Mobility Responses to Natural Shocks:

Evacuation, Displacement, and Household Income Recovery after Typhoon Morakot

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Abstract

The increasing intensity of natural disasters underscores the importance of current mitigating strategies. However, how do existing strategies affect recovery trajectories remain less discovered. This study investigates the economic impacts of evacuation and displacement in Typhoon Morakot which caused more than 700 deaths in Taiwan in 2009. Applying the instrumental variable method, this study identifies the effects of evacuation in the short run and displacement in the long run. 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. In the long run, the displacement effect is negative, accounting for nearly one-third of victims; average income. Some splitting sample analyses are also performed. Based on the results this study address suggestions about recovery strategies.

1. Introduction

Climate change has increased the frequencies and intensity of natural disasters, while economic exposure has risen as society developed (Johar et al., 2022; IPCC, 2021; Botzen et al., 2019). Disasters also contribute to relocation and migration (Deryugina et al., 2018). Amongst mitigating strategies, mobility responses such as evacuation and displacment are among the most observed actions related to safety. These include evacuation before or during disasters and migration or displacement afterward. However, people may choose to ride out disasters and ignore evacuation for economic concerns, regardless of whether it is in developed or developing countries (Alam, 2024; Hollis, 2021). These responses not only save lives but influence recovery processes. Moreover, these movements may bring uncertainty to victims' lives and work, causing variations in future recovery. Understanding the true effects of mobility responses therefore has crucial practical implications. Recognizing the pertinence of the mobility strategies, this study aims to examine the economic impacts of evacuation and displacement during the recovery process. A unique four-wave panel data in Taiwan that follows the victims of Typhoon Morakot in 2009 for more than five years is utilized, allowing a long-term assessment of income recovery.

Typhoon Morakot hit Taiwan between August 6th and 10th in 2009. Despite its intensity was between strong Category 1 and 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 dollars economic losses. The rainfall brought by Typhoon Morakot was unprecedented, far surpassing the previous record. Consequently, it brought several serious floods and landslides especially the southwestern region of Taiwan, particularly the mountainous rural areas, experienced the most severe impacts of floods and landslides. On August 9th, Shaolin, an Indigenous village in rural Kaohsiung, was completely buried by a landslide, which engulfed the area and lead to 491 victims. Smaller tragedies were also in nearby villages Nangisaru and Xinkai. The live-losing tragedies highlight the challenges of evacuation.

There were some villages that were evacuated successfully. An official report documented 17 successfully evacuated villages with varying damages levels to public and private assets. As a result, only one casualty was reported in these villages, and at least 858 people were saved (Chen, 2009). This fact underscores the importance of evacuation. Displacement, however, has continued to generate criticism and debate. The government implemented a permanent housing policy aimed at relocating communities and villages located in peripheral areas with higher risks. The victims were mostly Indigenous or lived in mixed-ethnicity villages. The policy and related regulations were implemented hastily, and victims had to decide within a short period whether to move into permanent houses. Permanent houses were mostly built by NGOs in collaboration with government. In total,

35 permanent housing communities were constructed, relocating 3,630 households (Tsai et al., 2022).

This study applies the instrumental variable approach to estimate evacuation and displacement effects. It investigates evacuation effect in the short-run recovery, that is, one year after Typhoon Morakot. It also assesses displacement effect in the long run, using all four waves of the panel, covering six years after the disaster. For a quick glimpse of the results, we find null evacuation effect in the short run. On the contrary, displacement has a negative impact on households' income, equivalent to about one-third of the average victim's income. The findings also indicate that the effect is concentrated among non-Indigenous victims, who suffer more income losses when displaced to permanent houses.

In the literature, evacuation has garnered more attention for its crucial role in risk reduction, with a major focus on 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 its consequences have received comparatively little discussion. Vigdor (2007) examines the transient effect on labor market participation of evacuation due to Hurricane Katrina. Leveraging on different mobility behaviors, Vigdor (2007) finds the divergent effects between evacuees, including returnees and long-term evacuees, and non-evacuees. The long-term evacuees face obstacles in getting their lives back on normal track. Sacerdote (2012) focuses on the effect on human capital,

investigating the academic performance of hurricane evacuees. The study finds declines in scores after one year following the hurricanes, but the evacuees' performances improved over a longer period.

Previous research on displacement generally finds its negative impacts. The social costs of displacement are substantial. It causes shocks in production and labor market and also lead to mental health problems (Salgado-Gálvez, 2018; Hori and Schafer, 2010). In case of large-scale displacement caused by civil conflict, a negative impact on consumption is found and the influence lasts two years (Fiala, 2015). The findings on natural disasters are similar. Short-term displacement causes the loss of well-being (Black et al., 2013). Moving to more distant places has also been found to lead to greater income losses than peripheral displacement (Hori and Schafer, 2010). Displacement affects not only those who leave, but also residents in destinations. The living costs rise in host places, while influences in other aspects are not consistent (Verme and Schuettler, 2021).

The influence of natural disasters may persist for a longer period. Hsiang (2010) finds that cyclones in Caribbean region have a lagged effect on contemporary sectoral GDP. 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 and her colleagues (Deryugina et al., 2018; Deryugina and Molitor, 2020) 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.

This study faces several identification challenges because of voluntary movement, geographical endogeneity, data scarcity, and mobility classifications. However, the data of Typhoon Morakot provides a unique case for tackling those issues. First, although modern societies often implement mandatory evacuation, and in some cases, forced displacement, it is not the case of Typhoon Morakot. At the time of the disaster, Taiwan had not yet enacted mandatory evacuation legislation, and the top-down warning system from central governments to local actors had not been fully established.

Regarding displacement, movements of victims were largely driven by housing destruction and the subsequent public permanent housing policy. Overlooking cultural and social influences, victims were forced to make difficult decisions within a short time by the policy. Households could either move into permanent housing or withdraw and find new places to live with higher acquiring costs. These conditions made the movements self-selected. In addition, due to geographical centrality and relative concentrated damaged areas, the relocation after Typhoon Morakot is unlikely to suffer from large geographical gaps as in larger countries such as the U.S. or China. Rather, the permanent

housing communities were often built near the original villages. Moreover, the victims and nonvictims were mostly distributed across rural Southern Taiwan, minimizing the pre-disaster demographical differences.

Data scarcity poses empirical difficulty. On the one hand, studies are often constrained to use cross-sectional data and therefore cannot distinguish the pre-disaster characteristics (Verme and Schuettler, 2021). On the other hand, studies may shift their focus to comparisons victims and non-victims incorporating external resources rather than focusing on victims solely (e.g. Deryugina and Molitor, 2020; Deryugina et al., 2018). However, such identification strategy aims at investigating the disaster effect rather than victims' behavioral consequences. The unique panel survey tracking the victims of Typhoon Morakot in Taiwan for six years and harness an allowing us exogenous variation and investigate the .

The current study lays multiple contributions. First, it is the first to focus on the effect of evacuation and displacement in rural areas over a midterm to long-term recovery time span. It is the first to cover these important disaster-related movements. 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 areas because of their vulnerability and reliance on natural resources. Second, recovery processes in rural areas are often different from urban counterparts. One

factor contributing to the disparity is the relative deficit of transportation infrastructure and the limited working opportunities in rural areas, which are also prominent reasons for rural residents to ride on disaster strikes. 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.

Third, the displacement effect addressed is a large-scale permanent housing policy. It has been at the center of debates in the recovery 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 due to administrative concentration. The finding therefore provides evidence for similar large-scale displacement strategy.

Also, this study shifts the focus in disaster study from disaster impacts to behavioral effect on recovery trajectories. Existing literature points out that socioeconomic status, financial resources, and asset levels, contribute to the adversities in the economic recovery process (Comerio, 2014; Fothergill and Peek, 2004). Few published studies focused on the impact of disaster-coping strategies. Rivera (2020) finds evacuation has negative impact on subjective recovery status across the victims of Hurricane Harvey.

The remaining part of the study is structured as follows. The next section details the identification and estimation strategies. The selection of instrumental variable is discussed in the two subsections. Section 3 introduces the data incorporated in the analysis and illustrates the general picture of the panel data. Section 4.1 and 4.2 presents the main body of the results. In Section 4.3 and 4.4, placebo tests and robustness checks are shown, together with the causal relationship examination introduced by Mogstad et al. (2019). The study summarizes and addresses some practical implications from the results.

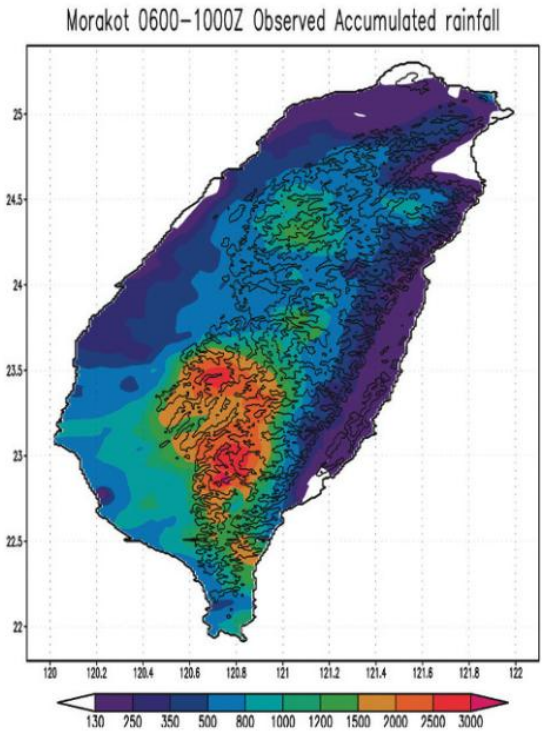


Figure 1 Observed rainfall during the Typhoon Morakot strike (August 6-10, 2009) (Retrieved from Yeh et al. (2011)). Note. The solid line indicates the contour of 1,000m.

2. Identification and Estimation

Finding a comparable comparison group poses empirical challenges to address evacuation and displacement effects. As mentioned, one strategy is to incorporate nonvictim data and identify causal effects of the disaster such as fixed effects (Deryugina et al., 2018) or difference-in-differences (DID) estimators (Deryugina and Molitor, 2020). However, their findings are disaster influence rather than effect of victims' mobility actions. To investigate victims' behavior, a more credible way is to identify subgroups of victims. For instance, Vigdor (2007) uses return behavior to distinguish victims and conduct a DID estimation, and Sacerdote (2012) allows samples to vary in each year before and after the disaster, allowing the maximum variation to maintain in the DID analysis. This method aligns with the current study. Other identification strategies are possible. With panel data, fixed effects method allows researchers to eliminate idiosyncratic unobserved characteristics (Botzen et al., 2019). 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 unobservable.

The treatment variable in this study, evacuation and displacement, invoke self-selection problem. Evacuation may be associated with many factors, such as perceptions

of potential threats of the approaching typhoon, household characteristics and composition, risk awareness, and perceptions of shelters, including transportation, cleanness, convenience, and comfortability, and so on. Similarly, the decision to relocate, or specifically, to be displaced into permanent housing, may be confounded by traits of original villages, decisions of neighbors and friends, distance to original places, design of permanent houses, and the complexity of the application process. This study employs instrumental variable methods to identify the effects of evacuation and displacement. The subsequent texts clarify the treatment and address the selection of the instruments.

2.1. The Target Effects

The outcome variable of interest is the monthly household income. In investigating the evacuation effect, the treatment variable is whether victims evacuate. In the displacement effect investigation, the treatment is residence in permanent houses. As noted above, the permanent housing policy enables us to understand the primary displacement effect for the victims of Typhoon Morakot. This policy allows us to isolate the displacement effect of living in permanent housing from multiple relocation paths.

Denoting the 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 evacuation effect τ can be written as the regression equation (1):

$$y_{it} = \beta_0 + \beta_1 x_{it} + \tau \cdot mov_{it} + \epsilon_i + u_{it},\ t \in [1,4] \quad (1)$$

where $mov \in$ {evacuation, displacement}. In the short run $t = 1$, the focus is on the evacuation, while displacement in the long run across all four periods. It should also be noted that the displacement is time-variant, while in the long run analysis, evacuation is time-invariant.

We also explore evacuation effect among different treatment groups while holding the controlled fixed. These effects can be estimated using splitting-sample analysis:

$$\begin{gathered} y_{it} = \gamma_0 + \gamma_1 x_{it} + \vartheta_1 \cdot mov_{it} + \epsilon_i + u_{it}, \\ mov = evacuation;\ i \in \{\text{temporary evacuee, non-evacuee}\} \end{gathered} \quad (2)$$

$$\begin{gathered} y_{it} = \gamma_0 + \gamma_1 x_{it} + \vartheta_2 \cdot mov_{it} + \epsilon_i + u_{it}, \\ mov = evacuation;\ i \in \{\text{displaced, non-evacuee}\} \end{gathered} \quad (3)$$

The displacement effect is basically the same with panel structure. To tackle the self-selected evacuation, this study employs instrumental variable approach. Let $\mathbf{z_i}$ denotes a vector of IVs, then the reduce-form is:

$$y_{it} = \rho_0 + \mathbf{z_{it}}'\boldsymbol{\rho} + \epsilon_i + u_{it} \quad (4)$$

The estimation of displacement effect hinged on panel instrumental variable (IV) estimators. The study conducts an alternative Hausman test for unbalanced panel in deciding between random effect instrumental variable (REIV) and fixed effect instrumental variable (FEIV) estimators proposed by Joshi and Wooldridge (2019), with the null assumes that idiosyncratic error has no prevalent influences. Intuitively, the method approaches FEIV estimators by including time averages of the exogenous

variables together with the instruments across periods in REIV estimators. The method is different from the traditional Hausman test under heteroskedastic scenarios and is designed for panel IV methods. It should be noted that the evacuation is time-invariant. Therefore, when we include evacuation in the long run analysis, the FEIV estimate will cancel out its' coefficient if the alternative Hausman test rejected the null hypothesis.

2.2. The Evacuation Effect

For the evacuation effect, the information sources of evacuation are used as instrumental variables. The eight types of information documented in the survey are categorized into two groups, which are information received from administrative agents and information received from others, including relatives, or neighborhoods. For information mediators such as television and radio, signal intensity and 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). Nevertheless, signal intensity is not available in this study. Information sources are directly related to evacuation during Typhoon Morakot (Huang et al., 2016), and are also related to underlying factors such as reception status and reliability (Yore and Walker, 2020; Sadri et al., 2017). In addition, different sources may have diverse impacts on evacuation (Lazo et al., 2015).

It is still possible that the information sources have certain relationship with post-disaster income. For example, receiving information about evacuation by a victim herself may indicate that a victim had greater awareness of the threat, which to some extent reflect certain types of personality. It might thus relate to post-disaster income. From this perspective, each source may have its own risks in violating the exclusion restriction. This study selects two sources, which are from administrative and from other people. Below, we argue that how both probably have no effect on the post-disaster income.

From an administrative viewpoint, although local governments were expected to warn residents to evacuate after the central government issued village-level notification, several exceptions that village heads did not comply with the process during Typhoon Morakot. Moreover, some residents were unwilling to evacuate (Lin, 2013), and some were misled by inaccurate forecasts that underestimated precipitation volume (Huang, 2014). With respect to information received from others, cell phone transmission was severely damaged during the typhoon. More than 28,000 telephones and 730 cell sites were reported malfunctioned during Typhoon Morakot (Central Emergency Operation Center, 2009). The transmission damage hindered the connection between dangerous areas and external information sources. The transmission corruption was mainly due to the exogenous realized precipitation, landslides, and windspeed brought by Typhoon Morakot. Therefore, variation in the two information sources depends on either local

officials' behavior taken during Typhoon Morakot, and realized disasters, and both are externally determined.

The LATE theorem is applicable since 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). For the evacuation effect, we particularly address if multiple instruments referring to various complier groups, which lead to substantial decreases in causality interpretation. This study provides an empirical test to argue that the compliers are statistically similar. We examine if the data meets the assumption of partial monotonicity proposed by Mogstad et al. (2021), which says that monotonicity holds conditioning on all other IVs. In addition, 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.

2.3. The Instrument for Displacement Effect

To identify the displacement effect in the long run, we construct a shift-share instrumental variable (SSIV) that is Borusyak-Hull (2023) style of exogenous shock design. The SSIV interacts a leave-one-out township-level measure of pre-disaster

exposure with typhoon-related shocks observed during Morakot. In particular, the share component is based on prior evacuation experience in the township, excluding the focal household, while the shock is forecast precipitation intensity at the time Typhon Morakot approaching. The logic is that households in areas with greater pre-existing disaster exposure may respond differently when they receive signals reflecting disaster levels, generating variation in movements that is plausibly external to any one household's post-disaster recovery path.

The shock component of the SSIV, the forecasted precipitation volume during Typhoon Morakot, merits further discussion. It is not rare to use observed rainfall as an instrument (e.g. Waldman et al., 20), but it cannot be used in this case because of the direct linkage between the realized damage and post-disaster income. In turn, the validity of forecasted rainfall is arguably held. 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 as well. The main forecasting technology at the time of Typhoon Morakot 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 since it is not realized. 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 and therefore provides very limited variation in the data.

In addition, the share component is constructed in leave-one-out form, so the instrument does not mechanically reflect the household's own prior behavior. This reduces the concern that the SSIV simply reintroduces household-level predispositions through the township average. A potential concern about the share is that it may correlate with village characteristics, which also influence post-disaster income. Some observations are less concerning due to their distribution sparse across mountainous areas and are far away from neighbors, where evacuation decisions were highly dependent on household conditions rather than through coordinated village responses. Moreover, once households are displaced, even before they move to permanent houses or other form of displacements, the influence of pre-disaster village traits on income is attenuated. Also, since we use evacuation experience as the share, it is possible that the share influences post-disaster income via evacuation. It can be eliminated by including time fixed effect.

Still, as of the shock, the estimation challenge arises since the forecast rainfall data is only at county level. The variations within counties are only distinguishable between

mountainous and plain areas. Therefore, we can expect that the SSIV may not be as good as normal IV. For this reason, this study also provides a robustness check using the other instruments that identifies an alternative margin of variation. Furthermore, the lack of variation also obstacles the study from applying Borusyak-Hull-Jaravel estimator. The alternative instrument for displacement is the status of applying for permanent houses. We will explicitly discuss the use of this IV in the corresponding result section.

Empirically, due to the idiosyncratic errors are often endogenous, fixed effect or first-differencing estimations are usually preferred. Nevertheless, the fact that evacuation and many controls 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. 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, $\mathbf{z_i} \equiv (\boldsymbol{z_{i1}}, \dots, \boldsymbol{z_{ik}})$, must satisfy exogeneity assumptions, $E(u_{it}|\mathbf{z_i}, \epsilon_i) = 0$ and $E(\epsilon_i|\mathbf{z_i}) = E(\epsilon_i) = 0$. 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. We report FEIV results to verify the REIV estimates.

3. 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. The surveys were conducted by the National Science and Technology Center for Disaster Reduction, an institute that focuses on disaster management and reduction. The data is unique in tracing all victim households applying for relocation subsidies after Typhoon Morakot. After data cleasing, the unbalanced panel contains 983 observations in the first period, 831 in the second period, 789 in the third survey year, and 681 in the final period. Pre-disaster conditions are constructed from retrospective questions in the first and the second periods. For simplicity, the four survey waves are denoted as periods 1-4 hereafter. This study also incorporates precipitation data recorded between August 7th and 9th, 2009, which are collected from the Central Weather Administration.

3.1. Descriptive Statistics of Key Variables

Definitions of the included variables are listed in Table 1, and their means are presented in Table 2. To avoid potential contamination of the estimation results from subsidies receive after the disaster, an adjusted income is computed. It is income net of migration subsidies that households could receive based on the household size. Information on household recovery costs is collected from the survey. If a victim reported

that her house was fully destroyed, then five million NTD is used as a proxy for recover costs. This amount is higher than the average cost of a house in the mountainous areas at that time. This intentionally high proxy is used to include other recovery costs, including land acquirement and settlement.

As Table 2 reveals, household income generally experienced a slight drop after Typhoon Morakot by comparing *income* and *Pre_income*. Post-disaster income grew quickly in subsequent survey years and increased substantially by 2015. For time-invariant variables such as temporary evacuation, means fluctuate because of data attrition. More than four-fifths of victims reported evacuating during Typhoon Morakot. The average household had 4.2 members before Typhoon Morakot, and this number drops slightly afterward. Within households, youths and elderly members together accounted for about 1.5 people in 2010, indicating that most households had around two or three grown-ups. Household size and the combined number of elderly and youth members declined in later survey periods. Some large households are observed and retained in the analysis because they reflect certain characteristics of the affected areas.

The unemployment rate was 27% before Typhoon Morakot, which is not shown in the table. It increased after the disaster and stabilized at around 40% level in the final two survey periods. In contrast, the share of farmers declined steadily and sharply after the disaster. The loss of farmland and the permanent housing policy, which moved people

away from their farmland, may explain the high unemployment rate and declining agricultural participation. The share of non-technical work began to fall between 2010 and 2011, reflecting limited employment opportunities in the affected areas. On the contrary, the share employment in public sector was more stable throughout the period. The share of Indigenous households remained consistently above 40% across the periods.

Table 1. Definition of Variables

Variables	Definition
Dependent variables	
Income	Monthly income of the household (in NTD)
Adjusted income	Income net of migration subsidies (in NTD)
Actions relevant to evacuation	
Evacuation	Victims evacuated during the Typhoon Morakot strike
Displacement	Victims displaced to permanent houses
Household's characteristics	
HHsize	Household size
Old	Number of elders in a family
Youth	Number of young people in a family
Jobnum	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
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_above	=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 respondents are currently not in labor force
Unemployed	=1, if respondent is unemployed

Table 1. (*cont.)* Definition of Variables

Variables	Definition
Exp_ty	Number of experiences of typhoon strikes
Exp_eva	Number of evacuating experiences
Impacts	
Memberloss	Number of family members loss during Morakot strike
Payforlive	Sustaining payment before settling in a place (NTD)
Facilityloss	Payment for recovering the house and land (NTD)
Rainfall7	The precipitation volume on the August 7th
Rainfall8	The precipitation volume on the August 8th
Rainfall9	The precipitation volume on the August 9th
Rainfall10	The precipitation volume on the August 10th
Sources of information about evacuation	
Admin	Received evacuating information from administrative agents
People	Received evacuating information from other people
Pre-disaster baseline economic conditions	
Pre_income	Household's monthly income before the strike
Pre_expense	Household's monthly expenses before the strike

Table 2. Descriptive Statistics for Individual and Households' Characteristics

Period	2010	2011	2012	2015
Number of obs.	983	831	789	681
Time-variant				
Income	28,049	32,460	33,242	36,545
Adjusted income	23,565	31,869	32,836	36,422
HHsize	4.314	4.047	4.019	3.993
Old	0.782	0.804	0.798	0.874
Youth	0.806	0.661	0.635	0.596
Jobnum	3.485	1.548	3.712	3.706
Age	53.71	49.04	55.98	58.28
Male	0.587	0.574	0.559	0.512
Married	0.625	0.619	0.598	0.602
Indigenous	0.419	0.422	0.416	0.433
Illiteracy	0.120	0.116	0.108	0.101
Junior	0.582	0.593	0.577	0.576
Senior	0.272	0.270	0.286	0.280
College	0.026	0.022	0.029	0.043
Farmer	0.223	0.152	0.125	0.073
Manager	0.049	0.075	0.137	0.170
Notech	0.202	0.081	0.086	0.095
Pns	0.160	0.229	0.233	0.226
Nonlabor	0.027	0.032	0.027	0.028
Unemployed	0.339	0.426	0.392	0.407
Displaced	0.296	0.413	0.556	0.549
Time-invariant				
Pre_income	28,789	27,720	28,986	29,794
Pre_expense	24,143	23,973	23,346	25,575
Exp_evac	0.286	0.290	0.284	0.300
Exp_ty	1.380	1.400	1.332	1.340
Die	0.054	0.051	0.054	0.054
Facilityloss	301.40	298.21	291.20	278.42
Payforlive	13,788	13,913	13,357	13,788
Pre_Income	28,789	27,720	28,986	29,794
Pre_Expense	24,143	23,973	23,346	25,575
Rainfall7	250.40	247.16	252.77	254.00
Rainfall8	749.29	744.61	752.77	757.06
Rainfall9	191.75	284.23	297.10	304.75
Rainfall10	126.49	125.80	127.21	124.11
Evacuated*	0.831	0.832	0.832	0.830
Adm	0.405	0.403	0.407	0.410
People	0.198	0.203	0.186	0.175

Unit of *Income*, *Expense* and *Payforlive*: NTD; *Facilityloss*: 10,000 NTD. Unit of *Rainfall7* to *Rainfall10* are in millimeter (mm). Due to null response, the number of evacuations for evacuation is 841.

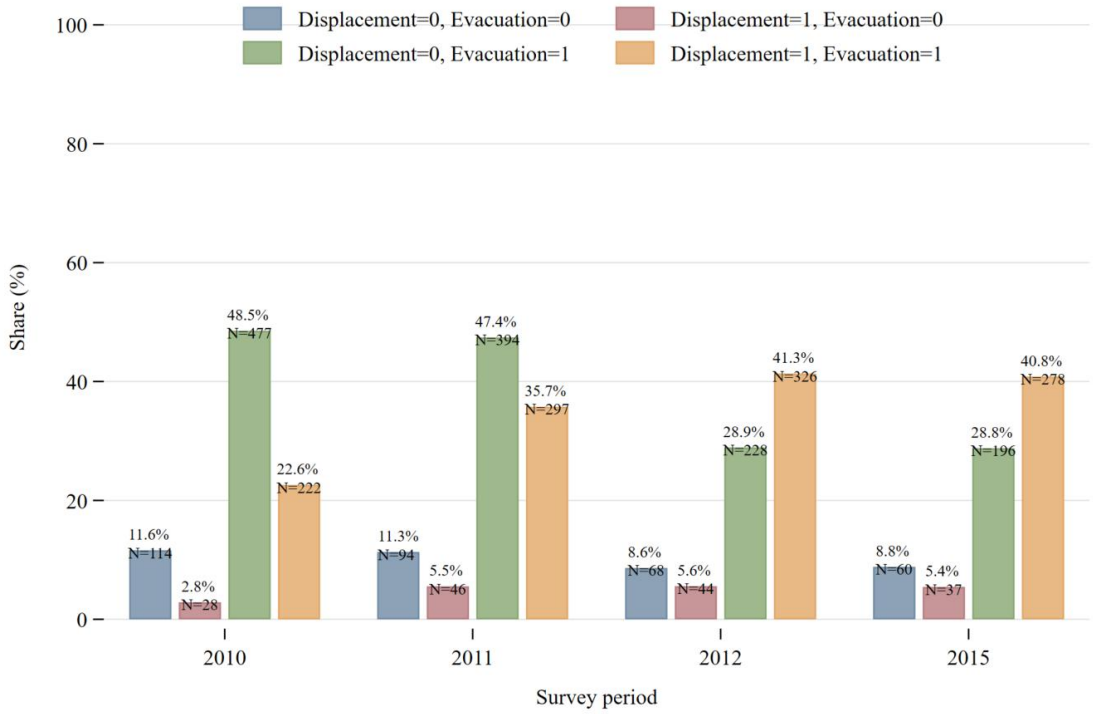


Figure 2. The Distribution of Evacuation and Displacement

3.2. Moving Patterns and Housing Decisions of the Victims

The victims' moving patterns and housing decisions were diverse. One may decide to evacuate and later apply for a permanent house and relocate to a permanent community. Figure 3 plots the frequencies of displaced to permanent houses in each period. From the first to the third period of the survey, the share of displacement increases. Nevertheless, Durgin the third to the last period, a downward trend appears, reflecting mobility even after victims are regulated to stay in the permanent houses. This trend concurs with the general critics to the permanent housing policy, either because the design failed to meet victims' demands, or administratively constrained some victims in claiming ownership of

the permanent houses. These reasons, alongside other factors, pushing some displaced victims to leave permanent houses.

Next, this study compares if significant income differences are shown among groups implementing evacuation or displacement. As Table 3 presents, the evacuated group has higher income across all four periods, comparing to the non-evacuees. In addition, for both groups of victims, their income mildly increases from the first to the last survey period. The between groups comparison reports no significant difference. The second panel of Table 3 shows a different pattern between displaced and non-displaced groups. The incomes of the non-displaced group are higher at 10% significance level. However, the difference dissipates in the later periods, and the displaced group have higher income than their counterparts in the second and third periods. The difference is even smaller in the last survey period. The observed pattern may come from 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.

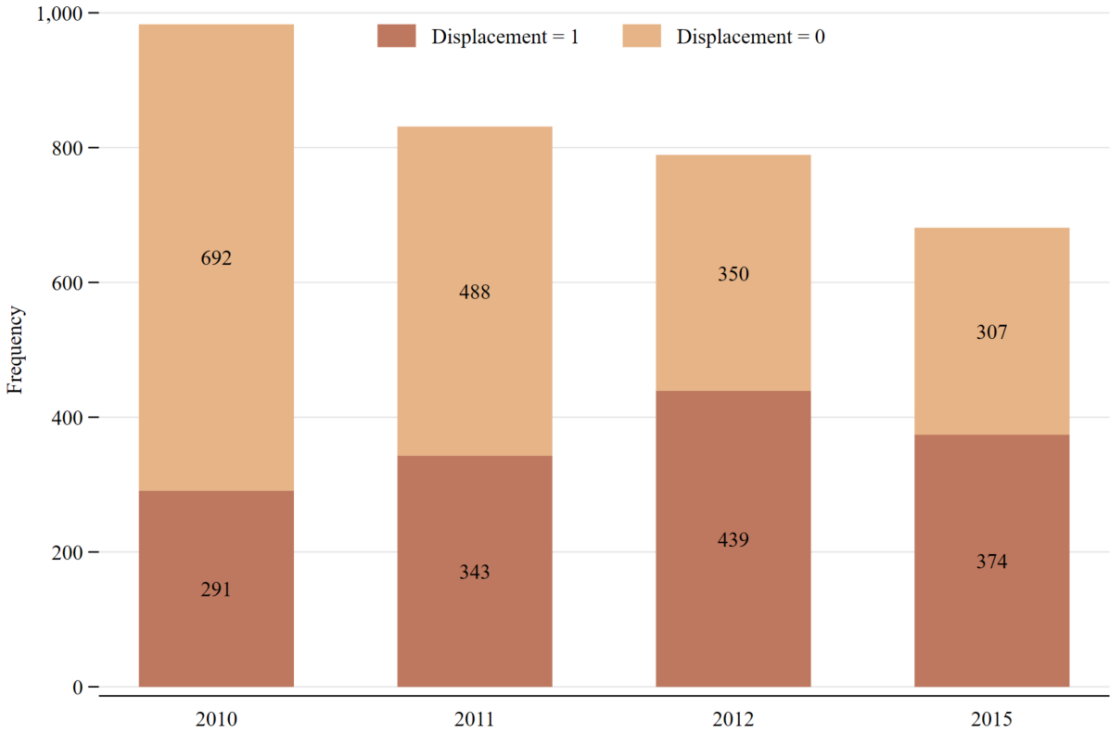


Figure 3. The Distribution of Living in Permanent Houses

Table 3. Dependent Variables of Different Housing Decisions

Panel 1: Evacuated				
Groups	2010	2011	2012	2015
	Mean (S.D.) [# of obs.]	Mean (S.D.) [# of obs.]	Mean (S.D.) [# of obs.]	Mean (S.D.) [# of obs.]
Evacuee	27,654 (852.6) [699]	27,395 (852.7) [691]	27,906 (933.0) [554]	28,723.6 (1,064.6) [474]
Non-evacuee	29,366 (1,945.6) [142]	29,321 (1,964.0) [140]	28,929 (2,044.6) [112]	30,154.6 (2,106.6) [97]
T-statistics	0.806	0.900	0.455	0.606
Panel 2: Displaced				
Displaced	26,959 (1,280.8) [291]	28,440 (1,266.4) [343]	29,841 (1,055.4) [439]	29,719 (1,160.1) [374]
Non-displaced	29,559 (888.3) [692]	27,213 (991.7) [488]	27,914 (1,187.8) [350]	29,886 (1,404.0) [307]
T-statistics	1.668	-0.763	-1.212	0.0916

4. Result

4.1. The Short Run Evacuation Effect

In effect, one can still divide sub-groups within the evacuees. One most-relevant movement related to evacuation is whether victims return to their original houses. Returning probably signals milder damage status and quick bounce back of the income. However, returning decision may also be confounded by factors, such as the recovery progress transportation, shelter conditions, or potential threats of soil erosion. This study addresses this issue by splitting the first-period sample into two groups, labelling them as returner and non-returner, and applying the same identification strategy as the evacuation effect. The control groups in both estimations are the same, which is the group of victims that did not evacuate.

The result of the evacuation effect obtained from 2SLS regressions is presented in Table 4 and 5, where full estimation of the full sample and the subgroups estimation results are reported. In both tables, the F statistics are all above the rule-of-thumb level of 10, indicating that the information sources are relevant to evacuation. In addition, the reduced form coefficients of the instrumental variables are presented in the subsequent Table 6. The insignificance of the instruments on both income measures shows that there is no direct influence on incomes, which partly verifies the exclusion restriction. It is worth noting that the limited observations in the returner subgroup may also produce less

precise estimates.

Overall, the evacuation effect is insignificant in the full sample and across subgroup estimations, even after netting the migration subsidies of Typhoon Morakot. The result does not support public perception of negative economic impact of evacuation. Furthermore, neither of the subgroup analyses support public perception. While a negative effect on adjusted income is observed in the non-returner group, the imprecise estimate does not confirm the effect.

Regarding the control variables, several of them benefit the post-disaster income. Especially, the size of household, age of household leaders, whether household leaders are married or with senior high degree, and working status, have positive effects range from hundreds to thousands. In general, individual characteristics have more positive impacts on income, while household size and the pre-strike household income are the only two variables having positive effects. Disaster-related variables are less substantial in determining income. The only significant coefficient that related to Typhoon Morakot strike is the number of family members who passed away, which lowers household income of 2,700 NTD, or $84.4. There are two possible explanations. First, casualty may not be working members in the households and do less harm to income on average. Second, the analysis does not account for death benefits and subsidies. These subsidies may account for part of household post-disaster income. In addition, the coefficient of the

evacuation experience before Typhoon Morakot shows that it has impact on income of around 2,900 NTD, or $90.6. Its magnitude is larger than the death number, which support that the death benefits offset parts of the family loss in a financial way.

Table 4. Full Estimation of Evacuation Effects

	Income		Adjusted income	
	Estimates	S.E.	Estimates	S.E.
First stage				
Admin	0.227 ***	0.035	0.227***	0.035
People	0.210 ***	0.037	0.210***	0.037
First stage F	21.84		21.84	
Evacuation	5,133.96	5,258.82	1,754.81	5,268.84
Pre_income	0.60***	0.08	0.60***	0.09
Pre_expense	-0.01	0.01	-0.01	0.01
exp_eva	-2,866.94***	1,090.44	-3,997.53***	1,140.01
exp_ty	257.34	284.76	258.26	297.27
HHsize	824.76***	266.25	220.56	254.49
Old	-40.15	844.78	256.93	759.67
Youth	-480.97	455.55	-520.03	487.18
Jobnum	50.17	71.59	59.91	77.29
Age	139.53**	64.34	153.51**	64.50
Male	-455.12	1,330.12	-464.28	1,511.20
Indigenous	1,883.42	1,934.82	1,908.35	1,805.95
Married	2,663.99***	725.87	2,245.84***	728.30
Junior	2,285.58	1,859.19	2,354.79	1,817.43
Senior	4,803.79**	2,446.92	4,951.16**	2,448.70
College_above	6,195.34	4,489.75	5,804.16	4,478.77
Farmer	1,870.59	2,264.58	2,394.29	2,387.38
Manager	6,815.07**	2,961.33	6,484.19**	3,080.67
Notech	4,890.24***	1,876.45	4,898.28***	1,750.06
Pns	8,074.53***	2,457.25	7,885.43***	2,595.63
Nonlbr	2,016.66	1,608.28	1,149.64	1,806.53
Die	-2,695.10***	850.46	-3,226.65***	882.72
Facilityloss	-14.29	12.11	-17.13	12.50
Payforlive	-0.01	0.01	-0.02	0.02

Table 4(cont.). Full Estimation of Evacuation Effects

	Income		Adjusted income	
	Estimates	S.E.	Estimates	S.E.
Rainfall7	-2.23	4.39	-2.13	4.55
Rainfall8	1.51	4.85	1.66	5.02
Rainfall9	-0.98	2.65	0.52	2.85
Rainfall10	-6.35	9.72	-9.30	11.06
Constant	-10,281.8*	5,547.03	-9,496.60*	5,650.92
P-value of over-identification F	0.755		0.970	
Number of obs.	873			

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

Table 5. Short-Run Evacuation Effect

	Income		Adjusted income	
	Estimates	S.E.	Estimates	S.E.
Full sample	5,134.0	5,258.8	1,754.8	5,268.8
Returner	12,393.1	7,688.6	12,955.4	8,134.7
Non-returner	4,267.4	13,120.4	-1,956.7	12,554.1
Controls				
Pre-disaster econ	◯		◯	
Disasters-related	◯		◯	
HH traits	◯		◯	
Personal traits	◯		◯	
Number of obs.	873			

Note: Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. The S.E.s are clustered at township level. Mean VIF: 1.62 no collinearity issue. First-stage K-P F-statistics: 21.84 for full sample; 46.45 for returners; 11.63 for non-returners.

Table 6. Short-Run Reduced Form Results

	Income		Adjusted income	
	Estimates	S.E.	Estimates	S.E.
Full sample				
Adm	952.07	1,328.85	370.86	1,360.35
People	1,482.8	2,007.53	421.19	1,958.40
Returner				
Adm	9,276.42	6,867.16	9,539.92	7,190.91
People	2,902.23	3,043.20	3,506.06	3,350.90
Non-returner				
Adm	38.72	1,263.69	-492.42	1,171.61
People	1,268.63	2,442.85	393.52	2,446.79

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

4.2. The Long Run Displacement Effect

The main results for the displacement effect on income and adjusted income are presented in Table 7 and Table 8. The model specifications are based on the same structure as in the cross-sectional analysis. The analysis also incorporates the other set of controls that excludes the individual characteristics, this is because of the practical survey issue that the survey-takers may switch within the time horizon of the four periods. The FEIV result is also reported for reference and as a robustness check. Both tables present the alternative Hausman test proposed by Joshi and Wooldridge (2019) for REIV verification before every analysis to examine whether the random effect assumption is unlikely to be violated. In the first two columns of Table 7, which represent different model specifications, the joint χ^2 statistic of the time averages of exogenous variables are

13.97 and 14.07, insufficient to reject the null hypothesis.

The first stage results in the two tables show large F-statistics in REIV models of about 55, while smaller but still sufficient of around 15 for FEIV model. The reduced form estimations show the significant relationship between the SSIV and the incomes. It is also worth mentioning that the signs of the first stages and reduced forms coefficients flipped between REIV and FEIV estimations, which suggests that the shift-share instrument captures different sources of variation under random- and fixed-effect assumptions. To be clearer, both the shift and shock component are determined before the strike. When using FEIV, it removes time-invariant household and location components and relies only on within-household variation. This may leave variation driven by timing, program implementation, or changing recovery needs, producing an opposite first-stage sign.

The reduced form coefficients of the instrument are significant across the estimations. In addition, we examine whether there is a systematic period-specific reduced form pattern. To do so, the sample is split into three equal subgroups by the instrument exposure. Next, we plot the first stage and the reduced form as in Figure 4. In Panel A, clear upward trends for all instrument exposure groups appear, with different speeds and magnitudes. This pattern suggests that permanent housing may primarily be prepared for certain victims at some period. In Panel B, the reduced form patterns are mixed. Since the SSIV

is constructed using information before the typhoon strike, the reduced form provides a check on whether the same exogenous variation that predicts government housing also appears in the income. Since the SSIV is time-invariant, the absence of a stable and systematic period-specific reduced-form pattern supports for not violating the exclusion restriction.

In general, the results show that displaced victims to permanent houses have a negative effect on income, even after controlling the relevant subsidies. Overall, victims who are displaced to permanent houses suffer monthly income losses for more than 10,000 NTD, equivalent to $312.5. The huge difference reflects how the displaced victims struggle to recover. Based on the average income of 2015, which is 36,545 NTD, or $1,142, nearly 30% deficit compared to the victim average for the displaced victims. The FEIV estimate also presents the same direction of the displacement effect with similar level, while the estimate is less efficient.

In Table 9, the split-sample analyses are performed, focusing on Indigenous and non-Indigenous groups. The displacement effects are negative in the two groups, but only significant in the non-Indigenous group. This is an interesting result since most of the previous study emphasizes the damage for Indigenous residents, their counterparts are overlooked. The current result shows that displacement to permanent houses is more crucial in the recovery for non-Indigenous victims than Indigenous.

From the long-term perspective, although a unified displacement strategy to permanent houses rapidly provides a stable place that is physically in better condition than temporary shelters and usually better than original places, it brings economic disadvantages to the victims in their recovery processes. The result proves that displacement slows income recovery, especially under a unified displacement strategy such as permanent housing.

Table 7. Long-Run Displacement Effects: Income

	REIV		REIV		FEIV		
	Estimates	S.E.	Estimates	S.E.	Estimates		S.E.
Displaced	-9,568.6 *	5,338.3	-11,275.2**	5,199.7	-11,157.8		14,070
First stage							
F statistic	54.34		55.82		14.84		
Exp_evac*RFC	-0.151 ***	0.016	-0.152***	0.016	0.184	***	0.048
Reduced Form							
Exp_evac*RFC	1,455.4 *	802.14	1,728.12**	769.33	-2,050.9	*	2,659.8
Controls							
Pre-disaster econ	◯		◯				
Disasters-related	◯		◯				
HH traits	◯		◯		◯		
Personal traits			◯		◯		
Alternative Hausman test	13.97		14.07				
#	3,284		3,284		3,725		

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

Table 8. Long-Run Displacement Effects: Adjusted income

	REIV		REIV		FEIV	
	Estimates	S.E.	Estimates	S.E.	Estimates	S.E.
Displacement Effect	-10,056 *	5,360.9	-11,754**	5,238.0	-11,450	14,186
First stage						
F statistic	54.48		55.93		14.84	
SSIV	-0.152 ***	0.016	-0.152***	0.016	0.184 ***	0.048
Reduced Form						
SSIV	1,531.5 *	808.14	1,803.6**	777.30	-2,104.5	2,695.9
Controls						
Pre-disaster traits	◯		◯			
Disasters-related	◯		◯			
HH traits	◯		◯		◯	
Personal traits			◯		◯	
Alternative Hausman test	14.82*		14.34			
Number of S.E.	3,284		3,284		3,725	

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

Table 9. Long-Run Displacement Effects: Income

	Indigenous		Non-Indigenous	
	Estimates	S.E.	Estimates	S.E.
Displacement Effect	-3,790.0	14,060.4	-14,226***	5,187.7
First stage				
F statistic	10.87		44.87	
Exp_evac*RFC	0.251 ***	0.076	-0.320***	0.033
Reduced Form				
Exp_evac*RFC	-952.56	3,661.6	4,318.9***	1,533.9
Alternative Hausman test	138.6***		8.99	
#	1,386		1,898	

Note: Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. The Indigenous group is estimated by FEIV method due to significant result from alternative Hausman test; the non-Indigenous group is estimated by REIV method.

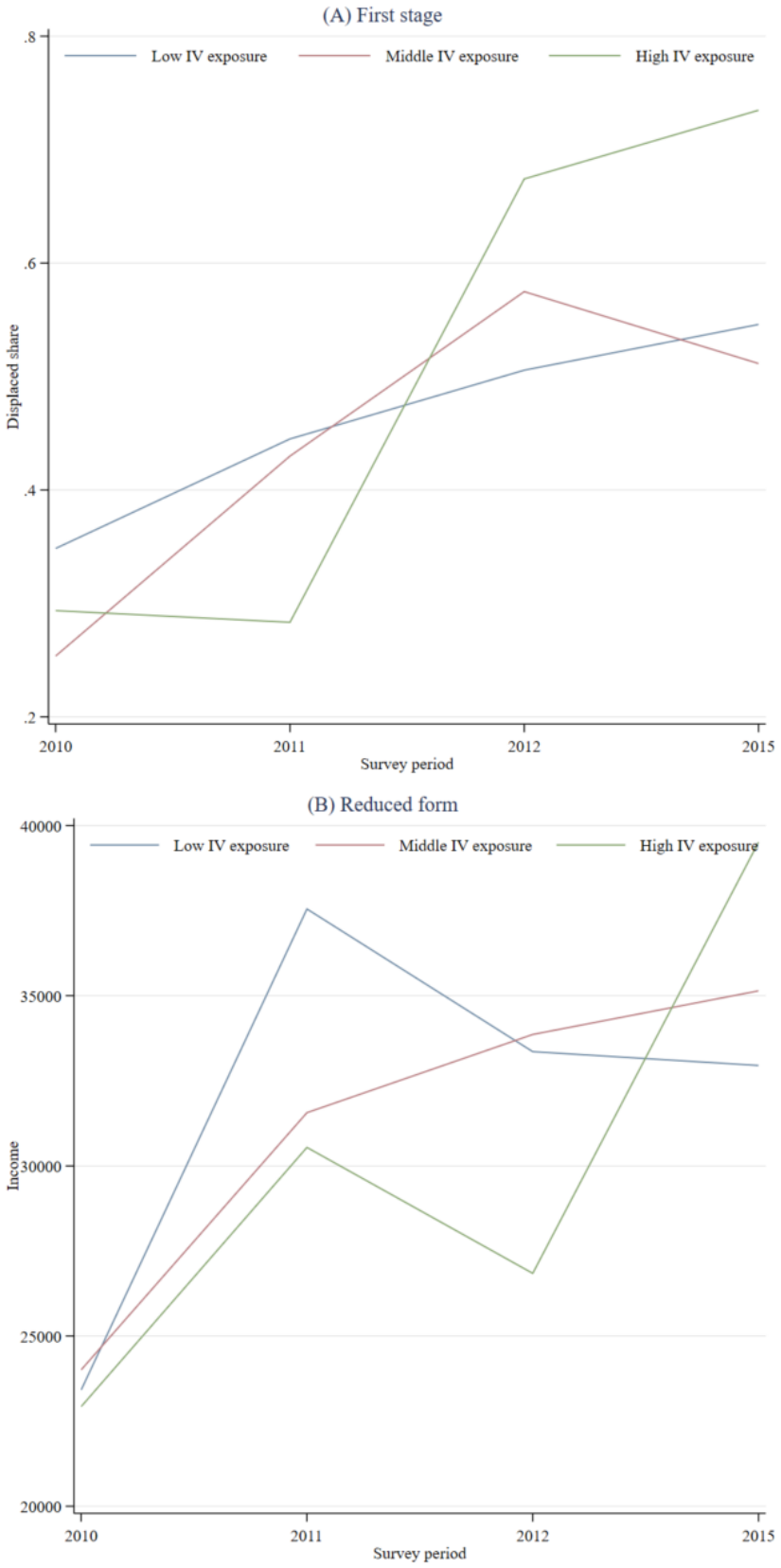


Figure 4. The Distribution of Living in Permanent Houses

4.3. Falsification, Placebo, and Robustness Tests

This study runs placebo tests to assess whether the finding of the evacuation effect is contaminated by confounding influences of the instrumental variables. We follow Danieli et al.'s (2026) recommendation in what they called negative-control-outcome (NCO) placebo test to assess the plausibility of the IV identification strategy. Specifically, pre-disaster income is used as the NCO because it was realized before Typhoon Morakot and should not be affected by post-disaster evacuation. Below, two placebo tests are presented. First, we run the same IV estimation with the pre-disaster income. Second, as Danieli et al. (2026) emphasize, this study assesses whether the instruments were systematically correlated with pre-disaster income. If so, this suggests that they capture baseline socioeconomic conditions and may create an alternative path from the instruments to the post-disaster outcome.

Table 10 reports both the conventional placebo 2SLS estimates and the reduced-form NCO tests. The 2SLS estimate of evacuation on pre-disaster income is statistically insignificant, indicating no evidence that instrumented evacuation is associated with the placebo outcome. The reduced-form test is especially useful because it directly examines whether the instruments are correlated with the NCO. The instruments remain relevant in the first stage, with a first-stage F-statistic of 22.3, but neither the IV placebo estimate nor the reduced form estimates are statistically significant. This pattern suggests that the IV

variation does not reflect pre-disaster income across respondents. Taken together, the placebo and reduced-form falsification tests provide supportive evidence that the instruments are not simply capturing pre-existing income differences.

Table 10. Short-Run Reduced Form Results

	Placebo Tests		NCO (Reduced Form)	
	Estimates	S.E.	Estimates	S.E.
Evacuation	4,541.7	8,245.9		
Instruments				
Adm	0.226***	0.034	1,729.6	1,872.6
People	0.210***	0.037	-348.0	2,413.6
First stage F	22.30			
Number of obs.	873		873	

Note. Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. The S.E. are clustered at town level.

For the displacement effect, we present two robustness checks. First, we use an alternative instrumental variable, a dummy variable indicating whether a household's application for permanent house is approved. The key mechanism hinged on the application process of permanent houses. The relevant act after Typhoon Morakot ensured that only the victims lost their houses, or victims with the parcels considered dangerous by the governments, can apply for the permanent house. Also, there were five main NGOs who played the roles of authorization in the application process. These NGOs decided if the applicants could have permanent house at all and its size. However, different NGOs

may have disparate standards. Some correspondents showed leniency to victims, while some did not. Such schematical design is exogenous to victim households since they only receive the results. It therefore creates an instrument *Approved*, which is similar to policy or administrative eligibility concept to investigate the displacement effect.

Notwithstanding, using *Approved* as instrument has an empirical caveat. Due to the survey design, *Approved* is not included in the first-period survey. The first-period observation therefore cannot be used. The alternative IV result is presented in Table 11. The first-stage estimation shows that the relevance assumption is met. The displacement effect has the same negative direction as in the SSIV estimation but smaller in the magnitude. The effects is 4,300 NTD loss in income, which is about $134.4. The milder effect comes from two reasons. First, the *Approved* instrument calculates the different complier group from the main result. From LATE theorem, victims who really move to permanent houses after they

In addition, this study in turn provides a supplementary two-way fixed effects analysis as a robustness check for the displacement effect. However, noted that since the displacement timing is not randomly distributed and the insufficient knowledge about whether parallel trend exists in pre-disaster periods, the FEIV estimate captures the average association between displacement status and income. In particular, we estimate the following regression:

$$y_{it} = \beta_0 + \boldsymbol{\beta}_1 \mathbf{x_{it}} + \tau \cdot Displaced_{it} + \epsilon_i + \lambda_t + u_{it}, t \in [0,4]$$

where income in $Displaced_{it}$ is an absorbing indicator, and it equals to one after household i is first displaced to a permanent house. The error term ϵ_i and λ_t denotes household and period fixed effects, respectively. The TWFE estimates τ, which captures the average within-household change in income after displacement relative to non-displaced or not-yet-displaced households. The pre-disaster period 0 is incorporated and the estimates are within household comparisons.

The TWFE estimates of displacement are reported in Table 12. No matter if the subsidies are deducted from income, the directions of the coefficients are consistently negative. On average, households experience income declines in income of 2,400 NTD, equivalent to $75, and slightly more if the income nets of subsidies. This result supports the main displacement effect. In effect, the current result, together with the main result reveal that the adverse effect of displacement, is not only across victim households, but also within households over time.

Table 11. Estimation of Displacement Effect (IV: Approved)

	Income		Adjusted income	
	Estimates	S.E.	Estimates	S.E.
First stage				
Approved	0.207 ***	0.041	0.207***	0.041
First stage F	25.64		25.64	
Refuced form				
Approved	-1,198.78	1,818.13	-1,373.63	1,819.18
Displacement	-5,797.28	8,924.91	-6,642.87	8,946.77

Note. Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. The FEIV results are reported due to rejection of the null of alternative Hausman test. The number of observations is 3,419.

Table 12. TWFE Estimation of Displacement Effect

	Income		Adjusted income	
	Estimates	S.E.	Estimates	S.E.
Displacement	-2,424.4**	1,077.3	-2,852.9***	1,083.1
Number of obs.	4,302		4,302	

Note. Both TWFE estimations control for the pre-disaster characteristics, disaster damage and intensities, household and personal traits, and period indicators.

4.4. Verification of Causal Interpretations of Evacuation Effect

In the previous evacuation analysis, the instrumental variables are the two information sources. The multiple instruments may be directed to various complier groups, complicating the interpretation by LATE theorem. Following Mogstad et al. (2021), this part delivers a pairwise estimation result, which examines if the estimates change if only one information source instruments for the action at a time while

controlling for other sources as exogenous. The partial monotonicity assumption proposed by Mogstad et al. (2021), that is, conditional on other instruments and exogenous controls, one instrument variable should meet the monotonicity assumption, preserves a positively conditional weighted LATE interpretation. This study also tests whether partial monotonicity is met following their concept, as shown in Table 9.

The results find positive weights for all three information sources while given the other two instruments fixed. In addition, both of the instruments have significantly positive first stages coefficients. The reduced forms are positive across the two margins as well. Therefore, the three instrumental variables follow the partial monotonicity assumption. These instruments may move different households into evacuation, so differences across columns should be interpreted as evidence that the local effects of evacuation may vary across margins of induced evacuation. The findings also align with the expectation that each information source crystalizes evacuation because some victims are more obedient to certain sources.

Table 13. Pairwise Comparison between Groups

Info	Evacuation		First stage		Reduced form	
sources	Estimates	S.E.	Estimates	S.E.	Estimates	S.E.
Adm	4,187.8	5,650.4	0.227 ***	0.034	952.07	1,328.8
People	7,065.9	9,081.0	0.210 ***	0.037	1,482.8	2,007.5

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. First-stage in F for adm-margin: 42.26; for people-margin: 31.64.

5. Discussion and Conclusion

Disaster recovery is a key element in building resilient rural areas. This study delves into the critical role of movement during disasters and in aftermaths by investigating how these behaviors affect post-disaster recovery. The aim of this study is to find the economic effects of the movements. From the case of Typhoon Morakot which hit Taiwan in 2009, the effects on post-disaster income of evacuation and a specific displacement of permanent housing policy are examined.

This study uses the instrumental variable method to address the self-selecting nature of evacuation and displacement. Particularly, the information sources are used as instruments for evacuation, and a shift-share designed variable is created as instrument for displacement. The findings show that in the one-year post-disaster period, evacuation does not have impact on income. In addition, in a longer term, the households relocated to permanent housing experienced substantial income declines. The non-Indigenous subgroup analysis indicates that displacement does more harm to their income then to Indigenous victims.

The above findings directly link to the practical disaster management strategy designs. On the one hand, while evacuation is necessary for most of the time as disasters approach, general public may hold negative perception toward the movement. The finding of the null evacuation effect is a new piece of evidence that helps evacuation promotion.

For evacuation, people may hesitate to leave their places or show disobedience due to economic concerns, which undermines their safety. The study alleviates people's concern by eliminating the possibility that evacuation causes asset losses. Furthermore, in Typhoon Morakot case, the evacuation was not mandatory. The result therefore also supports voluntary evacuation. On the other hand, the displacement effect points out that a large-scale displacement can cause severe economic losses to the residents. The permanent housing policy was implemented in haste without taking social and cultural aspects into account. The negative effects of displacement may thus partly reflect the costs of haste. Nevertheless, the opportunity cost for delayed supply of houses is delayed settlement of victims and could prolong the recovery process.

Typhoon Morakot offers insights applicable to areas facing similar disasters, particularly in rural and mountainous regions of East and Southeast Asia, where inhabitants are highly vulnerable to disasters of tropical cyclones, and evacuation and displacement are often adopted. The study reinforces the need for sculpturing better ways of practical implementations by providing similar housing policy but extending the application period and offering greater flexibility in housing and community designs, which may lower the opportunity cost of cultural and social capital losses. To achieve this, more detailed and careful implementing processes should be designed, participatory communication that encourages victims to provide their thoughts and needs.

The main limitation of this research is that the shift-share instrumental variable for displacement is lack of variations. This is due to the forecasted precipitations information at county level. There are still some limitations in the data used in this study. First, the survey does not follow the same respondents across periods. Same households may have different survey-takers for each survey year. Second, the pre-disaster information is limited, constraining the use of other causal identification strategies. In addition, the subsidies received were not clearly recorded, and the number of subsidies can be calculated. Most of the limitations are rooted in the scarcity of available data. Again, this highlights the difficulties in doing disaster research for social science. Researchers of this strand should accelerate their paces to enhance strategical designs under evidence-based construction and toward a resilient society.

References

Alam, E. (2024). Reasons for non-evacuation and shelter-seeking behaviour of local population following cyclone warnings along the Bangladesh coast. *Progress in Disaster Science*, 21, 100307.

Anttila-Hughes, J. K., and Hsiang, S. M. (2013). Destruction, disinvestment, and death: economic and human losses following environmental disaster. Available at SSRN: https://ssrn.com/abstract=2220501. Last access: July 28th, 2024.

Black, R., Arnell, N. W., Adger, W. N., Thomas, D., and Geddes, A. (2013). Migration, immobility and displacement outcomes following extreme events. *Environmental Science & Policy*, 27(1): S23-S43.

Botzen, W. J. W., Deschenes, O., and Sanders, M. (2019). The economic impacts of natural disasters: a review of models and empirical studies. *Review of Environmental Economics and Policy*, 13(2): 167-188.

Camp Coordination and Camp Management Cluster (CCCM Cluster) (2014). *The Mend Guide: Comprehensive Guide for Planning Mass Evacuation in Natural Disasters (Pilot Document)*. Available at: https://www.cccmcluster.org/sites/default/files/2018-10/MEND_download.pdf. Last access: February 8, 2024.

Central Emergency Operation Center (2009). *The Report of Disaster Respondence and*

No. 11. Released date and time: 13:00 of August 9, 2009. Available at: https://www.nfa.gov.tw/upload/cht/attachment/6ce08dd6334e058109bfb6fd07b5ce60.pdf. Last access: March 4th, 2024. (in Chinese)

Chen, C.-Y., (2009). Prevention, adaptation and warning measures to landslides during Typhoon Morakot. *Agricultural Policy & Review*, 207. Available from: https://www.moa.gov.tw/ws.php?id=20198. Last access date: July 1st, 2024. (in Chinese)

Collins, J., Ersing, R., Polen, A., Saunders, M., and Senkbeil, J. (2018). The effects of social connections on evacuation decision making during Hurricane Irma. *Weather, Climate, and Society*, 10(3): 459-469.

Danieli, O., Nevo, D., Walk, I., Weinstein, B., and Zeltzer, D. (2026). Negative control falsification tests for instrumental variable designs. *American Economic Review*, 116(4): 1380-1414.

Deryugina, T., and Molitor, D. (2020). Does when you die depend on where you live? Evidence from Hurricane Katrina. *American Economic Review*, 110(11): 3603-3633.

Deryugina, T. Kawano, L., and Levitt, S. (2018). The economic impact of Hurrican Katrina on its Victims: evidence from individual tax returns. *American Economic Journal: Applied Economics*, 10(2): 202-233.

Dillon, A., Mueller, V., and Salau, S. (2011). Migratory responses to agricultural risk in Northern Nigeria. *American Journal of Agricultural Economics*, 93(4): 1048-1061.

Farré, L., and Fasani, F. (2013). Media exposure and internal migration — Evidence from Indonesia. *Journal of Development Economics*, 102: 48-61.

Fiala, N. (2015). Economic consequences of forced displacement. *The Journal of Development Studies*, 51(10): 1275-1293.

Huang, S.-K., Lindell, M. K., and Prater, C. S. (2016). Who leaves and who stays? a review and statistical meta-analysis of hurricane evacuation studies. *Environment and Behavior*, 48(8): 991-1091.

Huang, C. J. (2014). The narratives of certainty and uncertainty in science communication: Morakot Typhoon report serves as an example. *Taiwanese Journal for Science, Technology, and Medicine*, 19: 73-116. (in Chinese)

Hollis, M. (2021). *Why the Gullah/Geechee Communities Don't Evacuate*. US FEMA. July, 2021. Available at: https://www.govinfo.gov/content/pkg/GOVPUB-HS5_100-PURL-gpo216205/pdf/GOVPUB-HS5_100-PURL-gpo216205.pdf. Last date of access: April 20, 2026

Hori, M., and Schafer, M. J. (2010). Social costs of displacement in Louisiana after Hurricanes Katrina and Rita. *Population and Environment*, 31: 64-86.

IPCC, 2021: Summary for Policymakers. In: Climate Change 2021: The Physical Science

Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press, pp. 3−32.

Johar, M., Johnston, D. W., Shields, M. A., Siminski, P., and Stavrunova, O. (2022). The economic impacts of direct natural disaster exposure. *Journal of Economic Behavior and Organization*, 196: 26-39.

Joshi, R., and Wooldridge., J. M. (2019). Correlated random effects models with endogenous explanatory variables and unbalanced panels. *Annals of Economic and Statistics*, 134: 243-268.

Lazo, J. K., Bostrom, A., Morss, R. E., Demuth, J. L., and Lazrus, H. (2015). Factors affecting hurricane evacuation intentions. *Risk Analysis*, 35(10): 1837-1857.

Lin, C.-C., Siebeneck, L. K., Lindell, M. K., Prater, C. S., Wu, H.-C., and Huang, S.-K. (2014). Evacuees' information sources and reentry decision making in the aftermath of Hurricane Ike. *Natural Hazards*, 70: 865-882.

Loebach, P., and Korinek, K. (2019). Disaster vulnerability, displacement, and infectious disease: Nicaragua and Hurricane Mitch. *Population and Environment*, 40: 434-455.

Mogstad, M., Torgovitsky, A., and Walters, C. R. (2021). The causal interpretation of two-stage least squares with multiple instrumental variables. *American Economic Review*, 111(11): 3663-3698.

Olken, B. A. (200). Do television and radio destroy social capital? Evidence from Indonesian villages. *American Economic Journal: Applied Economics*, 1(4): 1-33.

Peisakhin, L., and Rozenas, A. (2018). Electoral effects of biased media: Russian television in Ukraine. *American Journal of Political Science*, 62(3): 535-550.

Rivera, J. D. (2020). The impact of evacuating on short-term disaster recovery: A study of individuals affected by Hurricane Harvey living in Texas counties. *International Journal of Disaster Risk Reduction*, 44: 101424.

Sacerdote, B. (2012). When the Saints go marching out: long-term outcomes for student evacuees from Hurricane Katrina and Rita. *American Economic Journal: Applied Economics*, 4(1): 109-135.

Sadri, A. M., Ukkusuri, S. V., and Gladwin, H. (2017). The role of social networks and information sources on hurricane evacuation decision making. *Natural Hazards Review*, 18(3): 04017005.

Salgado-Gálvez, M. A. (2018). Estimating the lost economic production caused by internal displacement because of disasters. *International Journal of Disaster Risk Science*, 9: 496-506.

Shieh, J.-C., Chen, J.-S., and Lin, W.-I. (2013). Skip to permanence without transition? Policy-making in Post-Morakot reconstruction. *Taiwan: A Radical Quarterly in Social Studies*, 93: 49-86. (in Chinese)

Siebeneck, L. K., Lindell, M. K., Prater, C. S., Wu., H.-C., and Huang, S.-K. (2013). Evacuees' reentry concerns and experiences in the aftermath of Hurricane Ike. *Natural Hazards*, 65: 2267-2286.

Tanim, S. H., Wierbik, B. M., Reader, S., and Hu, Y. (2022). Predictors of hurricane evacuation decisions: A meta-analysis. *Journal of Environmental Psychology*, 79: 101742.

Tsai, S.-L., Tseng, M.-H., Deng, C.-Z., and Ochiai, C. (2022). Built environment characteristic of the permanent housing settlement after Typhoon Morakot. *Journal of Geographical Science*, 101: 55-84. (in Chinese)

United Nations Office for Disaster Risk Reduction (UNDRR) (2019). *Words into Action: Engaging for resilience in support of the Sendai Framework for Disaster Risk Reduction 2015-2030.* Geneva, Switzerland: UNDRR. Last Access: February, 8, 2024. Available at: https://www.undrr.org/sites/default/files/2023-03/58821_wiadisasterdisplacement190511webeng.pdf.

Verme, P., and Schuettler, K. (2021). The impact of forced displacement on host communities: A review of the empirical literature in economics. *Journal of Development Economics*, 150, 102606.

Vigdor, J. L. (2007). The Katrina effect: Was there a bright side to the evacuation of greater New Orleans?. *The B.E. Journal of Economic Analysis & Policy*, 7(1): 1-40.

Wang, C.-C., Chang, C.-S., Wang, Y.-W., Huang, C.-C., Wang, S.-C., Chen, Y.-S., Tsuboki, K., Huang, S.-Y., Chen, S.-H., Chuang, P.-Y., and Chiu, H. (2021). Evaluating quantitative precipitation forecasts using the 2.5 km CReSS Model for typhoons in Taiwan: an update through the 2015 season. *Atmosphere*, 12(11): 1501.

Waldman, M., Nicholson, S., Adilov, N., and Williams, J. (2008). Autism prevalence and precipitation rates in California, Oregon, and Washington counties. *Archives of Pediatrics and Adolescent Medicine*, 162(11): 1026-34.

White, S., Oates, S., and McAllister, I. (2005). Media effects and Russian elections, 1999–2000. *British Journal of Political Science*, 35(2): 191-208.

Wu, C.-C. (2013). Typhoon Morakot: Key findings from the journal TAO for improving prediction of extreme rains at landfall. Bulletin of the American Meteorological Society, February 2013: 155-160.

Yang, H.-H., Lee, H.-C., and Deng, C.-Z. (2018). Households' resources acquisition and life recovery under permanent housing policy of Typhoon Morakot disaster in Kaohsiung City. *Journal of City and Planning*, 45(4): 257-281. (in Chinese)

Yeh, T.-C., Kuo, H.-C., Lu, K.-C., Wang, S.-C., and Chen, Y.-L. (2010). Verification on the Typhoon Morakot track and rainfall forecast issued by the Central Weather Bureau. *Atmospheric Sciences*, 38(2): 85-98. (in Chinese)

Yore, R., and Walker, J. F. (2020). Early warning systems and evacuation: rare and

extreme versus frequent and small-scale tropical cyclones in the Philippines and Dominica. *Disasters*, 45(3): 691-716.

Appendix

Table A1. Split-sample Evacuation Effects: Income

	Returner		Nonreturner	
	Estimates	S.E.	Estimates	S.E.
First stage				
Admin	0.674 ***	0.071	0.107***	0.026
People	0.459 ***	0.106	0.097***	0.021
First stage F	46.45		11.63	
Evacuation	12,393.09	7,688.56	4,267.41	13,120.4
Pre_income	0.58***	0.11	0.59***	0.09
Pre_expense	0.25*	0.13	-0.01	0.01
Exp_eva	-6,148.15*	3,540.73	-2,535.05**	1,028.11
Exp_ty	-391.35	388.94	394.25	352.53
HHsize	-242.14	1,224.71	996.61***	300.33
Old	-1,099.32	1,584.66	-66.03	1,019.75
Youth	-200.20	1,047.07	-598.53	508.00
Jobnum	241.54	1,110.13	33.37	77.00
Age	63.97	58.59	151.44*	79.21
Male	-2,973.41	2,612.78	-296.26	1,544.10
Indigenous	-6,085.54	6795.51	2,448.97	2,093.06
Married	2,574.53	1,782.59	3,095.62***	1,084.22
Junior	10.80	2,864.78	2,661.02	2,310.75
Senior	4,273.24	3,404.75	5,224.90*	2,865.96
College_above	3,163.21	7,372.08	6,573.39	4,928.73
Farmer	-1,760.81	2,661.09	2,553.15	2,883.63
Manager	2,518.45	4,984.74	7,678.98**	3,774.42
Notech	2,518.52	2,001.64	5,389.76***	1,871.87
Pns	3,319.32	3,531.09	9,197.53***	2,466.55
Nonlbr	-915.53	3,066.87	3,768.13*	2,014.79
Die			-2,574.97*	1,375.15
Facilityloss	-82.79***	32.30	-12.04	12.72
Payforlive	0.09**	0.05	-0.01	0.02
Rainfall7	7.86	17.81	-4.27	4.15
Rainfall8	2.21	13.89	3.80	5.37
Rainfall9	-3.04	9.58	-1.84	2.86
Rainfall10	-39.83	40.31	-1.04	8.63
Constant	1,392.55	5,410.34	-14,252.00	11,836.8
P-value of over-identification F	0.442		0.523	
Number of obs.	157		716	

Note. Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. The S.E.s are clustered at township level. The coefficient of *Die* is not estimated due to lack of observation.

Table A2. Split-sample Evacuation Effects: Adjusted Income

	Returner		Nonreturner	
	Estimates	S.E.	Estimates	S.E.
First stage				
Admin	0.674 ***	0.071	0.107***	0.026
People	0.459 ***	0.106	0.097***	0.021
First stage F	46.45		11.63	
Evacuation	12,955.4	8,134.68	-1,956.69	12,554.1
Pre_income	0.57***	0.10	0.59***	0.10
Pre_expense	0.27**	0.13	-0.01**	0.01
Exp_eva	-7,414.50*	3,892.00	-3,475.00***	1,087.77
Exp_ty	-620.22	392.08	401.52	339.59
HHsize	-277.07	1,308.17	329.19	291.45
Old	-909.33	1,638.67	234.71	889.85
Youth	-97.97	1,084.62	-552.02	515.09
Jobnum	47.78	1,158.84	41.47	73.57
Age	47.03	63.89	155.33	75.65
Male	-2,107.83	2,429.85	-534.27	1,796.73
Indigenous	-5,844.65	7,376.71	2,626.11	2,069.30
Married	1,933.78	1,875.54	2,769.96***	997.87
Junior	-319.89	2,681.42	2,462.36	2,057.01
Senior	4,577.60	3,289.73	4,992.32*	2,859.78
College_above	4,179.29	7,680.39	5,272.02	4,956.61
Farmer	-1,808.36	2,762.93	3,175.58	2,878.06
Manager	1,601.38	5,399.87	7,223.29*	3,884.75
Notech	1,253.51	1,906.09	5,360.62***	1,685.61
Pns	2,699.40	3,756.31	9,254.52***	2,434.24
Nonlbr	-1,705.39	3,012.78	3,068.90	2,389.40
Die			-3,202.74**	1,334.00
Facilityloss	-85.61***	33.36	-13.13	13.35
Payforlive	0.05	0.04	-0.02	0.02
Rainfall7	7.92	18.45	-4.20	4.02
Rainfall8	1.30	14.21	3.08	5.23
Rainfall9	-2.61	10.00	0.79	2.96
Rainfall10	-36.72	40.89	-3.51	8.50
Constant	2,751.87	5,390.33	-10,249.6	11,536.2
P-value of over-identification F	0.509		0.667	
Number of obs.	157		716	

Note. Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. The S.E.s are robust S.E. The coefficient is of *Die* is not estimated due to lack of observation.

Table A3. Reduced Form for Full Sample

	Income		Adjusted income	
	Estimates	S.E.	Estimates	S.E.
Admin	952.07	1,328.85	370.86	1,360.35
People	1,482.81	2,007.53	421.19	1,958.40
Pre_income	0.60***	0.09	0.60***	0.09
Pre_expense	-0.01	0.01	-0.01	0.01
Exp_eva	-2,607.53***	954.06	-3,915.75***	1,036.98
Exp_ty	219.47	296.70	243.22	317.78
HHsize	839.94***	250.10	226.39	250.59
Old	-26.89	887.08	257.33	810.45
Youth	-472.17	462.28	-516.84	497.45
Jobnum	57.57	61.21	62.37	75.37
Age	134.34**	64.32	151.66**	66.36
Male	-522.60	1,426.03	-491.14	1,572.58
Indigenous	2,368.94	1,772.59	2,060.18	1,715.45
Married	2,856.52***	727.53	2,312.62***	743.84
Junior	2,363.48	1,673.78	2,362.05	1,644.83
Senior	4,718.86*	2,406.51	4,909.34**	2,396.84
College_above	5,579.91	4,363.66	5,586.75	4,396.67
Farmer	1,863.50	2,294.99	2,391.67	2,438.22
Manager	6,522.24**	3,045.60	6,386.42	3,177.93
Notech	4,939.93***	1,847.96	4,913.62***	1,748.85
Pns	8,101.18***	2,446.64	7,890.78***	2,616.51
Nonlbr	1,792.93	1,693.92	1,077.43	1,898.80
Die	-2,932.03***	806.74	-3,302.93***	874.03
Facilityloss	-12.15	12.04	-16.35	12.19
Payforlive	0.00	0.01	-0.02	0.02
Rainfall7	-0.80	4.46	-1.64	4.66
Rainfall8	1.11	4.61	1.51	4.85
Rainfall9	0.05	2.28	0.87	2.39
Rainfall10	-8.16	9.48	-9.83	11.02
Constant	-6,977.49	5,141.07	-8,336.20	5,280.08
Numbers of obs.	236			

Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. Mean VIF: 1.62 no collinearity issue.

Table A4. Reduced Form for Returners

	Income		Adjusted income	
	Estimates	S.E.	Estimates	S.E.
Admin	9,276.42	6,867.16	9,539.92	7,190.91
People	2,902.23	3,043.20	3,506.06	3,350.90
Pre_income	0.60***	0.09	0.59***	0.09
Pre_expense	0.23*	0.11	0.25**	0.11
Exp_eva	-2,887.14	2,501.70	-4,193.01	2,840.49
Exp_ty	-137.58	404.94	-352.69	414.79
HHsize	-1,321.48	1,416.00	-1,373.96	1,477.92
Old	-634.14	1,460.75	-441.73	1,557.14
Youth	246.13	1,013.10	346.56	1,072.58
Jobnum	1,053.99	1,147.32	868.85	1,184.16
Age	56.96	61.51	39.76	68.99
Male	-2,324.21	2,807.79	-1,355.35	2,549.41
Indigenous	-6,828.19	8,747.55	-6,430.20	9,297.47
Married	1,959.01	1,843.15	1,258.75	1,923.03
Junior	-757.64	3,066.36	-1,126.49	2,839.93
Senior	2,416.64	3,645.48	2,657.35	3,499.04
College_above	21.03	4,962.63	888.37	5,070.93
Farmer	-1,706.68	2,431.46	-1,767.13	2,521.26
Manager	1,492.64	5,599.55	629.22	6,293.81
Notech	3,754.95*	1,971.85	2,516.40	1,856.85
Pns	2,486.73	3,603.19	1,885.20	3,886.02
Nonlbr	-2,109.60	3,255.86	-3,030.09	3,577.10
Die	-27.47*	25.17	-28.07	26.54
Facilityloss	0.10	0.06	0.06	0.06
Payforlive	12.44	15.68	12.78	16.31
Rainfall7	2.97	15.20	2.26	15.58
Rainfall8	-5.21	11.20	-4.93	11.55
Rainfall9	-43.89	43.77	-41.67	44.56
Rainfall10	5,197.03	5,167.20	6,616.42	5,289.58

Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. Mean VIF: 1.62 no collinearity issue. The number of observations is 157.

Table A5. Reduced Form for Non-returners

	Income		Adjusted income	
	Estimates	S.E.	Estimates	S.E.
Admin	38.72	1,263.69	-492.42	1,171.61
People	1,268.63	2,442.85	393.52	2,446.79
Pre_income	0.59***	0.09	0.59***	0.10
Pre_expense	-0.01	0.01	-0.01*	0.01
Exp_eva	-2,480.63**	1,047.24	-3,362.65***	1,073.27
Exp_ty	369.81	356.52	442.15	367.55
HHsize	1,009.66***	277.43	308.70	286.38
Old	-29.82	1,096.96	280.72	954.41
Youth	-606.59	502.66	-537.59	520.92
Jobnum	45.02	60.16	37.10	75.34
Age	147.63*	85.92	158.06*	82.49
Male	-365.64	1,550.93	-473.05	1,727.08
Indigenous	2,661.97	2,048.19	2,628.84	2,077.05
Married	3,290.85***	915.64	2,665.15***	972.73
Junior	2,888.53	2,057.29	2,617.36	1,910.08
Senior	5,360.43*	2,849.29	5,113.63*	2,814.74
College_above	6,416.46	5,211.36	5,488.92	4,992.78
Farmer	2,703.48	2,723.06	3,123.14	2,727.62
Manager	7,153.88**	3,374.53	7,409.44**	3,427.01
Notech	5,358.61***	1,911.43	5,410.71***	1,786.52
Pns	9,293.15***	2,336.38	9,258.26***	2,378.54
Nonlbr	3,553.94	2,191.41	3,159.90	2,482.75
Die	-2,945.22***	763.34	-3,074.56***	808.11
Facilityloss	-11.48	12.03	-13.91	12.41
Payforlive	-0.01	0.02	-0.02	0.02
Rainfall7	-3.82	4.32	-4.39	4.39
Rainfall8	3.54	5.12	3.29	5.08
Rainfall9	-1.19	2.58	0.50	2.44
Rainfall10	-3.04	8.87	-3.37	9.47
Constant	-10,716.2*	6,374.66	-12,273.3*	6,372.57

Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. Mean VIF: 1.62 no collinearity issue. The number of observations is 716.

Table A6. LR Main Effect (SSIV)

	Income		Adjusted income	
	Estimates	S.E.	Estimates	S.E.
Reduced form				
SSIV	1,728.12 **	769.33		
First stage				
SSIV	-0.152 ***	0.016	-0.152***	0.016
First stage F	55.82		55.93	
Displacement	-11,275.2**	5,199.71	-11,753.69**	5,238.01
Pre_income	0.30***	0.03	0.30***	0.03
Pre_expense	0.00	0.01	0.00	0.01
Exp_evac	-712.78	1,041.15	-893.56	1,047.83
Exp_ty	-51.80	277.80	-41.03	283.85
HHsize	3,324.71***	451.80	3,115.78***	447.15
Old	-113.54	565.86	-125.98	573.99
Youth	-1,968.00***	478.33	-2,042.24***	488.32
Jobnum	629.98	468.62	599.73	458.02
Age	5.71	6.06	7.03	6.32
Male	-354.61	877.67	-334.19	880.18
Indigenous	1,934.68	1,350.75	1,945.08	1,364.62
Married	2,637.83***	962.15	2,589.41***	972.59
Junior	1,193.82	1,098.23	1,035.36	1,119.74
Senior	5,065.29***	1,426.96	4,974.33***	1,446.66
College_above	8,382.79**	3,342.31	8,112.17**	3,412.71
Farmer	1,117.85	1,168.48	1,341.09	1,191.82
Manager	9,152.96***	1,757.27	9,086.99***	1,772.23
Notech	5,995.52***	1,128.09	5,829.39***	1,145.38
Pns	8,148.30***	1,221.92	8,174.66***	1,227.21
Nonlbr	4,873.71***	1,867.38	4,451.56**	1,911.68
Die	-1,786.31***	683.87	-1,834.81***	682.46
Facilityloss	-2.94	8.21	-3.42	8.30
Payforlive	0.04**	0.02	0.04**	0.02
Rainfall7	2.10	4.09	1.57	4.09
Rainfall8	-4.50	4.03	-4.35	4.06
Rainfall9	-4.01	3.99	-4.23	4.01
Rainfall10	-7.54	7.43	-7.23	7.44
Period 2	7,807.66***	1,361.25	11,625.11***	1,355.94
Period 3	7,883.63***	1,634.72	12,019.10***	1,644.68
Period 4	10,604.40***	1,847.15	15,042.52***	1,855.88
Constant	4,651.27*	2,512.30	1,685.77	2,529.11

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

observations is 3,284.

Table A7. Reduced Form Estimation of the Displacement Effect

	Income		Adjusted income	
	Estimates	S.E.	Estimates	S.E.
SSIV	1,728.12**	769.33	1,803.58**	777.30
Pre_income	0.30***	0.03	0.30***	0.03
Pre_expense	-0.01	0.01	-0.01	0.01
Exp_evac	-1,682.25*	900.99	-1,901.87**	912.10
Exp_ty	85.65	266.66	102.06	274.32
HHsize	3,107.58***	436.06	2,889.06***	431.67
Old	33.26	549.31	28.09	558.39
Youth	-1,725.14***	454.20	-1,785.65***	464.79
Jobnum	645.20	465.60	616.19	455.54
Age	8.12	6.58	9.52	6.48
Male	-613.11	851.25	-602.15	855.08
Indigenous	-265.54	947.31	-357.16	961.09
Married	2,358.94***	910.66	2,291.76**	922.21
Junior	880.59	1,072.69	709.62	1,093.80
Senior	4,705.32***	1,397.65	4,595.82***	1,418.05
College_above	8,356.96***	3,242.70	8,066.96**	3,313.24
Farmer	1,769.77	1,100.12	2,020.92*	1,125.07
Manager	10,725.99***	1,604.70	10,736.07***	1,618.86
Notech	6,633.88***	1,072.41	6,503.97***	1,091.91
Pns	8,922.39***	1,132.72	8,985.36***	1,139.58
Nonlbr	5,234.74***	1,790.68	4,847.85***	1,829.19
Die	-2,274.38***	592.76	-2,344.76***	589.04
Facilityloss	-4.85	7.69	-5.41	7.77
Payforlive	0.02	0.02	0.02	0.02
Rainfall7	-1.64	4.05	-2.33	4.09
Rainfall8	-5.85	3.72	-5.76	3.76
Rainfall9	3.05	2.33	3.13	2.34
Rainfall10	-20.98**	9.26	-21.24**	9.32
Period 2	6,586.85***	1,207.04	10,355.40***	1,202.15
Period 3	4,775.54***	862.11	8,782.06***	884.68
Period 4	7,526.54***	1,052.75	11,838.17***	1,065.46
Constant	5,101.71**	2,540.15	2,154.30	2,558.65
Number of obs.	3,284			

Table A8. Full Estimation of the Displacement Effect (IV: Approved)

	Income		Adjusted income	
	Estimates	S.E.	Estimates	S.E.
First stage				
Approved	0.207 ***	0.041	0.207***	0.041
First stage F	25.64		25.64	
Refuced form				
Approved	-1,198.78	1,818.13	-1,373.63	1,819.18
Displacement	-5,797.28	8,924.91	-6,642.87	8,946.77
HHsize	2,574.94	501.95	2,341.65***	501.30
Old	-790.85	1,011.55	-745.91	1,022.74
Youth	-666.25	791.98	-556.13	797.86
Jobnum	3,019.30***	532.76	3,112.60***	527.09
Age	24.32*	14.41	24.50	15.88
Male	-3,284.97	4,767.44	-3,773.56	4,764.95
Indigenous	-4,118.68	4,841.11	-4,032.10	4,866.36
Married	1,944.18	1,640.23	2,236.00	1,661.49
Junior	-872.40	1,632.42	-1,124.39	1,665.98
Senior	-1,655.92	2,849.62	-1,581.05	2,891.65
College_above	1,564.44	5,738.87	1,836.22	5,808.91
Farmer	513.22	1,795.60	433.01	1,811.68
Manager	4,273.05*	2,387.43	4,019.57*	2,384.73
Notech	4,493.71**	1,772.95	4,354.95**	1,774.78
Pns	6,500.14***	1,737.89	6,289.59***	1,744.63
Nonlbr	645.08	3,178.33	-540.23	3,213.68
Period 3	-6,183.18***	1,577.79	-5,517.06***	1,579.09
Period 4	-1,971.48	1,521.06	-666.25	1,522.70
Constant	-5,797.28	8,924.91	-6,642.87	8,946.77
Number of obs.	3,419			

Significance level: ***: p-value≤0.01; **: p-value≤0.05; *: p-value≤0.1. The sample periods included are period 2 to 4. The reported results are estimated by FEIV method.