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Natural Disasters and Local Government Finance: Evidence from Typhoon Haiyan*

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Abstract

This paper examines how natural disasters affect low public finances and their interplay with intergovernmental transfers and external resources. We document the causal effect of a natural disaster on the allocation of local public resources the local government fiscal dynamics by exploiting the random nature of the 2013 Typhoon Haiyan, one of the most devastating natural disasters in recent history. Combining data on local government finance with reports on the level of damages caused by the typhoon, we employ several estimation strategies: we first rely on difference-in-differences and event study designs, and we further address a potential endogeneity concern by instrumenting the intensity exposure to the typhoon with distance to the storm path. We show that local revenue and public expenditures remain largely unaffected, except debt service, which are on average 15% lower in affected cities or municipalities. However, we document important heterogeneity in local revenue responses. We find no support for the moral hazard problem: our results indicate that external aid leads to higher local expenditures, particularly

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general public services, socioeconomic expenditures, including education and social services, and debt payments. These results highlight the crucial role of central government transfers in supporting local governments and mitigating the geographical economic disparities in the aftermath of exogenous shocks such as natural disasters.
Keywords: Natural disasters, local government finance, Haiyan/Yolanda

1 Introduction

Natural disasters can have consequences on economic growth (Cavallo et al., 2013; Carvalho et al., 2021). They affect development outcomes, such as health and employment, in high-income countries (Karbownik and Wray, 2019; Simeonova, 2011; Currie and Rossin-Slater, 2013) and lower-income countries (Oliveira et al., 2021; Anttila-Hughes and Hsiang, 2013; Sotomayor, 2013; Torche, 2011; Kirchberger, 2017). Since natural disasters often strike only parts of country, their adverse consequences can be mitigated by the reallocation of local public resources. It remains unclear how natural disasters or similar exogenous shocks affect the dynamics of local finances. For instance, poorer local governments may be unable to generate enough local revenues to offset the direct and indirect damage costs caused by a disaster. Their revenue losses, however, may be offset when external aid come pouring in. In such settings, how do local fiscal resources interplay with central government transfers and external funding sources to mitigate the local impact of a disaster?

In this paper, we aim to address this question and quantify the fiscal implications of a major disaster by building on an original dataset that compiles almost 10 years of municipality and city public finances data before and after the 2013 typhoon that wrought severe damages and displaced populations along its path. We then combine this information with disaster data from local and international sources on the number of affected families and houses damaged.

We present new evidence on how natural disasters affect the abilities of local governments to deliver services and generate resources for such services. We exploit the randomized nature of the Typhoon Haiyan (nationally known as Typhoon Yolanda) in 2013 to obtain the causal effect of a natural disaster on the generation and allocation of local public resources. In particular, we use an event study and a difference-in-differences approach that compare the outcomes of cities and municipalities affected by the typhoon with their counterparts off the storm path but within the provinces affected by the typhoon. We provide several tests in support of our empirical framework that rests on the common trends assumption. Yet one may be concerned that the results are confounded by factors affecting both local finances and the level of damage to public and residential infrastructures. We address this potential endogeneity issue by exploiting possible variations in the intensity of exposure to the typhoon of the affected localities with an instrument that measures the distance from the centroid of the city or municipality to the storm path.

The typhoon generally has no statistically significant on local government expenditures except for debt service. We estimate that a 1 percentage point increase in families displaced by the typhoon leads to a 0.22% lower debt payments. On average 31% of families were displaced by Typhoon Haiyan. This, therefore, translates to about 7% lower debt payments. This effect is short-run according to the event study analysis: the effect is statistically significant only during the first three years following the typhoon. This

result is qualitatively robust to the IV estimation strategy: the effect in absolute terms is double once the endogeneity is addressed.

We further document that the typhoon had no significant effect on local government income. We find statistically significant and negative effects on local sources such as tax on business and business income. However, these results are not robust when we consider the endogeneity correction.

We explore several mechanisms through which natural disasters could affect local budgets. Firstly, we investigate whether external aid[1] triggers a moral hazard behavior in local governments. Support from international aid agencies and other donors may have substituted for local revenue mobilization, at least for some those cities and municipalities with less affected tax bases. As of August 2014, around US$1.63 billion worth of relief pledges was already received from foreign governments and international organizations, according to an online portal set up by government to monitor such aid and other relief efforts (COA, 2014, p. 18).[2]

Secondly, we examine the role of displaced populations in the response of public finance. Ostensibly the relocated population expanded the demand for local public services

[1]External or foreign aid in this paper is measured by extraordinary receipts, grants, donations, and aid, which according to the Philippine Bureau of Local Government Finance Glossary of Terms include domestic and foreign grants and donations as well as other subsidy income and gains from foreign exchange, sale of assets, sale of investment, and premium on bonds payable. The Philippine Bureau of Local Government Finance Glossary of Terms was accessed on 18 March 2022 and was downloaded from https://blgf.gov.ph/wp-content/uploads/2016/08/Metadata.docx.

[2]Citing OECD estimates, Brucal et al. (2020, p. 8) noted that the Philippines received around US$493 million in Haiyan-related foreign aid in 2013-2014, and another US$498 million for post-emergency rehabilitation in 2014.

in their new locations which in turn put pressures on the concerned local governments to calibrate their public spending, raise more revenues, or both.

Thirdly, we empirically test how local finances of cities or municipalities are affected by a major disaster like Typhoon Haiyan. Poorer cities or municipalities may be consistently more affected by the typhoon in their capacity to collect and allocated local finances. We categorize our sample by income classes based on the City and Municipality Level Poverty Estimates of the Philippine Statics Authority. We then test whether local government finances of different cities or municipalities are adversely affected through a reduction in expenditures as well as tax and non-tax revenues as a result of a "devastated" local economy.

Our findings on the the indirect effect of natural disasters at the government level complement studies on the welfare effects on individuals or households. Using US data, Deryugina (2017) shows that affected households experienced an increase in disaster aid and social insurance transfers in the short and the long run, potentially offsetting the negative direct costs of the hurricane. But a greater focus on the effect of calamities on local governance is important, especially in many developing countries that adopted fiscal decentralization. Fiscal decentralization promises better service delivery to the local constituents, especially in their times of need. If the local government themselves are also affected by devastating calamity, they will be unable to provide for their constituents' needs.

Recent studies on the fiscal consequences of natural disasters demonstrate the adverse effects on local government budgets and the important role of intergovernmental transfers (Jerch et al., 2020; Miao et al., 2020; Noy et al., 2021). Examining the heterogeneous effect of natural disasters on varying sizes of local governments, this literature shows that the fiscal budget of larger subnational governments tends to be more robust to a disaster than small towns/cities. Political consideration could be a further factor affecting the allocation of local public resources following natural disasters, although the literature presents mixed results (Klomp, 2019; Karim and Noy, 2020; Accad, 2020).

Our paper closely relates to Jerch et al. (2020) that examines how hurricanes affect municipality budgets in the US. Our approach differs in several ways. We bring novel evidence on the effect of natural disasters on local public finances by examining how Typhoon Haiyan, one of the strongest typhoons in the recent past, affected local public expenditures and resources in the Philippines, a lower-middle income country regularly exposed to natural disasters. We tease out the causal effect of the typhoon, whose occurrence, intensity and path is exogenous to the affected cities and municipalities and the families there in. Further exploiting this natural experiment, we examine the interplay between local public finances, intergovernmental transfers and the role of foreign aid, and add our findings to the extant literature.

The rest of the paper proceeds as follows. Section 2 provides a background of the effects of Typhoon Haiyan and the role of local governments in mitigating them. Section

3 discusses the methodology, namely the difference-in-differences approach, event study, and instrumental variable strategy. Section 4 discusses the sources of data as well as provides summary statistics. Section 5 analyses the results and section 6 explores the mechanisms. The final section concludes.

2 Background

2.1 Typhoon Haiyan

The Philippines is prone to natural disasters. As the National Disaster Risk Reduction and Management Council of the Philippines (NDRRMC) puts it, the country experiences "geological and hydro-meteorological hazards due to its geographical and physical characteristics" (NDRRMC, 2014, p. 2). It is one of the most exposed countries to strong winds brought by typhoons (Hsiang and Jina, 2014).

Typhoon Haiyan made landfall in the eastern part of the Philippines on 8 November 2013 and left its western part on 9 November (Figure 1). Even in a county that has seen 720 cyclones between 1970 and 2019, Typhoon Haiyan was exceptional in intensity and for causing the most destruction and highest recorded death toll, so far. According to a government report (NDRRMC, 2013, pp. 2–5, 63), in the next two months after the typhoon, 6,300 people were reportedly died, more than 28 thousand were injured and an estimated 4 million more were displaced. Further, about 1.14 million houses were damaged, nearly half of them totally wrecked. The total cost of the damages to

infrastructure (roads, bridges, school buildings), the social sector (education, health, housing), the productive sector (agriculture, fisheries, mining, trade, industry, tourism), and others are put at 95 billion Philippine pesos (PhP), or more than twice that of the second most-damaging typhoon (locally known as Typhoon Pablo) in 2012. The same report mentioned that a total of PhP104.64 billion or US$2.34 billion is needed for post-Haiyan rehabilitation and recovery in the affected areas or sectors.

2.2 Public sector's response

Then President Benigno Aquino, Jr. signed Memorandum Order No. 62 on 6 December 2013 to create the Presidential Assistant on Rehabilitation and Recovery. The main tasks of the Presidential Assistant include the development of integrated short-term, medium-term, and long-term plans for the affected areas.[3] In August 2014, President Aquino received the Comprehensive Rehabilitation and Recovery Plan, which grouped the programs of the concerned national government agencies into five clusters: infrastructure, resettlement, social services, livelihood, and support (NDRRMC, 2014, pp. 92–101). Between 2013 and 2017, the national government released about PhP67.1 billion for rehabilitation in the most affected region, Eastern Visayas, accounting for nearly 46% of the total releases for all affected areas in the Visayas in the central Philippines.[4]

[3]Memorandum Order No. 62 series 2013 can be accessed at https://www.officialgazette.gov.ph/2013/12/06/memorandum-order-no-62-s-2013/. The Memorandum was accessed on 7 June 2022.

[4]See "PhP67-B released for Yolanda rehab since 2013" by Sarwell Meniano published on 21 February 2018 in the Philippine News Agency. This article was accessed on 16 June 2021 at https://www.pna.gov.ph/articles/1026022.

Following the unprecedented damages caused by Haiyan, the Calamity Fund (or, officially, National Disaster Risk and Management Fund), a major source of funds established to support disaster risk reduction and management activities, was made available to all agencies and local governments.[5] The fund covers activities such as reconstruction or rehabilitation of infrastructure, aid, and relief services. The other national sources of funds could be tapped include the Local Disaster Risk Reduction Management Fund, the Government Service Insurance System, which provides coverage for government-owned assets, and the People's Survival Fund. In 2013, the national government's Calamity Fund had an appropriation of around PhP7.5 billion, nearly all of which (99%) was already disbursed by end of July 2014 (COA, 2014, p. 10). Complementing the efforts of the national and local governments were the private sector, such as corporations and non-government organizations (NGOs), as well as foreign governments and international organizations such as EU, UN and USAID that provided significant rehabilitation, reconstruction or recovery assistances (COA, 2014; NDRRMC, 2013, 2014).

Given the size and allocation of the Calamity Fund and external aid, arguably they could have had an influence on local government finances and service delivery. However, we cannot determine from the available data how these funds were used or allocated by the recipient local governments for general public services, social services (education, health, housing and social welfare) and other expenditures. From the available official

[5]At the local level, the Calamity Fund corresponds to funds that each Local Government Unit (LGU) is required to set aside each year for unforeseen contingencies/emergencies. However, in times of disasters of great magnitude, the funds can also be sourced from national government agencies (COA, 2014).

financial reports of local governments, we can observe for each local government the annual total and various sources of revenues, both tax-based and non-taxed based, and those coming from external sources such as extraordinary receipts, grants, donations and aid. Tax revenues include incomes from real-property tax, tax on business, and other taxes. Regulatory fees from permits and licenses, service income, and business income are sources of non-tax revenues. We can therefore examine the effect of Typhoon Haiyan on these particular sources of local revenue and, in turn, on certain types of local expenditures, as will be shown later in table 8. To understand the effect of Haiyan on the fiscal performances of the affected local governments, we establish the counterfactual through quasi-experimental methods that we introduce in the next section.

3 Methodology

3.1 Difference-in-differences

We start the analysis by presenting a difference-in-differences (DID) design that compares the outcomes of cities and municipalities affected by the typhoon with those outside the storm path but within the provinces affected by the typhoon. We consider a province affected if it has at least one municipality or city affected by Haiyan. Our identifying assumption is that conditional on municipality observables, typhoon exposure is orthogonal to any municipality's unobservable characteristics that could affect its post-typhoon public finances. This method enables us to validly compare the relevant outcomes of the

affected LGUs with those spared by Haiyan. Our baseline specification is:

$$y_{ipt} = \delta(Family_{ip} \times Haiyan_t) + X'_{ipt}\Gamma + \mu_{ip} + \lambda_t + \epsilon_{ipt} \quad (1)$$

where y_{ipt} can either be local government expenditures or income in city/municipality i, province p, and year t. Outcome variables are expressed using the inverse hyperbolic sine transformation because of sufficiently large but with zero values in the variables[6]. $Family_{ip}$ is the share of displaced families in the total number of families affected by Haiyan in city or municipality i and province p. $Haiyan_t$ is a dummy variable equal to 1 if $t \geq 2013$ and 0 otherwise. The main coefficient of interest is δ which measures the differential impact of the typhoon on the local public finances of affected cities or municipalities relative to unaffected ones within the same province.

The results could still be biased if cities or municipalities on the storm path tend to be more exposed to natural disasters and are therefore different from those off the path in our analysis. To address this issue, we include a set of control variables, X_{ipt}, that includes a full set of trend effects based on elevation as well as population and poverty incidence at the city or municipality level. Depending on their initial states, such trend effects control for situations where the development paths of cities and municipalities, even without Haiyan, may differ over time. We use the pre-2013 values of these variables because we expect that the typhoon will affect the cities and municipalities differently, de-

[6]See for example Jerch et al., 2020.

pending on their initial values. We also control for central government transfers to city or municipality i with the Philippine Internal Revenue Allotment (PIRA). Financed through general taxes, the PIRA is the single most important source of revenue for most local governments in the Philippines (Diokno, 2012; Llanto, 2012). The amount transferred to local governments follows a fixed formula that is based on the locality's population, land area, and level (i.e., province, city, municipality) and the national government's internal revenues from three years ago. (Diokno, 2012). We include PIRA to represent factors that are not directly affected by Typhoon Haiyan in the set of control variables and zero in on locally-generated income from tax and non-tax revenues.

We further add city or municipality fixed effect, μ_{ip}, year fixed effect λ_t, province fixed effect, and a set of province-year trend effects to absorb persistent heterogeneity across municipalities, and unobserved factors that could simultaneously affect municipalities within the same province or in a given year. For example, since inflation is region-wide, its effects are the same for each city or municipality.[7]

3.2 Event study

To analyse the dynamic effects of the typhoon on local finances, we include a series of year dummy variables. Our event study specification is:

[7]Data on inflation at the city/municipality level is not available from official statistics, so we can not directly control for city or municipality-specific inflation rates.

$$y_{ipt} = \sum_{t \neq 2013} \delta_t (Family_{ip} \times Year_t) + X'_{ipt}\Gamma + \mu_{ip} + \lambda_t + \epsilon_{ipt} \quad (2)$$

where the variables are defined as above. $Year_t$ is a dummy variable for year t. This variable excludes 2013, the reference year.

3.3 Instrumental variable

Although Typhoon Haiyan presets a natural experiment that could justify the use of a difference-in-differences strategy, one could argue that some remaining threats could potentially bias our results. For instance, cities or municipalities in affected provinces could be reported as unaffected due to systematic measurement errors; unaffected cities or municipalities could be characterized by more sparse or fragile infrastructures if they are located in remote/rural areas or are less developed to begin with; location of cities or municipalities within provinces determine the vulnerabilities of their baseline characteristics such as the quality of housing that would otherwise be less affected were they in other locations. In this case, tour initial DID estimation strategy would underestimate the typhoon's full effect.

To gain further confidence in our findings, we test for the role of such potential endogeneity by using a shift-share instrument that interacts the national level occurrence of the typhoon, the post-2013 dummy, $Haiyan_t$, with the distance between the centroid of a city or municipality and the storm path, $Distance_i$. The instrument predicts the

level of destruction in a given municipality based on its distance to the storm path, which can be interpreted as a proxy of typhoon exposure.

The first-stage equation is given by:

$$Family_{ipt} = \beta(Distance_{ip} \times Haiyan_t) + X'_{ipt}\Gamma + \mu_{ip} + \lambda_t + \zeta_{ipt} \tag{3}$$

The coefficient of interest is on β which effectively measures the differential effect of the typhoon on the municipalities at varying proximity to the storm path, before and after Haiyan. From equation 3, we derive the predicted Family (with "hat") and plug it in our second stage of our two-staged least squares (2SLS) system, as follows:

$$y_{ipt} = \delta_1(\hat{Family}_{ip} \times Haiyan_t) + X'_{ipt}\Gamma + \mu_{ip} + \lambda_t + \eta_{ipt} \tag{4}$$

Our main identifying assumption is that the distance from the centroid of municipality i to the storm path is orthogonal to any unobservable municipality characteristics that may affect the outcome variable. The quasi-random nature of the typhoon trajectory and intensity provides support for this excludability assumption. Furthermore, the use of province-year fixed effects should address any remaining concerns about the possibility that some areas might be more frequently exposed to natural disasters.

4 Data

4.1 Sources

We draw data on city and municipality expenditure and income from the Philippine Bureau of Local Government Finance. We combine this data with information on cities and municipalities affected by Typhoon Haiyan from the Philippine National Disaster Risk Reduction and Management Council and the Department of Social Welfare and Development (DSWD). Specifically, the data from DSWD provides information at the city and municipality level on the number of affected families, displaced persons, and damaged houses, both partially and totally, within a 50-kilometer radius.

We calculate the share of displaced families in total families affected by Typhoon Haiyan and only include provinces with a non-zero share of displaced families in our analysis. The list of affected provinces by the typhoon is presented in a map of the Philippines in figure 1. Of the 14 affected provinces, 11 are provinces are in the central part of the Philippines, the Visayas.[8] Our total sample comprises 351 cities and municipalities between 2007 and 2018. Additional municipal-level data on population, poverty incidence and income class are collected from the Philippine Statistical Authority (PSA). The population data is based on the 2010 Census, while poverty incidence and income class are based on the 2012 and 2021 data. While the latest available income class is 2021,

[8]The Philippines consists of three main groups of islands. One of them is the Visayas, an archipelago in the middle part of the Philippines. Most of the provinces included in our analysis are in Visayas. The other two groups of islands are Luzon, the northern part of the Philippines, and Mindanao, the southern part of the Philippines.

we track any changes in the class based on a summary of changes compiled by PSA.

We obtain geographical data from various sources. Geo-coded data on the storm path was obtained from the local office of the United Nations Office for the Coordination of Humanitarian Affairs office in the Philippines. The data on elevation was collected from geographic imagery and elevation models extracted from the Humanitarian Exchange Database.[9] We also calculate the share of damaged houses in total families affected by Typhoon Haiyan. Figure 2 shows the geographical distribution of the intensity of the typhoon among cities and municipalities, measured by the share of damaged house per total families within cities or municipalities, using census data.[10] The share of damaged houses depends on baseline characteristics like housing quality. Since we do not have data on housing quality, we use the share of displaced families in baseline regression models, and check that our results are robust when the share of displaced families is replaced by the share of damaged houses.

4.2 Summary Statistics

Typhoon Haiyan affected 48% of cities and municipalities in our sample. Within these cities and municipalities, on average, the typhoon affected 31% of total households and damaged 34% of houses in affected cities/municipalities.

[9]The data was last accessed on 5 June 2022 at https://data.humdata.org/dataset/philippines-elevation-model.

[10]Our measure implicitly assumes that each housing unit is occupied by only one family. In reality, there could be many families that live under one roof, and our measure of intensity could be underestimating the true effect of the natural disaster.

The summary statistics in table 1 show the differences in the mean expenditures and incomes between the affected and non-affected municipalities within the typhoon ravaged provinces. Since the differences, even when statistically significant, do not account for the trends before and after the typhoon, they cannot be interpreted as causal effects. Nonetheless, the significant differences of the means of nearly all income and expenditures variables present a prima facie evidence to examine further the seeming negative impact of the typhoon on local government finances.

The central fiscal transfers constitute the bulk of local governments' income: the PIRA accounts for 72% of the latter. The remaining 28% of local government's income comes from local sources, including tax and non-tax revenues. At 16% percent, the share of tax revenues is almost twice as big as the share of non-tax revenues (9%).

Tax revenues consist of real-property tax, tax on business, and other taxes. Real-property tax and tax on business have almost equal contributions to total income. Each contributes around 8% of total income.

Among non-tax revenues, income from economic enterprises is the most important. Contributing 4% to total income, business tax revenues is followed by general income, service or user charges, and regulatory fees (permit and licenses), each of which contributes 2%. Extraordinary receipts (including aid, donations, and grants), as well as inter-local transfers, are less than 1% of total income.

On the expenditure side, general public services have the biggest share, at 59%, of

the total expenditures.[11]. Meanwhile, education services (education, culture and sports), health services, (health, nutrition, and population control), labour services (labour and employment), and housing (housing and community development) account for 4%. 9%, 0.02%, and 2% of total expenditures.

Another 15% of the total expenditures goes to economic services, while 4% goes to social services and welfare, which are intended to hep the poor, less privileged individuals, and those in emergency situations. Finally, debt service, which include payment of the principal and interest on outstanding debts, take up 8% of the total outlays.

5 Results

5.1 Effect of the typhoon on local government expenditures

We first show the consequences of the typhoon on local public expenditures, and then move to its impacts on revenue or income. The results of the DID estimation are presented in table 2. Columns 1 to 9 show the results with the following dependent variables: general public services, education, health, labour, housing, social welfare, economic services, debt service and total expenditures. All dependent variables are transformed with the inverse hyperbolic sine function. Each column includes all sets of baseline covariates described

[11] According to the Glossary of Terms, general public services "... covers sector expenditures for services that are indispensable to the existence of an organization [Local Government Unit]," which "... includes executive and legislative services; overall financial and fiscal services; the civil service; planning; conduct of foreign affairs; general research; public order and safety; and centralized services." However, this expenditure excludes "... general administration, regulation, research and other services of departments that can be identified directly under each specific sector." The Philippine Bureau of Local Government Finance Glossary of Terms was accessed on 18 March 2022 and was downloaded from https://blgf.gov.ph/wp-content/uploads/2016/08/Metadata.docx.

in the Methodology section.

DID estimation results suggest that the typhoon had negative effects on all outcomes except health, labour and housing. However, the effect is quantitatively small and statistically insignificant except for debt service, which includes payments of loan principal and interest expenses.[12] A 1 percentage point increase in families displaced by the typhoon leads to a 0.22% lower debt payments. On average 31% of families were displaced by Typhoon Haiyan. This, therefore, translates to about 7% lower debt service.

The results are consistent with those of the 2SLS estimation that are presented in table 4. Panel A of table 4 shows the effect of Typhoon Haiyan on local government expenditure, using distance from the storm path as an instrumental variable (IV) for families displaced by the typhoon. The regression model is given by equation 4 above. Panel B presents the first stage of the corresponding 2SLS regression, and it suggests that the instrument works. The coefficient of the distance to the storm path in the post-Haiyan period is negative and statistically significant. Further, the high Kleibergen-Paap F-statistic indicates our IV strongly identify the first-stage equation. The shorter the distance from the storm path is, the higher is the share of families displaced by the storm in a certain city or municipality, as can be expected.

The typhoon had a significant negative effect on debt service. The difference is the

[12]The Philippine Bureau of Local Government Finance defines debt payments as "expenditures for payment of loan principal, interest and other service charges for debts of LGU." The Philippine Bureau of Local Government Finance Glossary of Terms was accessed on 18 March 2022 and was downloaded from https://blgf.gov.ph/wp-content/uploads/2016/08/Metadata.docx.

magnitude of the effect. After correcting for the endogeneity in our IV estimation, the point estimate increases in absolute terms from 0.22% to 0.51%. A 1 percentage point increase in families displaced by the typhoon now results in a 0.51% lower debt payments. With 31% of families displaced by Typhoon Haiyan, debt service are lower by 15%.

Finally, the typhoon had a quantitatively small but significant positive effect on labour and employment. A 1 percentage point increase in the proportion of families displaced by the typhoon results in a 0.02% higher labour and employment expenditures. With the IV estimation, the coefficient estimate on labour and employment is similar but the effect loses statistical significance.

5.2 Effect of the typhoon on local government income

Typhoon Haiyan did not have any significant consequences on local government income. Table 3 replicates table 2 and presents the results of the DID estimation for local income. Columns 1 to 13 show the results with the following dependent variables: local sources, tax revenue, real-property tax, business tax, other taxes, non-tax revenue, regulatory fees, user charges, business income, and other general income, inter-local transfers, extraordinary receipts, and total income. As in table 2, each column controls the central government transfers PIRA and fixed effects. Except for extraordinary receipts, the effect of the typhoon is negative for all variables. As expected, the strongest negative effect is found on business income. Local sources, business tax, and inter-local transfers

have negative coefficients of similar magnitudes, whilst the effect of the typhoon on the other outcome variables is statistically insignificant. Meanwhile the corresponding 2SLS estimates are nearly the same as the DiD estimates, but none has remained statistically significant, however.

Table 5 suggests that typhoon Haiyan did not have any significant consequences on local government income. The results are consistent with those presented in table 3.

Overall, our baseline results indicate the typhoon had no strongly significant impact on local government. While mostly insignificant, the estimates are negative and therefore suggest adverse effects on local government income.

5.3 Event study

So far, we have documented the average effect of the typhoon over the sample period. However, the impact of the typhoon on local public finances might persist or weaken over several years. We explore in this subsection the evolution of the response to the typhoon and provide a test of the parallel trends assumption that is required for the causal interpretation of the DID estimates.

Figure 3 shows the dynamic effects of the Haiyan typhoon on local expenditures. The graphs plot the coefficient estimates of interaction terms between *Haiyan* and year dummies, including the baseline set of controls as in equation 2, and with corresponding 95% confidence intervals in dashed lines. We investigate the validity of our strategy that

hinges on the assumption that cities or municipalities unaffected by Haiyan approximate the local public finances of the cities or municipalities located on the path of the typhoon. The figures show no evidence of divergent pre-trends: during the pre-typhoon period, the point estimates are close to zero and insignificant. After treatment sets in, we observe a strong decline in debt service payments for the first three years after the typhoon, from 2014 to 2016, but recovering to insignificant levels in years 2017 and 2018. This result suggests that the effect of the typhoon on debt service was immediate and temporary..

Figures 4 and 5 present the dynamic effects of Haiyan on local income. The graphs show the coefficient estimates on the interaction term between $Family_{ip}$ and a year dummy, as shown in equation 2, along with 95% confidence intervals in dashed lines. While we find that the coefficient estimates are statistically insignificant before Typhoon Haiyan, some trends in pre-typhoon periods might affect the outcome in post-typhoon periods. We account for these dynamic effects by implementing the procedure developed by Freyaldenhoven et al. (2021). Figures 9 and 10 in the online Appendix provide further evidence that our baseline estimates are not driven by confounding time trends.

In the first two years following the typhoon, the effect on user charges, business income, and business tax become statistically significant and negative. This temporary effect fades away after the third year of the typhoon. As expected, the typhoon was followed by a massive surge in external or in extraordinary receipts (which include foreign aid and other typhoon-relief assistance) for the first two years. However, the high vari-

ability of the point estimate might indicate that aid was concentrated on a specific set of affected municipalities. Overall, the figures lay support for the parallel trend assumption underlying the DID analysis as well as the non-significance of the results in terms of local government income.

6 Mechanisms

To better understand the underlying mechanisms, we investigate how the effects of Typhoon Haiyan vary across different contexts. In particular, a shift in local public finances could be due to either (i) a surge in external or foreign aid, or (ii) an increase in displaced populations. We further present a heterogeneity effect analysis where we explore whether the distribution of municipality income differently affects local public finances. For each of the dimensions of heterogeneity studied, we interact it with the share of the family affected variable as instrumented by $Distance_i \times Haiyan_t$ like in equation 4.

6.1 Aid

The typhoon sparked an important mobilisation of resources, both nationally and internationally. Did national and foreign aid increase or decrease local finances? Aid can increase the number of resources available for local expenditures, for example in relief operations and rebuilding damaged public infrastructures, such as bridges and roads. Furthermore, local governments may overly depend on external assistance and thereby

be discouraged to collect local taxes or generate their own revenues. To examine these mechanisms, we first allow the effect of the typhoon to differ across municipalities according to the received aid support. Aid_{ipt} is extraordinary receipts, including national and foreign aid, grants, and donations, that are recorded as part of the local government budget, in city or municipality i in province p at time t. The treatment then becomes cities or municipalities affected by the typhoon in the post-2013 period and, at the same time, those that received aid, grants, and donations, including those from abroad. The regression that we estimate is given by:

$$y_{ipt} = \delta_2(\hat{Family}_{ip} \times Haiyan_t \times Aid_{ip}) + X'_{ipt}\Gamma + \mu_{ip} + \lambda_t + \theta_{ipt} \tag{5}$$

The results shown in tables 6 and 7 report the IV estimates of the triple interaction terms. As discussed above, aid may be associated with higher or lower expenditures. On the one hand, aid may increase the number of resources for relief and rebuilding efforts, for example. On the other hand aid may also induce moral hazard resulting in diminished efforts to collect local taxes. The triple interaction with Aid shows the results of estimating equation 5. The results support the former view more than the latter view. Aid led to higher local expenditures, including general public services, education, social, economic services, and debt payments. Payments of debt service are lower by 0.09% per family affected, or 2.79% on average if we are to consider the average number of families affected which is 31%. Social and economic services are lower by 0.07% per family affected,

or 2.17% on average. There is a 0.06% higher expenditure related to education, culture and sports, and this translates to 1.86% higher expenditure on average. General public services, the biggest local expenditure item, are higher by 0.05% or 1.55% on average.

However, aid did not lead to lower tax collection efforts. If anything, aid led to higher income from local sources, particularly non-tax revenues and other general income.

Indeed there were international agencies that dealt directly with cities or municipalities and "barangays" in their relief operations. If they transferred funds to local governments, then these funds would be recorded as extraordinary receipts. More likely, assistance in in-kind was provided to the local population in coordination with municipal or barangay officials or with local non-government organizations. If the DSWD transferred some cash donations to local government units, then they may appear as part of extraordinary receipts. These transfers may appear as extraordinary receipts and, in conjunction with the insignificant results, the lower local income is less likely due to moral hazard. However, our exercise only captures external aid that are recorded as part of the local government budget.

As mentioned above, the initial responses of the government and international agencies focused more on humanitarian and relief operations, such as the provision of temporary shelter, treatment of the injured and sick people, attending to water, sanitation and hygiene needs, provision of food and other basic necessities, and retrieval and burial of cadavers. There were also cash transfers provided to the beneficiaries of 4Ps, the Philippine

conditional cash transfer programme, topped up with additional cash from international agencies.[13] All of these may have helped local governments provide humanitarian and relief efforts. Hence, resources may have flowed into general public services, education, social services and welfare,[14] economic services, and debt payments.

6.2 Displaced populations and evacuation centres

Likewise, the effect of evacuation centres on local resources is also unclear, at least theoretically. A permanent increase in population may pressure the concerned local governments to meet the surge in demand for their public services by spending more on them. At the same time, local governments with effective disaster mitigation plans, including ready evacuation centres, may suggest them to be richer fiscally, located in disaster-prone areas, or both.

We can also expect that cities or municipalities that have evacuation centres may have inadvertently attracted or willingly accommodated displaced population from other areas. Are local finances higher or lower in local areas with more evacuation centres? If the increase in population is permanent, then local expenditures may increase, as argued above. On the other hand, the effect on local revenue is unclear. We expect that cities or municipalities with higher local revenue have more resources for planning, determining

[13]In their analysis of the local conditions post-Haiyan, Eadie et al. (2020) noted that the cash beneficiaries of the different aid agencies may have developed a dependency mentality.

[14]Social services and welfare spending are expenditures aimed to help "disadvantaged families and children," "handicapped," "distressed and displaced individuals and families," as well as "the aged," according to the Philippine Bureau of Local Government Finance Glossary of Terms. The Philippine Bureau of Local Government Finance Glossary of Terms was accessed on 18 March 2022 and was downloaded from https://blgf.gov.ph/wp-content/uploads/2016/08/Metadata.docx.

evacuation centres, and conducting drills to better prepare for natural disasters. However, the presence of evacuation centres can also be a symptom of being in a natural-prone area. This case may lower some local sources, such as tax on business, as a natural disaster like Typhoon Haiyan may disrupt local businesses. This is consistent with national government reports stating, for example, that "90 per cent of total damage and loss from Typhoon Haiyan were private assets and income, mostly from businesses" (NDRRMC, 2014, pp. 87–88). Thousands of small and medium enterprises in Eastern Visayas were totally damaged by the Typhoon.[15] We examine whether the effects are more or less adverse in cities or municipalities that hosted evacuation centres, $Evacuation_{ipt}$. The regression model that we run is as follows:

$$y_{ipt} = \delta_3(\hat{Family}_{ip} \times Haiyan_t \times Evacuation_{ip}) + X'_{ipt}\Gamma + \mu_{ip} + \lambda_t + \iota_{ipt} \tag{6}$$

The triple interaction with *Evacuation* in tables 6 and 7 shows the results of estimating equation 6. The results show that evacuation centres are not a symptom of higher population and higher local expenditure. The triple interaction with evacuation centres has no effect on local expenditures. Evacuation centres have no effect on local income either, except for business tax. Overall, the results suggest that evacuation centres and the population who temporarily use them have no significant short-run effects on local public finance.

[15]This information is based on "Business as usual for 'Yolanda'-hit MSMEs at Tacloban trade fair by Sarwell Meniano accessed on 16 December 2021 at https://www.pna.gov.ph/articles/1053039.

6.3 City or municipality income-class distribution

Finally, we explore the possibility that local finances are collected and allocated differently in municipalities at the upper tail of the income-class distribution. Cities or municipalities belonging to a higher class of income may be more prepared against external shocks like Typhoon Haiyan relative to low-income cities or municipalities. For example, richer municipalities may be able to borrow more easily from banks than poorer municipalities to make up for their budget shortfalls due to calamity. To test this hypothesis, we split our sample into quantiles based on the City and Municipality Level Poverty Estimates of the Philippine Statistics Authority and employ the identical 2SLS estimation approach described in the heterogeneity analysis.

$IncomeClass_{ip}$ takes a value from 1 to 6 with 1 as the highest income class and 6 the lowest income class.[16] The equation is presented by:

$$y_{ipt} = \delta_4(\hat{Family}_{ip} \times Haiyan_t \times IncomeClass_{ip}) + X'_{ipt}\Gamma + \mu_{ip} + \lambda_t + \kappa_{ipt} \qquad (7)$$

Figures 6 and 7 present the coefficient estimates of the triple interaction at each quantile of the income distribution along with the associated 95% confidence intervals.

[16]Based on the Philippine Statistics Authority, $IncomeClass_{ip}$ is equal to 1 for cities or municipalities with an average income of PhP450 million or more, 2 for those with an average income between PhP360 million and PhP450 million, 3 for those with an average income between PhP270 million and PhP360 million, 4 for those with an average income of PhP180 million and PhP270 million, 5 for those with an average income of PhP90 million and PhP180 million, and 6 for those with average income below PhP90 million. The data was downloaded from the Philippine Statistics Authority at https://psa.gov.ph/classification/psgc/ on 29 March 2022.

These figures show that on average local public finances are not consistently more (or less) affected by the typhoon in comparatively poorer municipalities when the overall effect of the typhoon is insignificant. Moreover, both figures show that the other parts of the distribution within a city or municipality, including the richest and the poorest quantiles, are largely unaffected just like the average.

However, the results are different when we investigate across cities or municipalities. The triple interaction with $IncomeClass$ shows the results of estimating equation 7. The results suggest that income class has no significant effect on local expenditure, except for education. Education-related expenditures are lower by 0.09% per family affected, or 2.79% on average if we are to consider the average number of families affected which is 31%.

Income class has a significant effect on local income. In particular, lower-income class cities or municipalities have lower income from tax and non-tax revenues, particularly real property tax, tax on business, regulatory fees, and service or user charges. The largest effect is on regulatory fees, which include franchising and licensing fees as well as business permit feeds. Income from regulatory fees is lower by 0.20% or 6.2% on average. User charges, which include payments for clearance and certifications, are lower by 0.17% or 5.27% on average. Income from business taxes and real property tax is lower by 0.14% or 4.34% on average and 0.12% or 3.72%.

Local governments may be unable to generate as many local revenues as before Ty-

phoon Haiyan due to the resulting losses to local businesses and reductions in local market activities on which business and real property taxes are imposed.[17] For humanitarian or other reasons, the local governments in the affected areas also may have levied lower taxes on their constituents. The city government of Bogo in the province of Cebu, for example, imposed reduced taxes on local real property owners in March 2014 following Typhoon Haiyan.[18]

The results taken together show the limitations of local governments under decentralisation to address the effects of some natural disasters and, at the same time, highlight the role of the central government in supporting them. Local revenues, particularly income from businesses and economic enterprises, are reduced. When a typhoon as powerful as Haiyan affects several provinces in several regions, central government interventions and foreign aid are crucial in relief and recovery operations.

7 Conclusion

Natural disasters have direct severe consequences on the well-being of the affected local populations, service delivery and financing capacities of local governments, and the development path of institutions. We compiled city and municipal-level data for the

[17]Under the fiscal decentralization program that started in 1992, local governments are allowed to impose taxes on real properties and business operations within their jurisdictions. Together these two principal sources of local revenues account for less than half of the average annual total revenues of local governments since 1992. Most local governments are heavily dependent on the central fiscal transfers (Manasan et al., 2005; Llanto, 2012).

[18]Information retrieved on 22 December 2021 from https://www.philstar.com/the-freeman/cebu-news/2014/03/15/1301104/due-damage-caused-Yolanda-bogo-city-offers-tax-discounts.

Philippines, covering the periods before and after Typhoon Haiyan devastated the central part of the country in towards the end of 2013, to investigate how natural disasters affect local public finances. Our findings demonstrate that Typhoon Haiyan had no statistically significant effect on local public income and expenditures, except for debt payments which significantly increased. This finding suggests that local governments are not fully using their taxing powers (such as fees, charges, and real estate property taxes) to face the fiscal imbalances that might result from external shocks. On the contrary, our findings suggest that intergovernmental fiscal transfers are the primary financing instrument upon which local governments rely (Capuno, 2001; Troland, 2016).

Beyond the absence of local government fiscal response, we contribute to the literature on natural disasters and finance in several ways. Firstly, we document that aid results in higher local expenditures, particularly general public services, education, social services and welfare, economic services, and debt service. These results find no support for a moral hazard behaviour by local government units. One possible reason for this effect is that the marginal benefit of spending on items targeted or partially supported by donors might be higher for local decision-makers. Aligning with the international community might also be more rewarding. Secondly, evacuation centres which are used here as proxy for possible displaced families from neighbouring towns temporarily sheltered in the locality, have no short-run effects on local expenditures and income. The external shock may have negatively affected the local resources of host local governments and this

in turn may have diminished their capacity to further support the displaced families. The displaced families in the evacuation centres may instead be directly supported by NGOs, private donors, or international organizations. Thirdly, we find that affected lower-income class cities or municipalities have lower local income from tax and non-tax revenues in the aftermath of the typhoon. Hence, our analysis highlights the considerable heterogeneity in the response of local fiscal finances in the aftermath of exogenous shocks.

Altogether, our results suggest that local governments with similar exposure to financial constraints during natural disasters such as typhoons might have similar risk exposure to other nation-wide shocks such as the COVID-19 pandemic. In the absence of strong and responsive financial support from the central government, fiscal decentralization, which largely leaves local governments to fend for themselves, could even aggravate the impact of external shocks such as natural disasters. In cases where the earmarked fiscal transfers are defined by a fixed allocated formula, as in the Philippines, the central government needs to step in with additional sources of funding for disaster relief through the disaster risk reduction programs. Further research is needed to fully understand to which extent those additional funds are coordinating with other external funding sources such as foreign aid and whether these overall funds are effectively targeting the most vulnerable communities.

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Table 1: Pre-Haiyan characteristics of municipalities inside and outside affected provinces

	Outside Haiyan path			Inside Haiyan path			Outside-Inside Haiyan path		
	Obs.	Sample mean	s.e.	Obs.	Sample mean	s.e.	Diff-in-means	s. e.	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Income									
Total local sources	1,086	0.17	0.19	993	0.14	0.15	-0.03	0.01	0.00
Total tax revenue	1,086	0.09	0.16	993	0.07	0.10	-0.02	0.01	0.00
Real property tax	1,086	0.05	0.10	993	0.04	0.07	-0.01	0.00	0.01
Tax on business	1,086	0.04	0.09	993	0.03	0.05	-0.02	0.00	0.00
Other taxes	1,086	0.01	0.01	993	0.01	0.01	-0.00	0.00	0.03
Total non-tax revenue	1,086	0.08	0.09	993	0.08	0.09	-0.01	0.00	0.09
Regulatory fees	1,086	0.02	0.02	993	0.02	0.03	-0.00	0.00	0.35
User charges	1,086	0.01	0.03	993	0.01	0.06	0.00	0.00	0.52
Income from business	1,086	0.04	0.05	993	0.04	0.04	-0.00	0.00	0.27
Other general income	1,086	0.02	0.04	993	0.01	0.02	-0.01	0.00	0.00
Inter-Local transfers	1,086	0.00	0.02	993	0.00	0.02	0.00	0.00	0.77
Extraordinary receipts	1,086	0.01	0.05	993	0.01	0.04	-0.00	0.00	0.03
Total current operating income	1,086	0.80	0.13	993	0.78	0.12	-0.02	0.01	0.00
Expenditures									
Total local expenditure	1,086	0.69	0.13	993	0.69	0.12	0.00	0.01	0.87
General public services	1,086	0.48	0.11	993	0.49	0.10	0.01	0.01	0.04
Education	1,086	0.02	0.04	993	0.02	0.03	-0.00	0.00	0.00
Health	1,086	0.09	0.04	993	0.09	0.03	-0.00	0.00	0.10
Labour	1,086	0.00	0.01	993	0.00	0.00	0.00	0.00	0.36
Housing	1,086	0.01	0.03	993	0.01	0.03	0.00	0.00	0.39
Social services	1,086	0.04	0.04	993	0.05	0.03	0.00	0.00	0.27
Economic services	1,086	0.12	0.08	993	0.12	0.07	0.00	0.00	0.43
Debt	1,086	0.07	0.11	993	0.06	0.11	-0.01	0.01	0.01

Source: Philippine Bureau of Local Government Finance

Table 2: The effect of Haiyan on local public expenditures

	General	Education	Health	Labour	Housing	Social	Economic	Debt	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Family × Haiyan	-0.0001	-0.0003	0.0004	0.0002*	0.0008	-0.0009	-0.0002	-0.0022**	-0.0001
	(0.0003)	(0.0006)	(0.0004)	(0.0001)	(0.0008)	(0.0007)	(0.0007)	(0.0009)	(0.0003)
Observations	4173	4173	4173	4173	4173	4173	4173	4173	4173
Municipalities	351	351	351	351	351	351	351	351	351

Notes: All regressions control for PIRA (central government transfers), population, municipality poverty estimates and elevation as well as city/municipality, year, province, and province-year fixed effects. The dependent variable in all regressions are transformed using the inverse hyperbolic sine function. Robust standard errors in parentheses are clustered at the city/municipality level.
*** p<0.01, ** p<0.05, * p<0.1

Table 3: The effect of Haiyan on local government income

	Local sources	Tax revenue	Real-property tax	Business Tax	Other taxes	Non-tax revenue	Regulatory fees	User charges	Business income	Other general income	Inter-local transfers	Extraordinary receipts	Total income
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Family × Haiyan	-0.0010*	-0.0006	-0.0002	-0.0012**	-0.0000	-0.0012*	-0.0006	-0.0007	-0.0024***	-0.0004	-0.0013*	0.0010	-0.0001
	(0.0005)	(0.0004)	(0.0004)	(0.0006)	(0.0003)	(0.0007)	(0.0006)	(0.0007)	(0.0009)	(0.0008)	(0.0008)	(0.0012)	(0.0002)
Observations	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173
Municipalities	351	351	351	351	351	351	351	351	351	351	351	351	351

Notes: All regressions control for PIRA (central government transfers), population, municipality poverty estimates and elevation as well as city/municipality, year, province, and province-year fixed effects. The dependent variable in all regressions are transformed using the inverse hyperbolic sine function. Robust standard errors in parentheses are clustered at the city/municipality level.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: IV estimation - Effect of the typhoon on local government expenditures

Panel A: Panel data estimation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	General	Education	Health	Labour	Housing	Social	Economic	Debt	Total
Family × Haiyan	-0.0005	0.0010	0.0005	0.0001	0.0004	-0.0009	0.0005	-0.0051**	-0.0001
	(0.0006)	(0.0014)	(0.0007)	(0.0002)	(0.0014)	(0.0013)	(0.0014)	(0.0020)	(0.0005)
Observations	4173	4173	4173	4173	4173	4173	4173	4173	4173
Municipalities	351	351	351	351	351	351	351	351	351

Panel B: First-stage of the corresponding 2SLS panel regressions									
	(1)	(2)	(3)	(4)	(5)	(6)	(8)	(9)	
Dependent variable:	Share family affected								
Distance to storm path × Haiyan	-38.295***	-38.295***	-38.295***	-38.295***	-38.295***	-38.295***	-38.295***	-38.295***	-38.295***
	(4.480)	(4.480)	(4.480)	(4.480)	(4.480)	(4.480)	(4.480)	(4.480)	(4.480)
Kleibergen-Paap F-statistic	73.08	73.08	73.08	73.08	73.08	73.08	73.08	73.08	73.08
Controls as in panel A	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All results are 2SLS estimations in panel A and first-stage estimates in panel B. The dependent variables in all regressions are transformed using the inverse hyperbolic sine function. Baseline controls are those presented in table 2. Robust standard errors in parentheses are clustered at the city/municipality level. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table 5: IV estimation - Effect of the typhoon on local government income

Panel A: Panel data estimation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Type of local income	Local sources	Tax revenue	Real-property tax	Business Tax	Other taxes	Non-tax revenue	Regulatory fees	User charges	Business income	Other general income	Inter-local transfers	Extraordinary receipts	Total income
Family × Haiyan	-0.0007	0.0000	0.0015	-0.0019	0.0011**	-0.0001	0.0020	0.0008	-0.0027	-0.0010	-0.0022	0.0013	-0.0004
	(0.0012)	(0.0009)	(0.0012)	(0.0016)	(0.0005)	(0.0016)	(0.0015)	(0.0011)	(0.0021)	(0.0015)	(0.0015)	(0.0020)	(0.0004)
Observations	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173
Municipalities	351	351	351	351	351	351	351	351	351	351	351	351	351
Panel B: First-stage of the corresponding 2SLS panel regressions													
Dependent variable:	Share family affected												
Distance to storm path × Haiyan	-38.295***	-38.295***	-38.295***	-38.295***	-38.295***	-38.295***	-38.295***	-38.295***	-38.295***	-38.295***	-38.295***	-38.295***	-38.295***
	(4.480)	(4.480)	(4.480)	(4.480)	(4.480)	(4.480)	(4.480)	(4.480)	(4.480)	(4.480)	(4.480)	(4.480)	(4.480)
Kleibergen-Paap F-statistic	73.08	73.08	73.08	73.08	73.08	73.08	73.08	73.08	73.08	73.08	73.08	73.08	73.08
Controls as in panel A	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All results are 2SLS estimations in panel A and first-stage estimates in panel B. The intensity of Typhoon Haiyan is proxied by the share of family affected in the total municipality population based on the 2010 Census. All dependent variables are transformed using the inverse hyperbolic sine function. Standard errors are below each estimate in parentheses and are adjusted for clustering at the city/municipality level. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table 6: The heretogenous effect of Haiyan on local public expenditures

	General				Education				Health			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Family × Haiyan	-0.0005	-0.0007	-0.0004	-0.0015	0.0010	0.0008	0.0014	0.0043	0.0005	0.0005	0.0005	0.0000
	(0.0006)	(0.0006)	(0.0007)	(0.0013)	(0.0014)	(0.0014)	(0.0016)	(0.0027)	(0.0007)	(0.0007)	(0.0008)	(0.0014)
Family × Haiyan												
×*Aid*		0.0005***				0.0006**				0.0001		
		(0.0002)				(0.0002)				(0.0002)		
×*Evacuation*			0.0001				-0.0006				0.0003	
			(0.0006)				(0.0013)				(0.0010)	
×*IncomeClass*				0.0003				-0.0009*				0.0002
				(0.0003)				(0.0005)				(0.0003)
Municipality FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Department-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173
Municipalities	351	351	351	351	351	351	351	351	351	351	351	351
Kleibergen-Paap *F*-statistic	73.08	27.51	23.42	24.04	73.08	27.51	23.42	24.04	73.08	27.51	23.42	24.04

	Labour				Housing				Social			
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Family × Haiyan	0.0001	0.0000	0.0001	-0.0003	0.0004	0.0005	-0.0000	-0.0011	-0.0009	-0.0012	-0.0017	0.0013
	(0.0002)	(0.0002)	(0.0002)	(0.0006)	(0.0014)	(0.0014)	(0.0016)	(0.0029)	(0.0013)	(0.0013)	(0.0013)	(0.0027)
Family × Haiyan												
×*Aid*		0.0002				-0.0003				0.0007*		
		(0.0001)				(0.0002)				(0.0004)		
×*Evacuation*			0.0001				-0.0004				0.0015	
			(0.0002)				(0.0017)				(0.0014)	
×*IncomeClass*				0.0001				0.0004				-0.0005
				(0.0001)				(0.0006)				(0.0005)
Municipality FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Department-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173
Municipalities	351	351	351	351	351	351	351	351	351	351	351	351
Kleibergen-Paap *F*-statistic	73.08	27.51	23.42	24.04	73.08	27.51	23.42	24.04	73.08	27.51	23.42	24.04

	Economic				Debt				Total			
	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)
Family × Haiyan	0.0005	0.0002	-0.0000	0.0010	-0.0051**	-0.0054***	-0.0042*	-0.0079**	-0.0001	-0.0003	-0.0002	-0.0008
	(0.0014)	(0.0014)	(0.0016)	(0.0028)	(0.0020)	(0.0020)	(0.0023)	(0.0038)	(0.0005)	(0.0005)	(0.0006)	(0.0011)
Family × Haiyan												
×*Aid*		0.0007***				0.0009**				0.0005***		
		(0.0003)				(0.0004)				(0.0002)		
×*Evacuation*			0.0006				-0.0005				-0.0000	
			(0.0014)				(0.0017)				(0.0006)	
×*IncomeClass*				-0.0000				0.0010				0.0002
				(0.0006)				(0.0008)				(0.0003)
Municipality FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Department-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173
Municipalities	351	351	351	351	351	351	351	351	351	351	351	351
Kleibergen-Paap *F*-statistic	73.08	27.51	23.42	24.04	73.08	27.51	23.42	24.04	73.08	27.51	23.42	24.04

Notes: All results are 2SLS estimations. Baseline controls are those presented in table 2. The instrument used is the interaction between distance to storm path and post-2013 Haiyan dummy. The dependent variables in all regressions are transformed using the inverse hyperbolic sine function. Robust standard errors in parentheses are clustered at the city/municipality level.
*** p<0.01, ** p<0.05, * p<0.1

Table 7: The heretogenous effect of Haiyan on local public income

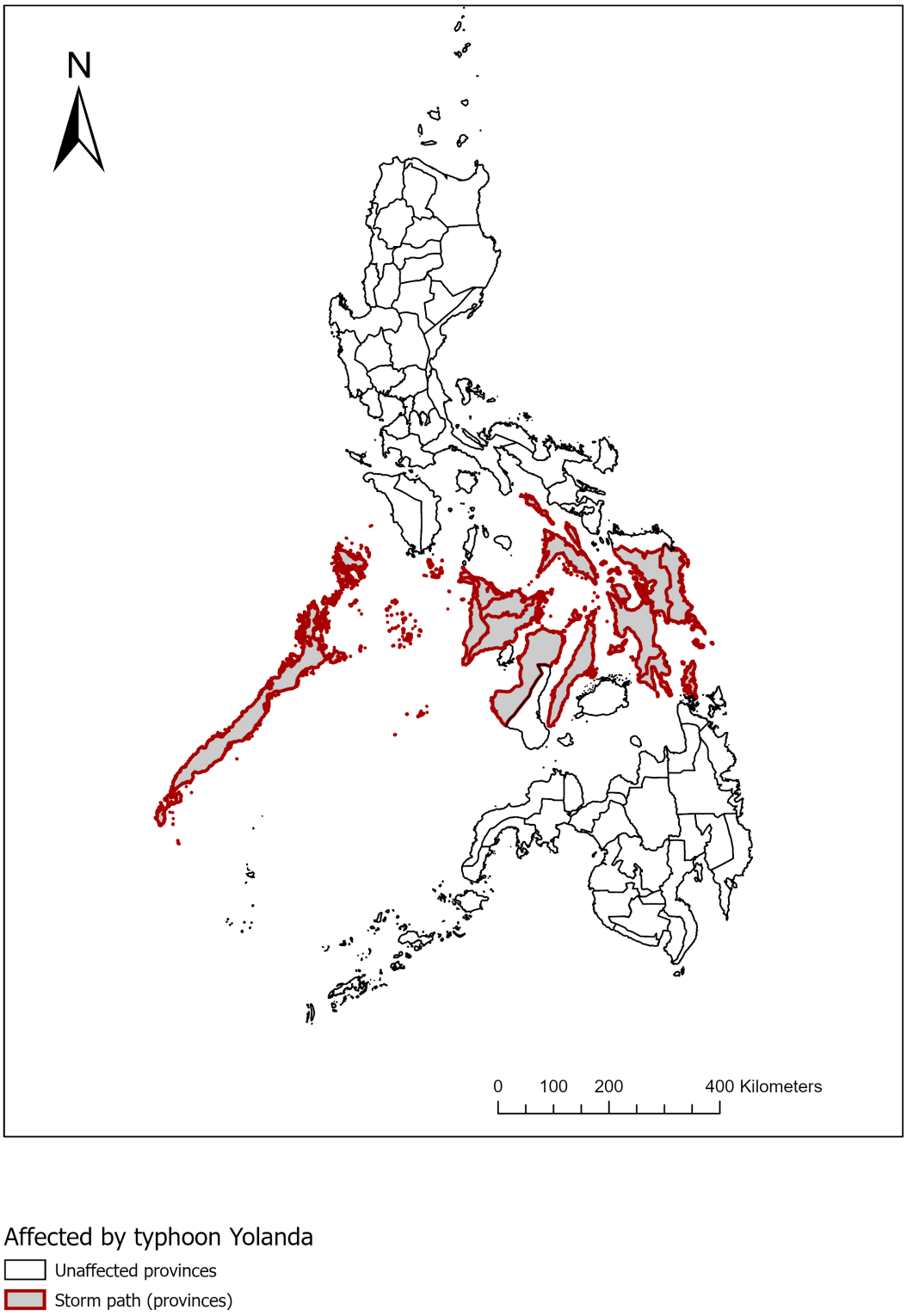
	Local sources				Tax revenue				Real property tax				Business tax			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Family × Haiyan	-0.0007	-0.0009	-0.0007	0.0009	0.0000	-0.0001	-0.0003	0.0037**	0.0015	0.0014	0.0015	0.0061***	-0.0019	-0.0020	-0.0030	0.0042
	(0.0012)	(0.0012)	(0.0014)	(0.0022)	(0.0009)	(0.0010)	(0.0011)	(0.0019)	(0.0012)	(0.0012)	(0.0014)	(0.0023)	(0.0016)	(0.0017)	(0.0018)	(0.0029)
Family × Haiyan																
×*Aid*		0.0006**				0.0003				0.0001				0.0001		
		(0.0002)				(0.0002)				(0.0002)				(0.0002)		
×*Evacuation*			-0.0005				0.0003				-0.0009				0.0027*	
			(0.0011)				(0.0010)				(0.0009)				(0.0014)	
×*IncomeClass*				-0.0004				-0.0009**				-0.0012***				-0.0014**
				(0.0004)				(0.0004)				(0.0004)				(0.0006)
Municipality FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Department-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173
Municipalities	351	351	351	351	351	351	351	351	351	351	351	351	351	351	351	351
Kleibergen-Paap *F*-statistic	73.08	27.51	23.42	24.04	73.08	27.51	23.42	24.04	73.08	27.51	23.42	24.04	73.08	27.51	23.42	24.04

	Other taxes				Non-tax revenue				Regulatory fees				User charges			
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
Family × Haiyan	0.0011**	0.0010*	0.0009	0.0024**	-0.0001	-0.0003	0.0003	0.0030	0.0020	0.0019	0.0016	0.0089***	0.0008	0.0008	0.0009	0.0071***
	(0.0005)	(0.0006)	(0.0006)	(0.0011)	(0.0016)	(0.0016)	(0.0019)	(0.0030)	(0.0015)	(0.0015)	(0.0018)	(0.0029)	(0.0011)	(0.0011)	(0.0013)	(0.0022)
Family × Haiyan																
×*Aid*		0.0002				0.0006**				0.0000				-0.0001		
		(0.0003)				(0.0003)				(0.0002)				(0.0002)		
×*Evacuation*			-0.0000				-0.0014				0.0009				-0.0006	
			(0.0007)				(0.0013)				(0.0013)				(0.0012)	
×*IncomeClass*				-0.0003				-0.0008				-0.0020***				-0.0017***
				(0.0002)				(0.0005)				(0.0005)				(0.0004)
Municipality FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Department-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173
Municipalities	351	351	351	351	351	351	351	351	351	351	351	351	351	351	351	351
Kleibergen-Paap *F*-statistic	73.08	27.51	23.42	24.04	73.08	27.51	23.42	24.04	73.08	27.51	23.42	24.04	73.08	27.51	23.42	24.04

	Business income				Other general income				Inter-local transfers				Total income			
	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)	(41)	(42)	(43)	(44)	(45)	(46)	(47)	(48)
Family × Haiyan	-0.0027	-0.0029	-0.0021	-0.0013	-0.0010	-0.0014	-0.0016	-0.0004	-0.0022	-0.0024*	-0.0022	-0.0040	-0.0004	-0.0008**	-0.0006	-0.0006
	(0.0021)	(0.0021)	(0.0024)	(0.0042)	(0.0015)	(0.0016)	(0.0018)	(0.0030)	(0.0015)	(0.0014)	(0.0016)	(0.0027)	(0.0004)	(0.0004)	(0.0005)	(0.0009)
Family × Haiyan																
×*Aid*		0.0005				0.0009*				0.0005				0.0012***		
		(0.0003)				(0.0005)				(0.0005)				(0.0002)		
×*Evacuation*			-0.0014				0.0008				-0.0005				0.0002	
			(0.0016)				(0.0016)				(0.0015)				(0.0005)	
×*IncomeClass*				-0.0002				-0.0002				0.0006				0.0001
				(0.0008)				(0.0006)				(0.0006)				(0.0002)
Municipality FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Department-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173
Municipalities	351	351	351	351	351	351	351	351	351	351	351	351	351	351	351	351
Kleibergen-Paap *F*-statistic	73.08	27.51	23.42	24.04	73.08	27.51	23.42	24.04	73.08	27.51	23.42	24.04	73.08	27.51	23.42	24.04

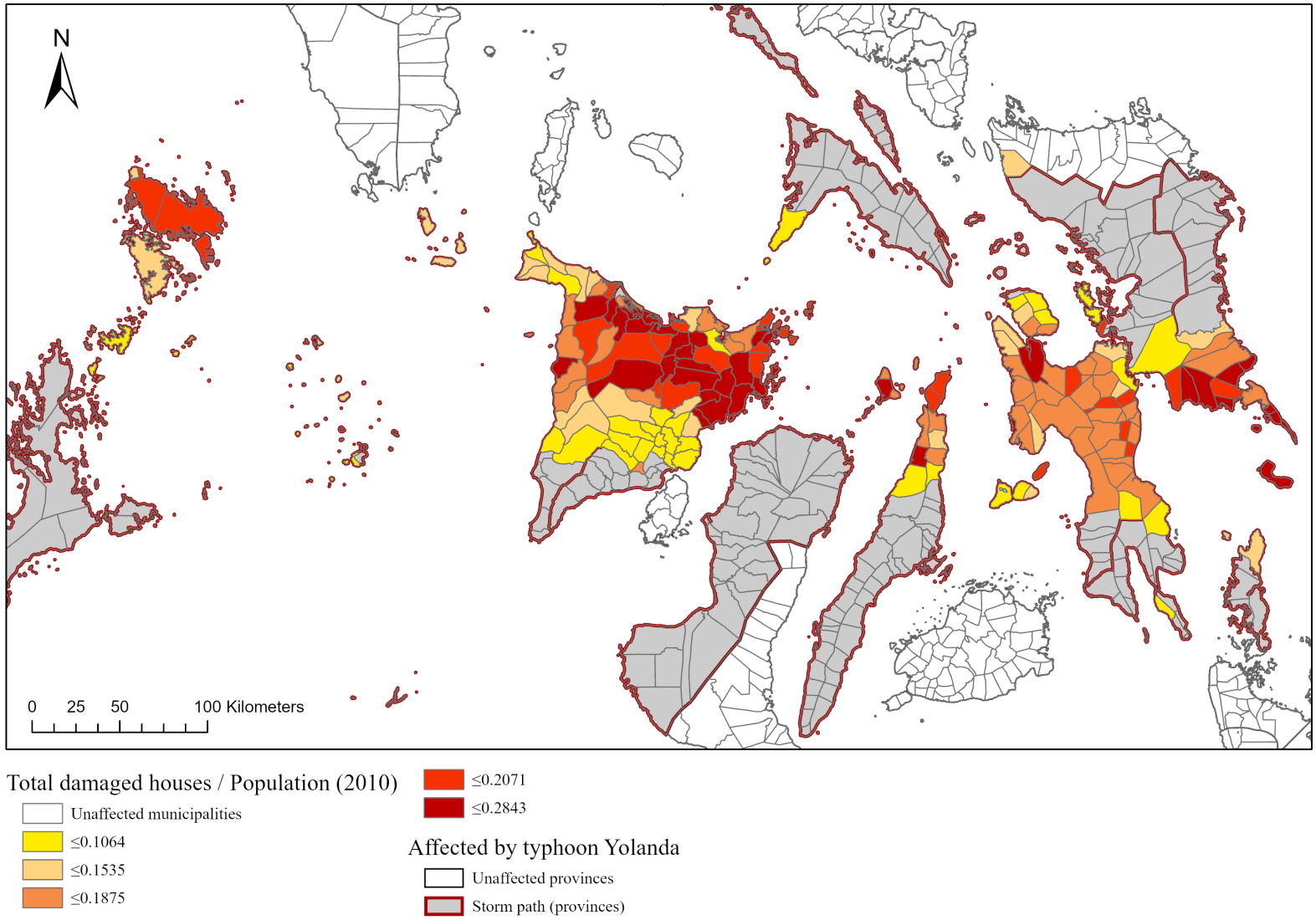
Notes: All results are 2SLS estimations. Baseline controls are those presented in tables 2. The instrument used is the interaction between distance to storm path and a post-2013 Haiyan dummy. The dependent variables in all regressions are transformed using the inverse hyperbolic sine function. Robust standard errors in parentheses are clustered at the city/municipality level.
*** p<0.01, ** p<0.05, * p<0.1

FIGURE 1: PROVINCES AFFECTED BY TYPHOON HAIYAN



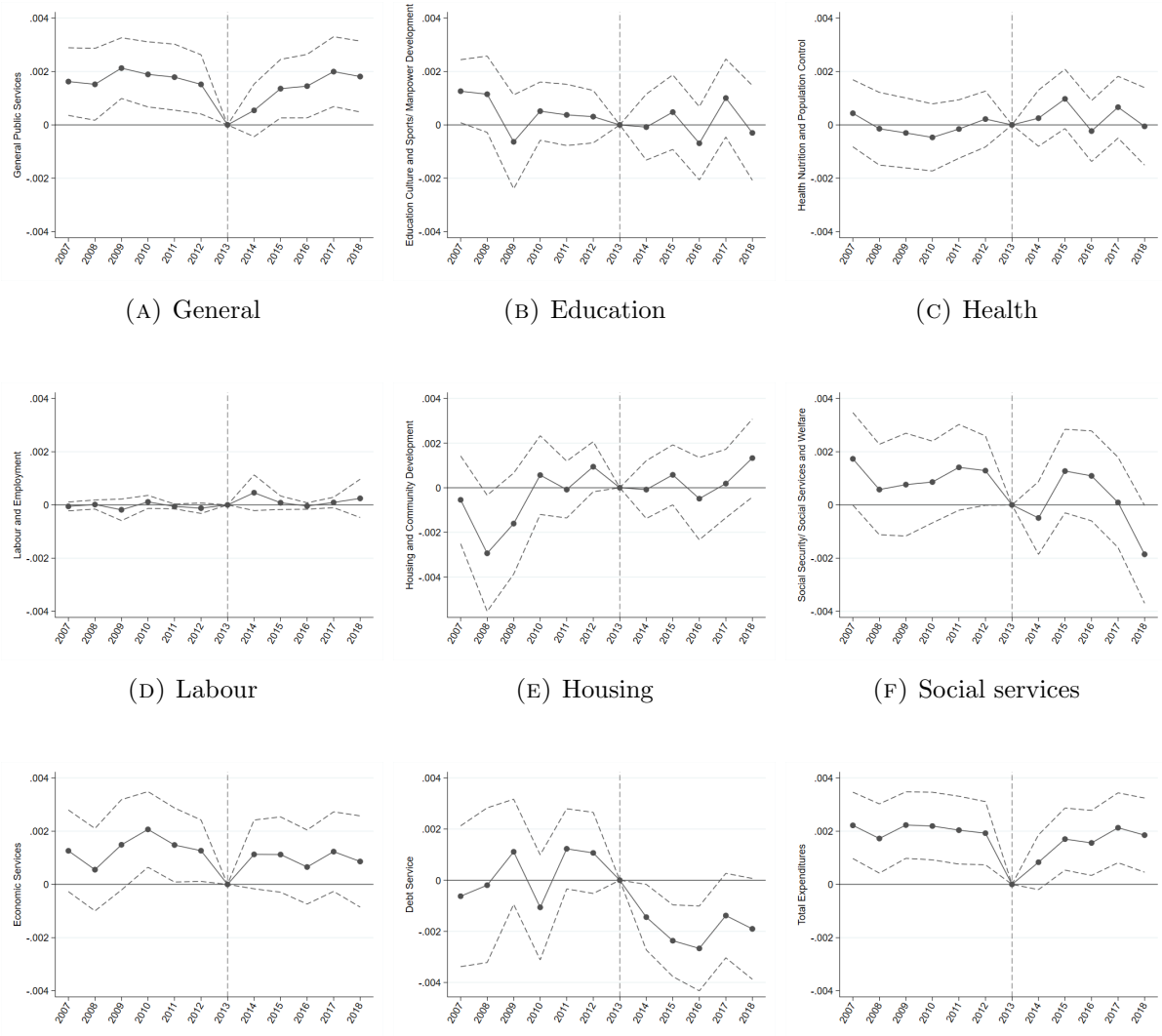
Notes: The map shows the provinces affected by Typhoon Haiyan, locally known as Typhoon Yolanda, in 2013. Provinces are identified as affected by the typhoon if they had families displaced by the typhoon. The information is collected from the Department of Social Welfare and Development and the National Disaster Risk Reduction and Management Council of the Philippines.

FIGURE 2: STORM PATH OF HAIYAN AND AFFECTED CITIES AND MUNICIPALITIES



Notes: The map shows the cities and municipalities affected by Typhoon Haiyan in 2013, along with the intensity of destruction. The total number of destructed houses is normalized by city or municipality population from the 2010 census. Information was collected from the Department of Social Welfare and Development and the National Disaster Risk Reduction and Management Council of the Philippines.

FIGURE 3: DYNAMIC EFFECTS OF THE TYPHOON ON LOCAL EXPENDITURES



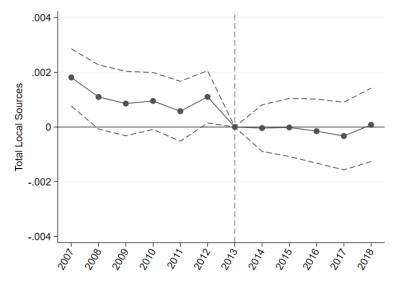
(A) General (B) Education (C) Health

(D) Labour (E) Housing (F) Social services

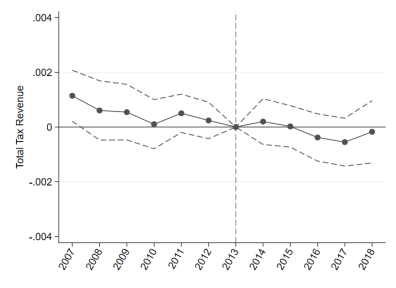
(G) Economic services (H) Debt (I) Total

Notes: Each graph plots the coefficient estimates of equation (2) along with their 95% confidence intervals. Each graph presents the δ_t coefficients on the interaction of a yearly indicator and the variable *Family*. Robust standard errors are adjusted for clustering at the city/municipality level.

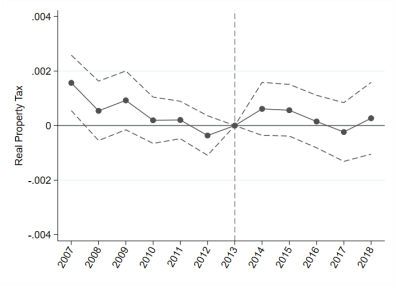
FIGURE 4: DYNAMIC EFFECTS OF HAIYAN ON LOCAL INCOME (I)



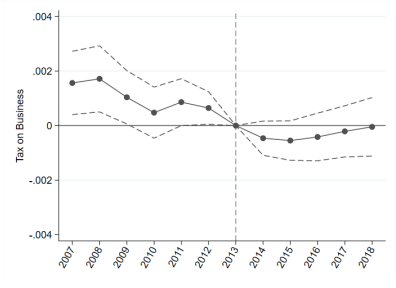
(A) Local sources



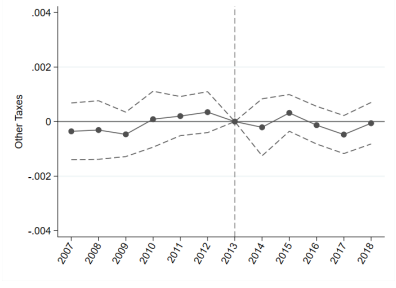
(B) Tax revenue



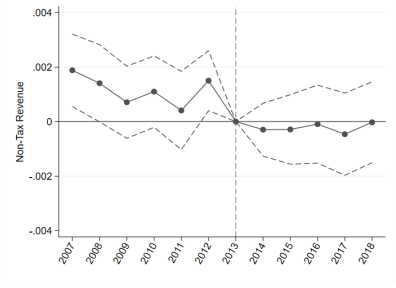
(C) Real-property tax



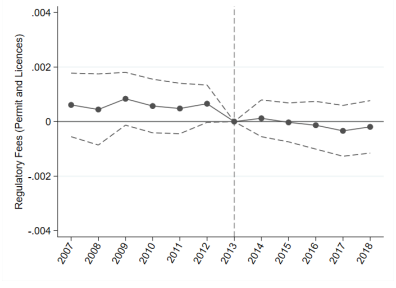
(D) Business tax



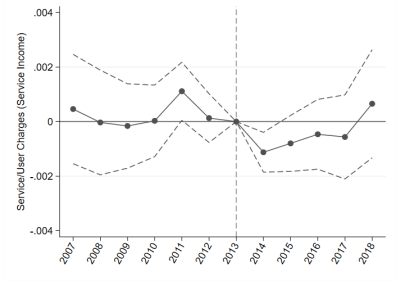
(E) Other taxes



(F) Non-tax revenue



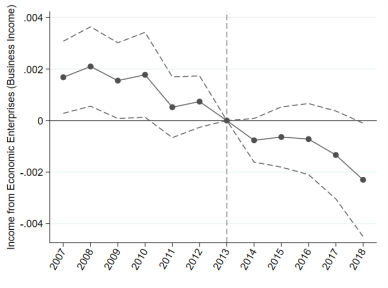
(G) Regulatory fees



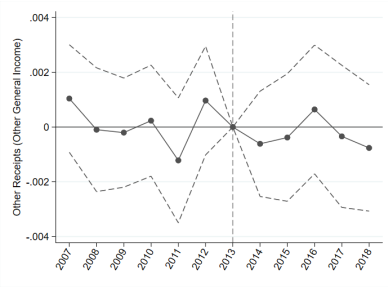
(H) User charges

Notes: Each graph plots the coefficient estimates of equation (2) along with their 95% confidence intervals. Each graph presents the δ_t coefficients on the interaction of a yearly indicator and the variable *Haiyan*. Robust standard errors are adjusted for clustering at the city/municipality level.

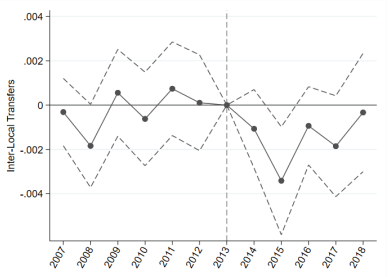
FIGURE 5: DYNAMIC EFFECTS OF HAIYAN ON LOCAL INCOME (II)



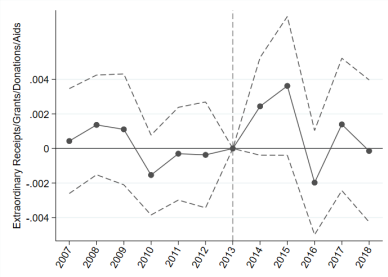
(A) Business income



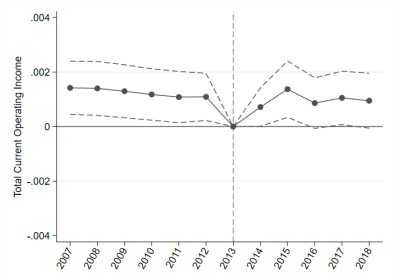
(B) Other general income



(C) Inter-local transfers



(D) Extraordinary receipts

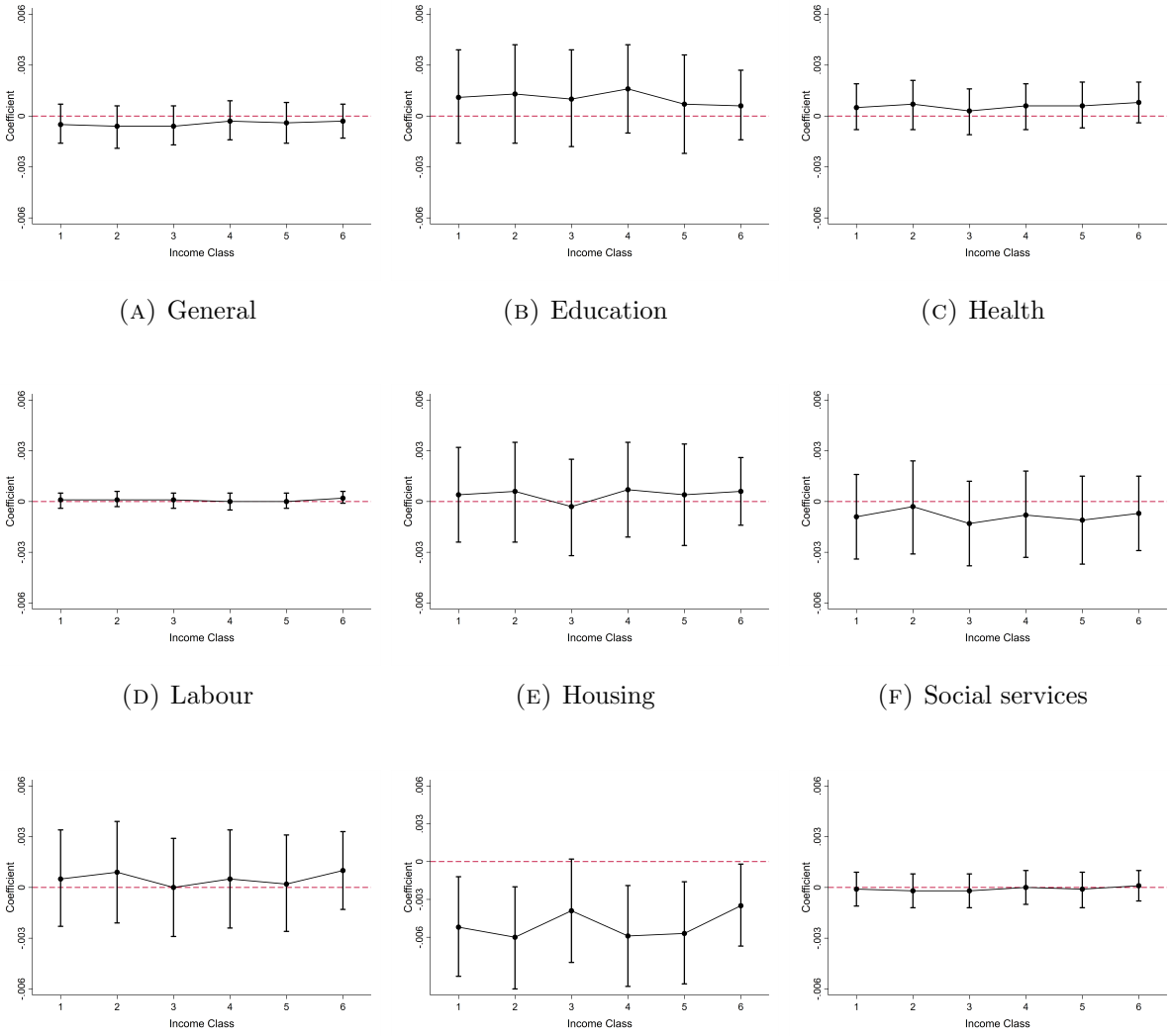


(E) Total

Notes: Each graph plots the coefficient estimates of equation (2) along with their 95% confidence intervals. Each graph presents the δ_t coefficients on the interaction of a yearly indicator and the variable *Family*. Robust standard errors are adjusted for clustering at the city/municipality level.

Appendix for online publication

Figure 6: Effects of the typhoon on local expenditures by City or Municipality income quantiles



(a) General (b) Education (c) Health

(d) Labour (e) Housing (f) Social services

(g) Economic services (h) Debt (i) Total

Notes: Each graph plots the coefficient estimates along with their 95% confidence interval of the share of family affected from the 2SLS estimation where the instrument is fully interacted with the quintiles of the municipality income distribution. All regressions include all baseline controls and standard errors are adjusted for clustering at the city/municipality level.

Variable	Name in records
General	General public services
Education	Education culture and sports/manpower development
Health	Health nutrition and population control
Labour	Labour and employment
Housing	Housing and community development
Social	Social security/social services and welfare
Economic	Economic services
Debt	Debt service
Total	Total expenditures
Local sources	Total local sources
Tax revenue	Total tax revenue
Real-property tax	Real-property tax
Business tax	Tax on business
Other taxes	Other taxes
Non-tax revenue	Non-tax revenue
Regulatory fees	Regulatory fees (permit and licences)
User charges	Service/User charges (service income)
Business income	Income from economic enterprises (business income)
Other general income	Other receipts (other general income)
Inter-local transfers	Inter-local transfers
Extraordinary receipts	Extraordinary receipts/grants/donations/aids
Total	Total current operating income

TABLE 8: Source: Philippine Bureau of Local Government Finance

FIGURE 7: EFFECTS OF THE TYPHOON ON LOCAL INCOME BY CITY OR MUNICIPALITY INCOME QUANTILES

(A) Local sources (B) Tax revenue

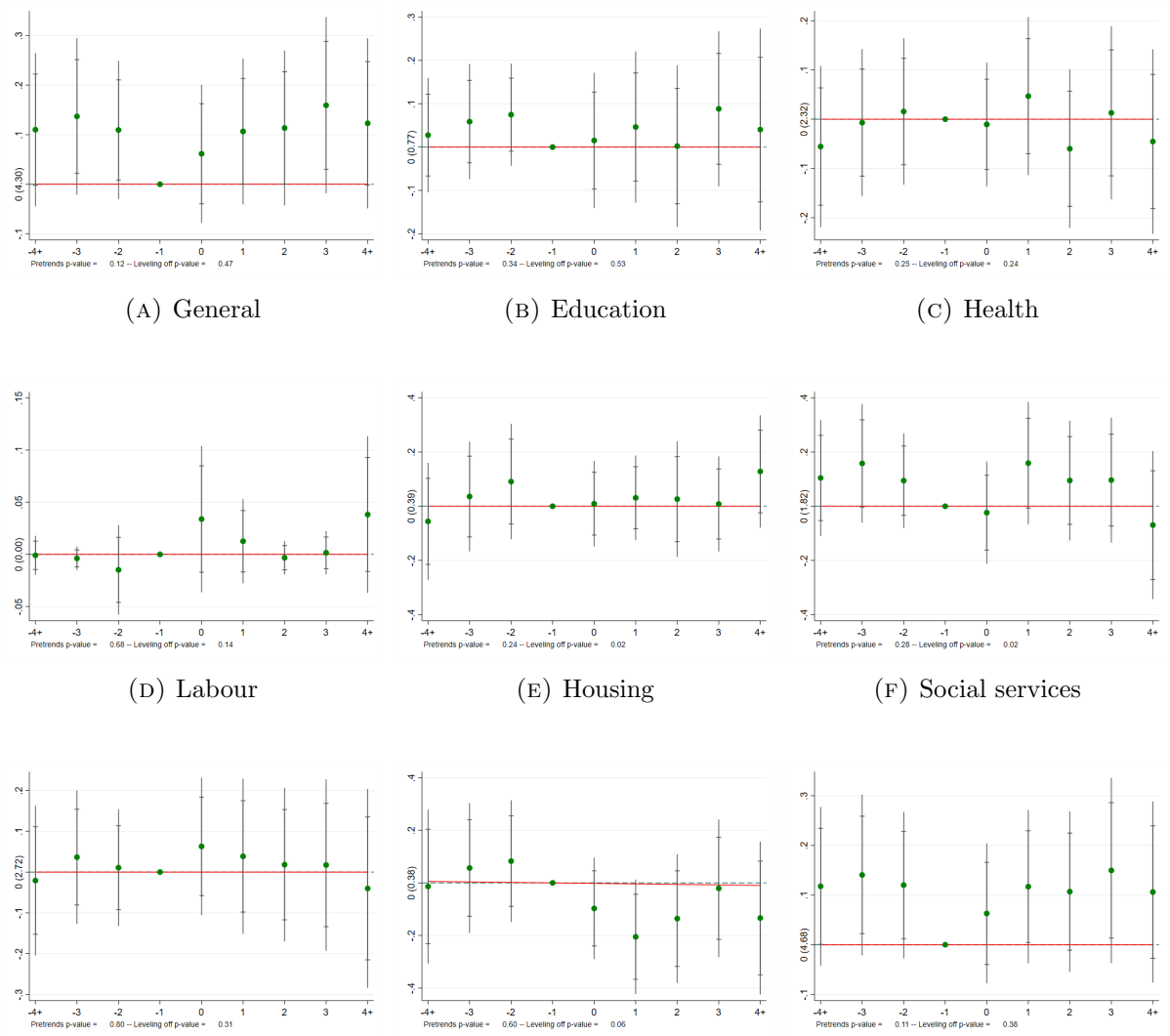
(C) Real-property tax (D) Business tax

(E) Other taxes (F) Non-tax revenue

(G) Regulatory fees (H) User charges

Notes: Each graph plots the coefficient estimates along with their 95% confidence interval of the share of family affected from the 2SLS estimation where the instrument is fully interacted with the quintiles of the municipality income distribution. All regressions include all baseline controls and standard errors are adjusted for clustering at the city/municipality level.

FIGURE 8: DYNAMIC EFFECTS OF THE TYPHOON ON LOCAL EXPENDITURES



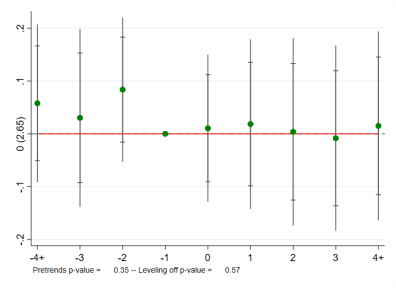
(A) General (B) Education (C) Health

(D) Labour (E) Housing (F) Social services

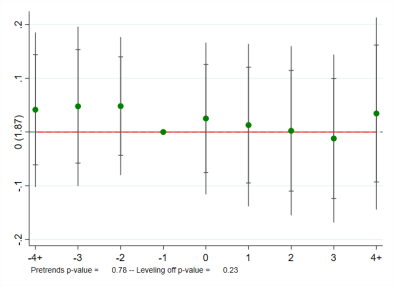
(G) Economic services (H) Debt (I) Total

Notes: Each graph plots the coefficient estimates of equation (2) along with their 95% confidence intervals. Event study estimates are obtained using the procedure developed by Freyaldenhoven et al. (2021) and implemented in the *xtevent* Stata package to account for potential pre-trends. Robust standard errors are adjusted for clustering at the city/municipality level.

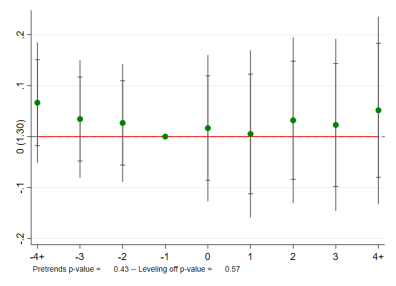
FIGURE 9: DYNAMIC EFFECTS OF HAIYAN ON LOCAL INCOME (I)



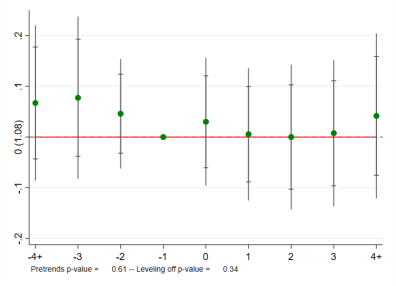
(A) Local sources



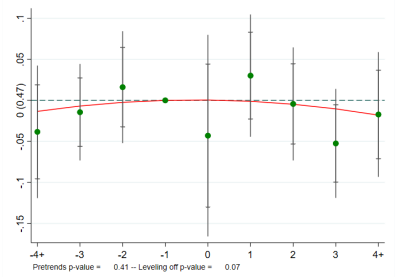
(B) Tax revenue



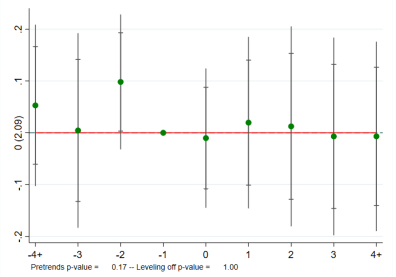
(C) Real-property tax



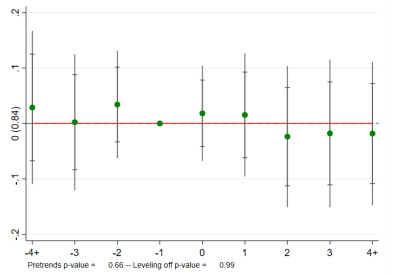
(D) Business tax



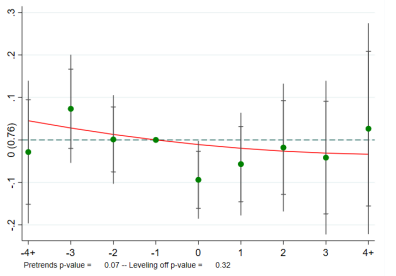
(E) Other taxes



(F) Non-tax revenue



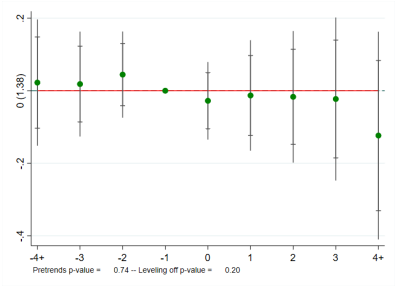
(G) Regulatory fees



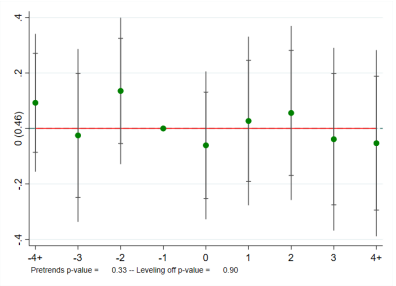
(H) User charges

Notes: Each graph plots the coefficient estimates of equation (2) along with their 95% confidence intervals. Event study estimates are obtained using the procedure developed by Freyaldenhoven et al. (2021) and implemented in the *xtevent* Stata package to account for potential pre-trends. Robust standard errors are adjusted for clustering at the city/municipality level.

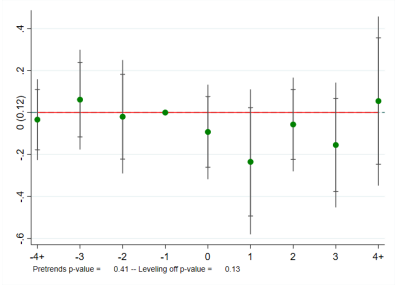
FIGURE 10: DYNAMIC EFFECTS OF HAIYAN ON LOCAL INCOME (II)



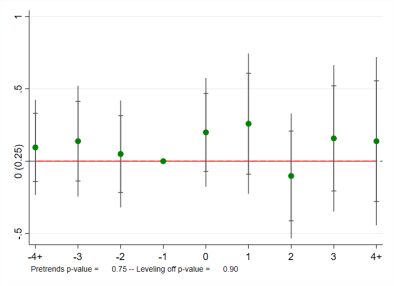
(A) Business income



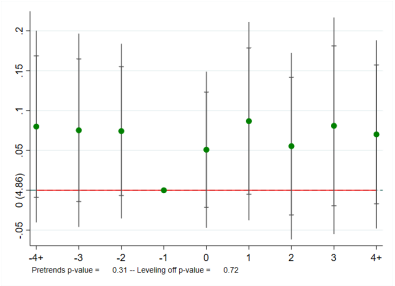
(B) Other general income



(C) Inter-local transfers



(D) Extraordinary receipts



(E) Total

Notes: Each graph plots the coefficient estimates of equation (2) along with their 95% confidence intervals. Event study estimates are obtained using the procedure developed by Freyaldenhoven et al. (2021) and implemented in the *xtevent* Stata package to account for potential pre-trends. Robust standard errors are adjusted for clustering at the city/municipality level.