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# HEALTH CARE EXPENDITURE AND FARM INCOME LOSS: EVIDENCE FROM NATURAL DISASTERS

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**ABSTRACT**

Farmers have higher rates of disability and illness than the general population and more volatile incomes due to frequent crop and livestock losses from extreme weather events. This raises concerns that sudden, weather-related drops in farm income could reduce access to health care for an already vulnerable population. We estimate the sensitivity of health care use to the loss in farm income brought about by natural disasters in Taiwan. To account for endogenous exposure to disaster risks, we estimate an instrumental variables model and find that farm income elasticities of demand for outpatient care and prescriptions range from 0.11 to 0.32. Reductions in health care use may be due, in part, to changes in time allocations within farm households.

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A data appendix is available at http://www.nber.org/data-appendix/w29898

## 1. Introduction

Farmers have high rates of illness, disability and mortality, leading to negative labor supply shocks and disruption of the agricultural supply chain (Variyam and Mishra 2005; Jones el at. 2009; Lee, Cha and Moon 2010; Chang and Meyerhoefer 2016; Wang et al. 2017; Lusk and Chandra 2021). In order to protect farmers from the negative economic consequences of illness and promote food security, many countries have special programs to subsidize farmers' health care purchases (Chang, Meyerhoefer and Just 2014). Traditional health insurance increases in generosity with the need for costly medical care, but it offers limited protection from income shocks that are not the result of illness (Cutler and Zeckhauser 2000).[1] Nonetheless, reductions to income can lead to lower levels of health care use for both preventive and acute care services, while increases in income have the opposite effect (Cheng, Costa-Font and Powdthavee 2018; Njagi, Groot and Aresenijevic 2021). Farmers are increasingly subject to negative income shocks, most commonly due to unpredictable and extreme weather events associated with climate change (Hertel and Rosch 2010; Yu and Goh 2021).

Understanding the consequences of income shocks for farmers' health care use is important for several reasons. Comparisons of income elasticities of demand for health care services between farmers and non-farmers provide an indication of whether health insurance grants farmers adequate access to care and protection from financial risk. In addition, the justification for public programs that subsidize farmers' health care costs is based on the implicit assumption that health care is a necessity. The latter consideration applies to public health insurance more generally, and has motivated much of the literature focused on the estimation of income elasticities of health care demand. The majority of studies on this topic

[1] Typical mechanisms to address income loss include subsidized premiums and cost sharing, but the difficulty accessing these benefits varies significantly by country (Schoen et al. 2010).

rely on country- or state-level panel datasets that include aggregate health care spending and income information. While recent aggregate estimates suggest that health care is a necessity, there is still much debate over the range of the income elasticity of demand for health care in the literature (Baltagi et al. 2017; Acemoglu, Finkelstein and Notowidigdo 2013; Farag et al. 2012; Costa-Font, Gemmill and Rubert 2011) For example, studies based on long time series data do not hold technology constant, and generally produce larger estimates than short time series (Ringel et al. 2002; Moscone and Tosetti 2010). Also adding to the debate is the discrepancy in estimates across different levels of aggregation, with individual or small area estimates generating smaller elasticities of demand than aggregate estimates (Moscone and Tosetti 2010; Getzen 2000; Blomqvist and Carter 1997).

There are very few recent micro-based estimates of the income elasticity of demand for health care services. A notable exception is Cheng, Costa-Font and Powdthavee (2018), which finds that lottery winnings increase the use of private, but not public health care services, with lottery income elasticities of demand that range from 0 to 0.26 for most services.  Earlier estimates likewise suggest that changes in income have a very small effect on health care utilization decisions, with elasticities in the range of 0.2 or less (Ringel et al. 2002; Kenkel 1994). We are aware of only three studies that estimate an income effect on farmers' health care use, and all are based on individual- or household-level cross-sectional data. Zheng and Zimmer (2008) estimates a two-part model on a sample of 261 U.S. farmers from the 1996-2001 waves of the Medical Expenditure Panel Survey, and fails to identify a statistically significant relationship between income and either health care expenditure or visits. Using a similar empirical specification and a sample of 3,292 farm households from the U.S. Agricultural Resource Management Survey, Mishra, El-Osta and Ahearn (2012) estimates a highly inelastic response of out-of-pocket health care expenditure to income in the range of 0.05 – 0.08.[2] Finally, Khalili et al (2021) estimates an income elasticity of out-of-pocket health care expenditure of 0.15 using a sample of 300 small-farm households in Fars Province, Iran. Limitations of all three studies include small sample size, self-reported information on health care use and the treatment of income as an exogenous variable.

Similar to Khalili et al (2021) who use variation in farm incomes due to drought, we investigate the impact of income variation from numerous natural disasters on health care use. Natural disasters represent a special type of income shock because they have the potential to affect health care use through multiple mechanisms. In regions with poor infrastructure and limited emergency management services, disasters could result in serious injury or even death (Hallegatte et al. 2017). Even in areas that are better equipped to protect residents, natural disasters can cause significant crop and livestock losses as well as damage to farm structures and equipment. All of these losses represent reductions in income that could reduce health care expenditure. Finally, natural disasters may alter the opportunity cost of time in seeking health care by shifting farmers' labor supply towards off-farm work in an effort to compensate for on-farm losses (Eskander, Fankhauser and Jha 2016; Chen and Vuong 2018; Xu, Klaiber and Miteva 2019).

We extend the literature on the relationship between natural disasters, farm income and health care expenditure in three important ways. First, we use a large population-based administrative dataset from the Farmer's Health Insurance (FHI) program in Taiwan, which contains approximately 3.5 million farmer-month health care claims. Because the FHI is a nationalized insurance program providing health care benefits to nearly all farmers, our analysis is free of self-selection into insurance coverage. Second, we account for the endogeneity of income, which previous studies have struggled to address due to a lack of

[2] The income elasticity from their log OLS specification is 0.05 and the elasticity estimate from their GLM specification is 0.08.

credible instruments or exogenous variations in income from policy or environmental changes (Acemoglu, Finkelstein and Notowidigdo 2013). The primary source of income variation in our models is the loss of farm product sales caused by natural disasters, such as typhoons and extreme wind, rainfall and temperatures. We measure farm income loss using future agricultural disaster payments, which are proportional to production losses. While the occurrence of natural disasters is beyond a farmer's control, income loss will vary depending on the level of self-protection. We address this endogeneity problem by exploiting longitudinal data on health care use and disaster payments over time, and employing a novel political instrument that causes variation in the level of disaster payments received from the government. We estimate income elasticities for different types of health care services (e.g. inpatient, outpatient, and prescription drugs) and for the treatment of several conditions (e.g. mental health disorders, injuries, and infections). Last, we translate disaster payment elasticities into farm income elasticities of health care demand and investigate the mechanisms through which natural disasters may affect health care use, including injury during the disaster event and changes to off-farm labor supply.

We find that the income loss from natural disasters results in a reduction in several types of health care. Overall, the farm income elasticity of total health care expenditure is 0.20, which is larger than estimates reported by Mishra, El-Osta and Ahearn (2012) and Khalili et al (2021), but similar to micro-based estimates based on the general population. In addition, we find that out-of-pocket health care expenditure is more responsive to changes in income than total health care expenditure. By analyzing expenditures specifically for mental health conditions, injuries and parasitic diseases, we rule out any direct effects on natural disasters on health care use through severe psychological distress, injury or reduced sanitation. Instead, we provide evidence that our estimates reflect the immediate impact of lost future income on discretionary health care expenditure due to financial constraints and changes in time allocations impacting the time cost of medical treatment.

Our estimates of the causal effect of farm income loss on health care use fit within a broader literature on the consequences of natural disasters for farmer well-being and coping strategies. As climate change increases the frequency and severity of crop and livestock losses, studies have investigated, for example, the implications for illness and later-life disability (Lohmann and Lechtenfeld 2015; Dinkelman 2016), consumption (Wahdat, Gunderson and Lusk 2021), educational expenditures (Khalili et al. 2020), disaster and crop insurance (Belasco, Cooper and Smith 2020; Schoengold, Ding and Headlee 2015; Miranda and Vedenov 2001), and multiple measures of economic development (FAO 2017; Karim 2018). Finally, our results have implications for health care policy. In particular, we find that sudden reductions in farm income could cause farmers to forgo or delay needed medical care. This raises the question of whether temporary reductions in health insurance cost-sharing amounts should be incorporated into disaster response policies.

## 2. Taiwan's Agricultural Disaster Relief Program and Political Preference

Taiwan is exposed to numerous natural disasters on a regular basis, including typhoons, extreme wind and rainfall from tropical storms or severe thunderstorms, and high temperatures (Bosner and Chang 2020). Instead of sponsoring crop insurance, the government of Taiwan operates an agricultural disaster relief program that provides cash payments to farmers in compensation for production losses attributable to natural disasters. The program represents a large percentage of the government's agricultural assistance budget, accounting for NT$ 277 million in costs from 2010 to 2019 (CoA 2020). Seventy percent of disaster payments compensate for production losses from typhoons, while heavy rainfall is the second most common reason for payments (14%).

The agricultural disaster relief program provides two different types of relief: regular aid and emergency aid. The former accounted for approximately 52% of disaster relief payments between 2014 and 2019, and the latter accounted for 48% of payments (CoA 2020). In the event of a natural disaster, famers are eligible to submit claims for regular aid if they sustain damage to at least 20 percent of their planted cropland or livestock herd. Once a claim is received by the government, an official visits the farm to verify the damage and make any necessary adjustments to the initial damage assessment. If the claim is valid, the farmer receives a payment equal to the number of damaged hectares times the per hectare compensation rate within 45-60 days after the claim is filed (Lin and Wang 2012). Emergency aid is sometimes allocated after particularly severe natural disasters impacting a large proportion of farmers. Local governments can apply for emergency aid on behalf of all farmers in the township. If emergency aid is granted by the central government, the approval process for payments is expedited, but the amount of the individual payments is calculated in the same manner as for regular aid (Lin and Wang 2012).

Regardless of the type of aid, the compensation rate is determined separately for each crop and livestock and set equal to half the production cost of lost output during the cultivation or rearing period. The rate is updated by the central government every five years. Because disaster program payments are based on a fixed rate and applied to the assessment of actual damage, they are similar to payments issued the Federal Emergency Management Agency (FEMA) in the U.S.

An important distinction between regular and emergency disaster aid pertains to the mechanism used to distribute payments. The government establishes an annual budget for agricultural disaster payments, and in the event of a disaster, the central government decides whether to issue payments. If the budget is sufficient to cover an approved disaster, payments are made to the applicant farmers in all townships. However, if the budget is insufficient to cover all claims or in the case of the emergency aid, townships are given a priority ranking. In some cases, the central government will authorize additional funds for emergency aid if the annual aid budget is exhausted. The use of a priority ranking for regular aid under budget constraints and for emergency aid subjects the aid allocation process to possible political manipulation. In particular, previous research has demonstrated that Taiwan's agricultural disaster payments are allocated in accordance with the political preferences of the central government (Chang and Zilberman 2014). This is because the criteria for establishing the priority ranking is subject to discretion, and townships whose populations provide the strongest support for the ruling political party are placed higher in the ranking than townships with many opposition supporters. As a consequence, farmers in opposition townships may not receive any aid in some cases. The political manipulation of disaster payments is not unique to Taiwan. For example, Garrett, Marsh and Marshall (2006) finds that higher levels of agricultural disaster payments in the U.S. were directed to states having congressional representatives with power over aid allocations. Likewise, Garrett and Sobel (2003) finds that nearly have of all U.S. FEMA disaster aid declarations are politically motivated.

Table 1 presents basic information on the prevalence of the natural disasters that occurred during our sample period (January 2009 – December 2012). There were more heavy rainfall events than any other type of disaster, but income losses from these events, as measured by the average disaster payment per recipient, were smaller than for the other disasters.[3] Typhoons resulted in the highest income loss (NT$ 9,850 per month per receipt), and affected the largest number of townships (615 township-events in total). High wind events resulted in the second highest income loss (NT$ 9,760 per month per receipt), but affected the fewest townships. Figure 1, panel A shows differences in the average level of

[3] Since we are unable to separately identify regular and emergency aid in our data, Table 1 contains total disaster payments.

agricultural disaster payments per recipient across townships in Taiwan. Payments were generally highest in the north-central and south-central regions of the island.

## 3. Theoretical Framework

In order to understand the effect of a disaster shock on a farmer's economic decisions, it is useful to establish a theoretical framework based on the conventional agricultural household model, extended to account for health production.[4] For simplicity, consider a unitary model of the farm household, where utility, $U$, is maximized over the consumption of market goods, $c$, leisure, $T_{leisure}$, and health, $H$. The household's stock of health is produced through the use of health care, $h$, market goods and time devoted to health production, $T_{health}$. Household earnings are derived from farm sales and off-farm work, $T_{off}$, at the wage rate, $w$.[5] Farm output is produced according a farm production function, $f(\cdot)$, from production inputs, $z$, and time devoted to farm production, $T_{on}$. Aside from leisure, farm work, off-farm work and health production, the household may devote time to home production, $T_{home}$. The natural disaster represents a random shock, $\varepsilon$, to both farm and health production. Therefore, the utility maximization problem is as follows:

$$
\begin{aligned}
& Max\ U(c, T_{leisure}, H) \\
& s.t. \\
& P_h \cdot h + P_z \cdot z + P_c \cdot c = P \cdot f(z, T_{on}; \varepsilon) + w \cdot T_{off} \qquad (1) \\
& H = g(h, c, T_{health}; \varepsilon) \\
& \bar{T} = T_{off} + T_{on} + T_{home} + T_{health} + T_{leisure},
\end{aligned}
$$

[4] For a comprehensive review of the standard agricultural household model without a health production function, see Singh, Squire and Strauss (1986) and Taylor and Adelman (2003).

[5] We do not include income from disaster payments in the model because we conduct our empirical analysis using data on health care use immediately after the disaster shock, before payments are issued by the government.

where $\bar{T}$ is the time endowment time, $P$ is the output price of farm production and $P_h$, $P_z$, and $P_c$ are the prices of health care, farm inputs and market goods, respectively. Solving the utility maximization problem yields the following reduced form demand functions for health care, farm inputs, market goods, and time allocations:

(2) $$y = q(P, P_h, P_z, P_c, w; \varepsilon),$$

where $y = \left(h, z, c, T_{off}, T_{on}, T_{home}, T_{health}, T_{leisure}\right)$.[6]

We estimate several reduced form versions of the health care demand function. In our first two empirical specifications health care demand is measured as the probability of a visit to a health care provider and as the number of health care visits. We also estimate a third specification where we multiply both sides of the equation (2) by $P_h$ so that demand is measured as health care expenditure. Using a separate dataset we estimate the demand for off-farm work, home production and farm sales.

The theoretical framework elucidates the potential mechanisms through which the disaster shock may affect farm income and the demand for health care. In particular, the disaster shock could have both a direct effect on health care demand as well as an indirect impact through changes in time allocations among different activities. For example, a natural disaster could increase time allocated to off-farm work in order to compensate for a loss in farm sales. Some of this increase could come at the expense of time devoted to the production of health, which includes time spent seeking medical care or implementing the recommendations of clinicians. While reductions in time devoted to health production could decrease the demand for health care, an increase in stress due to the disaster or a reduction in sanitary living conditions could increase the demand for health care. As a result, the net impact of a natural disaster on health care demand is theoretically ambiguous.

[6] Note that $T_{off}$ is obtained as a residual from the other time allocation demands and $\bar{T}$.

The theory also suggests that disaster shocks will decrease farm output through the destruction of crops or livestock and less time devoted to farm production, which will result in a reduction in farm income. The direct effect of farm income on health care demand can be specified through a quasi-reduced form function, where $P$ in equation (2) is replaced with $P \cdot f(\cdot)$. We derive the farm income elasticity of health care demand based on this reduced form equation by combining estimates of the causal effect of the disaster shock on health care use and causal effect of the disaster shock on farm income.

## 4. Empirical Approach

Our empirical study is based on the analysis of two population-based datasets. We first estimated models that link changes in future disaster payments to health care use and expenditure outcomes using FHI health care claims data. We use *future* disaster payments to measure farm income loss by merging disaster payment levels to the claims data during the month when the natural disaster occurred, which is approximately two months before farmers received their payments. From these models we constructed disaster payment elasticities of health care demand. Next, we estimated models that link changes in disaster payments to (gross) farm income loss and off-farm labor supply using the Agricultural Census survey in Taiwan. This step is necessary in order to calibrate changes in disaster payments, which are less than calculated production losses, to changes in total lost farm sales. In addition, incorporating these data allows us to investigate the potential changes in time allocations and income sources suggested by our theoretical framework. From this second set of models we constructed disaster payment elasticities of farm income. Using the two independently constructed elasticities, we then derived farm income elasticities of health care demand.

### *4.1 The two-part model of health care demand*

Health care utilization data are characterized by a mass point at zero expenditures or visits and a right-skewed distribution for non-zero values. Following the recommendations from numerous past studies on health care utilization modeling, we used a two-part model (TPM; Manning, Duan and Rogers 1987; Jones 2000; Buntin and Zaslavsky 2004).[7] The first part of this model measures whether the individual had any health care use and the second part of the model measures health care expenditures or visits among the sample with use. By combining the first and second parts of the TPM when constructing marginal effects, one can estimate the effect of covariates on a measure of unconditional health care use that applies to full population (Jones 2000). We specify the first part of the TPM using a probit model as follows:

$$\Pr\left(I_{ijt} = 1\right) = \Phi\left(\alpha_1 + \gamma_1 \times D_{jt} + \beta_1' X_{ijt} + \delta_j\right), \tag{3}$$

where $I_{ijt}$ is the binary indicator of health care use for farmer $i$ in township $j$ at time $t$, $D_{jt}$ is the level of disaster payments received two months in the future, $X_{ijt}$ is a vector of the explanatory variables, $\delta_j$ is a township fixed effect and $\alpha_1, \gamma_1, \beta_1$ are estimable parameters.

In the second part of the TPM, we used a gamma generalized linear model (GLM) with a log link to account for right-skewness in the conditional distribution when modeling health care expenditures, and a Poisson GLM when modeling visits and prescription fills.[8] The second part of the model, estimated on the sample of health care users, is specified as:

$$E\left(h_{ijt} \middle| h_{ijt} > 0\right) = \exp(\alpha_2 + \gamma_2 \times D_{jt} + \beta_2' X_{ijt} + \delta_j), \tag{4}$$

where $h_{ijt}$ is the level of health care expenditure or the number of visits and $\alpha_2, \gamma_2, \beta_2$ are estimable parameters. Both the first and second parts of the TPM include the same set of control variables (see Table 2) and dummy variables for year, month and township. By

[7] Both Zheng and Zimmer (2008) and Mishra, El-Osta and Ahearn (2012) use the TPM in their analyses of health care spending by U.S. farmers and farm households.

[8] We used a Park test to verify that each distribution is consistent with the proper specification for the conditional variance function (Manning and Mullahy 2001).

combining equations (3) and (4), we derived the unconditional expectation of health care expenditure or visits as:

(5) $$E(h_{ijt}) = \Pr(I_{ijt} = 1) \times E(h_{ijt} | h_{ijt} > 0).$$

We then calculated the disaster payment elasticity of health care demand as: $E_{hD} = \frac{\partial E(h_{ijt})}{\partial D_{jt}} \cdot \frac{\bar{D}}{\bar{h}}$ using the sample means of disaster payments ($\bar{D}$) and the outcome variable ($\bar{h}$). We calculated the standard errors of the TPM marginal effects using a block bootstrap routine with 500 iterations that is clustered at the township level, and the standard errors of elasticities using the delta method.

Our outcome variables include total health care expenditures on all services (including FHI and out-of-pocket copayments by patients), total outpatient expenditures, out-of-pocket expenditures on outpatient services, total inpatient expenditures, out-of-pocket expenditures on inpatient services, and total prescription drug expenditures, all in 2009 new Taiwan dollars (NT$) per month.[9] We also modeled the number of inpatient visits, outpatient visits and prescriptions per month.

*4.2 Log-linear model of farm income*

Similar to health care expenditure, the distribution of farm income is right-skewed, but with few zero values, so we specified the following log-linear model:

(6) $$\log(Y_{ik}) = \alpha_3 + \gamma_3 \times D_{ik} + \beta_3' Z_{ik} + \lambda_k + u_{ik}$$

where $Y_{ik}$ is the farm income of household $i$ in county $k$, $Z_{ik}$ is the vector of explanatory variables, $\lambda_k$ is a county fixed effect, $u_{ik}$ is a random disturbance term, and $\alpha_3, \gamma_3, \beta_3$ are estimable parameters. Given that $\gamma_3$ is the semi-elasticity of farm income to a one dollar change in disaster payments, we calculated the full elasticity using the sample mean of the disaster payment variable as: $E_{YD} = \hat{\gamma}_3 \cdot \overline{D}$. We computed the standard error of the elasticity using the delta method while clustering on county.

[9] The data do not contain out-of-pocket expenditures on prescription drugs.

Using the two aforementioned elasticities, we calculated the farm income elasticity of health care demand as:

$$E_{hY} = \frac{\partial \log(h)}{\partial \log(Y)} = \frac{\partial \log(h)/\partial \log(D)}{\partial \log(Y)/\partial \log(D)} = \frac{E_{hD}}{E_{YD}}. \quad (7)$$

Given that the numerator and denominator of equation (7) are estimated from different samples, we could only compute an upper bound of the standard error of $E_{hY}$ using the delta method.[10]

*4.3 Identification strategy*

Although the timing and severity of natural disasters is largely random, farmers engage in varying levels of self-protection from disaster risks. The unobserved preferences that determine their level of self-protection and susceptibility to income loss could be correlated with health care use. In addition, it is possible that both health care use and potential income losses from disasters are correlated with unobserved farmland productivity due, for example, to differences in soil quality. In order to address this endogeneity problem we estimated models of instrumental variables (IV) with township fixed effects using the nonlinear IV estimator developed by Carroll et al. (1995) and Hardin et al. (2003) for GLM models.

Our identification strategy is based on previous findings by Chang and Zilberman (2014) that townships in Taiwan containing a larger fraction of supporters of the ruling political party are granted higher priority for disaster aid than townships with fewer supporters. We constructed an instrument to measure the political importance of the township to the ruling party by taking the product of two variables measuring township vote counts in the 2008 or 2012 presidential election. The first variable is the number of votes for the incumbent political party divided by the number of votes for all opposing political parties,

[10] We assume positive covariance between $E_{hD}$ and $E_{YD}$. Our logic is that both elasticities are increasing in the proportion of farm income used to calculate disaster payments.

and the second variable is the total number of eligible voters in the township.[11] The first variable captures the political alignment of the township with the ruling party and the second variable represents the number of potential voters in the township (i.e. the potential political importance of the township).

This instrument is correlated with disaster payments in the first stage of the IV model because it causes variation in payments by affecting the probability that disaster payments are authorized. Since the level of disaster payments is determined by an administrative formula, we can model a farmer's disaster payment as the product of the payment level, $D_i$, with the Bernoulli random variable, $B_j$, such that $E(B) = p$, where $p$ is the probability that the disaster payment is authorized.[12] Our instrument generates changes in disaster payments by affecting the magnitude of $p$. Following a natural disaster, if $p$ is sufficiently large, $B_j = 1$, and each farmer in the township receives payment $D_i$.

Our identification strategy is consistent with findings from studies in political economy that political considerations are directly associated with the distribution of public funds (Persson and Tabellini 2000). There are several hypothesized mechanisms for political preference in the allocation of redistributive transfers. The core voter model purports that political parties target voters with consistent political preferences in order to build coalitions of support (Cox and McCubbins 1986), while another strain of the literature argues that politicians have the strongest incentive to divert funds to swing voters who may be more important to their chances of re-election in closely contested races (Diaz-Cayeros 2008). In the case of disaster aid, Garrett and Sobel (2003) finds that U.S. states politically important to the President have higher rates of disaster declaration approval, and that levels of disaster funding are higher in elections years. However, the aggregation of disaster approvals and aid

[11] The two major political parties in Taiwan are the Kuomintang (KMT) and Demographic Progressive Party (DPP). Between 2008 and 2016, the central government was controlled by the KMT.

[12] The probability mass function of $B$ is therefore: $P\{B = 0\} = 1 - p;\ P\{B = 1\} = p$.

to the state level makes it impossible to determine whether the intention of federal policy makers is to bolster support among core constituents or to target swing voters. Kousky, Michel-Kerjan and Raschky (2018) constructs an instrument for disaster aid that captures whether U.S. counties affected by floods are swing counties, and provides empirical support for aid approvals intended to influence swing voters. In contrast, Chang and Zilberman (2014) finds that allocations of agricultural disaster aid in Taiwan are consistent with the predictions of the core voter model.

The statistical power of our instrument is generated from a similar source of geographic variation in the perceived importance of specific townships to the ruling party's future electoral prospects. Panel B of figure 1 shows geographic variation in the average level of instrument across townships in Taiwan. The political importance of the townships to the ruling party is highest in the northern part of the island, and among several townships in central Taiwan and the southernmost part of the island. Notably, the townships in central and southern Taiwan with the highest political importance are also among those with the highest level of disaster payments per recipient (panel A of figure 1).

The first stage F-statistic for our instrument is 22.2 (bottom of first column of appendix table A2), which meets the conventional criteria for a sufficiently powerful instrument when both the instrument and endogenous variable are continuous (Stock, Wright and Yogo 2002). We expect our instrument to meet the exclusion restriction because vote shares should not directly influence individual health care spending after controlling for the supply of health care service providers in each township. To support our conjecture, we demonstrate that the instrument passes falsification and sensitivity tests designed to infer consistency with the assumed exclusion restriction.

## 5. Data

We constructed our primary analytic sample from population-based data on health care claims, administrative data on agricultural disaster payments, and voting records from national elections. We also created a secondary sample using agricultural census data to analyze how natural disasters affect labor supply allocations and farm sales. In both cases, we extracted control data from several other government sources that we merged to the main analytical samples.

### *5.1. Health care claims*

Our primary dataset was extracted from the administrative profile of the National Health Insurance program (NHI), which provides comprehensive health insurance benefits to 98% of Taiwan's residents (Chiang 1997). We obtained a 5% de-identified random sub-sample of NHI enrollees (one million individuals) from the National Health Institute in Taiwan, and selected adults aged 18 and older enrolled in the Farmer's Health Insurance Program (FHI) from January 2009 to December 2012.[13] The FHI differs from other NHI programs for private sector and government employees mainly by its insurance premium and supplemental benefits.[14] FHI enrollees pay 2.55% of total benefits in premiums, while other NHI enrollees pay 4.69% of total benefits in premiums, on average (NHI, 2020). Copayment amounts are the same for all NHI enrollees, regardless of program. Nearly all farmers in Taiwan are enrolled in the FHI. Our analytic sample contains monthly health care claims for just over 75 thousand farmers in each year, resulting in a final sample of 3,538,133 farmer-month observations between January and December from 2009 to 2012 (48 months in total).

[13] When drawing the 5% sub-sample of NHI enrollees, the Institute considered the distribution of population age and gender in each county. As a result, the sub-sample is nationally representative of the population of NHI enrollees in 2005.

[14] The FHI includes disability and maternity benefits, and a pension (Taiwan Bureau of Labor Insurance 2020).

From the claims records we constructed measures of health care utilization, including out-of-pocket (OTP) copayments and total payments that include both NHI and OTP payments. We also constructed variables to measure the demographic characteristics of farmers, including binary indicators for gender, ten-year age category (with a narrower category for those 18-25 and a broader category for those over 75), and the township of residence.

### *5.2. Agricultural census survey*

In order to obtain measures of off-farm labor supply and farm sales we used the 2010 agricultural census survey of Taiwan. Census data are collected through face-to-face interviews with all farm households registered in the national household census every five years, and serve as the primary source of information on farm production and farm household conditions (DGBAS 2010). There are 780,388 farm households in the 2010 agricultural census, and we removed households that did not engage in farm production during the survey year and those whose principle operator was at school or retired, leaving a sample of 634,076 households. We extracted the sales value of raw farm products, the total annual days of on-farm work by the principle operator, and indicator variables for whether off-farm work or house work was the main occupation of the principle operator. We also extracted demographic data on the principle operator to create control variables in our empirical models, including gender, education level (operator can't read, primary school, junior high school, senior high school, college or advanced degree) and age (less than 25, 25-34, 35-44, 45-54, 55-64, 65-74, 75 or older). Control variables for household and farm characteristics include the number of household members, the number of hired workers, farm size, and indicator variables for primary crop (rice, vegetable, fruit, other crop, livestock).

### *5.3. Agricultural disaster relief payments*

Our data on agricultural disaster relief payments to each township come from the Council of Agriculture in Taiwan. The data include information on the size of damaged farmland in each year and month, total payments issued by the program, and type of natural disaster. We divided total payments in each township by the number of recipients to create a measure of payments per farmer per month. We then disaggregated payments by the four disaster categories (typhoons, extreme temperature, heavy rainfall and high wind) and merged the disaster payment variables to the health care utilization data by township to the month the disaster occurred and to the 2010 agricultural census by township.

*5.4. National election profiles*

We obtained voting records for the 2008 and 2012 nationwide presidential elections from the Taiwan Central Election Commission in order to construct our political instrument. Between January 2009 and January 2012, we used vote totals and the vote ratio of the incumbent party to the opposition party from the March 2008 election, and for February through December 2012, we used vote totals and the vote ratio of the incumbent party to the opposition party from the January 2012 election. We then merged the political instrument to the health care utilization data by township, year and month. In the case of the 2010 agricultural census survey, we merged the instrument based on the 2008 election by township.

*5.5. Healthcare resources, land quality and other variables*

We collected data on several township characteristics that could be related to farmers' health care utilization. From the Taiwanese Ministry of Health and Welfare we obtained counts of the supply of health care providers (number of hospitals and clinics and the number of doctors) and from the Taiwanese Environmental Protection Administration we acquired data on local air pollution levels. Specifically, we constructed measures of the monthly average level of sulfur dioxide ($SO_2$) and carbon monoxide (CO) in each township.

Finally, we collected data on land quality from the Council of Agriculture and merged this information to the 2010 agricultural census survey at the township level. These data include average land slope and land height as well as the ratio of land prioritized for agriculture, and the ratio of land classified as agricultural land that is not prioritized for agriculture.

Table 2 contains sample statistics for all of the outcome and explanatory variables in the health care utilization models, computed using the full sample as well as the subsamples of townships with and without disaster payments. Nearly all measures of health care use are slightly higher in townships without disaster payments, but the differences in the sample means are not statistically significant. Demographic differences between the two groups of farmers are also minor. The one exception is in the supply of health care providers. In particular, there were 45.7 hospitals and clinics in townships without disaster payments, but only 32.2 hospitals and clinics in townships with disaster payments. Despite this discrepancy in the number of treatment facilities, the number of doctors is similar across the two sets of townships. Pollution levels are slightly elevated in townships without disaster payments.

Appendix table A1 contains sample statistics for variables from the 2010 agricultural census data for the full sample and the subsamples of townships with and without disaster payments. The average size of farms in Taiwan is relatively small (0.7 hectares) and 32% of farm operators work primarily off of the farm. Furthermore, 67% of farm operators are over the age of 54 and the average number of annual on-farm work days is only 93 out of a possible 238.[15] These statistics are consistent with findings by Chang, Meyerhoefer and Just (2014) that benefits associated with the FHI delay retirement and provide incentives for part-time farming. Rice and vegetable farming is more common in townships that did not receive

[15] We base the total number of work days per year in Taiwan, accounting for national holidays, on data from https://timesles.com/en/calendar/working/years/2021/

payments, while townships with payments were more likely to contain orchards and other fruit farms.

## 6. Results

*6.1 Main results*

We report the full set of coefficient estimates for the first stage of the IV model as well as the first and second parts of the IV- and non-IV-TPM for total health care expenditure in appendix table A2. Consistent with our identifying assumption and the findings of Chang and Zilberman (2014), the size of disaster payments allocated to the township in the first stage equation is increasing in the township's political alignment with the incumbent political party. Comparison of the IV and non-IV coefficient on disaster payments indicates a downward bias in the latter, suggesting there is greater health care use among farmers with unobserved preferences for risk avoidance and self-protection. In addition, we reject the null hypothesis of exogeneity in both the first and second parts of the TPM using a Durbin-Wu-Hausman test (bottom of table A2).

In the first two columns of table 3 we report the marginal effects and standard errors for the first part of the IV-TPM measuring the effect of disaster payments on the likelihood of health care use, and in appendix table A3 we report the marginal effect estimates and standard errors from the second part of the model measuring the level of the outcome among users of health care and the unconditional marginal effects based on both parts of the model. The disaster payment and farm income elasticities in the middle and right-most columns of table 3 are based on these unconditional estimates. Several interesting findings emerge from the marginal effect and elasticity estimates. First, an increase in disaster payments leads to a reduction in total, outpatient and prescription drug use and expenditure, but not inpatient use or expenditure. In particular, a one thousand dollar increase in agricultural disaster payments per recipient is associated with a 1.5 percentage point decrease in total and outpatient health care use and a reduction in total and outpatient expenditure (column 1, table 3).[16] Based on the disaster payment elasticities of health care expenditure in column 3 of table 3, a ten percent increase in disaster payments is associated with a 1.3 percent and 1.4 percent decrease in total and outpatient expenditure, respectively. With an elasticity of -0.07, prescription drug expenditures are the least responsive to changes in disaster payments, while OTP expenditures on copayments for outpatient services are the most responsive ($E_{hD} = -.21$). The disaster payment elasticity of outpatient visits ($E_{hD} = -.16$) falls within the range of the heath care expenditure elasticities.

The farm income elasticities of demand in column 5 of table 3 are larger in magnitude than the disaster payment elasticities because the disaster payment elasticity of farm income from the agricultural census data, at -0.65, is less than unitary. Given that the level of disaster payments is set at approximately 50% of production costs from lost output, the disaster payment elasticity of farm income is analogous to a production cost elasticity. The inelastic estimate of this elasticity indicates that farmers are able to protect some of their income from natural disasters by modifying their production process. They may, for example, compensate for negative shocks by adjusting farm household labor supply in different activities, which is not a component of costs incorporated into the disaster payment formula (Blundell, Pistaferri and Saporta-Eksten 2018).[17]

Despite the inelastic response of farm income to disaster payments, the farm income elasticities in column 5 still indicate inelastic demand for health care. OTP expenditure and visits are most responsive to changes in farm income, with an elasticities of 0.32 and 0.25,

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[16] A one thousand dollar increase in disaster payments causes a reduction in total and outpatient expenditure of NT$ 243 and NT$ 138 based on the unconditional marginal effects in column 3 of table A3.

[17] Blundell, Pistaferri and Saporta-Eksten (2018) demonstrates that households can reallocate time in different activities to smooth their marginal utility of consumption in response to uncertain exogenous shocks.

respectively. In comparison the farm income elasticities of total health care expenditure and drug expenditure are 0.20 and 0.11, respectively. With an estimated value of 0.19, the farm income elasticity of prescriptions is similar to total and outpatient expenditure.

*6.2 Sub-group estimates*

In table 4 we stratify the results by type of disaster. In all cases, the income loss from natural disasters leads to a reduction in health care utilization. Patient OTP payments for outpatient care are the most sensitive to income loss from disasters, with the disaster payment elasticity ranging from -0.11 for high wind damage to -0.39 for typhoon damage. In general, disaster payments are associated with the largest reductions in health care when a typhoon occurs, and the smallest reductions in use when there is crop damage from high winds. One possible explanation for this discrepancy is that the extent of damage to aspects of farms other than crops or livestock (such as buildings and equipment) is highest after a typhoon, resulting in a larger total income loss.

Next, we consider differences in the impact of natural disasters by type of farm. Our FHI data do not contain information on farm type, so we used the 2010 Agricultural Census to rank townships by the primary crop reported by each farmer. We then selected townships in the top 25% percentile of the ratio of rice, fruit/flower, or livestock farms relative to total farms. We focus on these agricultural products for several reasons. Rice is a staple food crop in Taiwan, which is highly correlated with food security, while fruit and vegetable crops have the highest market values. Livestock farms differ from crop farms in several ways, including their capacity to cope with natural disasters.

Table 5 contains the marginal effect estimates, disaster payment elasticities and farm income elasticities by township farm type and urban/rural classification. Total health care expenditure of rice farmers is most affected by income loss due to natural disasters ($E_{hD} = -.19$), followed by fruit/flower farmers ($E_{hD} = -.10$), and then livestock farmers ($E_{hD} =$

−.09), but the differences in the estimates are not large. However, the responsiveness of farm income to changes in disaster payments is more pronounced across farm types, leading to larger differences in the farm income elasticities of health care demand. In particular, the farm income elasticity of total health care expenditure for rice farmers is 0.32, followed by 0.14 for fruit/flower farmers and a statistically insignificant 0.09 for livestock farmers.

*6.3 Analysis of mechanisms*

Using the agricultural census, we explored the possible substitution between on-farm and off-farm work suggested by our theoretical framework to follow a disaster shock. Table 6 contains IV estimates of the impact of disaster payments on annual on-farm work days, whether the farm operator has an off-farm job that serves as their primary occupation, and whether the farm operator's main occupation is household work. The full set of coefficient estimates, including the first stage of the IV model, is contained in appendix table A4. Based on the elasticity estimates in table 6, a 10% increase in disaster payments is associated with a 2.7% decrease in on-farm work days and a 0.4% increase in the likelihood that a farmer shifts their primary occupation to an off-farm job. Although the agricultural census data does not contain information on off-farm work hours, the reduction in on-farm days implies an increase in off-farm work hours. A 10% increase in disaster payments is also associated with a 2.3% increase in the likelihood that a farmer shifts their primary occupation to house work, but only 3% of farmers engage mostly in household work, on average.

The increase in off-farm employment from natural disasters has implications for the use of health care. Because the majority of farmers are able to retain their FHI benefits when they switch primarily to off-farm work, the monetary cost of health care services will remain the same irrespective of occupation, but farmers could experience changes in the time cost of seeking health care. For example, if their off-farm work hours are inflexible or their off-farm jobs do not provide sick leave, their time cost of medical treatment could increase. Likewise, time costs will necessarily rise for farmers whose total work hours increase with the shift to off-farm employment.

In order to gain additional insight into what types of health care are most affected by natural disasters we estimate disaster payment elasticities stratified by treated condition and report the results in table 7. We focus on five common illnesses that could be affected by disaster shocks: mental health disorders, injury and poisoning, infection and parasitic diseases, digestive system disorders, and respiratory system disorders.[18] Natural disasters could directly impact mental health disorders through increased psychological distress, and injury, poisoning and infections through extreme weather or reduced sanitation (Hallegatte et al. 2017). Digestive system and respiratory disorders are among the largest categories of health care visits, and therefore, the most likely to be indirectly affected by disasters through changes in farm incomes and time allocations. Disaster payment elasticities for the treatment of digestive system disorders, such as gastroesophageal reflux disease, are larger, in some cases, than the elasticity estimates from the pooled sample reported in table 3. In addition, the elasticities for respiratory system disorders, such as acute respiratory infections, are all precisely estimated, but we are unable to identify any statistically significant effects of disaster payments on mental health disorders, injury and poisoning, and infections and parasitic diseases. These estimates suggest that natural disasters in Taiwan do not result in reduced sanitation or direct injury in most cases, and that the stress associated with disasters does not generally trigger the need for additional mental health treatment. Rather, natural disasters and associated losses in farm income reduce the treatment of common, less severe illnesses, which is consistent with a reduction in demand due to higher time costs.

*6.4 Falsification tests and sensitivity analyses*

[18] These categorizations are based on the ICD-9 codes.

To check whether our IV model could be capturing a spurious correlation between disaster payments and health care use, we conducted several sensitivity analyses and falsification tests. First, we regressed our instrument and control variables directly on farm income, health care use and conditional health care expenditure in townships without any disasters, and report the results in appendix table A5. If the instrument satisfies the exclusion restriction, we should expect no effect of the IV on the outcomes in this sub-sample. Consistent with the validity of the instrument, the coefficients on the IV are small and statistically insignificant. Next, we applied the method proposed by Conley, Hansen and Rossi (2012) to assess the robustness of the IV estimates under violations of the exclusion restriction. This requires the estimation of a modified version of the TPM described in equations (3) and (4), where the IV is permitted to have a direct impact on health care utilization, net of the endogenous variable and control variables. The modified TPM is:

(8) $$\Pr(I_{ijt} = 1) = \Phi(\alpha_1 + \gamma_1 \times D_{jt} + \beta_1' X_{ijt} + \delta_j + \rho_1 IV_{jt}),$$

(9) $$E(h_{ijt} | h_{ijt} > 0) = \exp(\alpha_2 + \gamma_2 \times D_{jt} + \beta_2' X_{ijt} + \delta_j + \rho_2 IV_{jt}),$$

where $\rho_1 = \rho_2 = 0$ when there are no violations of the exclusion restriction. Conley, Hansen and Rossi (2012) demonstrate how to construct valid confidence intervals for $\gamma_1, \gamma_2$ when $\rho_1, \rho_2$ are non-zero, which we show in appendix figure A1. Since the 95% confidence intervals only contain negative parameter values, the test supports a negative effect of disaster payments on health care demand, even under violations of the exclusion restriction.

Finally, we tested whether our estimates could be attenuated by the short-term liquidity effect of disaster payments. We measure health care use following the natural disaster, and approximately two months prior to when a qualified farmer would receive disaster payments. As a result, we expect that the reductions in health care utilization we identify capture the income loss from the disaster, not the anticipation of future disaster payments. To investigate a possible liquidity bias, we estimated IV models where the endogenous regressor is the one-month lag of disaster payments and models with the two-month lag of payments. Since disaster payments are issued 45-60 days following the initial claim, the one-month lag captures the effect of payments on health care use 15 days prior to the payment, while the two-month lag captures the effect around the time of the payment.

Table 8 contains marginal effect and elasticity from the models with lagged disaster payments. The magnitudes of the elasticities in panel A based on the one-month lag are only slightly smaller than estimates from the main models in table 3. However, there is clear attenuation of the estimates when we use a two-month lag in panel B, suggesting a positive bias due to the short term liquidity effect of the disaster payments at the time of payment. However, there is no evidence of bias in our main models.

## 7. Discussion and Conclusions

We investigate how income shocks from natural disasters affect famers' health care use and expenditure using administrative health care claims from Taiwan. The estimation of reliable income elasticities of health care demand requires that we develop strategies to measure the severity of income loss and correct for selection into varying levels of self-protection from disasters. By exploiting the fixed relationship between future agricultural disaster payments and production costs from lost output, we derive farm income elasticities of health care demand as the ratio of two component elasticities. The numerator is the disaster payment elasticity of health care demand, measured from health care claims, and the denominator is the disaster payment elasticity of farm income loss, measured from agricultural census data. In contrast to previous studies on farm income and health care use, we account for the endogeneity of income loss by using a political instrument that predicts the likelihood of disaster payment authorization. Previous research indicates that past support for the incumbent political party in townships affected by disasters influences payment authorizations, particularly when there are budget constraints (Chang and Zilberman 2014).

Our main results indicate that farm income loss from natural disasters reduces the use of outpatient health care services and prescription drugs, but not inpatient services. Disaster payment elasticities that capture only crop and livestock damage range from -0.07 for prescription drug expenditures to -0.21 for OTP expenditure on outpatient copayments. Accounting for all reductions in farm sales from natural disasters through the estimation of farm income elasticities of health care expenditure generates estimates that range from 0.11 for prescriptions drugs to 0.32 for OTP expenditure on outpatient services. While still inelastic, these farm income elasticities are larger than those reported by Mishra, El-Osta and Ahearn (2012) and Khalili et al (2021), which are based on cross-sectional associations. Our elasticities of total and outpatient expenditure and outpatient visits, however, are similar to the lottery income elasticities of demand for private health care services reported by Cheng, Costa-Font and Powdthavee (2018) for chest x-rays (0.26) and cholesterol tests (0.18).

After examining disaster payment elasticities of health care expenditure for specific medical conditions, we are able to rule out any significant direct effect of natural disasters on health through reduced sanitation or severe psychological distress. Rather, we find that higher disaster payments are associated with less treatment of common conditions, such as digestive and respiratory disorders. The remaining channels through which farm income loss may influence health care demand include changes in labor supply that affect the time cost of treatment and farmers' response to a reduction in expected income. Our supplementary analysis of the agricultural census suggests that natural disasters lead to modest changes in farmers' labor supply in the form of a reduction in on-farm work days and small increase in the likelihood of switching primarily to off-farm employment. Greater reliance on off-farm work could increase the time cost of medical treatment if it is associated with less flexible work hours, or if the total number of hours worked increases.

By construction, our farm income elasticities of health care demand reflect changes in expected income. We merge disaster payments to health care claims in the month the disaster occurred, which is prior to when the farmer would experience the actual loss of agricultural sales revenue from damaged crops or livestock (because it would not generally coincide with the harvest payment date), and approximately 45 – 60 days prior to the receipt of disaster payments. Since we verify that our estimates are not contaminated by a short-term liquidity bias associated with the receipt of disaster payments, we believe our estimates reflect expected income loss.

Changes in labor supply that result from farm income loss and differences in physical infrastructure may explain some of the differences in farm income elasticities of demand across farm types. In particular, one reason why health care use of farmers in urban areas may be less responsive to changes in farm incomes could be due to higher rates of off-farm employment that protect farmers financially from disaster shocks. The lower response to farm income loss by fruit/flower farmers and livestock farmers, relative rice farmers, could be due to their ability to protect their crops and livestock from adverse weather in structures, such as barns and greenhouses.

Our results have several implications for policies designed to increase access to health care by farmers. We find that the drop in expected income from natural disasters causes farmers to reduce their use of outpatient services and prescription drugs. Whether farmers forgo services for the treatment of acute conditions or preventive care, there is a concern that lack of health care in the short run could result in longer term health problems. For example, Chandra, Gruber and McKnight (2010) shows that a reduction in outpatient and prescription drug use due to higher cost sharing may lead to large future hospital costs. Ultimately, failure to address health problems could result in lower productivity and additional future income loss (Strauss and Thomas 1998; Michell and Bates 2011).

Out-of-pocket expenditures for outpatient care are the most sensitive to farm income loss, with an elasticity of 0.48 for rice farmers and of 0.32 across all farmers. While coverage under the national health insurance program in Taiwan is comprehensive, FHI enrollees do face deductibles and incur copayments when they visit providers. Policy makers may wish to consider the merits of suspending cost-sharing in the FHI program following natural disasters in order to minimize reductions in health care use. Recent estimates of price elasticities of health care demand indicate inelastic, but nonzero increases in health care use when prices decrease, suggesting that reductions in cost sharing could offset some of the negative effects of farm income loss on health care use after natural disasters.[19] This policy would be most effective following typhoons, which result in the largest reductions in health care use for a given decrease in farm income.

Our study has some limitations. In particular, we measure income loss indirectly through the allocation of disaster payments to farmers with damage to at least 20 percent of their crops or livestock herd. As a result, we fail to capture smaller income losses from natural disasters. In addition, our farm income elasticities are based on reductions in farm sales, and do not directly capture expenses associated with repairing damaged buildings or equipment. Finally, the variation in farm incomes we use to identify our estimates is uniformly negative. If farmers' use of health care services responds differently to increases in income than reductions in income, our income elasticities will not be generalize to situations where farmers gain income.

[19] For example, Meyerhoefer and Zuvekas (2010) estimate price elasticities of demand for physical health services and prescription drugs of -0.12 and -0.31, respectively, while Ellis, Martins and Zhu (2017) estimate an overall demand elasticity of -0.44.

Despite these limitations, this study provides the first causal estimates of farm income elasticities of demand for health care services, which are important to the design of policies intended to increase farmers' access to health care. In addition, the study quantifies the negative impact of natural disasters on health care utilization, which is a cost expected to grow in the future as climate change intensifies.

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**Table 1**. Type and prevalence of natural disasters, January 2009 – December 2012.

| Type | No. of events (A) | Total No. of affected townships (B) | Average No. of affected townships per event (C)=(B)/(A) | Average disaster payment per recipient (NT$ 1,000/month) (D) |
|---|---|---|---|---|
| Typhoon | 8 | 615 | 77 | 9.85 |
| Heavy rainfall | 13 | 449 | 35 | 6.70 |
| High wind | 2 | 7 | 4 | 9.76 |
| Extreme temperature | 9 | 274 | 30 | 9.71 |
| All events | 32 | 1,345 | 42 | 8.98 |

*Note*: Taiwan contains 358 townships. Source: Administrative profile of the agricultural disaster relief program in Taiwan.

**Table 2**. Sample statistics of analysis variables from NHI/FHI health care claims.

| Variable | Description | Full sample | | Townships w/o disaster payments | | Townships w/ disaster payments | |
|---|---|---|---|---|---|---|---|
| | | Mean | S.D. | Mean | S.D. | Mean | S.D. |
| *Outcome variables* | | | | | | | |
| Any use | Any health care use (0/1). | 0.60 | 0.49 | 0.60 | 0.49 | 0.59 | 0.49 |
| Total exp. | Health care expenditure on all services (NT$/mth). | 3,937 | 18,849 | 3,944 | 18,851 | 3,867 | 18,824 |
| Total exp. users | Health care expenditure on all services among users (NT$/mth). | 6,585 | 24,018 | 6,591 | 24,010 | 6,526 | 24,097 |
| Outpatient use | Any outpatient service use (0/1). | 0.60 | 0.49 | 0.60 | 0.49 | 0.59 | 0.49 |
| Outpatient exp. | Total expenditure on outpatient services (NT$/mth). | 2,009 | 6,429 | 2,012 | 6,426 | 1,986 | 6,457 |
| Outpatient OTP | Out-of-pocket expenditure on outpatient services (NT$/mth). | 149 | 262 | 149 | 263 | 143 | 252 |
| Outpatient visit | No. of outpatient visits per month. | 1.77 | 2.28 | 1.78 | 2.29 | 1.75 | 2.26 |
| Inpatient | Any inpatient service use (0/1). | 0.02 | 0.14 | 0.02 | 0.14 | 0.02 | 0.13 |
| Inpatient exp. | Total expenditure on inpatient services (NT$/mth). | 1,282 | 16,298 | 1,285 | 16,305 | 1,249 | 16,232 |
| Inpatient OTP | Out-of-pocket exp. on inpatient services (NT$/mth). | 70 | 1,063 | 71 | 1,065 | 68 | 1,042 |
| Inpatient visit | No. of inpatient visits per month. | 0.02 | 0.15 | 0.02 | 0.15 | 0.02 | 0.15 |
| Drug | Any prescription drug use (0/1). | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 |
| Drug exp. | Expenditure on prescription drugs (NT$/mth). | 646 | 2,976 | 647 | 2,966 | 632 | 3,069 |
| Drug prescript. | Number of prescription drugs per month. | 1.20 | 1.75 | 1.20 | 1.75 | 1.19 | 1.74 |
| *Control variables* | | | | | | | |
| Disaster | Disaster payments per farmer (NT$ 1,000/mth). | 2.08 | 160.14 | 0.00 | 0.00 | 22.17 | 522.88 |
| IV | Product of vote ratio and the number of voters. | 3.31 | 2.12 | 3.29 | 2.12 | 3.51 | 2.21 |
| Male | Male (0/1). | 0.51 | 0.50 | 0.51 | 0.50 | 0.51 | 0.50 |
| Age18_25 | Age 18-24 (0/1). | 0.00 | 0.04 | 0.00 | 0.04 | 0.00 | 0.05 |
| Age25_34 | Age 25-34 (0/1). | 0.03 | 0.17 | 0.03 | 0.17 | 0.03 | 0.18 |
| Age35_44 | Age 35-44 (0/1). | 0.09 | 0.29 | 0.09 | 0.29 | 0.09 | 0.29 |
| Age45_54 | Age 45-54 (0/1). | 0.15 | 0.35 | 0.15 | 0.35 | 0.15 | 0.35 |
| Age55_64 | Age 55-64 (0/1). | 0.18 | 0.38 | 0.18 | 0.38 | 0.18 | 0.38 |
| Age65_74 | Age 65-74 (0/1). | 0.24 | 0.43 | 0.24 | 0.43 | 0.24 | 0.42 |
| Age75+ | Age >=75 (0/1). | 0.31 | 0.46 | 0.32 | 0.46 | 0.31 | 0.46 |
| Clinics | No. of hospitals and clinics in the township. | 44.51 | 79.59 | 45.77 | 81.58 | 32.23 | 55.39 |
| Doctors | No. of doctors in the township. | 1.15 | 2.60 | 1.16 | 2.62 | 1.11 | 2.40 |
| $SO_2$ | Monthly average level of $SO_2$ in the township. | 3.64 | 1.26 | 3.70 | 1.26 | 3.08 | 1.08 |
| CO | Monthly average level of CO in the township. | 0.41 | 0.13 | 0.41 | 0.13 | 0.34 | 0.11 |
| N*T | | 3,538,133 | | 334,912 | | 3,203,221 | |

*Note*: All expenditures are measured in 2009 NT$.

**Table 3**. Responsiveness of health care utilization to changes in disaster payments and farm income.

| | Panel A. Health care expenditure | | | | | |
|---|---|---|---|---|---|---|
| | Use (0/1) | | Disaster payment elasticity | | Farm income elasticity† | |
| | M.E. | S.E. | $E_{hD}$ | S.E. | $E_{hY}$ | S.E. |
| Total expenditure | -0.015 *** | 0.002 | -0.13 ** | 0.05 | 0.20 ** | 0.10 |
| Outpatient exp. | -0.015 *** | 0.002 | -0.14 *** | 0.05 | 0.22 ** | 0.11 |
| Outpatient OTP | -0.022 *** | 0.003 | -0.21 ** | 0.08 | 0.32 * | 0.16 |
| Inpatient exp. | -0.002 | 0.002 | -0.15 | 0.11 | 0.22 | 0.19 |
| Inpatient OTP | -0.004 | 0.006 | -0.03 | 0.04 | 0.05 | 0.07 |
| Drug exp. | -0.020 *** | 0.002 | -0.07 *** | 0.02 | 0.11 ** | 0.05 |
| | Panel B. Number of visits/prescriptions | | | | | |
| | M.E. | S.E. | $E_{hD}$ | S.E. | $E_{hY}$ | S.E. |
| Outpatient visits | -0.015 *** | 0.002 | -0.16 *** | 0.06 | 0.25 ** | 0.12 |
| Inpatient visits | -0.002 | 0.001 | -0.13 | 0.11 | 0.20 | 0.19 |
| Drug prescriptions | -0.020 *** | 0.002 | -0.12 | 0.08 | 0.19 ** | 0.08 |

*Note*: N*T = 3,538,133. Standard errors are cluster-corrected at the township level. The disaster payment elasticity applies to unconditional health care expenditure. All models include year, month and township fixed-effects and the set of control variables reported in table 2. $E_{hD}$ is the disaster payment elasticity of health care expenditure; $E_{YD}$ is the disaster payment elasticity of farm income; $E_{hY}$ is the farm income elasticity of health care expenditure ($E_{hY} = E_{hD} / E_{YD}$), with standard error calculated using the delta method. ***,**,* indicate statistical significance at the 1%, 5% and 10% level. †Based on $E_{YD} = -0.65^{***}$ ($S.E. = 0.22$).

**Table 4**. Responsiveness of health care utilization to changes in disaster payments, by type of disaster.

| | Panel A. Typhoon (N*T=3,357,461) | | | |
|---|---|---|---|---|
| | Use (0/1) | | Disaster payment elasticity | |
| | M.E. | S.E. | $E_{hD}$ | S.E. |
| Total expenditure | -0.048 * | 0.026 | -0.18 *** | 0.04 |
| Outpatient exp. | -0.048 * | 0.025 | -0.25 ** | 0.13 |
| Outpatient OTP | -0.062 ** | 0.031 | -0.39 ** | 0.15 |
| Drug exp. | -0.058 * | 0.034 | -0.09 * | 0.05 |
| | Panel B. High wind (N*T=3,205,167) | | | |
| | M.E. | S.E. | $E_{hD}$ | S.E. |
| Total expenditure | -0.035 * | 0.021 | -0.06 | 0.04 |
| Outpatient exp. | -0.038 | 0.130 | -0.07 | 0.08 |
| Outpatient OTP | -0.044 * | 0.023 | -0.11 * | 0.06 |
| Drug exp. | -0.011 | 0.017 | -0.04 | 0.02 |
| | Panel C. Extreme temperature (N*T=3,319,287) | | | |
| | M.E. | S.E. | $E_{hD}$ | S.E. |
| Total expenditure | -0.017 *** | 0.002 | -0.14 ** | 0.07 |
| Outpatient exp. | -0.017 *** | 0.002 | -0.18 *** | 0.06 |
| Outpatient OTP | -0.028 *** | 0.004 | -0.25 *** | 0.07 |
| Drug exp. | -0.023 * | 0.013 | -0.08 | 0.04 |
| | Panel D. Heavy rainfall (N*T=3,318,101) | | | |
| | M.E. | S.E. | $E_{hD}$ | S.E. |
| Total expenditure | -0.009 ** | 0.004 | -0.11 ** | 0.04 |
| Outpatient exp. | -0.009 ** | 0.004 | -0.11 ** | 0.05 |
| Outpatient OTP | -0.022 * | 0.013 | -0.13 * | 0.08 |
| Drug exp. | -0.012 * | 0.007 | -0.02 | 0.02 |

*Note*: Standard errors are cluster-corrected at the township level. The disaster payment elasticity, $E_{hD}$, applies to unconditional health care expenditure. All models include year, month and township fixed-effects and the set of control variables reported in table 2. Each panel contains the set of townships affected by the given disaster and those without any disasters. ***,**,* indicate statistical significance at the 1%, 5% and 10% level.

**Table 5**. Responsiveness of health care utilization to changes in disaster payments and farm income, by farm type and location.

| | Use (0/1) | | Disaster payment elasticity | | Disaster payment elas. of farm income | | Farm income elasticity | |
|---|---|---|---|---|---|---|---|---|
| | **Panel A. Townships w/ a high percentage of rice farms (N*T=440,248)** | | | | | | | |
| | M.E. | S.E. | $E_{hD}$ | S.E. | $E_{YD}$ | S.E. | $E_{hY}$ | S.E. |
| Total expenditure | -0.034 *** | 0.006 | -0.19 *** | 0.04 | -0.59 ** | 0.25 | 0.32 ** | 0.16 |
| Outpatient exp. | -0.042 *** | 0.010 | -0.22 *** | 0.07 | -0.59 ** | 0.25 | 0.37 ** | 0.18 |
| Outpatient OTP | -0.043 ** | 0.016 | -0.28 ** | 0.11 | -0.59 ** | 0.25 | 0.48 ** | 0.24 |
| Drug exp. | -0.025 ** | 0.010 | -0.10 * | 0.06 | -0.59 ** | 0.25 | 0.17 * | 0.10 |
| | **Panel B. Townships w/ a high percentage of fruit/flower farms (N*T=420,492)** | | | | | | | |
| | M.E. | S.E. | $E_{hD}$ | S.E. | $E_{YD}$ | S.E. | $E_{hY}$ | S.E. |
| Total expenditure | -0.016 ** | 0.007 | -0.10 ** | 0.04 | -0.72 *** | 0.23 | 0.14 ** | 0.06 |
| Outpatient exp. | -0.016 ** | 0.006 | -0.12 ** | 0.05 | -0.72 *** | 0.23 | 0.16 *** | 0.05 |
| Outpatient OTP | 0.021 ** | 0.011 | -0.13 * | 0.07 | -0.72 *** | 0.23 | 0.18 ** | 0.08 |
| Drug exp. | -0.018 * | 0.010 | -0.05 | 0.08 | -0.72 *** | 0.23 | 0.07 * | 0.04 |
| | **Panel C. Townships w/ a high percentage of livestock farms (N*T=427,656)** | | | | | | | |
| | M.E. | S.E. | $E_{hD}$ | S.E. | $E_{YD}$ | S.E. | $E_{hY}$ | S.E. |
| Total expenditure | -0.008 | 0.005 | -0.09 | 0.06 | -1.06 *** | 0.41 | 0.09 | 0.07 |
| Outpatient exp. | -0.007 * | 0.004 | -0.10 | 0.06 | -1.06 *** | 0.41 | 0.09 | 0.07 |
| Outpatient OTP | -0.007 * | 0.004 | -0.10 | 0.07 | -1.06 *** | 0.41 | 0.10 | 0.08 |
| Drug exp. | 0.010 | 0.010 | 0.06 | 0.06 | -1.06 *** | 0.41 | -0.05 | 0.06 |
| | **Panel D. Urban townships (N*T=414,118)** | | | | | | | |
| | M.E. | S.E. | $E_{hD}$ | S.E. | $E_{YD}$ | S.E. | $E_{hY}$ | S.E. |
| Total expenditure | -0.006 * | 0.003 | -0.03 * | 0.02 | -0.52 | 0.48 | 0.06 * | 0.03 |
| Outpatient exp. | -0.005 * | 0.003 | -0.03 * | 0.02 | -0.52 | 0.48 | 0.07 | 0.07 |
| Outpatient OTP | -0.011 * | 0.006 | -0.04 * | 0.02 | -0.52 | 0.48 | 0.07 * | 0.04 |
| Drug exp. | -0.009 | 0.009 | -0.03 | 0.02 | -0.52 | 0.48 | 0.05 | 0.07 |
| | **Panel E. Rural townships (N*T=3,124,015)** | | | | | | | |
| | M.E. | S.E. | $E_{hD}$ | S.E. | $E_{YD}$ | S.E. | $E_{hY}$ | S.E. |
| Total expenditure | -0.020 *** | 0.005 | -0.15 ** | 0.07 | -0.71 *** | 0.18 | 0.21 ** | 0.10 |
| Outpatient exp. | -0.021 *** | 0.003 | -0.16 *** | 0.06 | -0.71 *** | 0.18 | 0.23 ** | 0.10 |
| Outpatient OTP | -0.024 *** | 0.006 | -0.26 ** | 0.13 | -0.71 *** | 0.18 | 0.37 ** | 0.18 |
| Drug exp. | -0.025 ** | 0.010 | -0.09 *** | 0.03 | -0.71 *** | 0.18 | 0.12 ** | 0.05 |

*Note*: Standard errors are cluster-corrected at the township level. The disaster payment elasticity applies to unconditional health care expenditure. All models include year, month and township fixed-effects and the set of control variables reported in table 2. ***,**,* indicate statistical significance at the 1%, 5% and 10% level.

**Table 6**. Responsiveness of labor supply to changes in disaster payments.

| | Disaster payment elasticity | |
|---|---|---|
| | $E_{\cdot D}$ | S.E. |
| On-farm work days | -0.27 ** | 0.13 |
| Main occupation is off-farm | 0.04 ** | 0.02 |
| Main occupation is household work | 0.23 *** | 0.08 |

*Note*: N = 634,076. Standard errors are cluster-corrected at the township level. All models include county fixed-effects and the set of control variables reported in appendix table A1. ***,**,* indicate statistical significance at the 1%, 5% and 10% level.

**Table 7**. Responsiveness of health care utilization to changes in disaster payments, by medical condition.

| | Panel A. Mental health disorders | | | |
|---|---|---|---|---|
| | Use (0/1) | | Disaster payment elasticity | |
| | M.E. | S.E. | $E_{hD}$ | S.E. |
| Total expenditure | 0.000 | 0.000 | -0.07 | 0.08 |
| Outpatient exp. | 0.000 | 0.000 | -0.10 | 0.11 |
| Outpatient OTP | -0.002 | 0.001 | -0.06 | 0.04 |
| Drug exp. | 0.000 | 0.000 | 0.06 | 0.06 |
| | Panel B. Injury and poisoning | | | |
| | M.E. | S.E. | $E_{hD}$ | S.E. |
| Total expenditure | -0.003 | 0.002 | 0.14 | 0.09 |
| Outpatient exp. | -0.003 | 0.002 | 0.32 | 0.27 |
| Outpatient OTP | -0.004 | 0.003 | -0.01 | 0.01 |
| Drug exp. | -0.003 | 0.002 | 0.33 | 1.17 |
| | Panel C. Infection, parasites, neoplasms, and congenital anomalies | | | |
| | M.E. | S.E. | $E_{hD}$ | S.E. |
| Total expenditure | -0.003 | 0.002 | -0.22 | 0.19 |
| Outpatient exp. | -0.003 | 0.002 | -0.17 | 0.23 |
| Outpatient OTP | -0.003 * | 0.002 | -0.18 * | 0.10 |
| Drug exp. | -0.004 | 0.004 | -0.12 | 0.26 |
| | Panel D. Digestive system disorders | | | |
| | M.E. | S.E. | $E_{hD}$ | S.E. |
| Total expenditure | -0.012 *** | 0.004 | -0.15 ** | 0.05 |
| Outpatient exp. | -0.012 *** | 0.004 | -0.14 *** | 0.04 |
| Outpatient OTP | -0.011 *** | 0.003 | -0.16 *** | 0.05 |
| Drug exp. | -0.009 ** | 0.004 | -0.12 * | 0.07 |
| | Panel E. Respiratory system disorders | | | |
| | M.E. | S.E. | $E_{hD}$ | S.E. |
| Total expenditure | -0.009 *** | 0.002 | -0.09 ** | 0.03 |
| Outpatient exp. | -0.009 *** | 0.002 | -0.06 ** | 0.03 |
| Outpatient OTP | -0.011 *** | 0.003 | -0.08 ** | 0.04 |
| Drug exp. | -0.010 *** | 0.003 | -0.11 ** | 0.05 |

*Note*: N*T = 3,538,133. Standard errors are cluster-corrected at the township level. The disaster payment elasticity applies to unconditional health care expenditure. All models include year, month and township fixed-effects and the set of control variables reported in table 2. ***,**,* indicate statistical significance at the 1%, 5% and 10% level.

**Table 8**. Responsiveness of health care utilization to changes in lagged disaster payments.

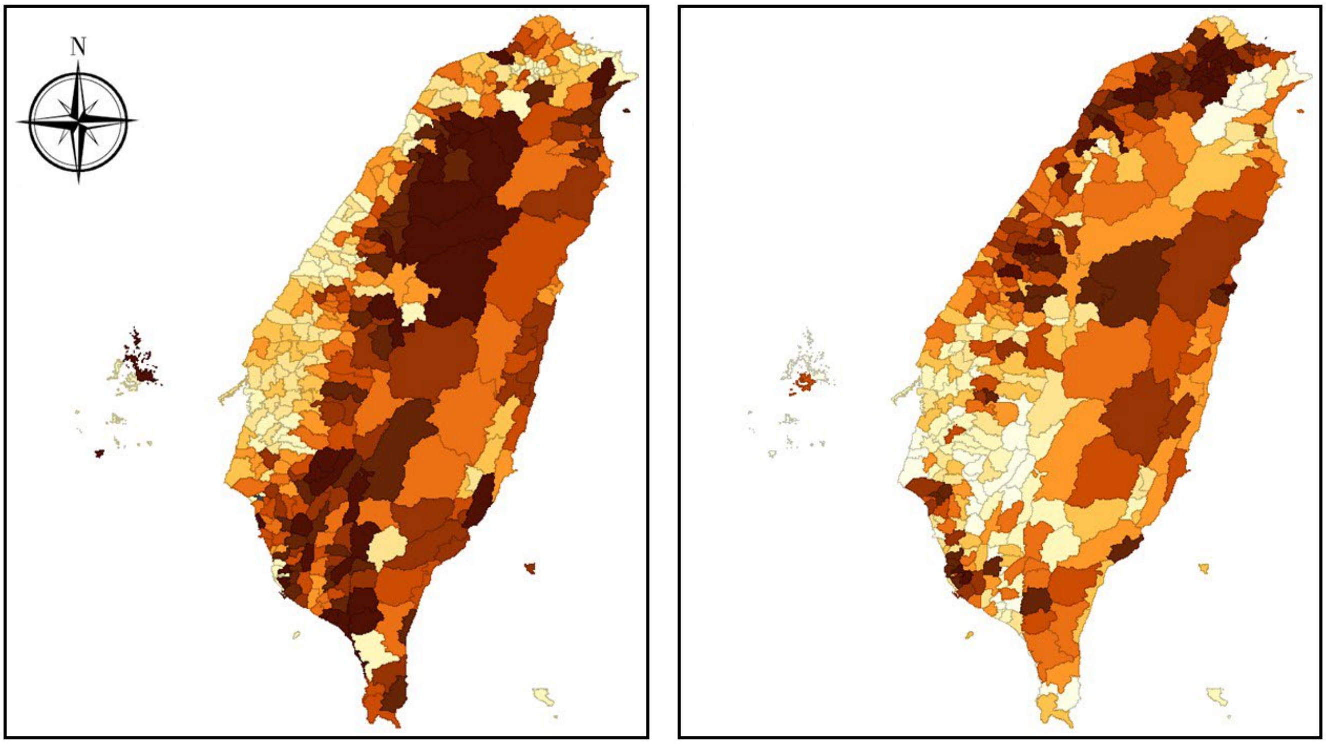
| | Panel A. One month lag of disaster payments (N*T=3,129,422) | | | |
|---|---|---|---|---|
| | Use (0/1) | | Disaster payment elasticity | |
| | M.E. | S.E. | $E_{hD}$ | S.E. |
| Total expenditure | -0.015 *** | 0.002 | -0.12 ** | 0.06 |
| Outpatient exp. | -0.014 *** | 0.002 | -0.12 ** | 0.06 |
| Outpatient OTP | -0.021 *** | 0.005 | -0.17 ** | 0.07 |
| Drug exp. | -0.019 *** | 0.003 | -0.07 ** | 0.02 |
| | Panel B. Two month lag of disaster payments (N*T=2,752,049) | | | |
| | M.E. | S.E. | $E_{hD}$ | S.E. |
| Total expenditure | -0.013 | 0.018 | -0.06 | 0.04 |
| Outpatient exp. | -0.013 | 0.017 | -0.09 * | 0.05 |
| Outpatient OTP | -0.017 * | 0.010 | -0.09 | 0.07 |
| Drug exp. | -0.017 | 0.012 | -0.05 | 0.05 |

*Note*: Standard errors are cluster-corrected at the township level. The disaster payment elasticity applies to unconditional health care expenditure. All models include year, month and township fixed-effects and the set of control variables reported in table 2. ***,**,* indicate statistical significance at the 1%, 5% and 10% level.

**Figure 1**. Geographic distribution of agricultural disaster relief payments and the political instrumental variable (IV) across townships in Taiwan.

Panel A: Disaster relief payments

Panel B: Political IV




*Note:* Darker colors indicate higher values of the variable. Panel A contains monthly average disaster payments per receipt in each township between January, 2009 and December, 2012 (NT$ 1,000/month). Panel B contains the political IV, defined as the vote ratio of the incumbent party to the opposition party multiplied by the number of eligible voters in each township, averaged across the 2008 and 2012 presidential elections.