Moving Actions Determine Rural Recovery Paths:

Evacuation and Displacement Effects in Typhoon Morakot

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Abstract

The increasing intensity of natural disasters underscores the importance of current mitigating strategies. However, the understanding of the existing strategies remains limited, despite their significance for potential victims in rural areas. This study examines the economic impacts of two moving behaviors in the aftermath of Typhoon Morakot which caused over 700 deaths in Taiwan in 2009. Applying the instrumental variable method, this study identifies the effects of evacuation and displacement on economic recovery in both the short- and long-term. Our findings on the short-term and long-term impacts of evacuation are diverse. After one year of the strike, evacuation has no effect on transitory post-strike income but benefits victims' economic recovery, while the positive effect of recovery is more substantial in a specific subgroup of victims who did not return within one month after the evacuation. The effect of evacuation in the long term is, however, negative for the displaced victims. We also find that the displaced victims recover slower than their counterparts economically. As the first empirical attempt to address the differential effects of evacuation on the Indigenous victims, this study finds that Indigenous evacuees in rural Taiwan recover better than their counterparts. This result enlightens possible unobserved factors in the cultural or societal context and thus sheds insight into the significance of building social-cultural capital in rural areas.

1. Introduction

Disastrous hurricanes and typhoons serve as natural experiments for studying the impacts of weather-related disasters (Deryugina et al., 2018; Deryugina and Molitor, 2020). Given the rising frequency of these unanticipated natural disasters, the significance of effective coping strategies, including evacuation and displacement, calls for further exploration to enhance inhabitants' capacity to reduce the impacts.

This study takes a perspective of disaster management, especially when economic recovery is the major concern. It focuses on the effects of two moving actions in a short and long time span on economic recovery: temporary evacuation and displacement. Evacuation and subsequent moving decisions vary widely in the disaster-experiencing and recovery processes. However, no existing studies provide evidence that takes both the on-site disaster-mitigating and the afterward resettlement strategies into consideration simultaneously. Moreover, the complexity of these disaster-induced actions, especially in evacuation, is often overlooked.

This study is the first to focus on the effect of evacuation in rural areas over a five-year span. It also contributes to existing knowledge of the displacement effect, especially in disaster literature. Past studies often focus on evacuation within or across metropolitans (Deryugina et al., 2018; Deryugina and Molitor, 2020). Nevertheless, disaster mitigation

and coping strategies are crucial for rural residents because of their vulnerability and reliance on natural resources. In addition, the post-disaster recovery process in rural areas does not evolve like that in metropolitan areas. One factor contributing to the disparity is the relative deficit of transportation infrastructure and the limited working opportunities in rural areas. Moreover, rural livelihoods depend highly on natural resources, and the earnings are, on average, less than those of urban residents. Natural disasters often push rural residents to migrate out because agriculture and other resource-dependent activities are severely affected (Dillon et al., 2011). With a focus on rural residents, this study facilitates the understanding of how residents in more complex terrains recover from a natural disaster.

The first coping strategy addressed in this study is evacuation. It is particularly important in meteorological events, which are not like other immediate disasters, such as earthquakes. With the modern advances in forecasting technology, people generally have enough time to prepare for evacuation when typhoons approach. In this research, a five-period unbalanced panel is utilized as the main data source. The case analyzed is the strike of Typhoon Morakot, which hit Taiwan in August of 2009 and caused 728 deaths, including two devastating incidents where landslides buried entire villages. The survey traced all subsidized households of the Morakot Migration Subsidy. That is, all the observations in the data are victims of Typhoon Morakot. As shown in Figure 2-1, the

southwestern region of Taiwan, particularly the mountainous areas, experienced the most severe impacts. The tragedy of losing lives highlights the challenges of effective coping strategies, including evacuation. Evacuation plays a prominent role in disaster mitigation, especially for weather hazards and disasters.

Defined by the UN Office for Disaster Risk Reduction (UNDRR, 2019; NRC, 2020: 59), evacuation is a temporary form of displacement that effectively reduces physical damages, occurring before, during, or after the disastrous event. During Typhoon Morakot, voluntary evacuation took place, whereas mandatory regulations were not implemented, nor was an early-warning system implemented. Most inhabitants did not evacuate during the strike until the typhoon was getting close (Office of the President, ROC (Taiwan), 2011). This self-selected behavioral issue complicates the inference procedure. Past studies used quasi-experiments or natural experiments to estimate parameters, such as the difference-in-differences approach (Deryugina and Moliter, 2020; Deryugina et al., 2018; Vigdor, 2007). This study utilizes the instrumental variable (IV) approach to identify the targeted effects.

On the other hand, displacement is forced, and victims cannot return to their places. Possible causes of displacement are natural disasters and, more often, human activities. In the case of Typhoon Morakot, the displacement is due to the destruction of the houses and the subsequent permanent housing policy. After the strike, the government

collaborated with NGOs and constructed permanent houses. While other alternatives could be provided to the victims, the permanent housing policy was aimed at relocating the communities and villages threatened by future disasters with high potential risks. The permanent housing directed the victims to leave their original places, without considering possible impacts in cultural and social aspects, in less than two years for most of the victims. This resulted in the construction of 35 permanent house communities and 71 relocated communities, with the relocated households amounting to 3,630 (Tsai et al., 2022).

The 2009 strike of Typhoon Morakot, also known as Typhoon Kiko in the Philippines, has been regarded as one of the most catastrophic typhoons to ever hit modern Taiwan. Despite its intensity being approximately that of a strong Category 1 or a low-end Category 2 hurricane on the Saffir-Simpson wind scale (Wu, 2013), it resulted in the most devastating disaster in Taiwan's recent history, causing 728 deaths and approximately $3.3 billion in damages between August 6th and 10th, 2009. The rainfall brought by Typhoon Morakot was unprecedented, far surpassing the previous record set by 1996 Typhoon Herb. Consequently, it led to serious floods in various areas of Taiwan. The excessive precipitation triggered enormous landslides and floods in southwestern Taiwan. On August 9th, Shaolin, an Indigenous village in rural Kaohsiung, was completely buried by a landslide, with 25,000,000 cubic meters of soil and rocks engulfing the area

and resulting in 491 victims. In Nangisaru village of Namasia District, although the local mayor successfully evacuated nearly 400 villagers, more than 20 were reported dead due to the lack of evacuation. Another tragedy was the Xinkai village in Liouguei District, where 32 deaths were reported.

In this study, three effects of evacuation are assessed. The primary goal is to identify the effects of evacuation by comparing all evacuees and displaced victims with those who did not leave their original residence during Typhoon Morakot. Inferencing this effect enhances the understanding of the consequences of voluntary evacuation. This study also provides a benchmark for the pooled effect of those who leave their places during disasters. Still, one other effect compares evacuees, i.e., victims who temporarily evacuated, with those who did not evacuate. This effect is termed the "evacuation effect." This effect is even more communicative regarding evacuation promotion, since people usually return to the original places, if possible, in the aftermath. The final effect put special emphasis on evacuees and displaced victims. A valid inference of such an effect helps advance the understanding of evacuation and displacement. In this study, the effect of displacement is considered in the longer term, simultaneously with the long-term effect of evacuation. Similar to the categorization in investigating the effects of evacuations, comparisons across different groups of victims are made as well.

Few published studies focused on the impact of disaster-coping strategies. Rivera

(2020) examines the effect of evacuation on subjective recovery status using data from Texas victims of Hurricane Harvey. The result reveals that the evacuation negatively affects the recovery in the short term. This study provides empirical supplements to complement the existing knowledge. Evacuation is prevalent but salient in saving residents' lives during emergencies. Evacuation behavior and its impact are not new in disaster studies. Several studies focus on the decision-making process or factors that affect evacuation (Pan, 2020). By conducting a survey, Pan (2020) found out that the official announcement of evacuation is the decisive factor, and another important element is the perception of the living environment. Nevertheless, evacuation may affect not only the status quo at the strike of disasters but also the condition of aftermaths. In this regard, a better understanding of coping strategies is urgently needed.

This study is closely related to resilience. First proposed as an ecological concept, resilience can be measured by "the magnitude of disturbance that the system can absorb within the same state or stability domain" (Holling and Gunderson, 2002). It can also be recognized as the adaptive capacity to keep the current function (Walker and Salt, 2012). Although the concept of stability domain has no direct counterpart in economics, the ability of an agent to regain her original level of economic performance after a disturbance has long been a topic of inquiry by economists. This study aligns with resilience by taking the time to achieve new stable states to measure adaptive capacity. At a short glance, the

research seemingly presents the economic bounce back to the original state, i.e., the pre-strike level. It should be noted that this essay does not concur with the perspective of engineering resilience, which emphasizes a single stable state (Angeler and Allen, 2016). The post-disaster living conditions for the victims changed tremendously in various aspects, to list a few, the natural environment, neighborhoods, structure of households, and occupations. Therefore, although this study pays attention to households' economic recovery, victims are transiting to different states of equilibrium after the typhoon strike.

The recovery process in the aftermath can be assessed from several aspects, such as housing and community renewal (Comerio, 2014). Victim households with low income or low socioeconomic status are found to have difficulties in recovery (Fothergill and Peek, 2004). Several factors contribute to the adversity, such as less disposable financial resources, housing, and worsened economic stress. Extending from the resilience perspective, the outcome of interest is the difference in household income between post- and pre-strike periods. By comparing current income to baseline income, i.e., pre-strike income, this study helps understand economic recoverability after the disaster. The results show that the evacuation caused household income recovery to decrease, which shed light on the current limitation in the execution and promotion of voluntary evacuation plans.

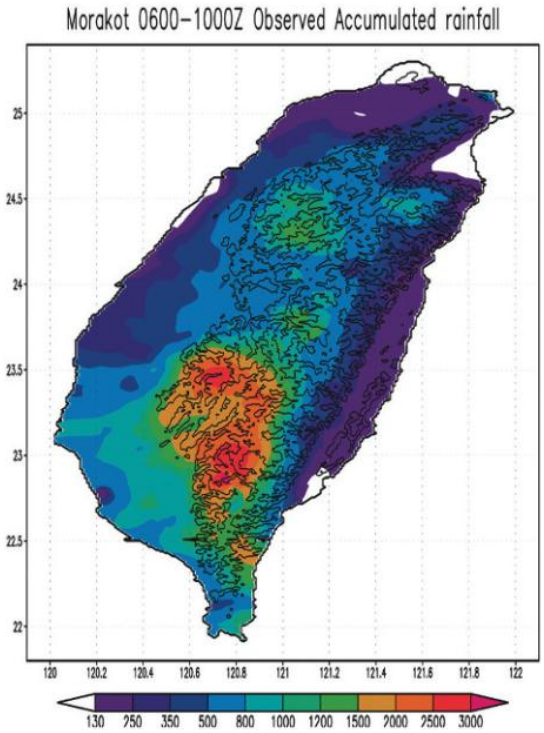


Figure 2-1 Observed rainfall during the Typhoon Morakot strike (August 6-10, 2009) (Retrieved from Yeh et al. (2011)). Note. The solid line indicates the contour of 1,000m.

2. Literature review

2.1. Evacuation Behaviors and Disasters

Evacuation has garnered attention for its crucial role in risk reduction. A major focus in the literature is identifying factors that influence evacuation decisions (e.g., Tanim et al., 2022; Collins et al., 2018; Lazo et al., 2015; Lin et al., 2014; Siebeneck et al., 2013). Nevertheless, prospects for impacts of evacuation are comparatively little. One prominent area of investigation is the impact on labor market participation. Drawing from the experience of Hurricane Katrina, Vigdor (2007) examines the transient economic effect of evacuation by comparing evacuees and non-evacuees. Evacuees are categorized based on different moving patterns into returnees and long-term evacuees. The study reveals the divergent effects between the two types of evacuees, confirming that the recovery process for long-term evacuees faces more obstacles, and short-term labor participation declines for evacuees. Besides Vigdor's direct economic assessment, Sacerdote (2012) focuses on the effect on human capital, investigating the long-term academic performance of hurricane evacuees. The study finds declines in scores after one year following the hurricanes, but the evacuees' test performances improve over a longer period. More recently, Rivera (2020) examined the psychological impact of evacuation, finding a negative effect on the subjective recovery status of victims of Hurricane Harvey.

Indeed, despite their contributions, the credibility of the evacuation effects

mentioned in Vigdor (2007) and Sacerdote (2012) may be compromised due to terminological ambiguity. The evacuation may cause misunderstandings with other terms. For instance, Vigdor (2007) categorizes evacuees as residents who did not participate in the survey after Hurricane Katrina, a similar definition to that of "migrator" in Deryugina and Moliter (2020), in which they focus more on migration issue rather than evacuation effect. Another issue is about the time dimension involved in these actions. Vigdor (2007) and Zissimopoulos and Karoly (2010) use the term "returnee" to refer to victims who returned within one year after evacuation, based on the information provided by the Current Population Survey (CPS). Nevertheless, return after one year may be due to several confounding reasons, compared to a more transient decision on return.

Various natural events draw researchers' eyeballs. Johar et al. (2022) focus on the experience of natural disasters and compare the economic impacts of different types of disasters between the residents who had experienced residential property loss and those who had not. It has been found that the direct economic losses of natural disasters increase over time because of the increasing population and development level (Botzen et al., 2019). Besides evacuating from natural disasters,

In terms of impact assessment, Hsiang's (2010) work estimates the effect of the hurricane on different industrial sectors in Caribbean-basin countries, and it also shows the lagged effect of cyclone intensity on contemporary sectoral GDP, which points out

the lasting impact of the disaster. In the Philippines, Anttila-Hughes and Hsiang (2013) show that typhoons decrease household income by 6.6 percent transitorily, and the impact lasts for years, especially for poor households. Hurricane Katrina motivates Deryugina et al. (2018) and Deryugina and Molitor's (2020) works, which elucidate the mid- and long-term impacts and conclude the economic performance or health status of migrants after years of the strike. Deryugina and Molitor (2020) find that Hurricane Katrina reduced the mortality rate by 3% of elders and disabled residents who originally lived in New Orleans. The victims who moved to places with lower mortality rates contributed to the result. However, Kaestner (2020) discusses the results in Deryugina and Molitor (2020) and concludes that they do not provide enough evidence to support the inferences. One of the reasons mentioned by Kaestner (2020) concerns the randomness of the health conditions of residents in New Orleans and the destination of migration. These discussions, again, pose the complexity of giving credible inferences in this strand of study.

The reasons for such a catastrophe are doubted to be either a lack of information or the residents not making voluntary decisions. The evacuation plan at the time of the strike was unclearly documented. After the disaster, Taiwan's government faced criticism for its late response in preventing negative damages. The President of Taiwan admitted to the delayed response by stating that "evacuation… in dangerous areas was not carried out until Typhoon Morakot… was in progress…" (Office of the President, 2011). The tragedy

spurred Taiwan's government to reform the disaster prevention system, which included amending the Disaster Prevention and Protection Act (Executive Yuan, 2014). Following Typhoon Morakot, the President emphasized that "disaster prevention is more important than rescue, and evacuation an even higher priority than prevention", which has become the central concept in disaster prevention efforts.

However, in some villages, local officials and police officers carried out evacuation efforts progressively and successfully. As a result of these prevention actions, causalities decreased, saving at least 858 people (Chen, 2009). Chen (2009) documented 17 successfully evacuated villages, where varying degrees of impact on transportation infrastructure or private properties were observed. Among the evacuated villagers, only one casualty was reported. These successful cases highlight the importance of evacuation compared to the previously mentioned tragedies.

2.2. Displacement Effects

In general, past research about displacement agrees upon its negative impacts, whether it is human-induced or caused by natural disasters. These impacts are multifaceted and overwhelm victims' livelihoods. A large portion of the literature emphasizes forced displacement induced by humans, such as conflicts and wars. Below, some critical findings in this line are reviewed, while the others are mainly about

displacement due to natural disasters.

Fiala (2015) examines the effect of displacement of civil conflict in Uganda. The displacement has a negative impact on consumption, and the effect lasts for two years at least. Fiala (2015) also finds that the recovery in consumption for the originally wealthier group is faster, while for the poorer group, the recovery almost stagnated. In terms of education and wealth levels, the impacts were substantial in all groups. The displacement affects not only those who leave but those who do not. Verme and Schuettler (2021) review 59 studies that examine the economic effect of forced displacement on original communities. They summarize that the impacts on wages and employment are not significant. The prices of food and living generally increase, but other prices may decrease.

Verme and Schuettler (2021) point out the difficulties of arguing the randomness of resettlement decisions and observed actions regarding human-induced displacement, and it is therefore better described as a quasi-experiment. Furthermore, when identifying the economic effect of displacement, the displacement has been instrumented by the distance between the resettlement and the original places, the governments' placement policy (Sarvimäki, 2011), and the occupations (Borjas and Monras, 2017; Braun and Mahmoud, 2014).

The findings on natural disasters are similar. Short-term displacement causes the loss of well-being (Black et al., 2013). Black et al. (2013) distinguish the three actions after

disasters- migration, immobility, and displacement. They conduct a systematic review and find that movers and non-movers are vulnerable to disasters. Furthermore, they point out that the economic downtown of the displaced is due to the failure to adapt to the change in environment. Moreover, temporary shelters may increase the risk of communicable diseases (Loebach and Korinek, 2019). Loebach and Korinek (2019) control for the personal fixed effects and estimate by a two-way fixed effects model that simultaneously measures the effects of displacement time and experience.

The social cost of displacement is huge. In Nepal, Salgado-Gálvez (2018) finds that the displacement after the Grokha earthquake caused a production loss of $406 million in GDP. Hori and Schafer (2010) find that after Hurricane Katrina and Rita, the displaced suffered from unemployment and mental issues. The victims who settled in a distant place suffered income losses, while no effects were found for those who settled in the same parish. The differences between the destinations found by Hori and Schafer (2010) highlight the fact that resettling in the same place is critical for victims' recovery.

2.3. Evacuation and Displacement

The nuanced meaning of evacuation is indeed crucial in the design and promotion of practical strategies. For immediate and foreseeable natural hazards, such as the adverse impacts of intense precipitation, evacuation refers to the process of moving people from

a hazardous location to a safer one temporarily. The time frame of evacuation is typically short, ranging from hours to weeks (CCCM Cluster, 2014: 16).

Nevertheless, in some cases, evacuations can transition into displacements, lasting for prolonged periods and even permanently, uprooting inhabitants and infringing on human rights. Additionally, the Norwegian Refugee Council (NRC, 2020) categorizes other forms of human mobility, such as voluntary migration and planned relocation. These discussions undermine the relevance of a clear definition of evacuation before examining the effects.

As McAdam (2022; 2020) addresses, whether in a practical or academic context, evacuation is vaguely defined, and fragmented discussions are ongoing, leading to misconceptions about its consequences. It is therefore crucial to distinguish between these terms. In the literature review process, economic research thus far has not observed this disparity. It should be emphasized that the current focus is on temporary evacuation. That is the effect on victims who evacuated before or when the typhoon struck but returned to their original places within a relatively short period. Crystalizing what evacuation entails highlights the complexity of identifying its effects.

Evacuation and displacement are closely related. With the increasing adoption of evacuations during disasters, the risk of displacement also arises (UNDRR, 2019: 28). NRC (2020) listed 10 kinds of negative effects caused by disaster displacement, including

short- and long-term impacts, physical and psychological. Kearns and Mason (2013) explicitly clarify the distinction between relocation and displacement. Displacement involves psychological and social means, which is often negative, whereas relocation refers to physical movement. In this study, displacement is used to denote the intangible and psychological shocks on the victims of Typhoon Morakot.

Amongst all the effects, financial losses and unemployment are the most direct economic impacts. Problems in property rights and losses in both human and social capital lead to long-term economic adversity. On the other hand, post-disaster recovery can be assessed from several aspects, such as housing and community renewal (Comerio, 2014). Victim households with low income or low socioeconomic status (SES) are found to have difficulties in recovery (Fothergill and Peek, 2004). Several factors contribute to the adversity, such as less disposable financial resources, housing, and worsened economic stress.

Evacuation and displacement are separate and should not be viewed as the same treatment. Indeed, evacuation usually leads to displacement. Some disastrous events such as landslides, destroy houses and infrastructures, and obstacle returning process. In such cases, if the initial destination after evacuation fails to meet certain requirements, such as safety, convenience, and comfort, victims may still consider returning to their original places or seeking a new destination when return is not allowed. Although not fully

investigated, empirical evidence shows differences between the long-term evacuees and the one-year returners after Hurricane Katrina (Vigdor, 2007) were facing two selection problems, hindering the direct causal interpretation.

Several housing strategies are relevant in post-disaster scenarios. Often, the housing conditions of the original places are intolerable after a disaster. Victims are forced to move to other places. To sustain victims' meager livelihood in the short term before they find feasible houses, governments around the world often construct temporary houses, which can be constructed within several days. Shelters such as public schools or arenas are also open to victims, functioning similarly to temporary houses. These short-term housing strategies are often regarded as a midway through disaster and recovery in the long term.

Several permanent house communities are constructed after the strike of Typhoon Morakot. Unlike previous disaster reconstruction processes, which often include a transitional step that provides transitional houses equipped with basic living functionalities to victims, the reconstruction strategy after Typhoon Morakot adopted by the government is the first time that led by NGOs rather than victims. Some victimized villagers were forced to decide if they wanted to apply for a free permanent house, which in many aspects, is largely determined by some NGOs or the government, including its location and design. The victims were asked to choose three alternatives: rent a house with a rental subsidy, buy a house with a subsidy, or be placed by the government. The

victims who decided to be resettled by the government in principle ended up in a permanent house.

Although the permanent housing program began with good intentions and was an appealing option for the victims since it was free, it triggered criticism from academics and communities. Indigenous people are the most affected group. Five months after the strike, the government determined 160 areas where resettlement was needed, amounting to 6,316 households with 19,191 victims, and nearly 14,000 were Indigenous people (Shieh et al., 2013). The resettled victims did not own the land's property rights, only acclaiming the right to a permanent house. Some permanent communities were far from the victims' original village. In addition, it was criticized that the fast-paced reconstruction process hurdles full consideration of societal and cultural facets, which makes the cultural legacy almost disconnected, especially for Indigenous people. Compulsory resettlement and village relocation are included in a special law for reconstruction after Typhoon Morakot. These were unprecedented in the disaster history of Taiwan and may be due to the immense number of destroyed houses in the strike and the power of several influential NGOs (Shieh et al., 2013).

It was also found that the reconstruction process caused cultural conflicts. Lin and Lin (2016) conclude that the major reasons include the physical distance of the resettled area to the original places, the change in lifestyle, and the lack of participation of local

people led to severe communication problems. Especially, Indigenous tribes were the most affected groups (Lin and Lin, 2016; Hsu et al., 2015).

3. Identification and Estimation

The study aims to estimate the effects of the evacuation and displacement on income recovery after a typhoon strike. Strategically, if treatment and control groups are clearly defined, and treatments of interest are randomly distributed across treated and control groups, the OLS regression can identify the treatment effects directly. When treatments are not exogenously determined, OLS estimates are biased, and other methods should be in place of OLS regression. Quasi-experiment methods, such as difference-in-difference (DID) produce causal interpretations if certain prerequisite assumptions are satisfied (Deryugina and Molitor, 2020; Deryugina et al., 2018; Vigdor, 2007). Matching also generates comparable results (Deryugina et al., 2018). Nevertheless, these methods are not exemplary with limitations. The matching method has been criticized for its caveats of strong ignorability (or, selection on observables) assumption. In addition, DID estimators are questionable without validating whether a parallel pre-trend exists. The credibility of DID estimators is dampened if the parallel trend assumption fails (Roth et al., 2023).

Other identification strategies are possible. Given panel data, the fixed effects method allows researchers to eliminate idiosyncratic unobserved characteristics (Botzen et al., 2019; Anttila-Hughes and Hsiang, 2013; Sacerdote, 2012). Sacerdote (2012) estimates the effect of hurricanes on the school performance of the evacuees. Rather than directly estimate the effect of evacuation, Sacerdote (2012), in turn, takes evacuees as subgroups and estimates the effect of the hurricanes. In such a setting, the fixed effects method is appropriate to eliminate unobservables. While Sacerdote's (2012) research controls for the confoundness of victims in the two hurricanes included in the analysis, one caveat has not been mentioned. In effect, it fails to deal with the self-selected problem of evacuation.

The treatment variable invokes a self-selection problem, which leads to biased estimates using OLS regression. Evacuation is possibly associated with many factors, such as the perceptions of potential threats of the upcoming strike, the characteristics and formation of a household, awareness of danger, and the perceptions of refugees, including transportation and comfortability, and so on. Similarly, the decision to live in a permanent house is also confounded with the decisions of neighbors and friends, the distance to the original place, the design of permanent houses, and the complexity of the application process. To tackle the self-selecting nature of the actions, this study uses the random effect instrumental variable (REIV) estimators.

3.1. The Target Effects

To fully understand the larger picture of the effects of different mobility patterns, this research separates targeted effects from the two actions related to evacuation: leaving and returning. In what follows, evacuating, or interchangeably called leaving, refers to the evacuation victims take during the strike. Returning refers to whether a victim's household returned to its original place within one month after the strike.[1] The additional inclusion of the returning behavior does not cloud the policy interest in identifying the effects of evacuation and displacement.

For ease of reading, the effects relevant to evacuation are termed leaving effect, evacuating effects for returners, and evacuating effects for migrators. Let y be the economic outcome variable. Define a dichotomous indicator lv as the action of leaving the original places during Typhoon Morakot, and let the other indicator rtrepresent the returning effect. According to the values of lv and rt, a victim's household i is a temporary evacuee if $lv_i = rt_i = 1$; displaced household if $lv_i = 1$ and $rt_i = 0$; non-leaver if $lv_i = 0$ and $rt_i = 1$; and the last group, called afterward evacuee since they leave their places after the strike, i.e., $lv_i = rt_i = 0$. Under the potential outcome framework, the leaving effect (τ) is the impact of leaving on a victim's household i had

[1] It may seem possible to estimate the effects of returning. However, since returning involves whether the housing condition is physically allowed, the decision is not fully self-selected but jointly determined by the housing condition in the aftermath. In other words, the effect of returning cannot be disentangled.

not left:

$$\tau = E\left[y_i|lv_i = 1\right] - E\left[y_i|lv_i = 0\right] \quad \text{(e2-1)}$$

This effect is the evacuation effect that would be thought of generally without considering the difference in actions in the aftermath. Notwithstanding, bearing the complexity of the actions, further effects addressing various moving patterns are needed. The evacuating effect for the returned (ϑ_1) is estimated by comparing the economic performance between temporary evacuees and had they been non-leavers:

$$\begin{aligned} \vartheta_1 &= E\left[y_i|lv_i = 1, rt_i = 1\right] - E\left[y_i|lv_i = 0, rt_i = 1\right] \\ &= E\left[(E(y_i|lv_i = 1) - E(y_i|lv_i = 0))|\, rt_i = 1\right] \end{aligned} \quad \text{(e2-2)}$$

The evacuating effect for the displaced (ϑ_2) is the difference between the displaced victims and afterward evacuees, both groups stay outside of the original places after one month of the strike:

$$\begin{aligned} \vartheta_2 &= E\left[y_i|lv_i = 1, rt_i = 0\right] - E\left[y_i|lv_i = 0, rt_i = 0\right] \\ &= E\left[(E(y_i|lv_i = 1) - E(y_i|lv_i = 0))|\, rt_i = 0\right] \end{aligned} \quad \text{(e2-3)}$$

The only difference between ϑ_1 and ϑ_2 is the conditional value of the returning behavior. If rt_i is randomized, then there should be no difference between ϑ_1 and ϑ_2. The returning action, rt_i, is determined both by the self-selected decision and damage level in the original place and the surrounding area. Therefore, rt_i is randomized is a plausible assumption since geographical traits determine the damage. Empirical evidence

will be provided in the result section. and can be examined with the empirical results.

Similarly, it is possible to identify three kinds of displaced effects. Let pmt_i be the other indicator for the victims who lived in a permanent or transitional house provided by the government or NGOs. The general displaced effect (φ) is defined under the potential outcome framework:

$$\varphi = E(y_i|pmt_i = 1) - E(y_i|pmt_i = 0) \quad \text{(e2-4)}$$

This effect measures the economic outcomes of living in a permanent house. By subgrouping victims, the displaced effects for the evacuees and for non-evacuees are, respectively,

$$\upsilon_1 = E(y_i|pmt = 1, lv = 1) - E(y_i|pmt = 0, lv = 1) \quad \text{(e2-5)}$$

and,

$$\upsilon_2 = E(y_i|pmt = 1, lv = 0) - E(y_i|pmt = 0, lv = 0) \quad \text{(e2-6)}$$

3.2. Estimation and Instruments

This study utilizes the REIV estimators. A valid instrument should satisfy two conditions: it cannot directly affect the outcome variables, which are post-strike incomes and differences in income, and it should be as-good-as-random assigned so that the treatment effect can be identified as in a laboratory experiment. Further, it must relate to leaving or permanent housing, which is called relevance condition. IV estimator can be

extended to heterogenous treatment effects as local average treatment effect (LATE) under the assumptions proposed by Imbens and Angrist (1994), a cornerstone of modern econometric research. Apart from the validity and relevance assumption of IVs, LATE requires an additional monotonicity assumption. This assumption addresses that an increment in the value of an instrument must have nonnegative effects on taking treatment. Accordingly, the interpretation of LATE changes based on the instruments selected identifying different compliers, i.e., those who switch from non-treated to treated as the value of an instrument increases. It is reasonable to presume that information resources obtain this characteristic because they positively correlate with the evacuation decision in several studies about weather disasters (Sadri et al., 2017; Huang et al., 2016; Lazo et al., 2015).

Below, two arguments supporting the selections of the instrumental variables for evacuation and permanent housing are expounded. A set of instrument candidates for leaving decisions is the information resources relevant to evacuation, whereas application status is used to instrument permanent housing.

From the literature, there are several external factors affecting the decision to evacuate in cyclones, such as the intensity (Jibiki et al., 2016; Smith and McCarty, 2009; Whitehead et al., 2000), the perceived type of damages (Whitehead et al., 2000), conditions of evacuation site (Pan, 2020). Human factors also take part in such decisions,

including demographical variables (Pan, 2020; Lazo et al., 2015; Smith and McCarty, 2009), experience in cyclones, mobility (Pan, 2020; Whitehead et al., 2000), neighborhoods' decision (Pan, 2020). Amongst all, information is a critical aspect, as summarized in Huang et al. (2016). The related factors include whether the message is received, whether it is on time, or whether the messages are clear (Yore and Walker, 2020). The reliability of the information sources is found to affect the decision (Sadri et al., 2017). In addition, different resources may have diverse impacts on evacuation (Lazo et al., 2015). Possible instrument variables may be found with these sound foundations of the understanding of evacuation.

Incorporating information sources as instruments is a new attempt in literature, especially those investigating behavioral changes. The information sources are correlated with many factors. For traditional information mediators such as TV and radios, the intensity of the signal and the number of channels are used as instruments in behavioral research, including consumption, voting, and migration (Peisakhin and Rozenas, 2018; Farré and Fasani, 2013; Olken, 2009; White et al, 2005). In this study, the eight types of information included in the survey are categorized into four groups, which are received from administrative agents, relatives, or neighborhoods, from the victim herself, and did not receive any information.

The randomness embedded in the information sources comes from multiple reasons.

From an administrative viewpoint, although the local governments should warn residents to evacuate as the central government released village-level notification during Typhoon Morakot, there were several exceptions that village heads did not comply with the process. Some residents were unwilling to evacuate (Lin, 2013), and some were misled by inaccurate forecasts that underestimated the volume of precipitation (Huang, 2014). Also, from the aspect of receiving information from others and finding information on a victim's own, the transmission of the mediators' signal suffered severe damages during the strike. Over 28,000 telephones and 730 cell sites malfunctioned during the strike (Central Emergency Operation Center, 2009), which hindered the connection between dangerous areas and external information sources. This transmission corruption was mainly due to the realized precipitation, landslides, and windspeed brought by Typhoon Morakot. Therefore, the randomness of the information sources hinges on local governors' behaviors and realized disasters, which can be regarded as externally decided.

A myriad of instrumental variable candidates are possible alternatives. Regarding leaving action, one such instrumental variable is the forecast of precipitation volume during the strike of Typhoon Morakot. It is not rare to use observed rainfall volume as an instrument (e.g. Waldman et al., 2008), but no previous study has used forecast data. In addition, realized rainfall volume cannot be used as the instrument in this case because the heavier the rainfall, the more severe the damage, directly affecting the dependent

variables. The validity of the instrument is arguably held because of the following reasons. First, rainfall is fully random by its nature, and the corresponding weather forecast, which can be regarded as a function of realized rainfall volume, is random mathematically. In addition, the main forecasting technology at that time was radars and quantitative precipitation forecasts (QPFs) (Wu, 2013; Yeh et al., 2010). QPFs are a functional method considering multiple factors affecting rainfall, such as terrain and information provided by radar networks (Wang et al., 2021). Furthermore, the forecast does not affect the pre- and post-strike period income. One concern that arises is that the forecast correlates with realized rainfall. This is not the case since the Central Weather Administration (CWA) only provided the county-level forecast at the time of Typhoon Morakot. This aggregate information eliminates possible correlation with detailed rainfall volume measured by townships or smaller units. Moreover, although the precipitation forecast was not accurate enough, the pattern still matters. That is, greater forecasted precipitation volume may bring greater damage. For these reasons, its validity may not hold.

Turning to the displacement effect. the instrumental variable selected is whether a victim's household applied for a permanent house. The key mechanism hinged on the application process of permanent houses. The local government originally conducted the process, but with the active participation of the five main NGOs, these NGOs played deterministic roles in the application process. The victims had to apply for a permanent

house, and the authorities would decide if the applicants could have one and its size. Nevertheless, the application process was dispatched to several NGOs, and different organizations may have disparate standards. Some correspondents showed leniency to victims, while some did not. In other words, applying for a permanent house does not mean having a permanent house. The observed application action can be considered as a consequence produced by several perceptions. For example, the cultural and social capital all affect the process of determining to apply. These perceptions in the short-term in the post-disaster society. do not have a direct impact on post-disaster income or differences in income. Therefore, the perceptions satisfy the validity assumption or exclusion restriction. The individual's perception of danger at a specific time is shaped by personality, which can be considered as a rather fixed characteristic. In this regard, Malone and Lusk (2018) have used a personality score to instrument perceptions of consumption choices of beer brands.

In terms of the LATE theorem, receiving information increases the probability of implementing evacuation. The information reception is determined at the time of the strike. It is time-invariant from the perspective of periods afterward. Moreover, the information sources announce the evacuation decision based on different backgrounds and judgments about the situation. Some were spontaneous and progressive, while some showed carelessness and irresponsibility. For instance, a news by the time showed that a

local government failed to announce evacuation even central government had warned of the danger of landslides over 8 times. The different innates and characteristics of these resources turned information communication complicated.

Nevertheless, under multiple instruments, the effects estimated could be problematic and cannot be deemed as LATE (Mogstad et al., 2021). Intuitively, the three information resources considered may correspond to different complier groups, and naively taking those as the same is arduous. For instance, it could be the case that, whilst the monotonicity of one instrument is satisfied, a complier may violate this assumption from the aspect of the other instruments. If this problem arises, it substantially decreases the causality interpretation. To mitigate the concern, this study provides two empirical comparisons to argue that the compliers are statistically similar. First, a relaxed version of monotonicity, the assumption of partial monotonicity proposed by Mogstad et al. (2021) is checked. This assumption states that conditioning on all other IVs, an increase in a certain IV must induce the treatment value to switch from without treatment to treated. In addition, they also show that the LATE of multiple IVs is a weighted average of all LATEs identified by each single IV if partial monotonicity is met. Empirically, this can be done through examining the first-stage regressions including a single instrument while controlling other instruments as right-hand-side variables. Second, the Abadie estimator (2003) is used to examine whether the different complier groups have statistically

different characteristics. If the differences among complier groups are substantial, then it is inappropriate to aggregate all LATEs together. This method also gains visibility since it provides pertinent information about the external validity of the treatment effect (Sungh and Sun, 2024; Marbach and Hangartner, 2020). The results of these issues will be presented in section 5.4.

Denoting the expected income in the period t of victim household i by y_{it}, and denote x_{it} as the individual's and household's characteristics. Let ϵ_i and u_{it} be idiosyncratic household effect and time-varying error terms. The average leaving effect τ can be written as the regression equation (e2-7):

$$y_{it} = \beta_0 + \beta_1 x_{it} + \tau \cdot lv_i + \epsilon_i + u_{it},\ t \in [1,4] \tag{e2-7}$$

where $i \in \{\text{temporary evacuee, non-leaver}\}$. In the short term, $t = 1$. The two evacuating effects are,

$$\begin{aligned} &y_{it} = \gamma_0 + \gamma_1 x_{it} + \vartheta_1 \cdot lv_i + \epsilon_i + u_{it}, \\ &i \in \{\text{temporary evacuee, non-leaver}\} \end{aligned} \tag{e2-8}$$

$$\begin{aligned} &y_{it} = \gamma_0 + \gamma_1 x_{it} + \vartheta_2 \cdot lv_i + \epsilon_i + u_{it}, \\ &i \in \{\text{displaced, afterward evacuees}\} \end{aligned} \tag{e2-9}$$

In short, the effects can be estimated simply by setting different combinations of the subgroups. The OLS regression estimates of τ and ϑs are biased due to the self-selecting decision of evacuation. Let $\mathbf{z_i}$ denotes a vector of IVs, (e2-8) and (e2-9) can be estimated by the 2-stage least square (2SLS) method. The first-stage regressions for (e2-

7) through (e2-9) are:

$$lv_i = \alpha_0 + \mathbf{z_i}'\boldsymbol{\alpha} + \epsilon_i + u_{it} \quad \text{(e2-10)}$$

The first-stage regression (e2-10) characterizes the relation between the instruments and the treatment variable, leaving. To satisfy the relevance condition, the estimated $\hat{\boldsymbol{\alpha}}$ should be significant. The reduced form for the three effects is:

$$y_i = \rho_0 + \mathbf{z_i}'\boldsymbol{\rho} + \epsilon_i + u_{it} \quad \text{(e2-11)}$$

The 2SLS estimator is calculated by dividing ρ with α. Similarly, for the displacement effect, the first stage reveals the relation between the instrument and the indicator of living in a permanent house. A twist here is that the displacement effect can appear in the long term, but the economic recovery is possibly influenced jointly by evacuation. Therefore, the following results consider the two effects simultaneously.

This study examines the effects of evacuation after one year of Typhoon Morakot and checks if its effects extend across years in all survey periods. In addition, the evacuation effect and the displacement effect are estimated simultaneously. This is due to the possible correlation between evacuation and living in a permanent house. For both effects, the reduced form is estimated by the OLS regression. In particular, for the displacement effect, the application for a permanent house means that the original house is hardly livable, and the direction of this relation should be negative.

The outcome variable y considered is twofold. First, cross-sectional data is used

for identifying short-term recovery effects. In cross-sectional analysis, the outcome variables are the household's monthly total income and the income difference between the first year after the Typhon Morakot and the income before the strike, $\Delta y_i = y_{i1} - y_{i0}$, where y_{i0} is the income of household i at period 0, i.e., the pre-strike income. This dependent variable assesses whether the economic performance of a victim household returns to its original state. Additionally, an unbalanced panel including all four post-strike periods, from the first year to the sixth year afterward, is used to examine whether the evacuation has a long-term role in the recovery process. The importance of an evacuation on contemporary income, if any, should fade out with time. Therefore, measuring income across several periods afterward does not provide significant economic meaning. In this regard, only one dependent variable, the difference between the income in each post-strike period and income prior to Typhoon Morakot, is considered in the panel analysis.

Usually, the above equations are estimated through the fixed effect or first-differencing approach, which cancels out the household fixed effect ϵ_i. Nevertheless, the fact that these behaviors are time-invariant hinders the utilization of these approaches. In this research, the random effect instrumental variable method (REIV) is employed as the main solution to tackle the self-selected evacuation behavior. REIV is an extension of the random-effect framework combined with IV.

Under the random-effect framework, the conditional expectation of the household fixed effect is zero, $E(\epsilon_i|\mathbf{x}_{it}) = 0$. The REIV further requires that a vector of valid IVs, $\mathbf{z_i} \equiv (\boldsymbol{z_{i1}}, \ldots, \boldsymbol{z_{ik}})$, must satisfy exogeneity assumptions, $E(u_{it}|\mathbf{z_i}, \epsilon_i) = 0$ and $E(\epsilon_i|\mathbf{z_i}) = E(\epsilon_i) = 0$ (Wooldridge, 2010: 351). In addition, as the requirement of the ordinary IV method, a set of IV candidates must correlate with the evacuation, $E(evac_i\mathbf{z_i}) \neq 0$, which is called relevance condition. In addition, to make sure the estimates are causal effects, $\mathbf{z_i}$ should not affect y_{it} directly. In other words, the effect of $\mathbf{z_i}$ is totally via the channel of $evac_i$. This condition is often called exclusion restrictions.

The necessary condition for the REIV estimator demands that unobserved victim households' characteristics do not correlate with all control variables. Although it can be examined statistically by tools such as the Hausman test for all control variables, one might still worry about whether this strict assumption holds.

4. Data

The data used are from four waves of *Social Impacts and Recovery Survey of Typhoon Morakot*, which surveyed the victims in 2010, 2011, 2012, and 2015, respectively. The surveys were conducted by the National Science and Technology Center

for Disaster Reduction, which is an institute that has a specialty in disaster management and reduction under the National Science and Technology Council. The data is unique in tracing all victim households applying for relocation subsidies after Typhoon Morakot. After deleting unreasonable values, the unbalanced panel contains 935 observations in the first period, 825 in the second period, 741 in the third survey year, and 542 in the last. The pre-disaster conditions are also constructed by retrospective questions in the first and the second periods, containing 977 observations. For simplicity, denote period 0 as the pre-strike period, and period 1-4 as the four realized surveys hereafter. This study also incorporates the precipitation data, recorded between August 7th and 9th, 2009, which are collected from the Central Weather Administration.

Two questions about evacuation were asked in the survey- "Did your family evacuate on the coming of Typhoon Morakot?" which is coded as a dummy variable, and "Where do you live after one month of the strike?". The second question has various alternatives, which are transformed into a dummy by recognizing that a victim household remains at its original place after one month of the strike. The first question serves as a criterion for implementing evacuation. Therefore, four types of victims can be identified. An observation in the sample is categorized as (temporary) evacuee if both questions have positive values. A victim is classified as "displaced" if she reported being evacuated but did not live in the original place. If one still lives in the original place and reports no

evacuation, then she is categorized as a non-leaver. Some observations report positively in the second question while having a zero value in the first question. These victims are categorized as afterward-evacuees. Following the definition in Section 3.1, the categorizing information is summarized in Table 2-1.

The effects defined earlier merit further explanations. The leaving effect is the impact of whether a victim reports that she evacuated, that is, the difference between those who evacuated, including temporary evacuation and displacement, and those who did not evacuate. The evacuation effect is the difference between those who temporarily evacuated and those who stayed but were not evacuated.

Table 2-1. Subgrouping the Sample and the Evacuation Effects

Subgroup	Evacuate (lv)	Live in the original place after a month (rt)
(Temporary) evacuee (TE)	1	1
Displaced victim (DV)	1	0
Non-leaver (NL)	0	1
Afterward evacuee (AE)	0	0

4.1. Descriptive Statistics of Key Variables

The definitions of variables and controlled values are listed in Table 2-2, and the descriptive statistics for key variables used in the following analysis are presented in

Table 2-3. Income and difference in income are deflated by setting the pre-strike year (2008) as the base period. The information of household recover costs is collected from the survey. If a victim reported that her house was fully destructed, then five million NTD is used as a proxy for recover costs, which is higher than the average costs of a house in the mountainous areas by that time. This number includes all necessary costs such as land recovery and preparation. As Table 2-3 shows, the household's income suffers a slight drop after Typhoon Morakot, but grows fast in the subsequent two survey years, and then takes a leap by 2015. For time-invariant variables such as temporary evacuation, the means of the variables fluctuate because of the attrition. Over three-quarter of the victims reported evacuated in the disastrous event. The household size has 4.2 members before the strike, and the number slightly drops afterward. Within the household, the youths and the elders sum to 1.5 people, which indicates that around two or three grown-ups in a household on average. Some large households in the census data are observed and kept them in the analysis since they reflect specific information in the affected areas.

In terms of survey-takers, nearly 60% of the respondents are male, while in the last survey the percentage drop to around half. The ratio of unemployment is high, reported 28% before the strike. It then escalates to a range between 35% to 41% in the aftermath, reflecting substantial impacts of the typhoon on human resources. On the contrary, the ratio of being a farmer decreases constantly after the strike. The loss of farmland and

relocation strategy that make people away from their homeland may be the cause. Working in public departments or private business is less affected while the percentages are rather steady across the periods. The share of the Indigenous family is consistent at around 42% across the periods.

The returning decision within one month after the strike that defines temporary evacuation is possibly due to the differences in the distribution of characteristics. Table 2-4 divides the observations into groups by the returning behavior, i.e., whether they returned to their original places within a month after the disaster. The ratios between returned and not returned victims remain stable, around one-fourth to one-fifth across the four years. The t-tests with unequal variances indicate that the disparities between the groups present in several aspects. Overall, the returned group has higher income in the first two periods, but lower than their counterparts in the third and fourth periods, with the only statistical difference appears in the third period.

Comparing the listed individuals' and households' characteristics in the first column of Table 2-4, the returned group has a higher proportion in farming but less in office or more stable works. This highlights the cases that the farmers were more prone to return to original places, where the parcels of land locate. The only two variables that show between-group differences consistently across the years are Indigenous family and senior high school degree. Significantly less share of Indigenous families in the returned group,

ranging from one-fourth to one-third depending on the survey period. On the other hand, a higher share- over 40% of victim households are Indigenous in the nonreturned group. Indigenous households on average are less willing to return. This difference may underscore that disparities exist rooted in cultural or habitual factors, but it is possible that Indigenous households suffered greater damages. In terms of the degree of senior high schools, the returned households have significantly less proportion of this level of education. Nevertheless, no difference in other educational levels is found.

In addition, in the first two periods, the numbers of younger generations within households are significantly lower in the returned group, while the gap narrows as the years pass. Compared to the numbers of older members, the younger members also show greater fluctuation across periods. One possibility is that younger generation returned to their hometown from urban areas to help their family or community.

It should be noted that some of the variables in Table 2-4 are time-invariant. Therefore, the columns in Table 2-4 represent changes in the sample due to attrition. Substantial disparities exist between the groups in disaster-related variables. The returned group on average has less experience of evacuation, suggesting an adverse selection of returning with accumulating experience. It is noteworthy that the reception of evacuation information is higher in the groups not returned. The proportion of not received any information about evacuation is also higher. The differences in information might play a

role in returning decision. In terms of the impacts, the returned group suffered less damages economically and physically. This may due to the heavier rainfalls in the areas that the group didn't return.

Table 2-2. Definition of Variables

Variables	Definition
Dependent variables	
Income	Monthly income of the household (NTD)
Inc_dif	Difference in income in period t and in period 0, $t \in \{1,4\}$ (NTD)
Actions relevant to evacuation	
Leave	Victims evacuated but did not return
Return	Victims evacuated and returned within 1 month
Household's characteristics	
HHsize	Household size
HH_old	Number of elders in a family
HH_youth	Number of young people in a family
Job_num	Number of family members who have jobs
Individual characteristics	
Male	=1, if respondent is a male
Age	Respondent's age (year)
Married	=1, if respondent is married and live together with her/his spouse
Married_other	=1, if respondent is married but does not live together with her/his spouse or her/his spouse had passed away
Indigenous	=1, if respondent reveals that her family is indigenous
Illiteracy	=1, if respondent is illiterate
Junior	=1, if respondent has junior high degree
Senior	=1, if respondent has senior high degree
College	=1, if respondent has college or graduate degree
Farmer	=1, if the occupation is farmer
Manager	=1, if the occupation is a managerial job
Notech	=1, if respondent's job is non-technical labor
Pns	=1, if respondent's job is public servant, police, or military
Nonlabor	=1, if respondent currently not in labor force
Unemployed	=1, if respondent is unemployed
Exp_ty	Number of the experiences of typhoon strikes
Exp_eva	Number of evacuating experiences

Table 2-2. *(cont.)* Definition of Variables

Variables	Definition
Impacts	
Memberloss	Number of the family member loss during Morakot strike
Payforlive	Sustaining payment before settle in a place (NTD)
Houserecover	Payment for recovering the house (NTD)
Carrecover	Payment for recovering vehicles (NTD)
Precip7	The precipitation volume on the August 7th
Precip8	The precipitation volume on the August 8th
Precip9	The precipitation volume on the August 9th
Permanent house	
House_PMT	Victims were living in "permanent houses"
Apply_PMT	Victims had applied for a permanent house
Sources of information about evacuation	
Admin	Received evacuating information from administrative agents
People	Received evacuating information from other people
Self	Received evacuating information from TV or radios

Table 2-3. Descriptive Statistics for Individual and Households' Characteristics

Period	Pre-strike	2010	2011	2012	2015
Number of obs.	977	935	825	741	542
Income	28,229.27 (23,307.17)	25,692.46 (16,094.84)	32,085.9 (24,558.8)	34,180.9 (24,424.8)	39,222.45 (29,593.74)
Inc_dif		-938.56 (16,235.41)	5,413.13 (26,333.3)	5,105.85 (26,895.5)	9,240.90 (31,082.82)
Leave		0.76 (0.42)	0.77 (0.42)	0.76 (0.43)	0.74 (0.44)
Return		0.18 (0.38)	0.17 (0.38)	0.18 (0.39)	0.18 (0.38)
HHsize	4.22 (2.37)	4.19 (2.53)	4.02 (2.35)	3.99 (2.36)	4.02 (2.46)
HH_old	0.80 (0.87)	0.77 (0.84)	0.78 (0.82)	0.82 (0.83)	0.86 (0.87)
HH_youth	0.63 (1.07)	0.76 (1.22)	0.67 (1.10)	0.61 (1.04)	0.54 (0.98)
Job_num	1.70 (1.22)	3.49 (2.53)	1.53 (1.19)	3.67 (2.30)	3.74 (2.35)
Male	0.59 (0.49)	0.58 (0.49)	0.57 (0.50)	0.56 (0.50)	0.53 (0.50)
Age	52.75 (13.80)	53.86 (13.95)	54.38 (13.71)	55.94 (13.76)	58.72 (13.07)
Married	0.61 (0.49)	0.61 (0.49)	0.60 (0.49)	0.60 (0.49)	0.60 (0.49)
Married_other	0.27 (0.44)	0.28 (0.45)	0.28 (0.45)	0.30 (0.46)	0.32 (0.47)
Indigenous	0.41 (0.49)	0.42 (0.49)	0.42 (0.49)	0.43 (0.49)	0.42 (0.49)
Illiteracy	0.12 (0.33)	0.13 (0.33)	0.11 (0.31)	0.10 (0.30)	0.10 (0.30)
Junior	0.56 (0.50)	0.57 (0.50)	0.59 (0.49)	0.57 (0.50)	0.56 (0.50)
Senior	0.28 (0.45)	0.28 (0.45)	0.28 (0.45)	0.30 (0.46)	0.29 (0.45)
College	0.03 (0.18)	0.03 (0.17)	0.02 (0.15)	0.04 (0.18)	0.05 (0.22)
Farmer	0.25 (0.43)	0.20 (0.40)	0.14 (0.35)	0.11 (0.32)	0.07 (0.26)
Manager	0.06 (0.24)	0.05 (0.21)	0.07 (0.26)	0.12 (0.33)	0.16 (0.37)
Nontech	0.18 (0.38)	0.20 (0.40)	0.09 (0.29)	0.09 (0.29)	0.10 (0.30)
Public	0.21 (0.41)	0.17 (0.38)	0.23 (0.42)	0.24 (0.43)	0.25 (0.43)
Nonlabor	0.03 (0.18)	0.03 (0.17)	0.03 (0.18)	0.03 (0.17)	0.04 (0.19)
Unemployed	0.28 (0.45)	0.35 (0.48)	0.42 (0.49)	0.40 (0.49)	0.39 (0.49)
Exp_ty	1.40 (1.82)	1.38 (1.75)	1.40 (1.81)	1.36 (1.72)	1.28 (1.66)
Exp_evac	0.30 (0.46)	0.29 (0.46)	0.30 (0.46)	0.30 (0.46)	0.31 (0.46)
Memberloss		0.05 (0.22)	0.05 (0.22)	0.05 (0.21)	0.06 (0.24)
Payforlive		14,552.09 (28,034.21)	14,632.4 (28,302.4)	13,504.2 (27,358.3)	14,484.13 (29,174.38)
Houserecover		3,074,262 (2,393,803)	3,094,918 (2,389,067)	2,918,861 (2,423,038)	2,734,985 (2,441,060)
Carrecover		3.98 (17.94)	4.19 (18.83)	5.04 (26.34)	4.98 (26.41)
House_PMT		0.28 (0.45)	0.40 (0.49)	0.54 (0.50)	0.51 (0.50)
Precip7		254.55 (132.48)	248.86 (128.54)	255.36 (135.14)	258.00 (138.83)
Precip8		788.24 (204.39)	781.14 (202.12)	781.41 (203.55)	786.22 (203.36)
Precip9		335.81 (233.81)	330.21 (230.13)	331.98 (238.81)	335.28 (231.87)
House_PMT		0.28 (0.45)	0.40 (0.49)	0.53 (0.50)	0.54 (0.50)
Apply_PMT		0.60 (0.49)	0.72 (0.45)	0.62 (0.49)	0.71 (0.45)
Admin		0.42 (0.49)	0.42 (0.49)	0.42 (0.49)	0.42 (0.49)
People		0.19 (0.39)	0.19 (0.40)	0.18 (0.38)	0.15 (0.36)
Self		0.05 (0.22)	0.05 (0.22)	0.06 (0.23)	0.06 (0.23)

Table 2-4. Descriptive Statistics for Variables Related to Typhoon Morakot

Period	2010			2011			2012			2015		
Groups	R	NR	Sig	R	NR	Sig.	R	NR	Sig.	R	NR	Sig.
Number of obs.	168	767	·	144	681		136	605		101	441	
Income	26.0	25.6	0.62	33.5	31.8	0.75	31.8	34.7	**0.09**	36.2	39.9	0.12
Inc_dif	1.34	-1.44	0.99	9.15	4.62	0.97	7.20	4.63	0.89	10.9	8.86	0.77
Leave	0.52	0.82	**0.00**	0.50	0.83	**0.00**						
HHsize	4.01	4.24	0.14	3.81	4.07	0.13	3.72	4.04	0.10	3.80	4.07	0.15
HH_old	0.77	0.77	0.50	0.84	0.76	0.85	0.87	0.81	0.76	0.89	0.86	0.65
HH_youth	0.50	0.82	**0.00**	0.34	0.74	**0.00**	0.56	0.62	0.28	0.51	0.54	0.39
Male	0.64	0.56	0.96	0.63	0.55	0.94	0.61	0.55	0.89	0.57	0.52	0.85
Age	58.1	52.9	1.00	58.8	53.5	1.00	60.1	55.0	1.00	62.6	57.8	1.00
Married	0.60	0.61	0.42	0.56	0.60	0.18	0.53	0.62	**0.03**	0.56	0.61	0.22
Married_other	0.27	0.28	0.36	0.30	0.28	0.68	0.34	0.29	0.87	0.34	0.32	0.64
Indigenous	0.27	0.45	**0.00**	0.24	0.46	**0.00**	0.27	0.46	**0.00**	0.31	0.45	**0.00**
Illiteracy	0.13	0.13	0.54	0.16	0.10	0.97	0.12	0.09	0.78	0.11	0.10	0.60
Junior	0.60	0.56	0.84	0.59	0.58	0.55	0.63	0.56	0.93	0.64	0.54	0.97
Senior	0.23	0.29	**0.07**	0.21	0.30	**0.01**	0.22	0.32	**0.01**	0.21	0.30	**0.02**
College	0.04	0.03	0.70	0.04	0.21	0.88	0.04	0.03	0.55	0.04	0.05	0.29
Farmer	0.23	0.19	0.86	0.11	0.15	0.11	0.12	0.11	0.57	0.08	0.07	0.62
Manager	0.04	0.05	0.35	0.10	0.07	0.84	0.15	0.12	0.80	0.15	0.16	0.36
Nontech	0.17	0.20	0.17	0.08	0.10	0.32	0.08	0.09	0.33	0.04	0.11	**0.00**
Pns	0.16	0.18	0.30	0.22	0.23	0.38	0.17	0.26	**0.01**	0.21	0.26	0.15
Nonlabor	0.05	0.03	0.89	0.05	0.03	0.86	0.04	0.03	0.80	0.04	0.04	0.56
Unemployed	0.35	0.35	0.45	0.43	0.42	0.60	0.44	0.39	0.87	0.49	0.36	0.99
Exp_ty	1.38	1.38	0.50	1.39	1.40	0.48	1.40	1.36	0.60	1.16	1.31	0.24
Exp_evac	0.17	0.32	**0.00**	0.17	0.33	**0.00**	0.19	0.33	**0.00**	0.19	0.34	**0.00**
Admin	0.35	0.43	**0.02**	0.33	0.43	**0.01**	0.35	0.44	**0.02**	0.36	0.43	**0.08**
People	0.11	0.21	**0.00**	0.10	0.21	**0.00**	0.12	0.19	**0.01**	0.11	0.16	**0.07**
Self	0.02	0.06	**0.00**	0.01	0.06	**0.00**	0.02	0.06	**0.00**	0.02	0.06	**0.01**
Noinfo	0.05	0.12	**0.00**	0.05	0.12	**0.00**	0.04	0.12	**0.00**	0.04	0.13	**0.00**
Memberloss	0.01	0.06	**0.00**	0.01	0.06	**0.00**	0	0.06	0.00	0.00	0.07	**0.00**
Payforlive	3.10	17.1	**0.00**	3.54	17.0	**0.00**	3.74	15.7	0.00	3.94	16.9	**0.00**
Houserecover	178	336	**0.00**	168	339	**0.00**	144	325	0.00	128	307	**0.00**
Carrecover	1.71	4.48	**0.00**	1.69	4.72	**0.00**	2.06	5.72	0.00	2.15	5.63	**0.02**
Precip7	228	260	**0.00**	226	253	**0.00**	230	261	**0.00**	225	266	**0.00**
Precip8	712	805	**0.00**	700	798	**0.00**	700	800	**0.00**	720	801	**0.00**
Precip9	229	359	**0.00**	221	353	**0.00**	228	355	**0.00**	238	358	**0.00**

Note. "R" stands for "Returned", and "NR" for "Not Returned." The third column in each year ("Sig.") stands for p-value of t-test with unequal variances. Bold font represents significance under 10% of confidence level. Unit of *Income*, *Inc_dif* and *Payforlive*: 1,000 NTD; *Houserecover*: 10,000 NTD. Unit of *Precip7*, *Precip8*, and *Precip9* are in millimeter (mm).

4.2. Moving Patterns and Housing Decisions of the Victims

The victims' moving patterns and housing decisions were diverse. One may decide to evacuate and return to her original place after a month of the strike. She may later apply for a permanent house and relocate to a permanent community. In this subsection, a brief comparison of different moving patterns is made. Figure 2-2 plots the frequencies of each subgroup categorized by whether a victim household lived in a permanent house in each period and if it returned to its original place within one month of the strike. For the non-returners, as shown in panel (a) in Figure 2-2, the frequencies of living in permanent houses are low in the first two periods, and the ratio increases in the third and fourth periods. On the contrary, nearly one-third of the returners lived in permanent houses and transient houses in the first period, and this ratio increased through the years.

This behavioral difference unveils the different decision patterns of the victims. If a victim decides to return to the original place, then it is less likely for her to relocate to a permanent house or other houses that the government provided. This may be due to two reasons. On the one hand, if the original places could provide meager conditions for living, the returned victims may be inclined to stay even when facing difficulties in the original places. The increment in the permanent house ratio was probably because of the subsidy requirements that victims should leave their original places. On the other hand, for non-returners their houses were probably damaged by the Typhoon Morakot. Therefore, they

had higher motivation for finding stable living conditions. Such differences explain why the frequencies of living in permanent houses vary between groups.

In Table 2-5, the average income and the average of the difference in incomes are calculated for each subgroup. There is a positive fluctuation in income for the returners who lived in permanent houses in the last period. For the non-returners who were not living in permanent houses, they have the highest income in the first three periods. In terms of the differences in incomes, the group of returned who lived in permanent houses has a better performance in the first and the last two periods.

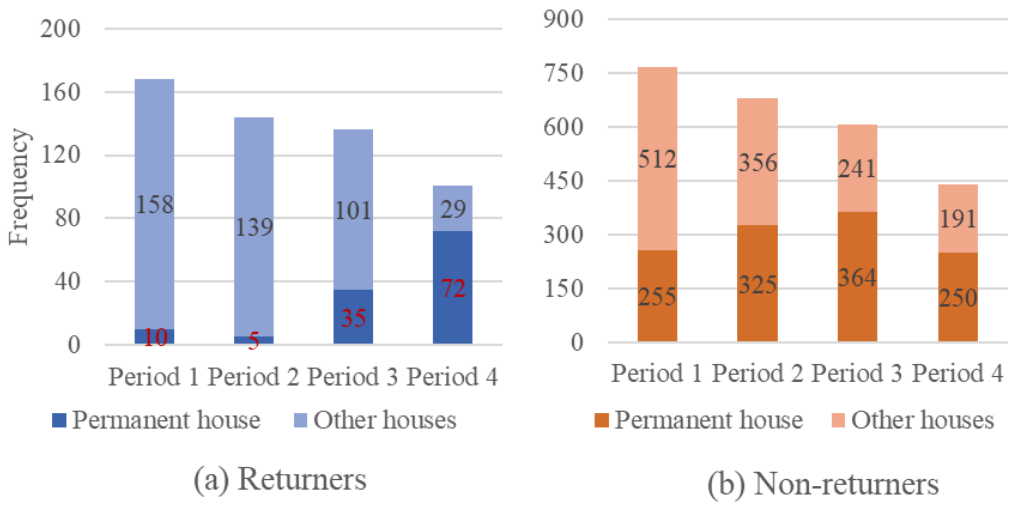


Figure 2-2. The Distribution of Living in Permanent Houses

Table 2-5. Dependent Variables of Different Returning Housing Decisions

Panel 1: Income				
Groups	2010	2011	2012	2015
	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)
Returner-House_PMT	24,500 (14,990.7)	28,000 (10,954.5)	31,285.7 (19,566.7)	49,482.8 (39,940.7)
Returner-Other houses	24,968.4 (16,243.54)	32,050.4 (26,435.7)	30,346.5 (21,980.2)	32,569.4 (23,088.8)
Non-returner-House_PMT	22,941.2 (14,734.4)	27,830.8 (20,328,8)	30,618.1 (20,211.4)	40,780 (28,032.8)
Non-returner-Other houses	25,332.0 (15,476.4)	32,612.4 (24,730.7)	37,489.6 (28,162.9)	41,858.6 (34,075.4)
Panel 2: Inc_dif				
Groups	2010	2011	2012	2015
	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)
Returner-House_PMT	578 (8,355.9)	12,353.8 (16,469.2)	5,127.1 (23,457.8)	17,190.8 (31,784)
Returner-Other houses	1,383.4 (11,585.2)	9,031.6 (25,850.8)	7,915.0 (19,592.4)	8,389.8 (18,994.1)
Non-returner-House_PMT	-1,363.1 (17,726.4)	2,345.6 (25,648.3)	2,053.3 (27,250.3)	9,959.5 (29,402.3)
Non-returner-Other houses	-1,473.3 (16,764.2)	6,703.2 (27,023.1)	8,534.2 (28,984.1)	7,414.2 (36,337.0)

5. Result

This section reports the estimation results of the effects of evacuation and displacement. The results contain two parts: short-term effects and long-term effects. On the one hand, for the results in the short-run, only the leaving effect and the two evacuating effects are reported, without taking living in a permanent house into account. This is because the permanent houses were constructed after six months to more than a year on average. Permanent housing is expected to have an effect in the longer term. On

the other hand, for the long-run results, the estimations include two self-selecting decisions, namely, evacuation and permanent housing.

5.1. Effects on Short-Term Recovery

The result of the leaving effect obtained from 2SLS regressions is presented in Table 2-6. The standard errors are heteroscedasticity-robust. From the first-stage results, the instruments, i.e., sources of evacuation information, have a positive effect on the evacuation decision. This means that whatever the sources of evacuating information was, the victims tend to evacuate from their places during the disaster after receiving information about evacuation. The leaving effect is positive in terms of the difference between the pre- and post-strike income, while it does not affect post-strike income. This result amplifies a general picture of the effects of evacuation in the recovery process.

In terms of control variables, the first column in Table 2-6 reveals that the determinants of post-strike income include household size, the number of younger generations within a household, the number of family members having a job, marriage status, educational levels, and whether a household lives in a permanent house. It is not surprising that individual and household characteristics affect income, and the estimated signs are shown as predicted. The results highlight the role of human resources and capital within a family in short-term recovery. On the family structure, bigger household size

contributes to better economic performance, but the number of younger generations within a family does not significantly affect income. In addition, household representatives show gender discrepancies, while male representatives have negative impacts. Nevertheless, the average effect overwhelms the male disadvantage if the representative is married. The magnitude of the educational impacts becomes larger as the level rises, albeit only senior and higher certificates are significant. However, the finding on housing conditions is rather novel in literature. Moving into permanent houses, besides the cultural and environmental impacts to victims that may arise during the relocation process, may cause more payment in facilities or electricity installations, resulting in a negative influence.

Regarding the second column of Table 2-6, the factors from several perspectives influence the economic recovery. From a cultural context, the identity of Indigenous has a positive effect at around NTD 2,900. This may highlight that cultural knowledge did benefit Indigenous people to better accommodate in the aftermath. The damage level negatively hinders the recovery. Specifically, a member loss during Typhoon Morakot decreases one-year income afterward by over NTD 10,000 on average. The rainfall volume on August 7th and 8th has opposite effects on recovery with limited influences.

For all evacuated and displaced households, leaving their original places benefits their incomes compared to the status before the strike. This result provides evidence that

moving out from home before, during, or after the strike enhances the post-disaster economic recovery in a one-year span after controlling for damages suffered. This means that evacuation is a necessary step in short-term accommodation of the aftermath. That is to say, evacuation is not only crucial in saving lives but also an economic sustaining factor for the victims.

Table 2-7 reports the evacuating effect for the returns in the short term. No evidence shows that temporary evacuees perform better than non-leavers since the leaving effects are not significant in both columns. In other words, the insignificant results suggest no difference in the recovery process for those who reported evacuating and staying home. In this subgroup comparison, the evacuating effect is a more direct comparison between those who stayed and evacuated than the previous estimated leaving effect. It should still be mentioned that due to the subgroups emphasized, the sample size shrinks to only 168 in the estimation.

Table 2-8 shows the short-term effect for the displaced. The estimated treatment effect on the difference in income is significant. Leaving has a positive effect on economic recovery for those victims who were displaced. Both displaced victims and afterward evacuees suffered severe damages in the strike. This finding shows that for these victims, evacuation is an appealing decision from the perspective of post-strike economic recovery, at least in the short term.

The estimated coefficients of the right-hand-side variables show high similarities across the tables, depending on the outcome variable of interest. Regarding post-disaster income, educational level and occupation are key determinants. The marriage status also shows highly consistent positive impacts on post-strike incomes. However, living in a permanent house does not have uniform effects across the tables but is only significant in the leaving effect estimation. On the contrary, regarding the other dependent variable, the number of significant coefficients is far less than the number of incomes. Most of the individual and household characteristics do not have significant effects. The variables associated with the impacts of Typhoon Morakot turn out to be pertinent in explaining the effects.

In Tables A2-1 through A2-3 in the appendix, the reduced form regressions are presented. That is the regressions of the dependent variables on the IVs and other control variables. The coefficients of the IVs are not significant for most of the regressions, except for self-collected information sources. This provides evidence for the randomness of the IVs conditional on these control variables. Furthermore, these reduced form effects can be regarded as an intention to treat estimates (ITT) (Kling et al., 2004), which reveal the direct effect of the various information sources. In this case, the victims who received information from TV or radio news had lower incomes in the aftermath but performed better in economic recovery on average.

Table 2-6 Estimation of Leaving Effect in the Short-Term

	Income		Difference in incomes	
	Estimates	S.E.	Estimates	S.E.
First stage				
Admin	0.644 ***	0.028	0.644***	0.028
People	0.636 ***	0.028	0.636***	0.028
Self	0.614 ***	0.033	0.614***	0.033
First stage F	179.64		179.64	
Leave	2,305.05	1,667.19	3,055.73*	1,774.40
HHsize	893.30*	540.19	-763.42	603.51
HH_old	534.07	660.80	-1,628.18	1,179.51
HH_youth	-779.24*	447.93	192.14	555.98
Job_num	1,037.44**	526.60	869.13	645.57
Male	-1,723.65*	1,014.93	11.64	1,343.35
Age	60.95	48.60	89.33	62.33
Married	4,438.16***	1,377.61	1,348.18	1,796.17
Marry_other	1,624.45	1,567.97	-350.99	1,947.61
Indigenous	17.79	1,191.82	2,895.23**	1,322.83
Junior	3,571.20**	1,469.15	-612.70	1,581.76
Senior	7,682.33***	1,866.66	-2,300.84	2,015.79
College	16,928.20***	3,732.83	-2,765.68	3,684.41
Farmer	-1,101.68	3,551.29	-2,835.54	2,239.78
Manager	9,590.70**	3,972.52	-9,224.50***	3,353.23
Notech	2,105.13	3,618.82	-373.18	2,308.93
Pns	3,681.36	3,662.04	-1,695.66	2,398.87
Unemployed	-4,485.16	3,496.20	-3,592.14*	2,133.44
Exp_ty	-499.59**	255.37	-126.26	319.66
Exp_evac	-1,611.16	1,017.97	-769.12	1,309.06
Memberloss	1,172.76	2,054.66	-10,437.73***	3,754.21
Payforlive	0.02	0.02	0.01	0.02
Houserecover	0.00	0.00	0.00***	0.00
Carrecover	-5.75	26.51	-10.84	45.04
House_PMT	-3,115.68***	1,088.39	-1,620.27	1,358.95
Precip7	3.70	4.33	-3.89	5.92
Precip8	-5.32	3.79	11.30***	4.05
Precip9	-4.73*	2.69	-8.26***	2.82
Constant	11,627.90*	6,039.96	-7,021.64*	5,710.11
P-value of over-identification F	0.652		0.543	
Number of obs.	935			

Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. Montiel Olea and Pflueger (2013) F statistics = 445.90

Table 2-7 Evacuating Effect for the Returned in the Short Term

	Income		Difference in incomes	
	Estimates	S.E.	Estimates	S.E.
first stage				
Admin	0.891 ***	0.044	0.891***	0.044
People	0.848 ***	0.061	0.848***	0.061
Self	1.007 ***	0.068	1.007***	0.068
First stage F	200.01		200.01	
Leave	329.12	2,779.39	820.68	2,644.63
HHsize	-224.25	1,307.50	-1,213.31	1,226.46
HH_old	1,107.82	1,636.53	-1,512.74	1,618.44
HH_youth	409.98	1,585.30	449.60	1,275.72
Job_num	780.46	1,238.75	1,213.72	1,154.00
Male	-3,685.93	2,713.87	1,368.40	2,364.62
Age	33.27	106.56	94.54	95.93
Married	7,707.88**	3,213.21	4,894.19*	2,659.19
Marry_other	5,378.45	3,464.60	1,858.66	2,711.01
Indigenous	7,299.44**	3,623.64	1,362.98	2,989.52
Junior	6,128.33*	3,230.81	-3,766.77*	2,287.82
Senior	8,679.95**	4,072.28	-3,999.42	2,906.11
College	19,414.51**	8,521.48	-1,992.79	4,350.81
Farmer	5,152.47	5,092.97	-2,335.96	4,317.13
Manager	13,635.16**	6,251.38	-1,866.91	9,072.49
Notech	11,678.96**	5,475.03	4,490.21	4,504.34
Pns	14,977.22**	5,992.82	49.48	4,403.49
Unemployed	569.51	5,276.31	1,919.68	3,981.55
Exp_ty	-636.03	531.56	-103.86	421.02
Exp_evac	-4,526.02	3,373.88	371.14	3,192.68
Payforlive	-0.04	0.06	0.10*	0.05
Houserecover	0.00	0.00	0.00*	0.00
Carrecover	222.10*	133.77	122.34	95.39
House_PMT	0.37	15.22	-2,185.30	2,850.10
Precip7	-12.10	8.66	9.66	12.14
Precip8	4.54	9.26	3.32	6.91
Precip9	9,434.30	11,439.71	-3.39	7.95
Constant	329.12	2,779.39	-8,125.87	9,030.09
P-value of over-identification F	0.057		0.742	
Number of obs.	168			

Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. Montiel Olea and Pflueger (2013) F statistics = 445.90

Table 2-8 Evacuating Effect for the Displaced in the Short-Term

	Income		Difference in incomes	
	Estimates	S.E.	Estimates	S.E.
First stage				
Admin	0.559 ***	0.034	0.559***	0.034
People	0.556 ***	0.034	0.556***	0.034
Self	0.529 ***	0.038	0.529***	0.038
First stage F	94.15		94.15	
Leave	2,157.37	2,156.50	4,194.07	2,599.87
HHsize	1,181.40**	536.30	-633.31	698.91
HH_old	401.20	721.00	-1,664.47	1,342.85
HH_youth	-824.52*	460.65	101.59	620.46
Job_num	902.93	553.23	790.13	761.25
Male	-1,610.41	1,084.40	-379.54	1,545.25
Age	78.54	54.48	90.56	75.02
Married	3,485.52**	1,555.31	777.29	2,136.76
Marry_other	281.43	1,770.32	-842.13	2,362.42
Indigenous	-574.25	1,236.97	3,117.69**	1,462.90
Junior	3,387.13**	1,601.31	-232.56	1,861.90
Senior	7,609.84***	2,045.27	-2,074.05	2,361.73
College	16,224.91***	3,924.70	-3,343.86	4,676.67
Farmer	-4,132.23	4,086.01	-3,627.30	2,708.30
Manager	7,166.98	4,592.98	-10,798.30***	3,617.84
Notech	-1,743.00	4,148.96	-1,462.27	2,670.48
Pns	-151.12	4,184.86	-2,613.83	2,761.72
Unemployed	-7,485.76*	4,002.11	-5,020.00**	2,462.15
Exp_ty	-437.34	305.31	-202.53	434.67
Exp_evac	-1,203.40	1,083.02	-662.21	1,471.15
Memberloss	1,062.05	2,115.55	-10,412.97***	3,820.93
Payforlive	0.02	0.02	0.00	0.02
Houserecover	0.00	0.00	0.00**	0.00
Carrecover	-12.05	27.08	-14.13	46.70
House_PMT	-3,362.66***	1,173.08	-1,738.52	1,513.33
Precip7	3.84	4.44	-7.25	6.92
Precip8	-4.28	4.30	15.03***	4.97
Precip9	-5.25*	2.95	-8.84***	3.12
Constant	14,162.49**	7,043.63	-8,709.16	7,338.37
P-value of over-identification F	0.509		0.362	
Number of obs.	767			

Note: Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. Montiel Olea and Pflueger (2013) F statistics = 248.87.

5.2. The Effects in a Longer Term

Incorporating all four post-strike periods, the effects are reexamined in order to find out if the effects relevant to evacuation spill to a longer period, affecting the post-disaster recovery process across a long term. The estimation methods in this section are mainly hinged on REIV estimators delineated earlier. To verify that the REIV estimators are plausible or, specifically, have an advantage over the FEIV estimators for retaining estimations for time-invariant control variables, the method for unbalanced panel proposed by Joshi and Wooldridge (2019) is used. Intuitively, the method approaches the FEIV estimators by including the averages of the instruments across periods in the 2SLS. The insignificance of these time averages represents the random-effect assumption holds. In other words, the time-invariant error term does not correlate with the exogenous variables. The method has an advantage over the traditional Hausman test under heteroskedastic scenarios. The corresponding results are shown in Table A2-4, in which joint significant coefficients of the additional time-averaged instruments are found in the displacement effect for the whole sample and for the displaced victims under the 10% confidence level. Therefore, the REIV estimates reported below are based on a stricter confidence level. In addition, the overidentification tests are also applied to ensure that the inclusion of multiple IVs does not impair estimation precision. The reduced form and the full estimations are presented in Table A2-5 and A2-6 in the appendix.

The model specifications are based on the same structure as in the cross-sectional analysis. The main differences are threefold. First, the dependent variable considered is the economic recovery, namely, the difference between pre- and post-disaster incomes. The reason is delineated at the beginning of the section. Second, the instrumental variables included are the information sources of evacuation, the dummy variable for permanent house application, and their interaction terms. However, the interaction terms are excluded for the returner group. Otherwise, the first-stage F statistics are lower than the rule-of-thumb of 10. This is probably because of relatively fewer observations in the group. Lastly, the survey periods and the county where a victim lived at each survey period are controlled. The economic performance is correlated with time, as the macroeconomic environment is expected to grow over the years. The spatial factor also plays a role in explaining economic recovery. For example, job market conditions and industrial development are different across townships.

The effects of the two coping strategies are summarized in Table 2-9. The complete results of the estimations are reported in the appendix. In Table 2-9, the first-stage F statistics for the three estimations all surpass the rule-of-thumb of 10, suggesting enough relevance between the IVs and the self-selected variables. Across the four periods, the victims performed worse if they lived in permanent houses, with an average of about NTD 7,500 of decrement. There is no noticeable effect of evacuation. In terms of different

moving patterns, on the one hand, for the victims who returned to their original places within one month after the strike, the typhoon impacted those who evacuated, with more than NTD 5,000 of loss. However, living in permanent houses has no statistically significant effect. On the other hand, for those who did not return, the impact of evacuation is insignificant. Instead, living in permanent houses has a negative effect of NTD 7,600. The impact of living in permanent houses is evident because of this non-returner subgroup. That is, for the victims who suffered severe damages and could not return to their places, simply providing permanent houses is, surprisingly, hurting them.

Interesting insights can be found by comparing the results with previous short-term results. Especially in the short term, the decision to live in permanent houses is regarded as exogenously determined. The negative effects of the control (*house_PMT*) suggest these victims suffered more severe consequences. The long-term results indicate that the negative impacts pass over time. Living in permanent houses impinges on victims' economic recovery across the post-disaster period. For the returned victims, evacuation is a must-do with adverse impacts. This result is different from the short-term result. However, the underlying explanation is unclear.

The estimates of other control variables in Table A2-2 in the appendix also reveal the spatial differences in recovery. In the total sample, the residency in Pingtung County and Tainan City, the performance in economic recovery is relatively slow compared to

the base group of Kaohsiung and Taoyuan Counties. On the contrary, residency in Taichung City is way better in income recovery, which amounts to nearly NTD 7,500. It may seem like the spatial advantage can offset the negative impacts of the permanent houses. Nevertheless, there was no construction of a permanent community in Taichung. As the reference group, Kaohsiung has six permanent communities, accounting for the fourth in rank among all counties and cities having permanent communities (Tsai et al., 2022). Therefore, the routes of retaining economic prosperity differ within the counties and cities having permanent houses, including Pingtung, Chiayi, Taitung, Nantou, Yunlin, and Tainan.

From the long-term perspective, although the permanent housing strategy rapidly provided the victims' houses better than temporary shelters, the current finding highlights the disadvantages. The result concurs with the findings of Yang et al. (2018), who show a slower income and employment rate recovery for residents in permanent houses. Permanent housing has been at the center of debates for decades, even before the strike of Typhoon Morakot, and it has been found to dampen the cultural and social capital, especially for the indigenous people (Tsai et al., 2022; Yang et al., 2018; Shieh et al., 2013). Notwithstanding, permanent housing enhances the victims' ability to gather and collect resources from related post-disaster policies.

Table 2-9. The Evacuation and the Displacement Effects in the Long-Term

	Full Sample		Returner		Non-returner	
	Estimates	S.E.	Estimates	S.E.	Estimates	S.E.
First stage F	60.01		12.88		32.34	
Leave	1,054.3	2,296.8	-6,575.3**	2,969.7	3,616.9	3,102.0
House_PMT	-7,939.0**	3,397.7	628.6	7,973.6	-7,722.6*	4,006.7
P-value of over-identification	0.266		0.668		0.250	
Number of obs.	3,043		549		2,494	

Note: Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1.

5.3. Verify Causal Interpretations and External Validity of the Effects

This section uses the method developed based on one of the propositions in Mogstad et al. (2021). In the short-term analysis, the instruments for leaving action include three information sources. The partial monotonicity assumption is thus a necessity to verify the causality of the leaving action and post-disaster incomes. The partial monotonicity assumption is weaker than the monotonicity assumption required in the original LATE theorem, which states that the monotonicity is met for each instrumental variable separately, conditional on other instruments. This is a reasonable assumption in the current case because some victims are more obedient to the administrative information, while some believe more in information collected by themselves.

Following Mogstad et al. (2021), I examine if the estimates change if only one information source instruments for the action at a time while controlling for other information sources as exogenous variables. The results not shown here indicate that the

leaving effects are insignificant as the IV changes in turn in the first stage and the other resources included in the second-stage regressions. As proved in Mogstad et al. (2021), under partial monotonicity assumption, the 2SLS estimands is a positively weighted average of LATEs estimated by single instruments. Further, the weights of each instrument can be tested if all are positive or not. The conditional correlation between the treatment of interest and an instrument can be estimated by a regression of leaving action on an instrument, conditioning on explanatory variables. The test results are shown in Table 2-10. In Table 2-10, the conditional correlations are all positive. Following the fifth proposition in Mogstad et al. (2021), the results imply that, by pairwise comparison, the weights for self-seeking or self-received information and for administrative and learned from other people, are both positive, while these weights, along with the coefficients can theoretically form the 2SLS estimates. The finding supports that the combined 2SLS estimates can be interpreted causally in this application.

Table 2-10. Pairwise Comparison between Groups

Information sources	Evacuating effect for the returned	
	Estimates	S.E.s
Adm	0.665***	0.071
People	0.538***	0.094
Self	0.534**	0.219
Observation	168	

Note. This table shows the regression of evacuation on each row. The standard errors are robust standard errors. Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1.

6. Conclusion

Disaster recovery is a key element in building resilient rural areas. This study delves into the critical role of coping strategies during disasters and in aftermaths. With particular focus on the widespread adoption of temporary evacuation and displacement rooted in permanent housing of resettlement strategy, the aim is to find the corresponding economic effects of these behaviors. It scrutinizes relevant evacuation effects in both the short and long term after a typhoon strike and investigates both the effects of evacuation and displacement in the long term. This research has found several interesting results that may not be straightforward, and these bring discussion to practical strategy designs.

The self-selecting nature of evacuation and housing decisions are addressed by employing the REIV method, and therefore, the results can be interpreted causally. The results indicate that evacuation positively affects income recovery within one year after the strike but has no direct benefits to post-disaster income. This finding is further amplified when comparing displaced victims with those who evacuated afterward. Nevertheless, the benefits of evacuation diminish in the long term. Especially when comparing the returner group, which consists of the victims who returned to their original residence within a month after the strike, the evacuation has a negative effect. The displacement effect in the long term is negative using the full sample, while the impact is largely due to the negative impact suffered by the non-returner group. These results

indicate that the current coping strategies do not economically incentivize people to adopt them. For evacuation, people may hesitate to leave their places or disobey due to economic concerns, which undermines their lives. Regarding displacement, the concern of sociologists and social workers became a reality that simply providing living places does not speed up the recovery process, but drags down the pace it.

Although a negative effect of evacuation is found in the long term, it should be highlighted that the current result does not recommend people stay at their houses when danger is approaching. The negative displacement effect does not simply state that the government of NGOs should not provide a livable infrastructure for victims. Instead, the results reinforce the need for sculpturing better ways of practical implementations that could potentially lead to diverse economic results. Indeed, both evacuation and permanent housing strategies are critical in a policy aspect, one during the disaster and the other afterward. However, the details of the strategy merit deeper consideration. In terms of helping victims overcome frustration after natural events, acknowledging that the same action or policy they took leads to distinct consequences underscores the necessity of designing different coping strategies.

The study could provide valuable references for future policies and strategy designs. It crystalizes how the authorizations could emphasize preparation for evacuation and offer prolonged economic aid and incentives for the victims. The perspective of recovery

further connects the results to the critical issue in practice. For instance, the Taiwan government has now promoted the preparation of backpacks or bags that facilitate evacuation with the most important life-sustaining materials. Proactive preparation may alleviate the financial concern if the authority disseminates information about collecting valuable things inside the evacuation bag. This may seem a naïve suggestion, but there were cases in which the victims could not apply for permanent houses for not having legal documentation of owning a house. Other ways are also possible, such as offering financial insurance for people who live in areas with a high potential for disasters to reduce the possible economic impacts.

Although technological progress renders a better forecast system, sturdier houses, and more rapid transmission of information, the coping strategies addressed in this research are still vital in people's lives. While the underlying mechanism is not found, prolonged care for evacuees is certainly in need. Authorities and relevant stakeholders should keep accompanying the evacuees and other groups. Also, permanent housing was regarded as a resettlement policy that assisted victims in finding houses to live in, and this goal was successfully achieved. Particularly in the aftermath of Typhoon Morakot, permanent housing inevitably causes displacement. The policy was implemented in haste without considering other aspects, causing more harm than good economically and resulting in a resilience loss from the economic view. A more detailed and careful

communication process should be carried out in future events to avoid the loss of cultural and social capital. One way to address this is to communicate in a participatory way that encourages victims to provide their thoughts and needs.

This study is unique in its composition of the data. All observations in the data are victims of the strike, but due to the difference in evacuating and applying for permanent houses, the treatment and control groups can be categorized. Special attention is devoted to the economic recovery of households. Unlike most research in disaster management and related effects, the current study provides comparisons among victims rather than comparing victims and populations intact from disasters. In particular, the victims are categorized based on two actions related to evacuation- temporary evacuation and return. This provides unprecedented findings that victims have diverse routes of recovery in the aftermath, which are affected by the coping strategies they made during and after the strike.

The case of Typhoon Morakot offers insights applicable to similar scenarios, particularly in rural and mountainous regions of East and Southeast Asia, where rural residents are highly vulnerable to disasters. The study suggests that the transient nonnegative effects may be attributed to received subsidies, while persistent negative effects over a longer timeframe imply incomplete economic recovery compared to pre-strike levels, warranting improvements in post-disaster subsidy design.

There are several limitations in the data used in this study. First, the survey does not follow the same respondents across periods. Same households may have different respondents in each survey year. Second, the data merely provide limited information about the key outcome variable, the monthly income of a household, which is provided in categorical responses. Therefore, to calculate the difference between the pre- and post-strike household income, the median of each category of income level is used as a proxy, while selected characteristics are controlled for in the main results reported, as the information of those variables was collected both in the pre- and post-strike period. Third, as noted before, the period 0 data is collected by recalling the scenarios before Typhoon Morakot. However, there is no specific assigned date for many questions, which may cause recalling errors. Moreover, without enough information to separate work incomes, the incomes in the aftermath include other incomes.

Apart from those limitations in the data, methodological issues may arise due to the REIV being less persuasive but the only way to obtain the desired coefficients. Future studies should work on more rigorous and systematic surveys so that more valuable insights can be found. There are different kinds of coping strategies with various types of events. However, researchers of this strand should accelerate their paces to enhance strategical designs under evidence-based construction and toward a resilient society.

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Appendix

Table A2-1. Reduced Form in the Short Term (1ST year): Leaving Effect

Variables	Income		Difference in income	
	Estimate	S.E.	Estimate	S.E.
Adm	1,697.91	1,212.63	1,735.27	1,351.34
People	777.29	1,348.45	1,761.14	1,630.48
Self	2,698.64	2,384.06	3,896.02 *	2,041.76
HHsize	952.30 *	553.11	-717.26	607.27
HH_old	543.96	667.58	-1,574.82	1,219.02
HH_youth	-781.09 *	453.16	197.71	552.23
Male	970.00 *	538.15	812.60	667.36
Age	-1,842.82 *	1,030.28	-99.20	1,374.13
Married	58.26	49.19	87.30	62.58
Married_other	4,444.92 ***	1,399.42	1,272.15	1,849.66
Aboriginal	1,633.24	1,589.05	-436.75	1,993.99
Illiteracy	-36.52	1,231.31	3,055.20 **	1,323.23
Junior	3,513.98 **	1,494.73	-480.42	1,663.07
Senior	7,685.12 ***	1,894.84	-2,125.42	2,094.38
College	16,670.61 ***	3,748.25	-3,067.63	3,767.59
Farmer	-999.88	3,613.67	-2,570.22	2,300.92
Manager	9,529.79 **	4,051.13	-9,226.99 ***	3,438.41
Nontech	2,133.03	3,683.49	-224.90	2,367.52
Pns	3,672.36	3,726.84	-1,578.86	2,460.57
Unemployed	-4,428.83	3,565.15	-3,410.61	2,198.18
Exp_ty	-530.39 **	258.16	-156.48	325.89
Exp_evac	-1,494.17	1,005.87	-547.79	1,328.35
Memberloss	1,086.11	2,055.79	-10,734.66 ***	3,838.91
Payforlive	0.02	0.02	0.01	0.02
Houserecover	0.00	0.00	0.00 **	0.00
Carrecover	-1.65	27.24	-6.53	45.68
House_PMT	-2,769.05 ***	1,048.28	-1,289.79	1,336.41
Precip7	4.18	4.31	-3.27	6.07
Precip8	-6.53 *	3.59	9.94 **	3.90
Precip9	-3.71	2.70	-7.29 ***	2.67
Constant	12,928.58 **	5,966.35	-5,718.09	5,569.06

Note. Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. The S.E.s are robust S.E.

Table A2-2. Reduced Form in the Short Term: Evacuating Effect for the Returned

Variables	Income		Difference in income	
	Estimate	S.E.	Estimate	S.E.
Adm	3,055.28	2,573.74	1,749.30	3,368.94
People	-1,070.88	4,765.95	-571.86	3,042.19
Self	-17,307.24**	7,729.63	-1,325.96	5,937.06
HHsize	178.01	1,439.23	-1,238.42	1,508.68
HH_old	745.19	1,773.21	-1,591.26	1,841.52
HH_youth	705.64	1,739.54	528.38	1,423.01
Male	498.76	1,420.74	1,249.60	1,384.76
Age	-4,404.92	3,035.68	1,037.62	2,767.46
Married	47.92	116.12	98.73	108.05
Married_other	7,333.82**	3,423.58	5,002.54*	2,954.81
Aboriginal	5,064.68	3,635.44	1,844.09	3,020.80
Illiteracy	5,244.49	3,851.98	362.79	3,767.61
Junior	5,104.11	3,493.50	-3,899.09	2,501.48
Senior	7,377.20	4,491.72	-4,242.31	3,207.09
College	18,745.85**	9,006.60	-2,105.76	4,797.53
Farmer	1,076.11	4,871.55	-3,046.98	4,974.25
Manager	9,077.97	6,483.40	-3,061.51	9,781.21
Nontech	7,942.85	5,230.58	3,828.81	5,195.38
Pns	10,795.14*	6,260.91	-815.77	5,102.15
Unemployed	-3,557.70	5,131.19	1,167.53	4,614.25
Exp_ty	-682.12	578.85	-113.74	480.69
Exp_evac	-4,538.16	3,856.48	789.62	3,322.01
Memberloss	12,975.10*	6,739.31	2,162.51	4,710.52
Payforlive	0.03	0.07	0.11 *	0.06
Houserecover	0.00	0.00	0.00	0.00
Carrecover	161.30	145.96	115.73	111.47
House_PMT	3,943.92	4,395.96	-1,702.72	3,069.12
Precip7	-2.35	16.95	9.05	13.50
Precip8	-12.52	9.27	3.21	7.74
Precip9	5.03	10.21	-3.08	8.73
Constant	14,401.44	12,275.13	-7,122.43	9,820.25

Note. Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. The S.E.s are robust S.E.

Table A2-3. Reduced Form in the Short Term: Evacuating Effect for the Displaced

Variables	Income		Difference in income	
	Estimate	S.E.	Estimate	S.E.
Adm	971.05	1,369.34	1,969.62	1,635.16
People	860.99	1,457.57	2,102.94	2,013.47
Self	3,552.03	2,424.04	4,994.12**	2,267.76
HHsize	1,267.02**	546.56	-529.54	706.33
HH_old	459.69	732.63	-1,582.37	1,396.19
HH_youth	-826.15*	463.15	116.68	606.46
Male	800.77	565.55	662.31	796.41
Age	-1,729.49	1,101.02	-553.82	1,573.22
Married	75.08	55.38	86.64	75.22
Married_other	3,398.42**	1,577.28	613.50	2,214.13
Aboriginal	272.92	1,801.32	-967.11	2,430.10
Illiteracy	-428.17	1,288.31	3,306.10**	1,461.60
Junior	3,417.23**	1,634.93	-81.04	1,978.43
Senior	7,665.97***	2,075.48	-1,882.10	2,473.45
College	15,730.08***	3,911.97	-3,815.33	4,846.10
Farmer	-4,025.84	4,177.22	-3,335.26	2,787.17
Manager	6,930.47	4,701.69	-11,033.09***	3,737.67
Nontech	-1,732.48	4,236.90	-1,352.63	2,750.12
Pns	-164.31	4,272.01	-2,546.71	2,840.12
Unemployed	-7,481.04*	4,091.75	-4,885.18*	2,580.44
Exp_ty	-459.80	308.56	-243.36	443.61
Exp_evac	-1,116.55	1,085.41	-454.78	1,525.63
Memberloss	744.40	2,090.62	-11,030.12***	3,906.06
Payforlive	0.02	0.02	0.00	0.02
Houserecover	0.00	0.00	0.00**	0.00
Carrecover	-8.52	27.97	-8.39	47.55
House_PMT	-3,112.30***	1,121.70	-1,276.04	1,480.74
Precip7	4.04	4.44	-6.70	7.14
Precip8	-5.26	3.99	12.94***	4.57
Precip9	-4.72	2.98	-7.61***	2.97
Constant	15,677.83**	6,783.26	-5,981.66	6,749.80

Note. Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. The S.E.s are robust S.E.

Table A2-4. Check the Validity of the REIV Estimators

	Overall		Returner		Non-returner	
	Estimates	S.E.	Estimates	S.E.	Estimates	S.E.
Mean Admin	22,544.2**	9,240.0	-14,669.6	20,850.3	24,359.1	9,808.4
Mean People	22,460.0**	9,096.5	-12,135.4	20,601.9	24,429.4	9,767.4
Mean Self	15,270.6	9,534.7	-10,263.6	21,736.4	15,796.8	10,134.0
Mean Apply_PMT	-5,015.1	7,943.8	-14,815.2**	7,510.7	-3,573.8	10,807.6
Joint significance (p-value)	* (0.062)		X (0.325)		* (0.056)	

Note. Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. The S.E.s are robust S.E. The joint Chi-square statistics is 8.97 for all sample; 4.65 for the returner; 9.21 for the displaced.

Table A2-5. Reduced Form of the Long-Term

	Full sample		Returner		Non-returner	
	Estimates	S.E.	Estimates	S.E.	Estimates	S.E.
Admin	426.89	1,620.32	-5,671.48**	2,789.00	1,981.72	1,954.93
People	418.79	1,838.60	-6,546.24*	3,963.32	1,823.57	2,179.71
Self	-4,665.52	3,145.64	-555.67	5,513.72	-3,680.66	3,478.88
Apply_PMT	-2,283.78 **	1,016.40	-667.65	2,497.04	-2,059.08*	1,149.48
HHsize	1,731.01 ***	390.06	860.53	965.33	1,925.72***	420.14
HH_old	-2,274.78 ***	861.95	-1,784.81	1,468.27	-2,148.05**	974.22
HH_youth	-374.78	514.75	-201.97	1,187.05	-338.04	579.32
Job_num	1,796.27 ***	425.32	2,993.00***	858.27	1,450.54***	484.27
Male	-673.03	1,446.16	3,807.93	2,474.59	-1,863.70	1,662.27
Age	111.25 *	60.46	39.48	86.54	115.45	73.32
Married	-1,620.56	1,918.03	255.68	2,665.00	-1,718.25	2,289.34
Marry_other	-1,517.68	2,002.91	3,213.66	2,752.49	-2,518.35	2,418.81
Indigenous	743.82 **	1,870.03	249.33	4,362.55	719.78	2,091.08
Junior	-2,977.12	1,389.11	-1,781.35	2,610.93	-3,149.99**	1,604.04
Senior	-5,159.64	1,849.09	-3,084.24	3,445.64	-5,327.94**	2,115.72
College	-1,722.86	4,346.42	8,553.30	7,382.51	-3,280.04	5,122.72
Farmer	-3,224.90	2,590.42	-9,022.05	4,477.74	-1,985.18	3,113.79
Manager	2,133.73 ***	2,911.60	-7,856.60	5,196.89	4,295.58	3,482.20
Notech	2,429.20	2,634.76	-2,206.83	4,219.44	3,300.65	3,174.84
Pns	3,493.95	2,625.90	-6,952.64	4,393.62	5,369.02*	3,154.88
Unemployed	-3,315.58 *	2,473.26	-5,740.03	4,034.80	-2,750.28	3,014.99
Exp_ty	-206.00	430.24	-905.78**	424.46	-170.76	554.24
Exp_evac	262.82	1,472.49	4,338.98	3,756.57	240.72	1,677.63
Memberloss	-11,810.05 ***	3,782.13			-11,735.96***	3,905.26
Payforlive	0.02	0.02	0.13*	0.07	0.02	0.03
Houserecover	0.00 **	0.00	0.00**	0.00	0.00	0.00
Carrecover	-3.12	37.12	103.02	137.19	-3.04	37.68
Precip7	-2.17	6.91	-1.60	10.64	-2.38	8.41
Precip8	2.58 **	5.03	1.32	6.62	4.44	6.33
Precip9	-0.86 **	3.36	-7.34	7.75	0.22	3.70
Period 2	10,300.69	1,107.75	14,132.03***	2,590.85	9,345.02***	1,231.87
Period 3	5,913.92	822.56	6,180.11***	1,763.76	5,924.32***	928.98
Period 4	9,882.60	1,139.33	9,826.22***	2,461.40	10,083.49***	1,291.47
Constant	-5,755.71	5,579.91	-2,800.48	9,576.78	-15,652.93**	7,472.87
Joint F test	0.93		0.22		0.15	

Note. Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. The S.E.s are robust S.E. The null hypotheses of joint F test: the coefficients of the four instruments are all zero.

Table A2-6 Full Estimations Results of the Long-Term Effects

	Full sample		Returner		Non-returner	
	Estimates	S.E.	Estimates	S.E.	Estimates	S.E.
Leave	1,005.73	2,296.78	-6,575.34**	2,969.74	3,616.92	3,101.97
House_PMT	-8,115.63**	3,397.67	628.58	7,973.64	-7,722.61*	4,006.72
HHsize	1,800.54***	392.64	986.09	1,003.99	2,073.79***	422.66
HH_old	-2,221.87***	865.79	-1,783.18	1,420.32	-2,119.85**	975.26
HH_youth	-511.82	515.68	-277.01	1,176.19	-564.20	582.84
Job_num	1,814.65***	423.56	2,928.57***	876.60	1,435.58***	476.18
Male	-551.87	1,452.97	3,864.40	2,420.06	-1,683.27	1,669.54
Age	105.55*	60.81	60.04	83.78	118.91	73.97
Married	-1,211.78	1,936.37	-150.92	2,687.68	-1,505.96	2,317.50
Marry_other	-1,287.13	2,023.11	2,859.80	2,826.55	-2,475.52	2,443.70
Indigenous	1,988.75	1,985.94	296.83	4,160.33	1,991.53	2,227.89
Junior	-2,560.30**	1,390.45	-1,936.41	2,559.64	-3,033.49*	1,593.29
Senior	-4,871.89***	1,858.87	-3,087.09	3,405.10	-5,313.87**	2,119.38
College	-2,472.01	4,376.68	7,952.12	7,305.10	-4,481.00	5,126.25
Farmer	-3,338.44	2,664.51	-8,972.55**	4,393.76	-2,310.89	3,189.88
Manager	1,621.54	2,997.55	-7,742.52	5,227.94	3,694.37	3,571.75
Notech	2,243.76	2,710.78	-2,079.51	4,083.79	3,098.71	3,249.99
Pns	3,370.61	2,698.01	-6,508.25	4,301.70	5,265.14	3,223.98
Unemployed	-2,965.91	2,550.69	-5,735.32	3,929.02	-2,437.61	3,094.19
Exp_ty	-229.58***	444.46	-899.89**	426.06	-168.88	570.02
Exp_evac	419.55	1,490.89	4,575.97	3,725.99	247.68	1,668.15
Memberloss	-11,181.1	3,923.02			-10,677.6***	4,065.75
Payforlive	0.02	0.02	0.14**	0.06	0.02	0.03
Houserecover	0.00	0.00	0.00**	0.00	0.00	0.00
Carrecover	-1.43	39.48	81.80	128.13	-4.23	39.81
Precip7	-4.08	7.14	0.63	9.32	-5.04	8.66
Precip8	5.69	5.61	-0.86	6.77	9.42	7.19
Precip9	-5.60	3.97	-5.72	7.69	-5.71	4.61

Table A2-6 (cont.) Full Estimations Results of the Long-Term Effects

	Full sample		Returner		Non-returner	
	Estimates	S.E.	Estimates	S.E.	Estimates	S.E.
Taichung	7,380.55***	8,461.87			7,576.71	8,426.56
Tainan	-2,475.17***	3,049.86	-4,097.93	4,163.95	-453.94	4,385.04
Pingtung	-3,950.72***	2,358.36	-2,204.60	3,580.71	-3,428.63	2,888.46
NewTaipei	664.30	9,108.68			1,345.08	9,137.40
Jiayi	-1,462.31	11,606.5			-6,297.50	12,248.2
Period 2	11,107.3***	1,224.35	13,889.9***	2,608.70	10,152.1***	1,388.29
Period 3	8,093.16	1,217.61	5,979.97**	2,514.86	8,064.71***	1,448.87
Period 4	11,931.0	1,515.43	9,548.69***	3,287.85	11,888.7***	1,748.67
Constant	-13,301.3*	6,518.88	-2,728.3	9,662.20	-19,282.3**	8,584.67
First stage F	60.10		12.88		42.95	
P-value of over-identification	0.266		0.668		0.250	
Number of obs.	3,043		549		2,494	

Note. Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. The S.E.s are robust S.E. For the returner group, memberloss and several county variables are omitted due to lack of observation. The reference county is Kaohsiung.