	0.06***	(5.87)
ln(Mpower)	0.06***	(5.30)	0.05***	(4.61)	0.05***	(6.14)
E	0.92***	(60.66)				
ln(EP_1)×E			-0.07***	(-5.58)	-0.05***	(-3.43)
ln(Electricity)×E			0.01	(0.99)	-0.00	(-0.42)
ln(Fertilizer)×E			-0.01	(-0.83)	-0.01*	(-1.99)
ln(Mpower)×E			0.06***	(8.02)	0.08***	(8.98)
ln(EP_1)×E×D_1					-0.16**	(-2.77)
ln(Electricity)×E×D_1					0.01	(0.21)
ln(Fertilizer)×E×D_1					0.28***	(4.07)
ln(Mpower)×E× D_1					-0.03	(-0.64)
ln(EP_1)×E× D_2					-0.14***	(-3.97)
ln(Electricity)×E× D_2					0.03	(1.68)
ln(Fertilizer)×E× D_2					0.11***	(7.73)
ln(Mpower)×E× D_2					-0.14***	(-3.82)
D_1×E	-0.26***	(-26.14)	-0.27***	(-22.72)	0.15	(0.30)
D_2×E	-0.11***	(-4.30)	-0.14***	(-6.04)	0.20	(1.29)
Constant	9.55***	(82.67)	9.54***	(74.03)	9.47***	(66.07)
N	1922		1922		1922	
R^2	0.9939		0.9939		0.9940	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Dependent variable is the logarithm of value-added of primary industry.

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Table 15. The Marginal Productivity of each Agricultural Inputs in the Extremely Seriously-affected and Seriously-affected Areas after the Earthquake

	Extremely seriously-affected area	Seriously-affected area
EP_1	0.23	0.25
Electricity	0.03	0.03
Fertilizer	0.33	0.16
Mpower	0.13	-0.01

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CHAPTER IV
CONCLUSION

In the afternoon of May 12, the 2008 Wenchuan earthquake struck the northeast part of Sichuan province of China, causing the huge amount of damage on human capital as well as economy. According to the study of Li et al. (2009) and Wu et al. (2012), the earthquake contributed 69,185 deaths, 374,174 injuries, 18,457 people missing, and the estimated direct losses were around US$ 124 billion. In terms of agricultural sector, FAO suggested that the agricultural sector of Sichuan province suffered $6 billion losses as the result of the 2008 Wenchuan earthquake, and this damage could take five to six years to recover. Given the sizeable damage on the economy and agricultural sector, the aim of this study is to further understand the potential long-term impact of the earthquake on the overall economy, different economic sectors and various levels of income group in the most damaged area. Also, the earthquake impact on the marginal productivity of the agricultural inputs were analyzed to clarify the reason of huge losses on agriculture.

The findings of our study suggested that the 2008 Wenchuan earthquake had the negative long-term impact on the overall GDP. Also, the negative and significant earthquake impacts differ across economic sectors, the secondary industry experienced the most severe damage and followed by the tertiary and primary industries. Among these three industries, the secondary and tertiary industries could not reach their projected growth even eight years after the earthquake, while the primary industry recovered five years after the earthquake. Moreover, the extent of the earthquake impact on the affected counties with different income-levels were not the same due to the structure of the industrial sector. The high-income counties suffered the largest damage and recovered five years after the earthquake, while the low- and medium- income counties only affected by the earthquake for one and three years, respectively.

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The results of the impact of earthquake on the agricultural sector indicated that the marginal productivity of the rural employed person in both damaged areas significantly decreased by an average of 15%. On the other hand, the marginal productivity of electricity consumption in both damaged areas increased by an average of 20% at the 1% significance level. The marginal productivity of machinery power dropped significantly only in the seriously-damaged area and remained the same in the extremely seriously-damaged area. Finally, there was no change in the marginal productivity of fertilizer consumption in both damaged areas.

Our case study of the Wenchuan earthquake confirms that the impact of a devastating earthquake could lead a long-term damage to an economy and cause changes in the marginal productivity of inputs. As it is very difficult to predict an earthquake, disaster mitigation policies, such as pre-impact recovery plan, disaster risk reduction, and management strategies should be established and implemented in the earthquake-prone area (Wu and Lindell, 2004; FAO, 2015). Also, due to the rapid growth of economic cost from earthquakes, a sound insurance system is required to alleviate the damage and risk from earthquakes (Wu et al., 2012).

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