Internal Labor Migration as a Shock Coping Strategy: Evidence from a Typhoon*

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Abstract

We analyze how internal labor migration facilitates shock coping in rural economies. Employing high precision satellite data, we identify objective variations in the inundations generated by a catastrophic typhoon in Vietnam and match them with household panel data before and after the shock. We find that, following a massive drop in income, households cope mainly through labor migration to urban areas. Households with settled migrants ex-ante receive more remittances. Non-migrant households react by sending new members away who then remit similar amounts than established migrants. This mechanism is most effective with long-distance migration, while local networks fail to provide insurance.

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Keywords: Risk Sharing; Internal Migration; Natural Disasters; Vietnam.

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"The prudent embark when the sea is calm – the rash when it's stormy."

New Zealand Proverb

We study the impact of a disastrous typhoon on poor rural households in Central Vietnam and the role that internal labor migration - both before and after this shock – plays for recovery.[1] Following a large adverse productivity shock, we identify internal remittances from long-distance labor migrants as the main shock coping strategy. Households receive remittances both from both ex-ante established migrant networks and new members sent away ex-post. While most existing evidence focuses on international migration, internal migration remains understudied in this context, which stands in stark contrast to its empirical scale, with the latter often being of one or two orders of magnitude larger than the former.[2] Our results have important implications for rural-to-urban migration dynamics given that climate change will likely increase the magnitude of extreme weather events thereby threatening agricultural livelihoods in risk-prone areas (Hijioka et al. 2014).

We draw on the exogenous variation in shock exposure generated by the landfall of Typhoon Ketsana in Vietnam during the 2009 monsoon season. Although not particularly strong in terms of wind speed, the storm entered the records as the most devastating one in Vietnam since 1990 because it triggered torrential rain and huge flooding, which heavily affected crop production in rural areas. The setting combined with a unique household panel dataset allows us to identify the causal effects of a strong aggregate income shock in migrant origin areas on internal migration and remittances.

Measuring the impacts of natural disasters is the subject of a large literature, but one which has traditionally relied on respondents' subjective self-reports of what they consider an adverse shock and its degree of intensity.[3] To reconstruct the typhoon's impact, we follow a novel approach and identify inundated areas using highly precise and objective geophysical satellite data (Dell et al. 2014), before, during, and after the passing of Ketsana. Another key feature of our study is that we distinguish the roles of ex-ante and ex-post migration strategies in household

[1]We consider ex-ante labor migration as a risk-sharing arrangement (Stark 1980), which allows households to smooth consumption through internal remittances from existing migrant networks. We differentiate it from ex-post migration with household members sent away to smooth income in the aftermath of a shock.

[2]For evidence on international migration, see, for example, Hanson (2009), Clemens (n.d.), for internal migration de Brauw and Harigaya (2007), De Weerdt and Hirvonen (2013), Bryan et al. (2014) and Jack and Suri (2014). Based on the 2009 census, the number of internal migrants in Vietnam between 2004 and 2009 was conservatively estimated at 6.6 million, compared to only 300,000 international migrants (Abella and Ducanes 2011).

[3]See, for example, Alvi and Dendir (2011) or Morris et al. (2002).

recovery, an important difference, which has largely been neglected in migration research thus far. Our paper is most closely related to a small number of (quasi-)experimental studies about the effects of adverse shocks in origin areas on migration and remittances outcomes.[4]

Our results indicate a massive drop in income induced by Typhoon Ketsana. The average household in our sample experiences a 10% drop in total annual income per capita, a number that reaches 50% for the most affected households. For a drop in total income per capita of around 700 USD, two thirds come from losses in crop income. The income shock translates into total consumption losses of 100 USD, with the decline in food consumption being the main driver. Among a multitude of potential shock coping mechanisms, we find that households cope mainly through long-distance internal labor migration to urban areas. Households with ex-ante settled migrants receive, on average, around 250 USD from these labor migrants in response to the shock. Around 17% of non-migrant households react by sending members away for work, who then earn less than established ones, but send remittances of similar magnitude.

The main contribution of our study is to highlight the mechanisms used by rural households to smooth income and consumption in the context of a large aggregate shock.[5] The adverse impacts of aggregate natural disasters are generally well documented both at the macro- and micro-level.[6] In the face of aggregate shocks, local risk-sharing arrangements as well as income diversification within the household tend to fail because of high spatial correlation (Fafchamps et al. 1998, Dercon 2002, Zylberberg 2014). We show that, in such cases, a viable coping strategy is to rely on insurance networks with long-distance migrants.

Risk-sharing through remittances was first described in the context of the New Economics of Labour Migration (NELM) literature (Stark and Bloom 1985), which conceives of migration as a collective household strategy to diversify income sources

[4]However, most of these studies focus on international migration and the ex-post shock coping mechanism of remittances exclusively. For an overview, see McKenzie and Yang (n.d.). A related literature also investigates similar effects for changes in migrant destination conditions (Yang 2006, 2008b, McKenzie et al. 2014).

[5]An overview of the literature on risk management and shock coping in the context of developing countries is provided by Dercon (2002) and Townsend (1995). See, for example, Jacoby and Skoufias (1998), Kochar (1999) on the diversification of income sources, precautionary financial savings Paxson (1992), asset depletion Rosenzweig and Wolpin (1993), Fafchamps et al. (1998), Kazianga and Udry (2006), borrowing from formal financial institutions Eswaran and Kotwal (1989), Morduch (1995) or informal sources Udry (1994), Fafchamps and Lund (2003). Publicly provided or commercial insurance solutions can also help smoothing consumption Deryugina (2013), but are currently not available in Vietnam on a universal scale.

[6]See Dell et al. (2014) for an overview and Thomas et al. (2010), Arouri et al. (2015) for evidence on Vietnam.

and loosen financial constraints through remittances.[7] There is a large literature investigating the insurance role of remittances, both in the context of internal (Lucas and Stark 1985, Rosenzweig and Stark 1989) and international migration (de la Brière et al. 2002, Clarke and Wallsten 2003, Gubert 2002).[8] Relying mainly on self-reported household data for the identification of income shocks, most of these studies find evidence in favor of the insurance hypothesis of remittances. More recently, a growing (quasi-)experimental literature has emerged, studying the effects of aggregate income shocks at the origin on remittances and relying on exogenous variations in shock exposure. Using household panel data from the Philippines, Yang and Choi (2007) and Yang (2008a) show that economic losses caused by rainfall shocks and hurricanes lead to increases in remittances at the household and national level respectively. Our study contributes directly to the literature by showing that, in the aftermath of Typhoon Ketsana, internal remittances from long-distance labor migrants is the most important coping mechanism and insures incurred losses at the origin to around 20% on average. In addition, we show that short-distance insurance networks are ineffective in the face of Ketsana: remittances from local labor migrants do not respond and the shock reduces the probability of sending a migrant to a nearby location, which illustrates that these work opportunities become relatively less attractive.[9]

Moreover, our results allow us to go beyond the test of the insurance hypothesis by differentiating remittance responses between ex-ante and ex-post established migrant networks. In other words, we make use of this natural experiment for comparing the effectiveness of households' previous income diversification efforts through past out-migration from the rural areas with out-migration in the aftermath of the shock and subsequent remittances. In this sense, we also relate to the strand of the migration literature which investigates natural disasters as a cause of rural out-migration.[10] Contrary to the remittances as insurance literature, there seems to be no clear consensus whether aggregate disasters lead to internal migration in developing countries. For example, while some studies find higher internal migration

[7]In contrast to classic theories that focus mainly on individual decision making based on rural-urban income differentials (Harris and Todaro 1970), the NELM literature emphasizes agricultural households' risk aversion as a major cause of rural-to-urban migration in developing countries

[8]For an overview of the literature on the economics of remittances, see Rapoport and Docquier (2006) for theoretical considerations and Yang (2011) for a review of evidence.

[9]Blumenstock and Fafchamps (2014) study internal remittances in the Rwanda and find that mobile phone transfers are used to insure affected households and that these transfers increase with the geographical distance between individuals. Molina Millán (2014) finds that young migrants provide insurance to their households of origin affected by drought shocks and that the level of insurance increases when migrants and households are exposed to less correlated rainfall shocks.

[10]Belasen and Polachek (2013) provide a useful review of this literature.

incidence following natural disasters (Gray and Mueller 2012b, Badiani and Safir 2008, Beine and Parsons 2015), others find ambiguous or negative effects (Gray and Mueller 2012a, Tse 2011). These contradictory effects may stem from the fact that an aggregate shock can increase the incentive for labor migration through the loss of income generating opportunities at the local level, while at the same time increasing the financial barriers due to a loss of household assets needed to finance migration upfront (Phan and Coxhead 2010). In our study, we find that Typhoon Ketsana increases the probability of having a long-distance labor migrant by around 17% for households without pre-established migrants. Conditional on having a long-distance labor migrant (ex-ante or -post), internal remittances insure incurred losses at the origin to around 40%.

In the last part of this paper, we describe the migration outcomes for ex-ante established and ex-post sent migrants. We find that, in general, migrants find jobs extremely quickly and earn a wage far above the rural standards. The findings are in line with the rural-urban income differential hypothesis postulated by classic migration theories (Harris and Todaro 1970).[11] Compared to established migrants, newly-sent migrants from affected villages search for employment for a shorter period, and with less recourse to job agencies. They also favor migration to the two industrial centers of Vietnam: Hanoi and Ho Chi Minh City. We interpret this observation as a type of *hastiness* to generate much needed income as quickly as possible in order to compensate losses at the origin. Accordingly, despite similar observed intrinsic characteristics (e.g. age, sex, education) to established migrants, newly-sent migrants earn around 25% less. These results relate to Bryan et al. (2014) who provide experimental evidence on the effects of seasonal migration in rural Bangladesh. Randomly assigning a cash transfer to households affected by seasonal famine, they find that the treatment induces 22% of households to send a new migrant. In line with our findings, treated and newly-sent migrants earn less relative to the established ones, which is attributed to a lack of experience.

The remainder of the paper is structured as follows. Section 1 briefly provides the background for our impact evaluation, namely the patterns of typhoon impact in rural Vietnam, the data, the empirical strategy and some descriptive statistics. Section 2 presents the main results, and we briefly conclude in Section 3.

[11] Classic migration theories describe cities as being constituted of a modern urban sector and an unskilled traditional urban sector (e.g. construction) absorbing the excess labor supply. Urban migrants start in the unskilled sector before transferring to the modern sector (Todaro 1980, Cole and Sanders 1985). Along these lines, we find that excess labor supply, i.e. our newly-sent migrants, end up more often in unskilled occupations than established migrants

1 Background and Data

1.1 Typhoon Ketsana

Vietnam is regularly hit by tropical storms forming in the West Pacific basin: between one and five of them are recorded every season between June and November. The geographical range of risk-prone areas in Vietnam extends roughly between the latitudes 12^o and 22^o North and within 150 kilometers inland from the coast. Very few of the tropical storms are sufficiently strong to be officially classified as typhoons. On average, the typical district along the risk-prone areas of Vietnam experiences one tropical storm per year, but only one typhoon of Category 2 or higher every 15 years, which makes the latter events relatively rare and unexpected.[12]

We focus on Typhoon Ketsana, which entered the records as the most devastating storm in Vietnam since 1990 (Guha-Sapir et al. 2015). On the 29th of September 2009, after having brought severe destruction to the Philippines, Ketsana made landfall approximately 60 km south of the city of Da Nang in Central Vietnam and directly affected 14 surrounding provinces. With wind gusts reaching sustained speeds of around 150 km/h at some locations (Category 2), Ketsana did not belong to the strongest typhoon category in terms of wind speed, but it brought torrential rainfalls over two days and massive flooding. In Thua Thien Hue (herein after referred to as Hue), one of our survey provinces, the daily precipitation on September 29th was larger than the average monthly precipitation for this time of the year, and resulting flood levels were unprecedented (Nguyen et al. 2013).

According to official estimates, Ketsana affected 2.5m people in Vietnam, killed 182 of them, and caused direct capital losses of approximately 1% of GDP (Guha-Sapir et al. 2015).[13] Importantly, interventions of government authorities, NGOs, and public organizations could neither prevent nor substantially alleviate the impact of the typhoon.[14]

[12] The Saffir-Simpson Hurricane Scale classifies tropical storms into five categories by their sustained wind speed. To be classified as a typhoon, a tropical storm must have maximum sustained winds of at least 119 km/h (Category 1). The highest classification in the scale, Category 5, is reserved for storms with winds exceeding 251 km/h. Between 2000 and 2010, only three other typhoons of Category 2 or higher made landfall in Vietnam, each affecting different provinces.

[13] In our sample of rural households, which was located closer to the typhoon than the average Vietnamese household, we estimate *indirect* losses to be 4% of household income.

[14] Disaster prevention efforts were initiated on the 27th of September by the Central Committee for Flood and Storm Control (CCFSC), which also coordinated international donor agencies' relief actions. On the morning of the 28th of September, 24 hours before the typhoon made landfall in Vietnam, the Vietnamese Prime Minister issued an urgent telegraph to all ministries in potentially affected provinces, commanding the evacuation of the populations most at risk. However, by the time the typhoon made landfall, far less households were effectively evacuated than planned. Local army forces were also deployed to help farmers save their crops, but actions could not be realized in time before landfall. In our household data, we find no precautionary harvest activities before the

1.2 Treatment

Due to the different weather disasters associated with the passing of a typhoon (e.g. wind speed, rainfall, flooding, or landslides) the construction of a uniform exposure measure is non-trivial. Here, we choose to account for the most important source of destruction related to this event – local flooding. In order to capture the extent to which villages were affected by the typhoon, we propose a direct measure of inundation based on the analysis of satellite images and an indirect measure, i.e. the intensity of rainfall, which we use as a robustness check. In what follows, we describe the construction of both measures.

Local inundation The dominant economic activity in our surveyed regions of Vietnam is agriculture, especially paddy cultivation. Gnerally, the extent of crop damage due to flooding depends on several factors: the degree of submergence (i.e. excess depth of water), the temperature, the plant growth stage and height, whether the roots are usually under water, etc. While most crops already suffer severe damages through waterlogged soil, even for wetland species like paddy, floods causing complete submergence for sustained periods of time can be catastrophic (Bailey-Serres and Colmer 2014). In what follows, we describe how we proxy the presence of excess depth of water at the surface in the aftermath of the catastrophe, and how we control for normal submergence in wetland paddy fields.

In order to obtain an indicator of floodings caused by Typhoon Ketsana, we proceed as follows. First, we collect the two daily satellite images of Vietnam recorded by NASA's Moderate Resolution Imaging Spectroradiometer (MODIS)[15] for a window of 15 days (from the 26th of September to the 10th of October), and treat them such as to extract a daily measure of ground water coverage in the neighborhood of each village with 250m precision. We then deduce how much excess water there was in the aftermath of Typhoon Ketsana compared to normal times (i.e. before and one week after the event took place). The left panel (a) of Figure 1 displays one such satellite image with true color composites for South Indochina (i.e. parts of Vietnam, Laos, Cambodia, and Thailand) on the 6th of October 2009, about a week after the passing of Ketsana. The right panel (b) uses a different color band visualization, i.e. the Normalized Difference Vegetation Index (NDVI), which is commonly used in remote sensing programs to quantify vegetation or ground water

disaster's onset and only negligible disaster relief activities ex-post. We estimate cash and in-kind transfers to be small and not correlated with real losses.

[15] MODIS is a key instrument aboard two NASA satellites Terra and Aqua, which provide daily images of different zones of the globe with up to 250m precision. The data can be publicly accessed at: http://earthdata.nasa.gov/data/near-real-time-data/rapid-response/modis-subsets.

coverage in a given location.

Figure 2 displays an NDVI before and after comparison of the satellite imagery for selected areas in our survey provinces. The left panel depicts the index one week before the landfall of Ketsana in selected areas of Ha Tinh (picture (a)) and Hue province (c), with blue colors indicating ground water coverage. The right panel shows the exact same details six days after landfall. Comparing both panels, one can clearly identify a substantial extension of ground water coverage in both provinces, with the coastal areas of Hue being almost completely inundated. While large contiguous areas of water coverage can be identified easily by visual inspection, smaller local inundations, which are spatially scattered around our villages are not directly visible and need to be filtered from these images.[16]

The bottom panel (c) of Figure 1 is obtained by applying the same filter as Sakamoto et al. (2007) and depicts ground water coverage in blue colors for each pixel of 250m solution. We rely on this filter because we believe it is the one best suited for the specific application to Vietnamese agriculture as it is designed to detect inundations with peak water levels above 1 meter in the Mekong Delta region. There are two concerns with this approach. First, while our measure is targeted to capture business disruption in agricultural activities, other income activities may also be affected and the filter imperfectly captures their exposure. Second, even for agriculture or aquaculture, there may exist a residual measurement error, and we cannot rule out completely that some of the pixels that we identify as being inundated are normally-irrigated paddy fields.

Based on the treated NDVI images, our data provides two distinct daily observations of water turbidity, which we average to derive a daily estimate of ground water coverage for each pixel. For each surveyed village of our study and each day of the covered period, we then compute the percentage of pixels inundated in a radius of one, two, five, and ten kilometers around the village. Given the spatial resolution of 250m, there are approximately 1,250 pixels and thus the same number of independent observations of ground water coverage in a radius of five kilometers. Assuming that agricultural activities are randomly allocated in the village neighborhood, our measure corresponds to the daily probability of a field being submerged by water. Figure 3 displays the average share of flooded areas for selected intervals *before* (26th to 28th of September 2009), during *landfall* (29th and 30th of September), in the *aftermath* (1st to 5th of October), and long *after passing* of Ketsana (6th to 10th of October). It shows that 12% of the median village is inundated between the 1st and

[16] There are different methods to identify water turbidity from the NDVI index, see for example, Rogers and Kearney (2004) and Sakamoto et al. (2007).

the 5th of October. This number rises up to 77% for the most affected village. In contrast, only 1% of the median village is still under water between one week and ten days after the catastrophe.[17]

Our preferred treatment indicator is constructed as the percentage of area inundated within a radius of five kilometers around village v in the *aftermath* (i.e. between the 1st and 5th of October).[18] We exclude the two days during *landfall* of the typhoon because the remote sensing measurement error is large in the presence of heavy cloud coverage. In contrast, the cloud coverage over our survey provinces in the *aftermath* is relatively low. Relying on this treatment definition allows us to capture the number of days during which fields are inundated while reducing the noise induced by potential remote sensing measurement errors. Assuming a random allocation of agricultural activities around the village, our treatment corresponds to the expected share of days during which a field has been inundated in the aftermath of Typhoon Ketsana. Figure 4 displays the geographic distribution of our treatment indicator T_v at the commune level, i.e. the mean of two distinct village observations within each cluster. Note that our empirical strategy relies on within-province variation in the treatment, rather than variation across provinces. In a similar fashion, we also define a measure of inundation during normal periods. We define the *propensity* P_v as the percentage of area submerged within a radius of five kilometers around the villages *before* and *after* the passing of Ketsana.

One concern is that our treatment may be related to some local geographic characteristics, which may also influence agricultural activities in normal times. In this regard, we collect a range of measures for village topography (e.g. being located in a coastal area, mountains, plains, etc.) and we also construct an alternative treatment, directly based on rainfall, which is described next.

Precipitation In addition to the observation of local inundation with a 250m-precision, we use daily rainfall estimates between the 26th of September and the 7th of October 2009 as a robustness check.[19] Based upon this data, we construct

[17]The very high aftermath measures illustrate the magnitude of the flood shock, and the very low measures between the 6th and the 10th of October indicate that our treatment does not systematically include normally inundated areas such as wetland paddy fields or shrimp farms as being submerged in water.

[18]We use the five kilometer radius because the data on crop production in 2008 indicates that 95% of farming plots are located within a distance of five kilometers around the households of each survey village. Our results are, however, robust to using alternative radiuses.

[19]We use re-analysis data provided by the National Oceanic and Atmospheric Administration's (NOAA) Rainfall Estimation Algorithm Version 2 (RFE 2.0), which combines rain gauge measurements and different sources of satellite data. This product provides daily precipitation estimates for all years covered by the household survey, recorded at a resolution of 0.1 degrees (approximately 11 kilometers at the equator) and can be publicly accessed at

the rainfall R_v during *landfall*. As with the inundation treatment, we construct a measure P_v^r for the average daily rainfall *before* landfall and *after* the passing, so as to capture variations across villages in rainfall during normal monsoon days. We repeat this exercise during the same period for the preceding years 2001 to 2008. Figure 5 displays the excess rainfall $R_v - P_v^r$ for the three survey provinces in our analysis. Compared to our inundation-based treatment (Figure 4), the precision is much lower and we lose considerable variation within districts. Nevertheless, the advantages of this measure are that it correlates little with each village-specific topography and captures part of the immediate impact during *landfall* that we miss with our satellite images due to cloud coverage.

Finally, both the inundation and rainfall treatment indicators are negatively correlated with the usual precipitations in the same period (computed between 2001 and 2008). Our treated villages are not particularly used to heavy precipitations. More importantly, the magnitude of the shock in the most affected villages would be unprecedented for *any* village. Indeed, upon landfall, the average *daily* rainfall accumulation in our sample was higher than the *monthly* historical rainfall average (1900-2009) in Vietnam in September (271mm). In the most affected villages, rainfall accumulation during the two days exceeded the average monthly rainfall accumulation by three standard deviations.

1.3 Household data

Our empirical analysis draws on a unique multi-topic panel dataset collected within the framework of the project "Vulnerability to Poverty in Southeast Asia". The project was carried out as a panel survey in three waves (2007, 2008, and 2010) and includes about 2,200 households in 110 communes with two villages each, located in the rural provinces of Ha Tinh, Hue, and Dak Lak.[20] Ha Tinh and Hue province rank in the lowest income quintiles in the country with their population predominantly engaging in small-scale agriculture and limited self- and off-farm employment.

While migration is a frequent phenomenon in these provinces,[21] complete attrition in the panel is relatively low with rates around two to three percent per wave. Accordingly, we are left with 2,148 household observations in 2008. For our main empirical analysis, we provide estimations including the full and a balanced version of the sample including only households interviewed in all waves to understand the role of attrition. Importantly, in addition to being small, attrition is not correlated

ftp://ftp.cpc.ncep.noaa.gov/fews/S.Asia/data.

[20] See Hardeweg et al. (2007) for further details on the sampling procedure.

[21] For a general overview of internal migration patterns in Vietnam, see de Brauw and Harigaya (2007).

with our treatment.

Table 1 provides summary statistics for the full sample and by provinces for the pre-disaster wave 2008. The average household in our study provinces has 4.4 permanent members (excluding migrants) and 1.2 working-age male members (between 16 and 59 years). Two thirds report farming as their main occupation, and the share of agricultural income in total income is relatively high at around 50 percent on average (75% for the median household).[22] Other income components constitute earnings from self-employment (15% of total income), off-farm labor earnings (17%), and formal transfers from government institutions including insurance payments (11%). With a total income of 1,154 USD (PPP) per capita the sample households are significantly poorer than the average national household with 2,890 USD (PPP) per capita in 2008. This is due to the sample selection, which targeted rural provinces away from the relatively richer urban centers of Hanoi and Ho Chi Minh City. Our households report relatively low monetary savings on average (70 USD per capita), and most of them report zero savings. In contrast, households have a relatively high stock of outstanding loans (730 USD per capita), which are predominantly mortgages from formal sources such as public and commercial banks. Their consumption patterns are those of poor rural households: 50% of total consumption goes to food expenditure while 37% is spent on non-food items such as cloths, personal care supplies, and fuels. Spending on education and health services is of lower magnitude (10% of total consumption).

38% of our sample households have at least one internal migrant. Thereof, 25% have at least one *labor* migrant and 21% of those go to long-distance destinations (i.e. to another district or province relative to their respective household of origin).[23] Households at the origin maintain strong financial ties with their migrants. In 2008, migrant households received 116 USD per capita from labor migrants while sending out 36 USD per capita to them, which implies positive net remittances of 80 USD per capita per year. Labor migrants tend to target urban areas as destinations, particularly the big industrial centers of Ho Chi Minh City in the South and Hanoi in the North in order to look for off-farm employment opportunities.

There are some important differences between provinces that are worth mention-

[22] We define total income as income from domestic sources (such as agriculture or self-employment) including government transfers (such as pensions) net of any private transfers, i.e. excluding remittances.

[23] We classify a household member as an internal migrant if, within the 12 months reference period of each survey, the person was at least 16 years of age and was declared to belong to the household, but spent more than half of the time (at least 180 days) away at another location inside Vietnam and did not commute. We define labor migrants as migrants for whom the household's respondent declared that the person left because of a “job opportunity” or “job search”.

ing. Ha Tinh province (column 2) is the Northernmost province in our sample with relatively low temperatures during the winter months. Therefore, paddy cultivation predominantly follows a one season pattern and takes place during the summer months from April to October only. Hence, agricultural income during the winter season is relatively low. This stands in contrast to the provinces further in the South where two cropping cycles per year are standard and agricultural incomes during the winter are significant. Internal migration incidence in Ha Tinh is high with 49% for all migrants and 31% for long-distance labor migration, and families rely heavily on remittances. Net remittances from these networks are also the highest among our sample with 250 USD and 120 USD respectively. Despite being the poorest province of our sample, Hue's economy (column 3) is more diversified than Ha Tinh's with income from labor and self-employment over total income being higher. Migration is less frequent (22% of households with long-distance labor migrants). In contrast to the other two provinces, Dak Lak (column 4) is located in Vietnam's central highlands and is land-locked. Due to Dak Lak's climatic conditions, agriculture plays a major role with many cash crops such as coffee, fruit, and vegetables being grown on a large scale. Thanks to these favorable conditions Dak Lak is the richest province in our sample with an average income per capita of 1,552 USD. Agricultural activities contribute to almost 75% of the total income, and migration plays a minor role in Dak Lak.

1.4 Empirical strategy

To estimate the impact of Typhoon Ketsana on a broad range of socio-economic outcomes, we use a difference-in-difference approach and identify the household response from variations along the treatment between the pre-treatment period (2008) and the post-treatment one (2010).

Our treatment may be correlated with some omitted variables, e.g. geographic characteristics, and villages that differ on those dimensions may follow different trends. In the benchmark specification, we control for province/wave fixed effects and allow villages with different inundated areas in normal periods P_v to have different trends (in robustness checks, we also allow villages with (i) different topography, (ii) different long-term exposure to typhoons, and (iii) different average rainfall to have different trends). We thus identify our effect on variations over time for villages of the same province and with the same level of surface water coverage during normal times.

We estimate the following baseline equation:

$$Y_{hvpt} = \beta_0 + \beta_1 T_v \times \mathbb{1}_{t=2010} + \beta_2 T_v + \beta_3 P_v \times \mathbb{1}_{t=2010} + \beta_4 P_v + \gamma X_{ht} + \delta_{pt} + \varepsilon_{hvpt}, \quad (1)$$

where h indexes the household, v stands for village, p for province, and t indexes time (t=2008 or 2010). Y_{hvpt}, our dependent variable, will be either migration incidence, remittances, or income/consumption depending on the specification. T_v is the exposure to inundation in a radius of 5 kilometers around our survey villages in the aftermath of Typhoon Ketsana. Propensity P_v is the water coverage within the same radius during normal times. The vector X includes time-varying socio-demographic characteristics of the household, such as the household composition (i.e. number of prime-age males, females, children, and elderly household members) and the age and gender of the head. δ_{pt} is a set of province-specific wave fixed effects to account for changes in living conditions over time in each province. ε_{hvpt} is the error term with standard errors clustered at the commune level, given that there exists some spatial correlation in our treatment.

We estimate three different specifications of this equation. First, we estimate (1) over the sample of all households. Second, we estimate it for the sample of households that are interviewed in all waves. Third, we estimate a panel regression on all households:

$$Y_{hvpt} = \beta_0 + \beta_1 T_v \times \mathbb{1}_{t=2010} + \beta_2 P_v \times \mathbb{1}_{t=2010} + \alpha_h + \gamma X_{ht} + \delta_{pt} + \varepsilon_{hvpt},$$

in which α_h are household fixed effects capturing time-invariant household unobservable characteristics.

To summarize, we are conducting a difference-in-difference analysis comparing affected and unaffected villages with similar propensities to be affected, before and after the shock. With the panel specification, we fully control for observed and unobserved time-invariant factors. We include ground water coverage before and one week after as a proxy for normal periods in all specifications. Our treatment is derived from an unpredictable and random event – a typhoon hitting particular locations in Vietnam. In order to test that villages exposed to different levels of treatment have parallel trends ex-ante, we run a placebo specification between wave 1 and 2, i.e. between May 2007 and May 2008. We replicate our benchmark strategy as if the typhoon hit during the 2007 monsoon season, two years before the actual occurrence:

$$Y_{hvpt} = \beta_0 + \beta_1 T_v \times \mathbb{1}_{t=2008} + \beta_2 P_v \times \mathbb{1}_{t=2008} + \gamma X_{ht} + \delta_{pt} + \alpha_h + \varepsilon_{hvpt}. \quad (2)$$

Note that this specification is a direct test for the presence of pre-treatment differential trends.[24]

There may remain some concerns that our treatment is not fully exogenous because some unobserved geographic characteristics may explain the exceptional floods in some areas. For instance, soils may differ in their capacity to absorb water and these differences that reflect natural advantages or technological disparities are imperfectly captured by P_v. To better isolate pure exogenous variations in the exposure to the typhoon, we first add topographic controls interacted with wave fixed effects to capture potential heterogeneity in trends for coastal villages or villages close to a river. Second, we use the alternative precipitation treatment R_v as a substitute for T_v and estimate the following two-stage panel Instrumental-Variable specification:

$$\begin{cases} T_{vt} = b_0 + b_1 R_{vt} + b_2 P_{vt} + b_3 P^r_{vt} + cX_{ht} + d_{pt} + a_h + e_{hvpt} \\ Y_{hvpt} = \beta_0 + \beta_1 \widehat{T_{vt}} + \beta_2 P_{vt} + \beta_3 P^r_{vt} + \gamma X_{ht} + \delta_{pt} + \alpha_h + \varepsilon_{hvpt} \end{cases}, \tag{3}$$

in which the variables $\{V_{vt}\}_{V=T,R,P,P^r}$ denote the interactions $\{V_v \times \mathbb{1}_{t=2010}\}_{V=T,R,P,P^r}$.

Compared to specification (1), here we only use the variations in flooding T_v implied by rainfall R_v once controlled for normal conditions P_v, P^r_v. One advantage of such a specification (or the reduced form specification in which rainfall R_v is the treatment) is that it excludes differences in soil absorption conditions (whether natural or human-made) from our identification. There is, however, one important drawback. The resolution for the alternative treatment R_v is poor compared to the treatment T_v, and when we run comparisons between the two indicators (not reported), only our preferred treatment T_v keeps its predictive power. For these reasons, our preferred specification is specification (1) with treatment T_v and we use specifications with the rainfall measure only as a robustness check.

2 Results

This section is organized as follows. First, we analyze how our treatment – excess inundation due to Ketsana – affects income and how households smooth consump-

[24] Since we rely on a difference-in-difference specification, we do not need the sample of treated villages to be the same as spared villages in 2008. However, in order to interpret our coefficients, it is useful to perform a simple mean comparison between treated and untreated areas before the occurrence of the shock (i.e. a balance test): $Y_{hvpt} = \beta_0 + \beta_1 T_v + \beta_2 P_v + \gamma X_{ht} + \delta_p + \varepsilon_{hvpt}, \quad t = 2008$. As can be seen in Table A5, treated villages are richer than the average village in the province, one explanation being that they tend to be located on plains that are more suitable for agriculture. We also find some differences in the means of labor migration incidence, with treated villages exhibiting slightly higher migration rates. There are, however, no systematic differences in remittance patterns. Naturally, when we repeat the comparison exercise in 2010, the two groups diverge markedly along this dimension.

tion through internal remittances received from labor migrants. Second, we focus on household migration strategies. In particular, we assess whether additional remittances received by affected households come from already-established migrants (*ex-ante*) or newly-sent members (*ex-post*). We then provide some descriptive evidence on the differences between ex-ante and ex-post labor migrant performance in terms of job market outcomes.

For all specifications but the placebo checks, we restrict our sample to the 2008 (ex-ante) and 2010 (ex-post) household observations. Since the 2010 survey defined the reference period between May 2009 and April 2010, our estimates capture short-term effects up to 8 months after the shock. All monetary variables are reported in USD (PPP) per capita terms, i.e. normalized by the number of permanent household members (excluding absent migrant members). For the sake of simplicity, we report all coefficients for a theoretical change in the dependent variable due to a full inundation exposure (100% area flooded) compared to none (0%). However, as we are applying a continuous treatment indicator which, in practice, ranges between 0 and .77, one can also interpret our estimates as follows: multiplying our coefficients by .77 (resp. .2) gives the treatment impact between the most and least affected households (resp. of one additional standard deviation). All estimations below are reported in three different specifications: In the first column, we present equation (1) estimated with all households. In the second column, we restrict the sample to households that are interviewed in all waves. In the third column, we report the result of the panel regression on all households.

2.1 Income shocks and shock coping instruments

In order to study how the treatment affects the budget constraint of households, we first analyze how income responds and show which activities are most disrupted by the shock. We then assess the extent to which households manage to smooth consumption. We finally describe which consumption-smoothing instruments mainly respond to the treatment.

A way to understand this exercise is to write down the budget constraint of the household. In period t, the household receives a revenue $y_t = \sum_a y_t^a$ from its different activities indexed by a, receives transfers $\tau_t = \sum_s \tau_t^s$ from different sources s, and adjusts its asset position Δb_t. Transfers are negative if there is a net outflow from the household and Δb_t is positive if the household saves during the period. The household consumes $c_t = \sum_c c_t^c$ where c denotes the different categories of consumption.

$$y_t + \tau_t - \Delta b_t = c_t.$$

The treatment supposedly lowers income y_t, and we want to investigate whether $\tau_t - \Delta b_t$ is sufficiently large to allow the household to maintain constant consumption. We also go beyond the aggregate quantities and investigate (i) which activities are the most disrupted, (ii) which transfers respond the most, and (iii) whether the consumption basket changes.

Income We estimate equation (1) for different measures of income (not including transfers) starting with total income per capita y_t (net of informal transfers, such as remittances). We then restrict the analysis to income per capita generated by the most affected activity, i.e. crop income. We then further disaggregate crop income into the two predominant crop cycles in our survey provinces, the Summer/Autumn and Winter harvest. We calculate crop income separately for paddy rice, the major staple in Vietnam. We expect income from the Summer/Autumn harvest to be affected because Ketsana made landfall shortly before the beginning of that season's harvest activities. As a placebo check, we repeat the same exercise for an income source that should not be affected by the shock given its timing, i.e. Winter paddy rice. The results are presented in panel A of Table 2. Looking at the first line, our estimations predict a strong decrease in income per capita. The coefficient is economically and statistically significant and indicates a loss of about 700 USD per capita for a household living in a village that is completely inundated compared to one which is spared. This amount translates into an income loss of 50% for the most affected households.[25] Looking at more disaggregated income sources, it appears that the drop in total income is mainly driven by a 450 USD decrease in crop income (second line) which accounts for roughly 60% of the loss in total income.

There should be some variations in the extent to which crops are affected, for instance, due to variations in harvesting seasons. As the paddy rice harvest is usually gathered between September and November depending on the local climate of the province, its production is directly affected by the typhoon. The third line reports the losses for income per capita generated by Summer/Autumn paddy rice (85 USD). In contrast, the fourth line reports the estimates for Winter paddy rice. As expected, the income generated by Winter crops is quite uncorrelated with the treatment, given that the planting activities start around December, long after the impact of Ketsana. If anything, the coefficient for Winter paddy rice is positive, because households may be attempting to catch-up from the previous harvest losses by investing more in the following one. Note that our coefficients are remarkably

[25] Calculated by multiplying the coefficient with the maximum treatment of 0.77 and divided by the average income.

similar across the different specifications, indicating that attrition is not a major concern.

In Table 3, we also report the impact on alternative sources of income generated from livestock, hunting, wage employment, or self-employment. We find that none of those components are significantly lower in affected areas. It is however important to note that there is a negative but non-significant coefficient both for wage employment and self-employment, which might indicate that the disaster also disrupted other economic activities apart from agriculture. Unfortunately, the share of the rural population employed in these occupations is low and our tests are underpowered.

Consumption We now turn to consumption (panel B of Table 2). We do find a negative, but not significant effect of Typhoon Ketsana on total consumption per capita (first line). This effect appears to be entirely driven by a sharp decline in food expenditure (second line). However, as we can see in the following lines, households also seem to substitute between different consumption categories. For example, the coefficient on non-food consumption is small but positive. This result is consistent with the interpretation that households may spend more in the aftermath of a typhoon in order to repair housing damages and replace broken durable assets. We cannot identify any changes in spending patterns on health and education items.

In summary, while some substitution between non-food and food consumption appears to take place, net consumption per capita still decreases by around 100 USD (approximately 15% of the initial income loss), almost entirely driven by a reduction in food consumption. This implies that the average household is able to smooth a large part of the initial shock, while some uninsured risk remains.

Remittances and other transfers We have provided evidence that our treatment translates into an income shock and a much lower decrease in consumption. We now focus on the second and third terms of our budget constraint $\tau_t - \Delta b_t$, i.e. the transfers with third parties and changes in borrowings/savings, and investigate which of these instruments mitigate the income shock and stabilize household disposable income.

Table 4 reports the estimation of equation (1) for net remittances per capita sent by labor migrants. As shown in the second line, households in affected villages receive extra remittances of around 120 USD per capita, coming from labor migrants outside of the district of their households of origin, while they receive nothing from local labor migrants located in the same district (about -10 USD, first line). One interpretation is that local labor migrants are also affected by the shock, which prevents them from insuring the household. In contrast, long-distance migrants are not affected by the typhoon because they are usually going to large and unaffected cities (Ho Chi Minh City or Hanoi for the majority of them).[26]

These findings support the theoretical claim put forward by the NELM literature that labor migration can be used as a risk reduction strategy that helps to diversify income sources across space or sectors. More diversified migration networks, e.g. those with long-distance labor migrants, are more effective. The correlation between income at the source and at the destination is low, which allows regressive transfers to members affected even by aggregate shocks such as Typhoon Ketsana.

There are other networks of mutual support from whom the households may receive transfers. In panel A of Table 5, we report the response of remittances from non-labor migrants (first line), informal transfers provided by relatives from the extended family and friends (second line) and redistribution from social assistance and security programs (third line). We find that none of those transfers are significantly higher in affected areas. Instead, public redistribution and transfers from non-labor migrants are negatively correlated with the treatment. An explanation for the latter result is that, as with local labor migrants, some households usually benefit from a stream of remittances from non-labor migrants who are mostly local. In the aftermath of the typhoon, these migrants are also affected and do not send remittances anymore. We also estimate how our treatment affects transfers from formal insurance providers and show that such payments play a negligible role (fourth line) illustrating the low coverage of commercial insurance products in rural areas of Vietnam.

Finally, we examine the effects on household borrowing and savings Δb_t. In panel B of Table 5, we summarize household adjustments in response to the treatment. Looking at households' net financial position (i.e. the change in the stock of savings minus the change in the stock of borrowing), we find that it decreases by -170 USD. We also examine the change in the stock of tangible household assets (-120 USD) in the second line.[27] The negative signs of the two coefficients may be an indication that households also resort to dis-saving and asset depletion coping strategies. However,

[26] We do not observe the precise migrant destination apart from Ho Chi Minh City and Hanoi and, therefore, cannot condition the analysis on shocks at the migrants' location. We only observe whether or not migrants are in the same district or province as the household, or in another province, and we observe when the destination is Ho Chi Minh City or Hanoi. One explanation behind the lower effect found for migrants outside the province is that some migrants work in urban and industrial areas of the *same* province, which offer wage labor opportunities (often the provincial capital). In the third line, we would not capture the remittances sent by these workers.

[27] The sum of these coefficients is between 100 and 300 USD for our preferred specification, which (i) is quite large compared to remittances and (ii) can explain the gap between the income loss and the consumption drop once controlled for the rise in remittances.

none of these coefficients are statistically significant. The reason why we cannot reject the null hypothesis in these specifications is because there are few households with reported savings or non-mortgage borrowings and our specifications are severely underpowered.

Robustness checks In the first robustness check, we test the parallel trends assumption of our difference-in-difference approach by running specification (2). We report the results in Table A1. As shown, we do not find any significant correlations between the treatment and the trends of our main variables of interest before the occurrence of Typhoon Ketsana.

In the second robustness check (see Table A2), we provide the results derived by using the alternative rainfall treatment indicator for our main variables of interest, i.e. income and remittances from labor migrants. In column 1, we report the results of specification (1). The results are quite similar to the benchmark specification, however, the standard errors are slightly larger and we do lose predictive power because our rainfall measure is much less precise than the flood measure.[28] In the second column, we report the estimates for specification (2) explaining, in a first stage, variations in flooded areas by variations in rainfall. The first stage is strong: even controlling for wave/province fixed effects, flooded areas and rainfall are highly correlated. For the second stage, the results are qualitatively similar to those obtained with the specification (1) (see Tables 2 and 4). There are income losses that are compensated by remittances, but only from long-distance labor migrants, and these remittances account for around 20% of the initial losses.

It should be noted here that the IV-coefficients in Table A2 are of magnitude two to three larger than their counterparts obtained with specification (1). There are two main explanations for these differences. First, affected villages enjoy better agricultural conditions (see Table A5) and are subject to a higher risk of inundation because they are less likely to be located in mountainous terrain. With our two-stage specification, we only use the variation in inundations induced by variations in rainfall, which are arguably orthogonal to the topography. Our estimates may then be larger because the response to the shock is lower in our richer and more risk-prone areas. Supporting this interpretation, our coefficients are generally larger in specification (1) when we control for topography (see Table A3). Second, there is heterogeneity across our provinces in how variations in rainfall predict variations in

[28]The maximum variation in excess daily precipitation level recorded during the 29th and 30th of September is 35 cm (see Figure 5 in the Appendix). Once multiplied with the coefficient for long-distance remittances (3.60), we find that additional remittances per capita in the most affected village are 125 USD higher than in the least affected village.

flooded areas. While the first stage generally displays a strong positive correlation between the two treatments, we do find a lower level of correlation especially for Dak Lak, which was less affected by Ketsana. Hence, relative to specification (1), specification (2) puts less weight on households in Dak Lak. Excluding Dak Lak from specification (1) almost bridges the gap with our estimates in specification (2).[29]

In our third robustness check, we control for potential geographic differences between affected and spared villages, which may explain why these villages differ in 2010 (our main specification already includes household fixed effects). In column (1) of Table A3, we include the interaction of wave fixed effects with a set of geographic village characteristics (i.e. being located in the mountains, at a river or coast or on a plain or slope) such as to control for differential trends across different geographic zones. In column (2), we control for the long-term propensity to be affected by typhoons. We construct the average annual frequency of a commune being exposed to a typhoon (proxied by its distance from the eye of the typhoon) using all typhoons between 1945 and 2006 and interact this with our wave fixed effects. We provide the results for a radius of 50 kilometers from the eye of each typhoon, but they are robust for 30, 70 and 100 kilometers (not reported). In column (3), we include the interaction of wave fixed effects with the average rainfall during the exact same period (26th of September to 10th of October) for the years 2001 to 2008.

Further, our results are also robust to alternative definitions of migration. In our benchmark specification, we define migrants to be those members of the household of origin who are absent for at least 180 days during a 12 months reference period. In column (4) of Table A3, we replicate the exercise and redefine migrants as members having left the household for more than 3 months, thereby capturing more short-term migration as well. In all these robustness checks, our conclusions remain the same and the point estimates are very similar.

In our fourth robustness check, we report a logarithmic specification for income in Table A4, and we find that the treatment incurs a 80-90% drop in total income. In our benchmark specification, remittances are normalized by the number of permanent household members. In Table A4, instead, we normalize remittances by total household income (net of remittances) and estimate specification 1 for these normalized variables. The disadvantage of the last specification is that (i) total income is also affected by the shock which tends to bias our estimates upward, and

[29]While Ha Tinh and Hue exhibit very similar dynamics in response to the shock, Dak Lak appears to be relatively unaffected and our estimates are much noisier. This is due to (i) the lower exposure to the treatment and (ii) the lower vulnerability of farmers in this province. Consequently, our identification essentially comes from Ha Tinh and Hue.

(ii) total income is a noisy measure, which increases the standard errors. Nonetheless, our conclusions still remain unchanged. Our results are also robust when we use non-normalized nominal values, or nominal values normalized by the number of adult equivalent members (not reported).

Moreover, we also test for a potential "price bias" introduced by the use of nominal values for our income specifications. In affected villages, prices may change and nominal values could capture these variations. We construct the average rice sales price per kg at the village level as reported by each household and verify that price variations between 2008 and 2010 are not related to the typhoon. The result (coefficient: -0.014, SE: 0.083) implies a non-significant difference of 1 cent between the most and the least affected place.[30] Similarly, there may exist changes in borrowing conditions. We construct the average borrowing rate as reported by each household. Variations between 2008 and 2010 in these rates are not related to the typhoon. The result (coefficient: 4.25, SE: 4.78) implies a non-significant difference of 4% between the most and the least affected village.

2.2 Migration as a response to the shock

From the previous analysis, we conclude that the presence of long-distance labor migrants helps households to alleviate the initial income shock. In what follows, we intend to distinguish these effects for two different migration networks that households rely on in the aftermath of Typhoon Ketsana, i.e. the ones established before the shock (ex-ante) and after the shock (ex-post). In this regard, we raise the following questions: Are households with ex-ante labor migrants more likely to receive remittances in response to the shock than their counterparts without established migrants? To what extent does the shock induce new out-migration from affected areas and what is their remittance behavior?

Already-established migrants versus newly-sent migrants In this section, we separate our sample into two subsamples, households with at least one migrant in 2008 and households without any migrants in 2008. Naturally, the two subsamples differ along observable characteristics. The sample with ex-ante migrants is generally richer and relies less on crop income. However, as shown in Table A6, the response to the treatment is not too different between the two groups. Households with at least one long-distance migrant in 2008 incur the same income losses as households

[30]Indeed, rice markets in Vietnam are internationally well integrated: 50% of the sample report prices in 2010 between 61 and 69 cents, consistent with world prices.

without any migrants in 2008.[31] The desire for consumption smoothing between subsamples should therefore be similar.

In Table 6, we estimate specification (1) for each subsample with (i) the presence of each type of migrants in 2010 and (ii) net remittances by types received in 2010 as dependent variables. Panel A shows the estimates for the subsamples of households without any migrants in 2008. First, we focus on local migration, i.e. households without any migrants in the same district in 2008. We find that the treatment is negatively and significantly correlated with the probability of having at least one such migrant in 2010. Affected households are 10% less likely to send a local migrant, and remittances from these migrants are 10 USD lower. Second, we consider households without any migrant in a different district in 2008 (including those in different districts of other provinces). The estimate indicates that the treatment is positively and significantly correlated with the probability of having at least one such migrant in 2010 being 17% higher. The higher incidence of migration also translates into 65 USD of additional remittances from long-distance migrants.

In panel B of Table 6, we present the results for the ex-ante migrant subsamples. Households with a migrant in the same district in 2008 are very few (they are more numerous in 2010), so our tests are underpowered for identifying their response to the treatment more precisely. When we focus on households with a migrant in a different district in 2008, the treatment significantly increases the remittances received in 2010 from such migrants by around 260 USD, which is about 40% of the initial income shock.

To summarize, we find that households with a long-distance migrant in 2008 are generally better insured than households without any such migrants. However, within the latter category of households, treatment still increases remittances by 65 USD, due to the higher migration incidence of 17%. A simple back-of-the-envelope computation implies that each newly-sent long-distance migrant sends about $60/0.2 \approx 300$ USD, a number that is similar in magnitude to remittances sent by established migrants. Households send additional migrants in response to the shock and, when they do so, these migrants perform equally in terms of remittance sending behavior.

Interestingly, there seems to exist a substitution between long-distance and short-distance migration for households without migrants, and affected households tend to have fewer local migrants after the shock. These results are consistent with a model in which potential migrants can choose their destinations and our treatment

[31] In Table A7, we provide the same mean comparison exercise as in Table A5 for the two subsamples separately. We do not find systematic differences between treated and control households.

affects the relative attractiveness of these destinations.[32]

Finally, we cannot find strong heterogeneity in the response to the treatment along household characteristics (other than having an established migrant in 2008 or not). For instance, households that possess assets worth more than $2,500$ USD are as affected as poorer households and are equally likely to send a new migrant in response to the shock. The capacity of poor households to send a migrant to the city may be related to the particular Vietnamese context in which migrants can find low-skilled work quickly and easily as we argue in the next section.

Some evidence on the migration outcomes of newly-sent migrants For this analysis, we restrict our analysis to long-distance migration households, i.e. the ones with members having spent at least 6 months in *another district* relative to their origin. To analyze each migrant's job history, we take advantage of the individual information included in the survey data.[33] Based on this data, we construct a set of variables characterizing migrants' job search efforts and outcomes for each migrant and wave. We extract the monthly wage, the total income earned over the past year, the job sector, the type of labor contract signed (permanent versus temporary), and whether the worker was hired because of specific skills (education or vocational training). In order to understand the obstacles that new migrants may face, we also collect the job search duration and the sources of information used to find the current job. We then collapse the data at the household level.

In Table 7, we first separate the descriptive statistics between established migrants from ex-ante migrant households (first column) and new migrants from ex-ante non-migrant households (second column). Established migrants show a significantly higher monthly income, which is not explained by differences in sectors. For any given sector, the monthly wage of newly-sent migrants is between 25 and 35% lower than for established migrants. These income differences may be explained by the lower job tenure of newly-sent migrants. In addition, the job-worker match appears to be worse for newly-sent migrants, with the fraction of individuals who declare that they have been recruited for their skills being significantly lower than that of established migrants (22% against 32%). Along migrant-specific observables,

[32]There are two potential explanations for this effect and we cannot distinguish them in our analysis. First, local migrants might migrate further away from affected areas in order to find better employment opportunities. Second, they might return to their household of origin in order to help in reconstruction.

[33]Here, we also rely on migrant tracking data collected in 2010 alongside the post-disaster household survey. Unfortunately, this survey was only conducted in 2010 and, due to tracking difficulties, it suffers from considerable attrition. We use this information as a consistency check for the migrant data reported by the household.

however, newly-sent and established migrants appear quite similar.

Second, we divide the group of new migrants from ex-ante non-migrant households into 2 categories – treated (third column) and untreated (fourth column) – defined along their exposure to Ketsana.[34] We find that new migrants coming from treated households earn 50 USD less than new migrants from untreated households and this difference does not appear to be driven by sectoral differences. We believe this may be due to differences in migrants' intrinsic characteristics or the quality of the migrant-job match. There are several indications in favor of the latter interpretation. First, treated migrants are much less selected for their particular skills (15%) than untreated migrants (26%). Second, treated migrants invest much less time in their job search. Only 42% declare having searched for more than a week against 61% for the untreated subsample and only 3% had access to external information sources during their search against 12% for untreated new migrants.

Note that we cannot interpret the differences in Table 7 as identifying a causal impact. First, migrants from treated households may be intrinsically different than the other migrants due to selection. Second, we cannot control precisely for the destination or for the dates of migration.[35] Nonetheless, the descriptive statistics are consistent with the description of urban migration in transition economies (Todaro 1980, Cole and Sanders 1985). Todaro (1980) documents the existence of an unskilled sector with spot hiring, which serves as a stepping stone to modern occupations. In line with this interpretation, our newly-sent migrants and particularly those from treated households, end up working in occupations with low skill requirements, and they find these occupations with minimal search efforts. In contrast, established migrants work in more demanding occupations. More importantly, these results provide evidence that the "traditional" urban sector may not only be a stepping stone, but also an efficient and flexible shock coping device for rural households when their rural activities are disrupted. Jobs are easy to find and wages are high compared to agricultural incomes, with the amount of remittances sent to the most affected household equivalent to only three to four months of wage employment in the city.

[34] We regress our treatment T_v on propensity P_v and province fixed-effects and consider the residual T_v^r, i.e. the excess share of inundated areas compared to normal times relatively to the province average. We choose $\bar{T}$ such that treated households constitutes one third of the total sample of households and we classify our households as treated or control by their position relative to $\bar{T}$.

[35] One empirical strategy could be to consider a double difference specification in which we compare migrants sent just before the typhoon to migrants sent just after, from treated versus control households (controlling for destination). We cannot implement such a strategy because migrant departure dates and destinations are observed imperfectly.

3 Concluding remarks

Drawing on exogenous variations in the impact of an aggregate natural disaster in rural Vietnam, we showed that households suffer significant income losses, which are partly alleviated through remittances from internal labor migrants. The effectiveness of this instrument increases with the spatial distance between the affected household and the migrant sender. Interestingly, we also find evidence that this natural disaster acts as push-factor, spurring rural out-migration in the short-term. Households without migrants before the shock are more likely to send one when they are affected and when they do so, new migrants send similar amounts of remittances in the aftermath compared to established ones, despite their income being lower. Together, these findings support the case that internal labor migration provides an effective shock coping instrument to agricultural households in developing countries, a large-scale phenomenon which has thus far been understudied in the economic literature.

With our quantitative analysis, we cannot provide a complete assessment of the returns to internal migration and the dynamics of rural-urban migration. Nevertheless, based on our findings, policies that enable people to harness the benefits of internal migration more systematically, for example through the abolishment of barriers to internal migration (Abella and Ducanes 2011) or cost-effective support programs (Bryan et al. 2014), should be further evaluated. There are two important limitations to our research. First, our estimates represent short-term effects only and, therefore, do not allow to draw direct conclusions about the long-term consequences of natural disasters and climate change dynamics. This is an interesting field of study for future research and poses interesting questions: Do new migrants pushed away by the disaster learn the true cost of migration, and does it foster future migration from affected villages? As large migration inflows to urban centers occur following natural disasters and add to the existing inflows due to the structural transformation in developing countries, to what extent can cities successfully absorb these inflows (Poelhekke 2011)? Second, we do not account for negative spill-over effects from increasing urbanization, which might have important repercussions for the assessment of general welfare effects. While the effects of immigration at the destination have been studied intensively at the international level, there is still big scope for future research in the context of internal migration in developing countries.

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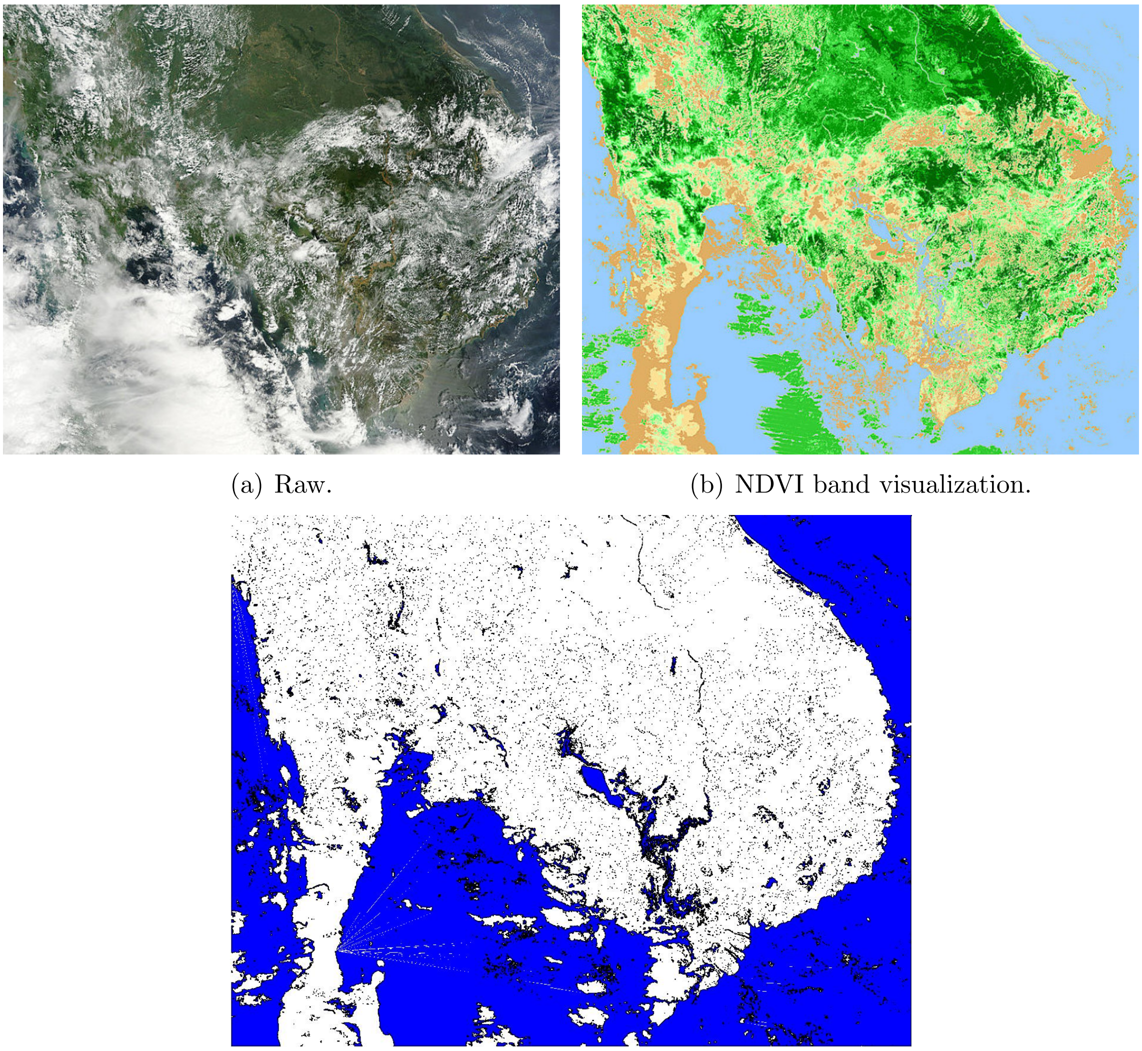
A Figures and tables

Figure 1. Satellite image – treatment (06/10/2009).



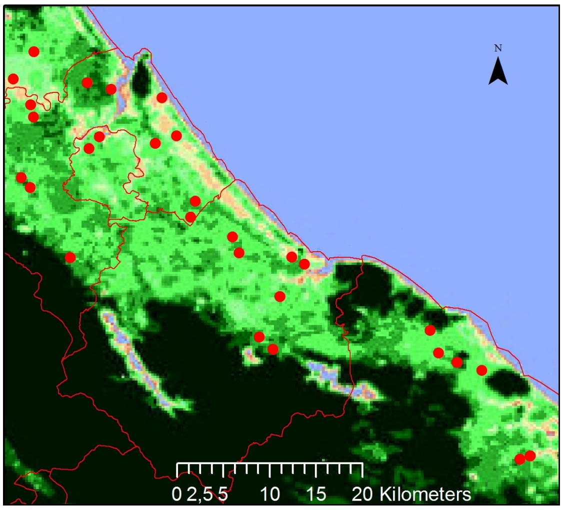
(a) Raw.

(b) NDVI band visualization.

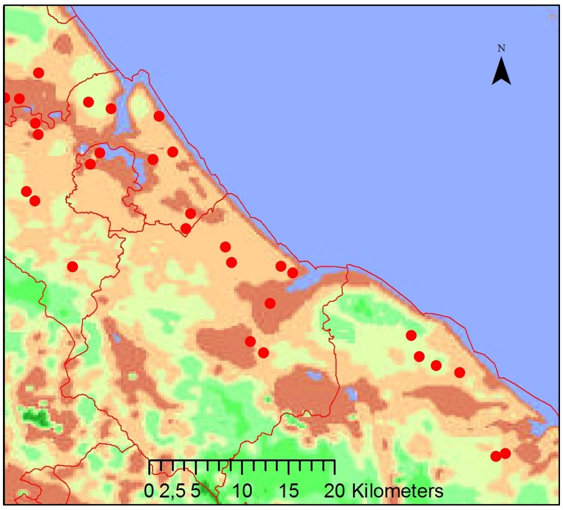
(c) Surface water.

Sources: MODIS subsets (Indochina, 6/10/2009), URL: http://lance-modis.eosdis.nasa.gov/imagery/subsets/?project=fas.

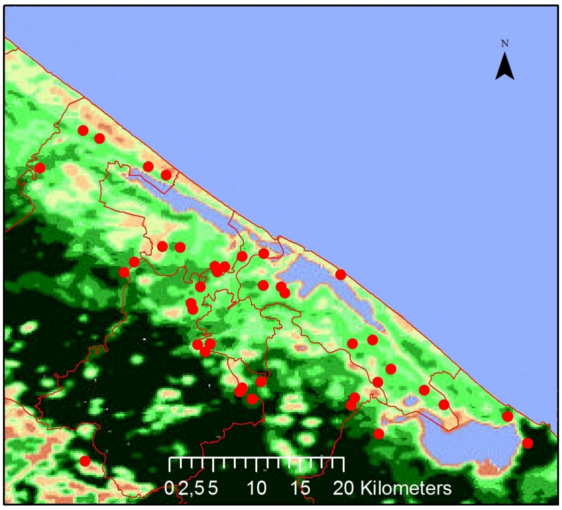
Figure 2. NDVI index satellite imagery: Picture comparison before and after Typhoon Ketsana for selected areas.



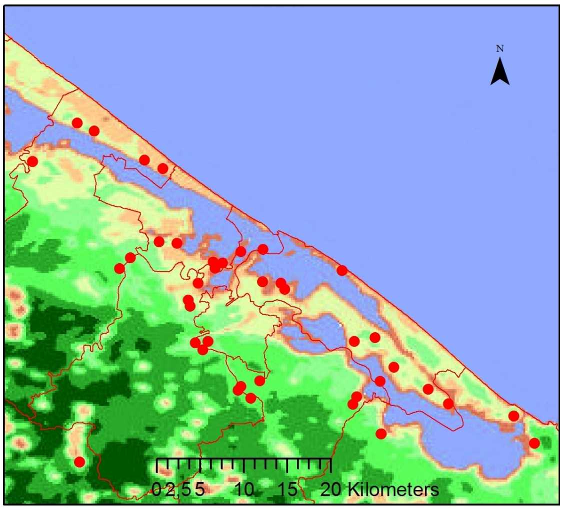
(a) Ha Tinh, 22/09/2009.



(b) Ha Tinh, 05/10/2009.



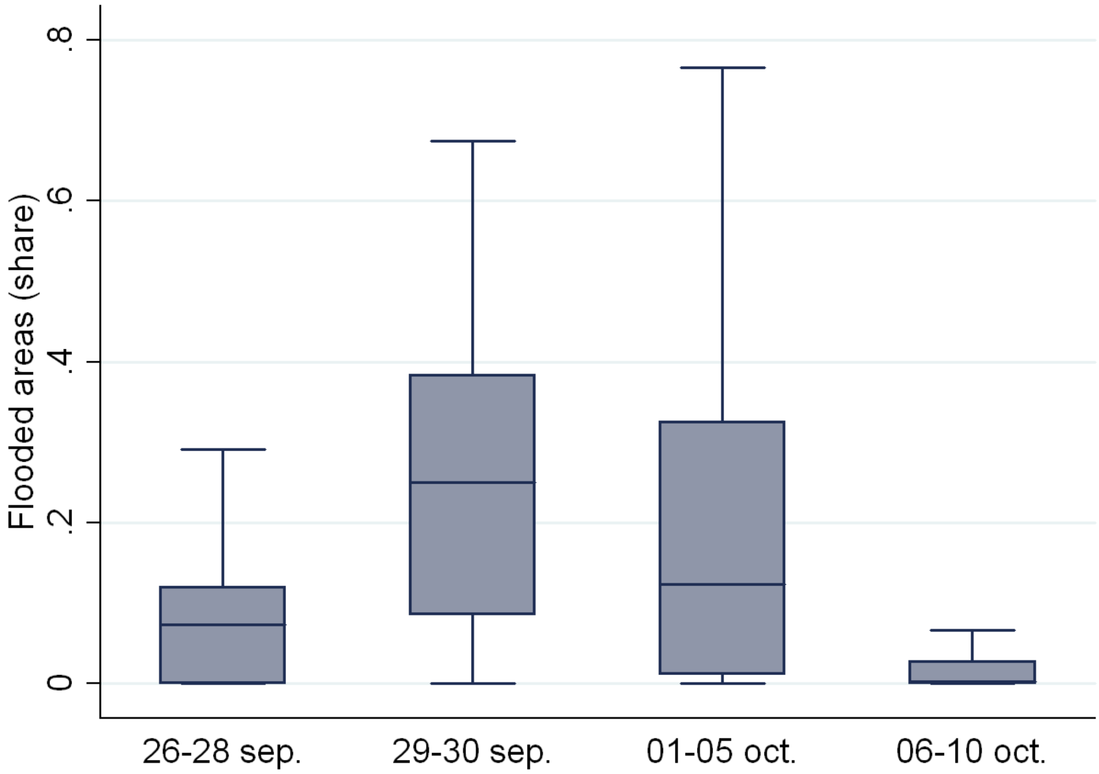
(c) Thua Thien Hue, 22/09/2009.



(d) Thua Thien Hue, 05/10/2009.

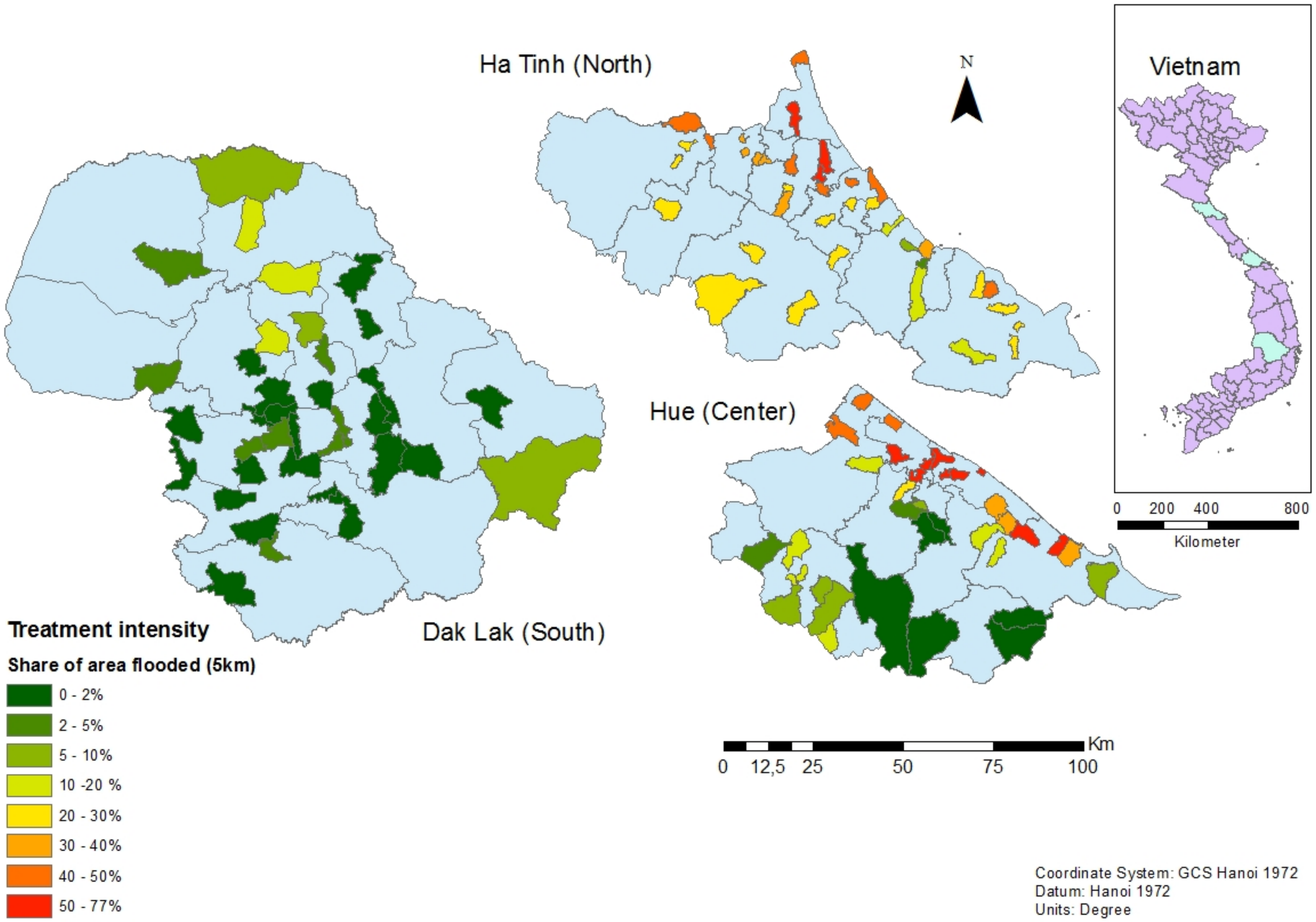
Note: Comparison of NDVI imagery one week before (22nd of September) and after (5th of October) the landfall of Typhoon Ketsana in Vietnam. Red dots represent survey villages and red lines district boundaries. Source: MODIS subsets (Indochina and China 5, 22/09/2009 and 05/10/2009). URL: http://lance-modis.eosdis.nasa.gov/imagery/subsets/?project=fas.

Figure 3. Share of area flooded over time.



Note: Share of flooded areas for selected bins of days *before* (26th to 28th of September 2009), during *landfall* (29th and 30th of September), in the *aftermath* (1st to 5th of October), and long *after passing* of Ketsana (6th to 10th of October) in a radius of 5 kilometers around the survey villages. Source: Authors' calculations based on MODIS inundation data.

Figure 4. Treatment intensity across communes.



Source: Authors' calculations based on MODIS inundation data in the aftermath of the typhoon, i.e. between the 1st and 5th of October in our three survey provinces. Each colored cluster represents the average treatment intensity (share of area inundated around sample locations) for the two sample villages in each commune based on our preferred specification of a five kilometer radius. Light blue clusters represent non-survey areas without underlying treatment data.

Table 1. Descriptive statistics by province in 2008.

Sample	All	Ha Tinh	Hue	Dak Lak
Observations	2148	713	699	736
Household Demographics				
Number of Men (16-59)	1.22	1.02	1.22	1.41
Number of Women (16-59)	1.27	1.15	1.23	1.41
Number of Dependents	1.87	1.69	2.01	1.92
Household Head				
Main occupation: farmer	.66	.67	.58	.72
Age	48.9	52.4	49.4	45.2
Years of schooling	6.72	8.37	5.50	6.22
Female	.16	.17	.17	.15
Household Income†				
Total income	1,154	1,110	847	1,552
Agricultural income	585	367	208	1,153
Self-employment income	183	138	217	195
Labor income	197	184	194	213
Formal transfers	128	198	111	76
Transfers relatives	62	94	61	30
Household Expenditure†				
Total expenditure	1,253	1,216	1,181	1,356
Food expenditure	631	582	626	680
Non-food expenditure	466	446	437	515
Education expenditure	70	100	45	65
Health expenditure	50	55	35	60
Household Finance†				
Total borrowings	730	729	481	967
Total savings	70	85	38	85
Migration†				
Total migration incidence	.38	.49	.36	.29
Total net remittances	28	83	-8	8
Long-distance labor migration incidence	.21	.31	.22	.11
Long-distance labor migrant net remittances	17	37	24	-9.6
Local labor migration incidence	.037	.034	.041	.037
Local labor migrant net remittances	-0.24	-0.66	0.93	-0.96

Source: "Vulnerability to Poverty in Southeast Asia" Panel Survey - 2008. †: All monetary variables are expressed in total USD (PPP) per capita.

Table 2. Income and consumption losses due to the treatment.

PANEL A: Income	(1)	(2)	(3)
Total	-648.88**	-654.57**	-724.56***
	(304.49)	(303.96)	(273.12)
Crop income	-406.62***	-406.17***	-462.16***
	(152.56)	(154.76)	(157.00)
Crop income (Summer/Autumn paddy)	-81.39***	-83.06***	-84.55***
	(29.94)	(30.71)	(30.14)
Crop income (Winter paddy)	15.37	15.37	15.38
	(56.29)	(57.83)	(55.20)
Observations	4,193	4,144	4,193
Sample	All	No attrition	All
Controls (household characteristics)	Yes	Yes	Yes
Province $\times$ Wave fixed effects	Yes	Yes	Yes
Household fixed effects	No	No	Yes

PANEL B: Consumption	(1)	(2)	(3)
Total	-59.24	-59.59	-105.11
	(216.45)	(216.51)	(204.78)
Food	-170.69	-169.94	-187.08*
	(112.41)	(112.37)	(103.84)
Non-food	114.86	114.40	95.07
	(125.24)	(125.27)	(122.72)
Education/Health	6.05	5.54	-0.75
	(55.36)	(55.42)	(58.79)
Observations	4,196	4,147	4,196
Sample	All	No attrition	All
Controls (household characteristics)	Yes	Yes	Yes
Province $\times$ Wave fixed effects	Yes	Yes	Yes
Household fixed effects	No	No	Yes

Each cell displays the result of a separate regression (specification (1)). We only report the Difference-in-Difference coefficient, i.e. the coefficient before the treatment interacted with a dummy for the wave 2010. Robust standard errors in parentheses are clustered at the commune level. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All variables are expressed in USD (PPP) per capita, i.e. adjusted by the number of permanent household members excluding migrants. Total income is net of informal transfers, such as remittances.

Table 3. Income losses due to the treatment – other activities.

VARIABLE	(1)	(2)	(3)
Livestock	-31.14	-26.50	-44.47
	(98.22)	(96.49)	(103.10)
Hunting	47.39	99.27	43.05
	(44.80)	(43.65)	(42.92)
Wage employment	-103.01	-114.46	-104.80
	(134.01)	(132.06)	(121.98)
Self-employment	-76.18	-78.30	-70.95
	(135.23)	(136.59)	(131.27)
Observations	4,193	4,144	4,193
Sample	All	No attrition	All
Controls (household characteristics)	Yes	Yes	Yes
Province $\times$ Wave fixed effects	Yes	Yes	Yes
Household fixed effects	No	No	Yes

Each cell displays the result of a separate regression (specification (1)). We only report the Difference-in-Difference coefficient, i.e. the coefficient before the treatment interacted with a dummy for the wave 2010. Robust standard errors in parentheses are clustered at the commune level. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All variables are expressed in USD (PPP) per capita, i.e. adjusted by the number of permanent household members excluding migrants.

Table 4. Remittances from labor migrants in response to the treatment.

VARIABLE	(1)	(2)	(3)
Local labor migrant remittances	-10.69	-10.80	-10.28
(same district)	(9.74)	(9.80)	(9.77)
Long-distance labor migrant remittances	118.19***	120.07***	122.53***
(different district)	(44.04)	(44.80)	(45.16)
Long-distance labor migrant remittances	73.67**	74.99**	75.20**
(different province)	(36.01)	(36.53)	(37.46)
Observations	4,243	4,188	4,243
Sample	All	No attrition	All
Controls (household characteristics)	Yes	Yes	Yes
Province × Wave fixed effects	Yes	Yes	Yes
Household fixed effects	No	No	Yes

Each cell displays the result of a separate regression (specification (1)). We only report the Difference-in-Difference coefficient, i.e. the coefficient before the treatment interacted with a dummy for the wave 2010. Robust standard errors in parentheses are clustered at the commune level. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All variables are expressed in USD (PPP) per capita, i.e. adjusted by the number of permanent household members excluding migrants. Remittances from labor migrants in different districts is the sum of remittances from migrants in (different districts of) different provinces and those in different districts of the same province relative to the respective household of origin.

Table 5. Transfers from other third parties (non-labor migrants, relatives and friends, public redistribution, insurance) and borrowing/savings.

PANEL A: Transfers			
	(1)	(2)	(3)
Non-labor migrants remittances	-152.59*	-158.32**	-184.00**
	(78.02)	(79.97)	(77.33)
Transfers from relatives/friends	75.80	73.81	73.06
	(97.75)	(98.22)	(98.05)
Public redistribution	-89.41	-92.06	-92.35*
	(57.94)	(56.70)	(52.10)
Insurance transfers	6.91	6.64	6.54
	(13.20)	(13.40)	(13.40)
Observations	4,243	4,188	4,243
Sample	All	No attrition	All
Controls (household characteristics)	Yes	Yes	Yes
Province × Wave fixed effects	Yes	Yes	Yes
Household fixed effects	No	No	Yes

PANEL B: Borrowing/dissaving			
	(1)	(2)	(3)
Net liquid assets	-36.20	-37.29	-171.47
	(257.54)	(259.33)	(283.97)
Tangible assets	-56.76	-73.62	-121.29
	(246.94)	(247.15)	(225.36)
Observations	4,243	4,188	4,243
Sample	All	No attrition	All
Controls (household characteristics)	Yes	Yes	Yes
Province × Wave fixed effects	Yes	Yes	Yes
Household fixed effects	No	No	Yes

Each cell displays the result of a separate regression (specification (1)). We only report the Difference-in-Difference coefficient, i.e. the coefficient before the treatment interacted with a dummy for the wave 2010. Robust standard errors in parentheses are clustered at the sub-district level. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All variables are expressed in USD (PPP) per capita, i.e. adjusted by the number of permanent household members excluding migrants. Non-labor migrant remittances and transfers are net of the amount sent. Net liquid assets is the present value of the net assets, i.e. savings minus the stock of outstanding loans.

Table 6. Remittances from labor migrants in response to the treatment – subsamples without/with established migrants in 2008.

PANEL A: No migrants in 2008			
	(1)	(2)	(3)
Local labor migrant incidence	-0.103**	-0.103**	-0.075*
(same district)	(0.045)	(0.045)	(0.046)
	[4,098]	[4,046]	[4,098]
Local labor migrant remittances	-9.86	-10.01	-9.30
(same district)	(8.34)	(8.37)	(8.05)
	[4,094]	[4,042]	[4,094]
Long-distance labor migrant incidence	0.152	0.157*	0.169*
(different district)	(0.093)	(0.095)	(0.091)
	[3,358]	[3,312]	[3,358]
Long-distance labor migrant remittances	65.19**	66.48**	65.18**
(different district)	(31.47)	(32.05)	(31.28)
	[3,352]	[3,310]	[3,352]
Sample	All	No attrition	All
Controls (household characteristics)	Yes	Yes	Yes
Province × Wave fixed effects	Yes	Yes	Yes
Household fixed effects	No	No	Yes

PANEL B: Migrant in 2008			
	(1)	(2)	(3)
Local labor migrant incidence	0.219	0.260	0.277
(same district)	(0.517)	(0.537)	(0.626)
	[157]	[152]	[157]
Local labor migrant remittances	-233.36	-277.59	65.22
(same district)	(442.38)	(479.05)	(307.13)
	[153]	[148]	[153]
Long-distance labor migrant incidence	0.095	0.094	0.129
(different district)	(0.192)	(0.192)	(0.162)
	[891]	[880]	[891]
Long-distance labor migrant remittances	257.89**	253.02**	253.02**
(different district)	(119.37)	(119.42)	(120.22)
	[889]	[878]	[889]
Sample	All	No attrition	All
Controls (household characteristics)	Yes	Yes	Yes
Province × Wave fixed effects	Yes	Yes	Yes
Household fixed effects	No	No	Yes

Each cell displays the result of a separate regression (specification (1)). In the first (resp. last) two lines of panel A, we select the sample of households without a migrant in the same district (resp. in a different district) in 2008. In the first (resp. last) two lines of panel B, we select the sample of households with a migrant in the same district (resp. in a different district) in 2008. We only report the Difference-in-Difference coefficient, i.e. the coefficient before the treatment interacted with a dummy for the wave 2010. Robust standard errors in parentheses are clustered at the commune level. The number of observations for each specification is displayed between brackets. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. Transfers are expressed in USD (PPP) per capita, i.e. adjusted by the number of permanent household members excluding migrants.

Table 7. Descriptive statistics – migrants in 2010.

	Established migrants	Newly-sent migrants		
		All	Treated	Untreated
Observations	[239]	[155]	[56]	[99]
Monthly income	492.79	378.90	352.17	394.01
	Services and industry			
Fraction of migrants	.821	.849	.877	.830
Monthly income	502.87	389.48	344.68	416.26
	Agriculture			
Fraction of migrants	.070	.050	.035	.060
Monthly income	344.06	239.81	192.98	255.42
	Public sector			
Fraction of migrants	.120	.119	.105	.130
Monthly income	416.40	304.63	407.72	257.05
	Migrant characteristics			
Age	26.40	25.01	25.20	24.90
Male	.608	.597	.675	.553
Education (>9th grade)	.512	.551	.546	.558
	Match migrant-job			
Hanoi, Ho Chi Minh City	.361	.359	.473	.294
Permanent contract	.423	.364	.385	.360
Skilled job	.315	.220	.157	.260
	Job search			
Search more than 1 week	.526	.534	.421	.610
Average search time (weeks)	1.51	1.04	.790	1.18
Recourse to job agencies	.120	.087	.035	.118

Source: Panel - 2010. The unit of observation is the household and we report the number of observations in each category between brackets. For households with more than one migrant, we calculate our measures as the mean of these migrants with equal weights. Established migrants are migrants from households in which a migrant was already present in 2008 and newly-sent migrants are migrants from households without migrants in 2008. To divide newly-sent migrants into 2 groups along treatment, we regress our treatment T_v on propensity P_v and province fixed-effects, and consider the residual T_v^r, i.e. the excess share of flooded areas compared to normal times relatively to the province average. We choose $\bar{T}$ such that treated households constitutes 1/3 of the total sample of households. Treated newly-sent migrants are migrants from families without migrants in 2008 exposed to a residual $T_v^r > \bar{T}$. Untreated newly-sent migrants are migrants from families without migrants in 2008 exposed to a residual $T_v^r \leq \bar{T}$.

II. Appendix

Table A1. Pre-treatment trends – placebo checks using waves 2007 and 2008.

VARIABLES	(1)	(2)
Total income	393.79	400.73
	(310.08)	(308.75)
Total consumption	200.16	201.40
	(182.96)	(184.21)
Local labor migrant incidence	-0.05	-0.05
(same district)	(0.03)	(0.03)
Local labor migrant remittances	13.79	13.93
(same district)	(16.38)	(16.55)
Long-distance labor migrant incidence	-0.04	-0.04
(different district)	(0.08)	(0.08)
Long-distance labor migrant remittances	-47.51	-44.23
(different district)	(38.20)	(37.96)
Long-distance labor migrant incidence	-0.03	-0.02
(different province)	(0.08)	(0.07)
Long-distance labor migrant remittances	-24.85	-18.69
(different province)	(34.49)	(34.31)
Observations	4,156	4,156
Sample	All	All
Controls (household characteristics)	Yes	Yes
Household fixed effects	No	Yes

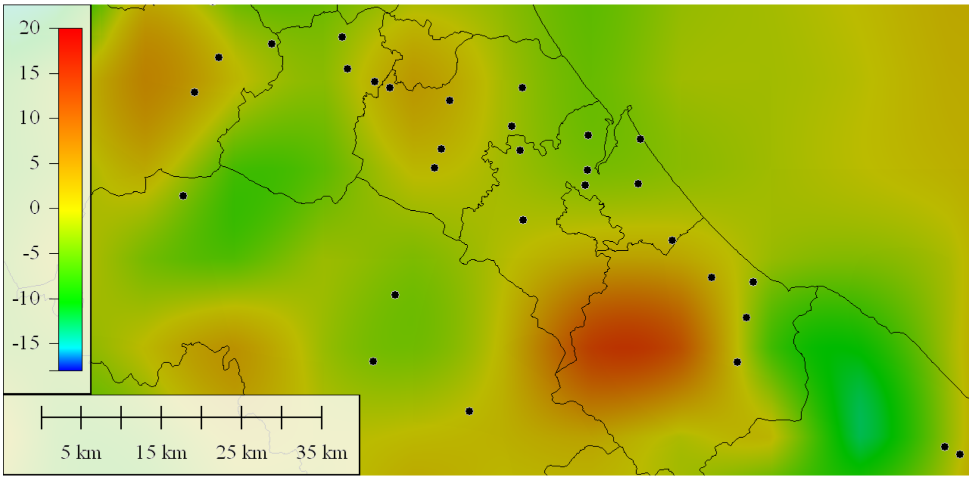
Each cell displays the result of a separate regression (specification (1) with the waves 2007 and 2008 instead of 2008 and 2010). We only report the Difference-in-Difference coefficient, i.e. the coefficient before the treatment interacted with a dummy for the wave 2008. Robust standard errors in parentheses are clustered at the commune level. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All variables are expressed in USD (PPP) per capita, i.e adjusted by the number of permanent household members excluding migrants.

Table A2. Income losses and remittances (robustness checks using the rainfall treatment).

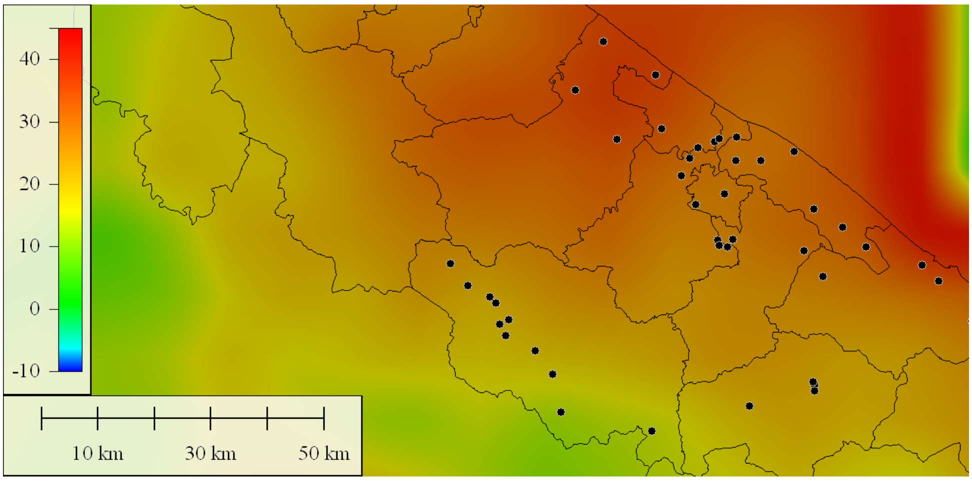
Specification	OLS	IV (second stage)
VARIABLES	Rainfall treatment	Flood treatment
Total income	-20.86**	-2329.43**
	(10.02)	(1052.20)
Local labor migrant remittances	-0.37	11.33
(same district)	(0.52)	(58.89)
Long-distance labor migrant remittances	3.51**	372.76**
(different district)	(1.59)	(150.75)
Long-distance labor migrant remittances	2.53*	233.09*
(different province)	(1.41)	(123.12)
Observations	4,223	4,223
Sample	All	All
Province × Wave fixed effects	Yes	Yes
Controls (household characteristics)	Yes	Yes
Household fixed effects	Yes	Yes
Specification		IV (first stage)
VARIABLES		Rainfall treatment
Flood treatment		0.00888***
		(0.00066)
Cragg-Donald F statistic		181.84
Observations		4,223
Sample		All
Province × Wave fixed effects		Yes
Controls (household characteristics)		Yes
Household fixed effects		Yes

Each cell displays the result of a separate regression. In the first column, we use specification (1) with the rainfall treatment and we only report the Difference-in-Difference coefficient, i.e. the coefficient before the treatment interacted with a dummy for the wave 2010. In the second column, we estimate a two-stage specification in which the flood treatment is first explained by the rainfall treatment (first stage). We control for the average rainfall in the period 26/09-10/10 in 2007 and 2008 (separately). Robust standard errors in parentheses are clustered at the commune level. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All variables are expressed in USD (PPP) per capita, i.e. adjusted by the number of permanent household members excluding migrants.

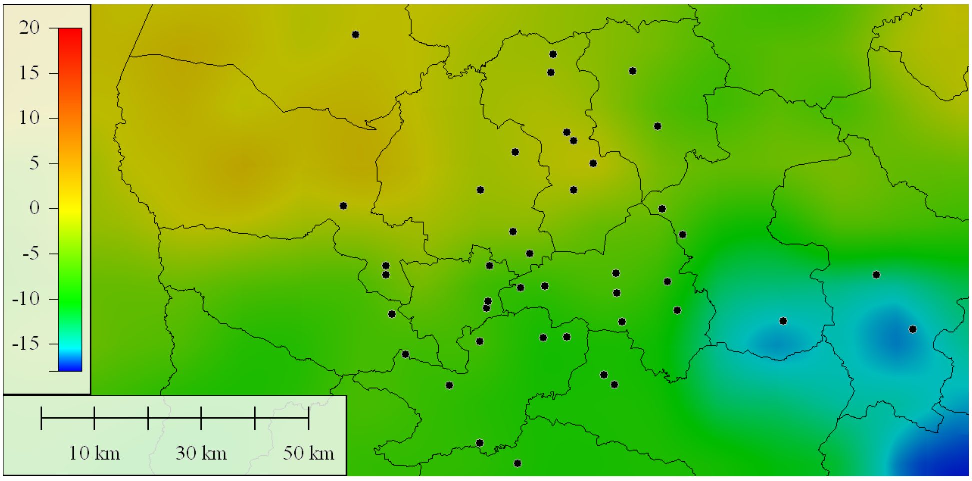
Figure 5. Rainfall intensity during the passing of Typhoon Ketsana.



(a) Ha Tinh province.



(b) Thua Thien Hue province.



(c) Dak Lak province.

Note: Excess rainfall estimates (measured in centimeters) in survey provinces on the 29th and 30th of September 2009 compared to 26th and 27th of September and 1st to 5th of October. Source: NOAA RFE 2.0 data.

Table A3. Income losses and remittances from labor migrants in response to the treatment – robustness checks controlling for village topography, historical average rainfall and volatility (26/09-10/10), long-term propensity to be affected by typhoons and using an alternative definition for migrants.

VARIABLES	(1)	(2)	(3)	(4)
Income	-754.81**	-680.84**	-437.50*	
	(284.17)	(270.24)	(262.71)	
Local labor migrant remittances	1.74	-10.04	-6.25	-8.89
(same district)	(7.34)	(9.59)	(11.44)	(9.72)
Long-distance labor migrant remittances	144.89**	132.68***	130.19***	121.67***
(different district)	(46.56)	(45.05)	(47.19)	(42.47)
Long-distance labor migrant remittances	93.55**	84.41**	68.23*	74.29**
(different province)	(39.82)	(37.41)	(39.47)	(34.20)
Observations	4,243	4,243	4,223	4,244
Sample	All	All	All	All
Province × Wave fixed effects	Yes	Yes	Yes	Yes
Controls (household characteristics)	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Controls (village topography)	Yes	No	No	No
Controls (historical exposure to typhoons)	No	Yes	No	No
Controls (average rainfall and volatility)	No	No	Yes	No
Definition migrants	180 days	180 days	180 days	90 days

Each cell displays the result of a separate regression (specification (1) with fixed effects). We only report the Difference-in-Difference coefficient, i.e. the coefficient before the treatment interacted with a dummy for the wave 2010. In (S1), we control for the village topography (mountains, coasts, slope, valley, and rivers) interacted with the wave. In (S2), we control for long-term propensity to be affected by typhoons interacted with the wave (i.e. the average annual percentage of a district area at most 50kms from the passing of a tropical typhoon between 1945 and 2006). In (S3), we control for the historical average rainfall and volatility in the period 26/09-10/10 between 2001 and 2008. In (S4), we define migrants as members having been away for more than 90 days instead of 180 days. Robust standard errors in parentheses are clustered at the commune level. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All variables are expressed in USD (PPP) per capita, i.e. adjusted by the number of permanent household members excluding migrants.

Table A4. Consumption and remittances response to the treatment – robustness checks (logarithmic specifications and normalized remittances).

VARIABLES	(1)	(2)	(3)
Total income (logarithm)	-0.893**	-0.785**	-0.895**
	(0.403)	(0.389)	(0.380)
Local labor migrant remittances	-0.006	-0.006	-0.003
(same district, fraction of income)	(0.011)	(0.011)	(0.011)
Long-distance labor migrant remittances	0.129***	0.129***	0.134***
(different district, fraction of income)	(0.045)	(0.046)	(0.045)
Long-distance labor migrant remittances	0.110***	0.109***	0.113***
(different province, fraction of income)	(0.041)	(0.041)	(0.041)
Observations	4,255	4,188	4,255
Sample	All	No attrition	All
Controls	Yes	Yes	Yes
Province $\times$ Wave fixed effects	Yes	Yes	Yes
Household fixed effects	No	No	Yes

Each cell displays the result of a separate regression (specification (1)). We only report the Difference-in-Difference coefficient, i.e. the coefficient before the treatment interacted with a dummy for the wave 2010. Robust standard errors in parentheses are clustered at the commune level. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. In the first line, we consider the logarithm of the variable expressed in USD (PPP) per capita, i.e. adjusted by the number of permanent household members excluding migrants. In lines 2-4, labor migrant remittances are expressed per unit of household income, i.e. income from domestic sources including government transfers net of any informal transfers, i.e. excluding remittances.

Table A5. Correlation between observables and the treatment in 2008.

	Coefficient	Standard error	P-value	Observations
		Income		
Total income	740.51	240.87	0.003	2,117
Crop	697.78	209.53	0.001	2,117
Self-employment	145.00	113.02	0.202	2,117
Wage	14.07	81.04	0.862	2,117
Subsidies	2.75	86.13	0.975	2,117
		Consumption		
Total consumption	366.38	238.85	0.128	2,098
Food	258.92	101.64	0.012	2,098
Non-food	55.25	132.86	0.678	2,098
Education	-17.97	41.10	0.663	2,098
Health	49.93	30.91	0.109	2,098
		Labor migration		
Incidence				
Local (same district)	-0.05	0.03	0.094	2,098
Long-distance (different district)	0.20	0.12	0.088	2,095
Long-distance (different province)	0.22	10.91	0.044	2,095
Remittances				
Local (same district)	-3.94	2.34	0.095	2,096
Long-distance (different district)	-10.70	37.97	0.779	2,095
Long-distance (different province)	3.51	26.25	0.894	2,095
		Other smoothing instruments		
Transfers from friends	17.45	62.46	0.781	2,144
Savings	-27.75	72.00	0.701	2,144
Borrowing	186.28	422.65	0.660	2,144
		Long-distance labor migrants' characteristics (different district)		
Income	17.87	39.09	0.649	453
Age	0.78	2.61	0.764	453
Male	-0.07	0.16	0.639	453
Education	0.08	0.18	0.652	415

Source: "Vulnerability to Poverty in Southeast Asia" Panel Survey - 2008. Each line is the result of a separate regression (specification **??**). Only the coefficient before the treatment variable is reported. Income, expenditures, and transfers are expressed in USD (PPP) per capita, i.e. adjusted by the number of permanent household members excluding migrants.

Table A6. Income losses due to the treatment – comparison between households with and without established migrants.

	Total income (1)	Crop income (2)
Treatment	-633.76**	-460.36**
	(289.55)	(184.00)
Treatment × Long-distance labor migrant	-273.36	34.23
(different district)	(391.08)	(202.11)
Observations	4,186	4,185
Sample	All	All
Controls (household characteristics)	Yes	Yes
Province × Wave fixed effects	Yes	Yes
Household fixed effects	Yes	Yes

Robust standard errors in parentheses are clustered at the commune level. We only report the Difference-in-Difference coefficient, i.e. the coefficient before the treatment interacted with a dummy for the wave 2010. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All income variables are expressed in USD (PPP) per capita, i.e. adjusted by the number of permanent household members excluding migrants.

Table A7. Correlation between observables and the treatment in 2008 – within the sample of households with/without labor migrants in 2008.

	With labor migrants in 2008				Without labor migrants in 2008			
	Coefficient	SE	P-value	Observations	Coefficient	SE	P-value	Observations
			Household Income					
Total income	512.21	327.17	0.121	450	870.04	280.77	0.002	1628
Crop (Rice)	133.63	76.82	0.085	450	70.24	106.90	0.512	1628
Self-employment	161.68	123.34	0.193	450	163.07	146.01	0.267	1628
Wage	53.06	100.99	0.601	450	23.49	114.81	0.838	1628
Subsidies	158.52	188.01	0.401	450	-24.27	74.74	0.746	1628
			Consumption					
Total consumption	-291.92	413.67	0.482	443	633.62	255.95	0.015	1655
Food	51.20	173.79	0.660	443	332.25	113.73	0.004	1655
Non-food	-315.15	290.9	0.281	443	215.96	134.32	0.111	1655
Health	100.80	72.63	0.168	443	35.12	31.99	0.275	1655
Education	-140.85	90.17	0.122	443	26.85	34.10	0.433	1655
			Remittances					
Local labor migrants (same district)	-8.16	6.21	0.192	448	-2.99	2.64	0.261	1692
Long-distance labor migrants (different district)	-131.48	116.00	0.260	448	-	-	-	-
Long-distance labor migrants (different province)	-71.75	97.19	0.462	448	-	-	-	-
			Other Smoothing Instruments					
Savings	110.65	80.77	0.174	453	-49.66	93.92	0.598	1692
Borrowing	373.84	393.93	0.345	453	177.36	513.14	0.730	1692

Source: "Vulnerability to Poverty in Southeast Asia" Panel Survey - 2008. For the two samples (households with or without a labor migrant in 2008 – different district), each line is the result of a separate regression (specification **??**). Only the coefficient before the treatment variable is reported. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.