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

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**Abstract**

This paper examines how natural disasters affect local public finances and their interplay with intergovernmental transfers and external resources. Exploiting the randomized nature of the 2013 Typhoon Haiyan, one of the most devastating natural disasters in recent history, we document its causal effect on the local government fiscal dynamics. Combining data on local government finance with reports on the level of damages and using difference-in-differences with instrumental variable to analyze the data, we show that local public revenue and expenditures remain largely unaffected, except for debt payments. However, we find important heterogeneity in local revenue responses: poorer cities and municipalities raised comparatively lower revenue in the aftermath of the Typhoon. We also provide evidence that external funding did not lead to lower tax collection efforts, but instead leads to higher local expenditures, suggesting that disaster aid does not cause a moral hazard problem in local governments' spending decisions.

**JEL Classification: H71; H72; H84; Q54**

**Keywords: Natural disasters, local government finance, disaster aid, Haiyan/Yolanda**

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# 1 Introduction

Natural disasters can have adverse consequences on economic growth, long-term development and poverty (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). Natural disasters pose substantial fiscal risks and generate major budget volatility. Even in high-income countries with strong disaster risk management schemes, major disasters can severely affect local development (Deryugina et al., 2018). While damage costs tend to be high, the adverse consequences of natural disasters can be mitigated by mobilising and allocating resources to high-risk areas, since natural disasters often strike only parts of countries. Yet, in settings where local budget sources are tightly constrained, such local fiscal policy efforts might be too limited to be effective. 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. They may be more financially constrained to allocate more resources ex-ante to reducing vulnerabilities (Laframboise and Loko, 2012). Natural disasters may further have long-term adverse effects on the provision of local public services through reduced fiscal expenditures. On the other hand, their revenue losses may be partially offset if central governments seek to increase spending for disaster relief by channelling resources to disaster areas, or when external aid pours 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? Although a multitude of channels could support local development, local public responses and international aid are essential financial instruments that have been used to mitigate natural disasters (OECD, 2019).

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 ten years of city and municipality public finances data from the Philippines before and after the 2013 Typhoon Haiyan (nationally known as Typhoon Yolanda), one of the most powerful typhoons in recorded history (Schiermeier, 2013). As the typhoon wrought severe damages and displaced populations along its path, we combine the local fiscal information with disaster data from local and international sources on the share of displaced families within local communities.

We present new evidence on the short and medium-term effects of natural disasters on the abilities of local governments to deliver services and generate resources for such services, and the interaction of local fiscal policy with national and international aid. We tease out the causal effect of the typhoon, whose occurrence, intensity, and path are exogenous to the affected cities and municipalities and the families therein, to estimate its effect on the generation and allocation of local public resources. In particular, we use event study analyses and a difference-in-differences strategy that compares the outcomes of cities and municipalities affected by the typhoon with their counterparts off the storm path but within the affected provinces.

Our identification strategy depends on the "unprecedented fury" of Typhoon Haiyan and its "unimaginable destruction" on affected cities and municipalities (NDRRMC, 2014, pp. 21, 46). Typhoon Haiyan entered the Philippine Area of Responsibility on 6 November 2013 and made its first landfall two days later over Guiuan, Eastern Samar. The Typhoon had a devastating impact on the affected regions' infrastructure, roads, hospitals, schools, and public services. The severity of the impact on areas it ravaged was unanticipated and unprecedented, and we, therefore, argue that most, if not all, of its effects, were felt during and after the disaster. Importantly, the exceptional aspect of the event leaves little room for any meaningful anticipation effects: local officials receive a government alert on the potential exceptional threat of the typhoon less than 24 hours before its landfall (NDRRMC, 2013).

We perform a battery of sensitivity analyses and falsification tests, including changes in the sample definition, and damage measures to confirm the robustness of our empirical results. We further address the potential endogeneity of displaced families by exploiting highly possible exogenous 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. We further demonstrate the validity of our results to an alternative measure of typhoon intensity exposure, using wind speed data as in Jerch et al. (2023).

The typhoon generally has no statistically significant effect on local government expenditures, except for debt payments. We estimate that a 1-percentage point increase in families displaced by the typhoon leads to 0.22% lower debt payments. With 31% of families displaced by Typhoon Haiyan, this 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. Our results are qualitatively robust to the instrumental variable estimation strategy: the effect in absolute terms is more than double once the endogeneity is addressed. The result is to be interpreted with regard to the Philippine local budget autonomy. Local governments maintain control and decision power over the major part of their budget revenue, and are allowed to use some additional resource funds from their Local Calamity fund when affected by a disaster. The result with debt payment reduction might be explained by the short-term lending arrangements in debt payment granted to the affected cities and municipalities in the aftermath of the disaster. 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 the tax on business and business income. However, these results are not robust when we consider the endogeneity correction. Overall, these findings complement prior studies on local government expenditures and public debt payments in high-income economies (Jerch et al., 2023; Noy, Okubo, et al., 2021).

We then explore several mechanisms through which a negative shock could affect local budgets. First, we investigate whether external aid[1] triggers a moral hazard problem in local fiscal responses. How local governments are financed matters (Gadenne, 2017). Support from international aid agencies and other donors may have substituted for local revenue mobilization, at least for those cities and municipalities with more affected tax bases.[2] Given the substantial aid inflow that followed Typhoon Haiyan, we find no evidence that external aid caused moral hazard behavior in local governments' decisions.

Second, we examine the role of displaced populations in the response to public finance. Ostensibly the relocated population (mostly within cities or municipalities) inevitably expanded the demand for local public services, which in turn put pressure on the local governments to calibrate their public spending, raise more revenues, or both (Hochrainer-Stigler and Mechler, 2019). The results, however, show that local public finances remain largely unaffected by the increased number of displaced population, both in the short and medium terms, highlighting the likely existence of barriers to generating and mobilizing additional public resources.

Third, we empirically test how the local finances of cities or municipalities are affected

[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 (BLGF) Glossary of Terms includes domestic and foreign grants and donations as well as other subsidy income and gains from foreign exchange, sale of assets, sale of investments, and premium on bonds payable. Information was accessed on 18 March 2022 from `https://blgf.gov.ph/wp-content/uploads/2016/08/Metadata.docx`.

[2]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 the government to monitor such aid and other relief efforts (COA, 2014, p. 18). 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.

by a major disaster like Typhoon Haiyan based on their initial capacity to mobilize resources. Poorer cities or municipalities may be consistently more affected by the typhoon in their capacity to collect and allocate local finances. We categorize our sample by income classes based on the Philippine Statistics Authority. We show that poorer cities/-municipalities are more exposed to a reduction in their capacity to generate revenue both from income and non-income tax in the aftermath of a disaster. This finding corroborates the fact that the fiscal budgets of larger subnational governments tend 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 research contributes to the growing literature on the fiscal consequences of natural disasters. We extend prior research to document how natural disasters affect local public finances and their dynamics in relatively lower-middle-income settings. While recent studies demonstrate the adverse effects of natural disasters on local government budgets and the crucial role of intergovernmental transfers (Jerch et al., 2023; Miao et al., 2020; Noy, Okubo, et al., 2021) and on government support for environmentally friendly legislation (Elliott, Nguyen-Tien, et al., forthcoming) in high-income settings, less is known about the effect of natural disasters on local governments, which might be less equipped to absorb the cost of disasters (Laframboise and Loko, 2012). As natural disasters are more common and affect more people in low and middle-income economies, we aim to fill the gap in the literature by examining the responsiveness of local fiscal policy with limited resources to a negative exogenous shock in a decentralized context and by exploring the intermediary role of the external funding sources.

Our findings on the indirect effect of natural disasters at the government level complement studies on the welfare effects on individuals or households and firms. 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. Elliott, Liu, et al. (2019) find substantial but short-lived negative effects of typhoons on manufacturing firms in China. 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 if the incentives of the elected leaders are aligned with their constituents. For instance, an increase in revenue tax collection could offer higher benefits to local constituents than from fiscal transfers (Gadenne, 2017). Yet during times of hardships, the financial capacity of local governments may be insufficient to maintain the provision of local public services. If the local government themselves are also affected by the devastating calamity, they will be unable to provide for their constituents' needs.

The rest of the paper proceeds as follows. Section 2 provides a background of the effects of Typhoon Haiyan and the public sector response. Section 3 discusses the sources of data as well as provides summary statistics. Section 4 discusses the methodology, namely the difference-in-differences approach, event study, and instrumental variable strategy. Section 5 analyses the results, section 6 provides robustness checks, and section 7 explores the mechanisms. The final section concludes.

# 2 Background

## 2.1 Local governments and fiscal decentralization

The first administrative layer in the Philippines corresponds to a region. In this administrative structure, provinces are geographically and politically sub-divided into municipalities and cities, which form the Local Government Units (LGUs), and then *barangays* ("villages").[3]

The 1991 Local Government Code established fiscal decentralization in the Philippines to give greater fiscal autonomy to local governments and give decision-making powers to local councils over budget control and spending (Llanto, 2012). The Local Government Code further entails a central government transfer to each local government unit, the Philippine Internal Revenue Allotment (PIRA). The PIRA is an unconditional, formula-based grant obtained from national tax collection and its allocation varies according to the type of local government: 23% to provinces and (highly urbanized) cities, 34% to municipalities, and 20% to *barangays* (Llanto, 2012, p. 59). The PIRA represents

[3]See for example the Philippine Standard Geographic Code (PSGC) database at https://psa.gov.ph/classification/psgc/, which is updated based on the recommendations of the interagency Technical Working Group on Geographic Code. The file was downloaded on 24 March 2022.

approximately 65% of local government income, a share that has remained stable during the last decade and which highlights the dependency of LGUs on external funds (Diokno-Sicat, Castillo, et al., 2021).

LGUs have two sources of local income, locally raised revenues and external sources. Local revenue is comprised of local tax revenues, whose main source for LGUs is real property and business taxes, and non-tax revenues which essentially come from economic enterprises, user fees, and eventually LGU assets (Diokno-Sicat, Adaro, et al., 2020). Local tax revenues represent approximately 9% of national government tax collections (Diokno-Sicat, Castillo, et al., 2021). On top of the unconditional PIRA grant, LGUs can also obtain financing via funds granted by national government agencies under the conditions that they meet certain performance and equity-based criteria and spend on areas prioritized by the national agencies (Diokno-Sicat, Adaro, et al., 2020). Regarding the PIRA, the grant can be freely used by LGUs as long as they spend 20% of it on local development projects identified as a priority under their local development plans. Finally, local governments are required to allocate 5% of their regular revenues to the Local Disaster Risk Reduction Management Fund "to support disaster risk management activities such as, but not limited to, pre-disaster preparedness programs including training, purchasing life-saving rescue equipment, supplies and medicines, for post-disaster activities, and for the payment of premiums on calamity insurance".[4] This aspect of

[4]See Section 21 of Republic Act 102121 of https://ndrrmc.gov.ph/attachments/article/1320/JMC_No_2013-1_re_Allocation_and_Utilization_of_LDRRMF.pdf. The file was last downloaded on 25 November 2022.

the local government budget autonomy is central to our analysis: in times of disasters, local governments should have a sufficient budget to flexibly reallocate resources towards disaster priority areas such as preparation, rehabilitation and recovery.

Overall, revenues of LGUs contributed to an average of 2.6% to Gross Domestic Product (GDP) between 2009 and 2018, while their share of income sources to GDP was approximately 1.2% (Diokno-Sicat, Castillo, et al., 2021).

## 2.2 Typhoon Haiyan

The Philippines is prone to natural disasters. The country frequently experiences "geological and hydro-meteorological hazards due to its geographical and physical characteristics" (NDRRMC, 2014, p. 2). Although the Philippines is one of the most exposed countries to strong winds brought by typhoons (Hsiang and Jina, 2014), evidence shows that the country has managed to adapt to its hostile environment over the past few decades and mitigate the negative impact of natural disasters on its economy and the number of fatalities (Bakkensen and Mendelsohn, 2016). Yet, the category 5 super Typhoon Haiyan that hit the Philippines in November 2013 was unlike ordinary typhoons. With maximum sustained winds estimated by the Joint Typhoon Warning Center to have reached 195 miles per hour (315 km per hour) at landfall, it was one of the strongest and largest typhoons ever recorded in the world (Schiermeier, 2013).

Typhoon Haiyan made landfall in the eastern part of the Philippines on 8 November

2013 and left its western part the following day ( Figure A1 in the online Appendix). As the typhoon traversed through the country, its intensity did not diminish and caused an exceptional level of destruction and casualties on its path. According to the Philippines National Disaster Risk Reduction and Management Council (NDRRMC) (NDRRMC, 2013, pp. 2–5, 63), in the next two months after the typhoon, about 6,300 people reportedly died, more than 28,000 were injured and an estimated 4 million more were displaced. Further, about 1.14 million houses were damaged, nearly half of them totally wrecked. Some neighbourhoods were entirely swept away by the typhoon. Schools, churches and other community centres were used as evacuation centers prior to and in the immediate aftermath of the typhoon, although more than two thirds of these infrastructures were either damaged or completely destroyed by the disaster (NDRRMC, 2014). The total cost of the damages to infrastructure (roads, bridges, school buildings), the social sector (education, health, housing) and the productive sector (agriculture, fisheries, mining, trade, industry, tourism) approximates 95 billion Philippine pesos (PhP), or about 1% of the Gross Domestic Product (GDP). The same report mentioned that a total of PhP104.64 billion (or US$2.34 billion) was needed for post-Haiyan rehabilitation and recovery in the affected areas or sectors. According to the Department of Finance, half of this amount was released by the Department of Budget and Management in 2014 to support government relief and rehabilitation efforts in the affected provinces.[5] In particular, 9% of this

[5]The fund was coming from the National Budget, the Calamity Fund and the National Disaster Risk Reduction and Management Fund and was allocated to national government agencies, government-owned corporations and LGUs. The information was obtained from https://www.dof.

national fund was allocated to LGUs for the rehabilitation of their public infrastructures, which were mostly municipality halls, evacuation centers, police and fire stations.

### 2.3 Displaced populations

The vast majority of displaced populations found temporary shelter in evacuation centers in the immediate aftermath of the typhoon. While most of the 4 million displaced returned to their original homes within 6 months following the typhoon, approximately 26,000 affected persons were still waiting in temporary shelters and an estimated 200,000 people were living in unsafe homes that could remain vulnerable to other hazards. The government supported the reconstruction of homes in safer areas, but 98% of the affected population remained in its original local area (Sherwood et al., 2015). Indeed, relocation might have been perceived as an additional burden for families because of possible lack of integration, lower employment opportunities, or lower access to public services (IFRC, 2016). Furthermore, beneficiaries of the government conditional cash transfer program (4Ps) and Senior Citizens (eligible for discounts and sometimes cash allowances) are tagged to their home municipalities. Relocating to new municipalities would entail significant experience delays in receiving national government benefits. Families relied on family loans and government emergency funds to rebuild their houses, while those with more limited means moved to bunkhouses. Hence, while the 2013 Typhoon Haiyan had

`gov.ph/p52-b-released-to-yolanda-victims-since-2013-dbm`, and was last accessed on 25 November 2022.

only a transitory effect on displaced families, its negative consequences on the financial situation of the affected families might have been more enduring.

## 2.4 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.[6] On 16 December, a Reconstruction Assistance for Yolanda plan is published to guide government plans for the recovery and reconstruction, with US$2.8 billion for immediate needs and short-term interventions during the first twelve months. 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 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.[7]

Following the unprecedented damages caused by Haiyan, the Calamity Fund (or, offi-

[6]See Memorandum Order No. 62 series 2013, accessed on 7 June 2022, from https://www.officialgazette.gov.ph/2013/12/06/memorandum-order-no-62-s-2013/.

[7]See "PhP67-B released for Yolanda rehab since 2013" by Sarwell Meniano published on 21 February 2018 in the Philippine News Agency accessed at https://www.pna.gov.ph/articles/1026022on16June2021.

cially, 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 upon request.[8] The fund covers activities such as reconstruction or rehabilitation of infrastructure, aid, and relief services. The other funds made available to local governments and sourced from the national budget 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, dedicated to climate change-related projects. 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 the European Union, the United Nations, and the United States Agency for International Development (USAID) that provided significant rehabilitation, reconstruction, and recovery assistance (COA, 2014; NDRRMC, 2013, 2014).

Given the size and allocation of the Calamity Fund and external aid, arguably they could have influenced 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

[8]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).

and social welfare) and other expenditures. From the available official financial reports of local governments, we can observe for each local government a decomposition of annual fiscal expenditures and revenues. We can therefore examine the effect of Typhoon Haiyan on these particular sources of local revenues and, in turn, on certain types of local expenditures, as will be shown later in Table A1. 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 Conceptual framework

We develop a simple conceptual framework that enables us to consider how local governments affected by the Typhoon may shape their decision to allocate resources after the disaster and the interplay with the central government and foreign donors, and motivate specific hypotheses to be tested in our empirical analysis. Consider that local governments have control over the allocation of their resources within their municipalities and can fully observe local needs and damages after the typhoon. The central government declares the state of emergency for the affected municipalities, which allows affected municipalities to request financial aid to the central government. Since, international aid flows through the central government budget, donors do not play a direct role in this model.[9]

[9] Foreign aid can also comprise technical cooperation, or financial support to local or international humanitarian aid organizations. In such cases, aid is not recorded in the government's budget. Omitting this potential large fraction of aid that is off-budget could potentially bias the estimated effect of aid on

The allocation of resources in the aftermath of the typhoon will depend on the capacity of the local government to reallocate existing funds, potentially mobilise new resources, and the additional aid support that it will receive.

We consider the local government's strategies under the following approaches. Firstly, the typhoon could damage the local economy, reduce public revenues, local expenditures, and increase local needs (income effect). The typhoon heavily damaged both public infrastructure and the tax base of the local authority. Local governments might struggle to reallocate resources for reconstruction and relief expenses due to their limited capacity to generate or mobilise additional resources in the direct aftermath of the typhoon. External aid will be used to relieve some of the financial constraint of the local government, without any strategic utilization of it by the local authorities.

Secondly, higher external aid or government financial support could lower tax collection effort and/or entail a reallocation of public funds to other targeted items (substitution effect). While aid is to be spent on pre-specified areas in agreement with the central government, these external resources are disbursed directly to local governments, and constitute a direct increase in their local budget. Local governments could use the additional funding to decrease their own share of local resources on the aid-targeted items and reallocate the freed resources to other items. Alternatively, local governments may use the additional external funding to reduce their own tax collection effort.

local fiscal's response. However, evidence shows that government's expenditures tend to be not responsive to off-budget aid (Van de Sijpe, 2013).

Furthermore, local governments may have enough fiscal capacity to mobilise new resources to affected items, such as through using their savings and/or raising their level of debt to increase public expenditures in the direct aftermath of the typhoon. As discussed in the previous section, local governments are required to allocate 5% of their regular revenues to the Local Disaster Risk Reduction Management Fund, which could consequently be used in the rehabilitation and reconstruction phase along with deficit financing. However, the latter will depend on the local governments' access to debt markets and their existing level of debt, which might worsen after a disaster (Benali et al., 2018).

This latter local government's action might be the most plausible in high-income settings, where local governments might even reduce taxes (Noy and Nualsri, 2011). However, in low-and middle income countries like the Philippines, where most local authorities highly depend on central government transfers, this latter assumption is much less plausible.

Both income and substitution effect could be in operation at both times, and in either the same or different directions. The overall effect may further depend on specific characteristics of local governments, such the existing resources or their fiscal capacity. Hence, the overall net effect is essentially an empirical question.

# 4 Data

## 4.1 Sources

We draw data on city and municipality expenditure and income from the Philippine Bureau of Local Government Finance (BLGF). The data comprises 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. The dataset further provides a detailed breakdown of public expenditure that we describe in Table A1 in the Online Appendix. 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 the 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.

As a proxy for the intensity of typhoon exposure at the time of the disaster, 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.[10] In section 7, we explore the robustness of our results by including all regions with a non-zero

[10] Our results remain both quantitatively and qualitatively similar when we use the share of damaged or totally wrecked houses as a proxy for typhoon intensity exposure.

share of displaced families. We also address the potential endogeneity of families displaced with an instrumental variable strategy. Of the 14 affected provinces, 11 provinces are in the central part of the Philippines, the Visayas.[11] Our total sample comprises 352 cities and municipalities between 2007 and 2018. Additional city/municipal-level data on population, poverty incidence,[12] and income class are collected from the Philippine Statistics Authority (PSA). The population data is based on the 2010 Census, while poverty incidence and income class are based on the 2012 data. We use the latest available income class classification in 2021.

We obtain geographical data from various sources. Geo-coded data on the storm path and wind speed 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.[13] We also calculate the share of damaged houses in total families affected by Typhoon Haiyan. Figure A1 shows the geographical distribution of the intensity of the typhoon among cities and municipalities, measured by the share of damaged houses per total number of families within cities or municipalities, using

[11]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 the Visayas. The other two groups of islands are Luzon, the northern part of the Philippines, and Mindanao, the southern part of the Philippines.

[12]Poverty incidence is defined as the proportion of families or individuals whose income are below the poverty threshold. The poverty threshold is calculated as the food threshold/(food expenditure/total expenditure). See page 19 of the 2012 Municipal and City Level Poverty Estimates by the Philippine Statistics Authority.

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

census data.[14] The share of damaged houses depends on baseline characteristics like housing quality. The exceptional strength of the Typhoon along its path throughout the Philippines left little possibilities to spare richer families with comparatively better equipped houses (for instance, The Philippine Building Code required before the disaster that walls of buildings should withstand at least 250 kph, whilst the Typhoon Haiyan had recorded wind speed over 300 kph). Yet, 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/municipalities, on average, the typhoon affected 31% of total households and damaged 34% of houses in affected cities/municipalities.

The summary statistics in Table 1 show the pre-Haiyan city/municipality characteristics, along with a balance test on these characteristics to explore potential differences between the affected and non-affected cities/municipalities within the typhoon-ravaged provinces. We notice significant differences in most of the pre-Haiyan city/municipality characteristics between affected and non-affected cities/municipalities. In particular,

[14] 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.

cities/municipalities affected by the typhoon tend to be more rural, less densely populated and with lower revenues. We address this concern in our empirical strategies in several ways: first, by accounting for the pre-event characteristics and city/municipality fixed effects; second, by explicitly testing the pre-trends assumption in the event-study design; and third, by predicting the intensity of the typhoon-related destruction from the distance to the storm path.

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 9% of total income.

Among non-tax revenues, income from economic enterprises is the most important. Contributing 3% to total income, business tax revenue (income from business) is followed by general income (2.5%), service or user charges (2%), regulatory fees, such as feeds on permit and licenses (2%), and extraordinary receipts, including aid, donations, and grants (0.7%). Inter-local transfers are less than 1% of total income.

On the expenditure side, general public services have the biggest share, at 56%, of the total expenditures.[15] Meanwhile, education services (education, culture and sports), health services, (health, nutrition, and population control), labor services (labor and

[15] 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." This information was accessed at https://blgf.gov.ph/wp-content/uploads/2016/08/Metadata.docx on 18 March 2022.

employment), and housing (housing and community development) account for 4%. 9%, 0.02%, and 2.3% 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 help the poor, less privileged individuals, and those in emergency situations. Finally, debt payments, which include payment of the principal and interest on outstanding debts, take up 10% of the total outlays.

# 5 Methodology

We explore the effect of typhoon Haiyan on local public expenditures and income through a difference-in-difference estimation approach and with an instrumental variable strategy. Our outcomes for local expenditures are general, education, health, labor, housing, social, economic, debt and total expenditures. For 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 and total income. These outcome variables are described in the Online Appendix.

## 5.1 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 city or municipality affected by Haiyan. In the Robustness Section, we demonstrate that our results are robust to changing the definition of our control group by extending it to all cities/municipalities that belong to a region (instead of a province) that was affected by the typhoon. Our identifying assumption is that conditional on city/municipality observables, typhoon exposure is orthogonal to any city/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 Local Government Units (LGUs) with those spared by Haiyan. Our baseline specification is:

$$y_{ipt} = \delta(ShareFamily_{ip} \times Post2013_t) + X'_{ipt}\Gamma + \mu_i + \lambda_{pt} + \epsilon_{ipt} \tag{1}$$

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 to account for the skewness of their distributions.[16] $ShareFamily_{ip}$ is the share of displaced families in the total number of families affected by Haiyan in city or municipality $i$ and province $p$.[17] $Post2013_t$ is a dummy variable equal to 1 if $t > 2013$ and 0 otherwise. The main coefficient of interest is $\delta$ which measures the differential impact of the typhoon on the local public finances of affected cities or municipalities

[16]We prefer this transformation to the logarithm function that would require arbitrarily adding 1 unit to the outcome variables. However, our results are robust to the choice of transformation since the values of all the outcome variables are large, the IHS transformation is almost identical to a logarithm transformation with an upward shift of log(2) (Aihounton and Henningsen, 2021).

[17]Note that the share of family affected is not time varying as we only consider it to capture the intensity exposure to the one-time typhoon event.

relative to the 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, defined as interactions of time dummies with pre-2013 characteristics. 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, depending 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 based on the locality's population, land area, and administrative level (i.e., province, city/municipality) from the previous three years (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, $\mu_i$, to account for unobservable invariant characteristics of cities or municipalities, and province-year fixed effect $\lambda_{pt}$ (i.e. province fixed effect, year fixed effect, and their interaction, province-year fixed effect), to absorb unobserved factors that could simultaneously affect cities/municipalities within the same province in a given year. Following (Cameron et al., 2011) we adopt a two-way clustering at city/municipality and province-year levels to allow for both the correlation of errors within cities/municipalities across years and for spatial correlation across cities/municipalities based on spatial proximity in a given year.

## 5.2 Event study

The specification in equation (1) implicitly assumes that the typhoon effects on local public finances are constant across affected and unaffected municipalities. To relax this assumption and analyse the dynamic effects of the typhoon on local finances, we include a series of year dummy variables. Our event study specification is:

$$y_{ipt} = \sum_{t \neq 2013} \delta_t (ShareFamily_{ip} \times Year_t) + X'_{ipt}\Gamma + \mu_i + \lambda_{pt} + \epsilon_{ipt} \tag{2}$$

where the variables are defined as above. $Year_t$ is a dummy variable for year $t$. This variable excludes 2013, the reference year. Since Typhoon Haiyan struck the Philippines on November 8 and 9, 2013, most of the observed effects should start in 2014. However, we explore the robustness of our results to using 2012 as a reference year. The time-varying parameters $\delta_t$ capture the interactions of event years and the intensity exposure to the typhoon, the share of family affected. The parameters trace out the effect of Typhoon Haiyan on the outcome of interest in affected municipalities relative to the municipalities outside the storm's path. Estimates of $\delta_t$ for $t < 2013$ capture the differences in the outcome among municipalities within and outside the 2013 storm path before Typhoon Haiyan.

### 5.3 Identification assumption

Several challenges could threaten the validity of our strategy. First, our identification assumption could be violated if cities/municipalities that we define as in the control group get indirectly but substantially and durably affected by the typhoon, through increased migration or re-routed public funds, generating changes in local public finances. In this case, our estimation strategy would underestimate the typhoon's full effect. While we cannot completely rule out this possibility, the evidence does not support it. As discussed in Section 2, the typhoon triggered a large but temporary population displacement, with the majority of affected people having returned to their original local community within the 6 months preceding the disaster. Furthermore, displaced families took refuge in temporary shelters that were essentially located within their own municipalities, as they faced the emergency situation upon the imminent arrival of the typhoon.

Second, since the Philippines is frequently exposed to typhoons, our identification strategy could potentially ignore *pre* or *post*-2013 typhoons and wrongfully attribute the observed effects on local finances to Typhoon Haiyan. If some cities or municipalities in a province are comparatively more likely than others to be exposed to a typhoon, some endogenous sorting could be observed where more exposed cities/municipalities would host a comparatively higher share of lower-income and risk-averse households, and a lower share of firms and small businesses for example. However, Figure A2 in the Online Appendix displays all typhoons of category 4 and 5 on the Saffir–Simpson scale between 2003 and 2018 that crossed the municipalities that are used either as treated or controlled in our DID estimation setting. The figure indicates that only one typhoon (internationally called Typhoon Ruby and locally Hagupit) traversed in 2014 some of the municipalities included in our data sample during the 15-year period. Yet, Typhoon Ruby was significantly less powerful than Typhoon Haiyan, and its total financial effect was estimated to be less than 5% of the total financial loss estimated for Typhoon Haiyan (NDRRMC, 2014). This evidence gives us confidence that the regions affected by typhoon Haiyan have not been historically more exposed to typhoons, at least in the period considered, and our DID strategy should not be tempered by the effect of additional typhoons during the period of our analysis. Furthermore, the possibilities to migrate to safer areas are limited by the fact that the whole country is at a high risk of exposure to natural disasters (NDRRMC, 2014). In addition, as pointed out earlier, the cost of moving and adjusting to a new home might be high, especially for those who have limited means of disposing properties (e.g. land) left behind and then acquiring new ones in the other location.

Third, although Typhoon Haiyan presents 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; unaffected cities or municipalities were more resilient to natural disasters through higher investments in infrastructures; 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. Since the 2013 Haiyan typhoon was of an exceptional intensity (one of the strongest ever recorded), we expect that most cities and municipalities would not differ significantly in their capacity to resist the strength of the typhoon once we control for the city/municipality characteristics defined above unless cities and municipalities in the control and treatment groups differ systematically, and in huge proportions, in their investments to climate-resilient infrastructures. As the Philippines remains a lower middle-income country with a vast majority of cities or municipalities that possess limited resources and strongly depend on the government's financial transfers, this assumption is unlikely to hold. Nonetheless, we address the issue in two different ways: i) by replacing the share of displaced families with the estimated wind speeds of the typhoon in municipality $i$, and ii) by using an IV strategy presented in the next section. Note however that using wind speed data, as in Jerch et al. (2023), is not our preferred approach for this particular setting as the only available wind speed estimates are produced at a 6-hour interval, along a relatively large swath. Further, the exceptional intensity of the Typhoon barely dissipated as it crossed the Philippines and emerged on the Eastern side the following day. As a consequence, this alternative measure generates little variability, as shown in Figure A3 in the Online Appendix, where islands with different shares of families affected have similar wind speed. Since wind speed is arguably less prone to endogeneity, we use it as a validation exercise, but prefer to use an alternative instrumental variable to address the endogeneity of the share of families displaced.

## 5.4 Instrumental variable

To address the issue and 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 $Post2013_t$, with the distance between the centroid of a city or municipality and the storm path, $Distance_{ip}$. The instrument predicts the level of destruction in a given city/municipality based on its distance to the storm path, which can be interpreted as a proxy for typhoon exposure.

The first-stage equation is given by:

$$ShareFamily_{ipt} = \beta(Distance_{ip} \times Post2013_t) + X'_{ipt}\Gamma + \mu_i + \lambda_{pt} + \zeta_{ipt} \tag{3}$$

The coefficient of interest is on $\beta$ which effectively measures the differential effect of the typhoon on the cities/municipalities at varying proximity to the storm path, before and after Haiyan. From equation 3, we have a just-identified IV model with one excluded instrument; we derive the predicted affected Family ($Fa\hat{m}ily_{ip}$) and plug it in our second stage of our two-staged least squares (2SLS) system, as follows:

$$y_{ipt} = \delta_1(Share\hat{F}amily_{ip} \times Post2013_t) + X'_{ipt}\Gamma + \mu_i + \lambda_{pt} + \eta_{ipt} \tag{4}$$

where we include the same set of fixed effects and control variables included in equation (1) while using a two-way clustering at city/municipality and province-year levels.

A central identifying assumption is that the distance from the centroid of city/municipality $i$ to the storm path is orthogonal to any unobservable city/municipality characteristics that may affect the outcome variable. The “a priori” random nature of the typhoon trajectory and intensity provides support for this excludability assumption. The exceptional strength of the typhoon as one of the highest ever recorded in the world further supports this statement. The absence of any other typhoons of category 4 or 5 that followed a similar path through the municipalities affected by Typhoon Haiyan between 2003 and 2018 also suggests that the overall region is not particularly prone to natural disasters, and makes the region even historically less exposed than other areas in the country (Figure A4). Nonetheless, 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. We report in the Results section the Kleibergen-Paap F-statistic and show that the relevance condition of the IV holds.

Lastly, one could be concerned that the actual path taken by Typhoon Haiyan followed a path that was anticipated by the weather forecast, allowing a subset of municipalities with comparatively higher financial characteristics to take sufficient measures to limit the devastating effects of the typhoon. However, the path and relative strength of Typhoon Haiyan became more certain with only about two days between entering the Philippine Area of Responsibility and its first landfall. This left local governments limited time, resources and preparation capacity to find adequate solutions that would protect local populations and public infrastructures aside from taking precautionary measures and initiating pre-emptive evacuation of families living in areas forecasted to be on the storm path to safer ground (NDRRMC, 2014). There is also evidence of communication deficiency around Typhoon Haiyan, where routine transmission of information about the ongoing typhoon may not have been properly interpreted as an exceptional event (Wilson et al., 2015; Lejano et al., 2016). Hence, we can reasonably assume that once conditioned on their observable characteristics, cities and municipalities did not systematically differ in their response capacity to mitigate the devastating impact of the typhoon.

# 6 Results

## 6.1 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 report the results with the following dependent variables: general public services, education, health, labor, housing, social welfare, economic services, debt payments, and total expenditures. Each column includes all sets of baseline covariates described in the Methodology section.

In panel A, The DID estimates suggest that the typhoon had negative effects on all outcomes except health, labor and housing. However, the effect is quantitatively small and statistically insignificant except for debt payments, which include payments of loan principal and interest expenses.[18] A 1-percentage point increase in families displaced by the typhoon leads to a 0.22% lower debt payments. With an average share of displaced families of 31% by Typhoon Haiyan, this translates to a 7% reduction of debt payments. In the online appendix, Table A2 Panel A2 shows that our results are robust to using wind speed estimates as an alternative measure of the intensity of the typhoon: all results on expenditures remained qualitatively unchanged, while the magnitude of the reduction in debt is slightly lower but with similar statistical significance.

[18]The Philippine BLGF defines debt payments as "expenditures for payment of loan principal, interest and other service charges for debts of LGU". This information was accessed in March 2022 from https://blgf.gov.ph/wp-content/uploads/2016/08/Metadata.docx.

The results are consistent with those of the 2SLS estimation that are presented in Table 2. Panel B of Table 2 reports the IV estimates of the effect of Typhoon Haiyan on local government expenditure. Panel C presents the first stage of the corresponding 2SLS regression, and suggests that the instrument is a strong predictor for typhoon exposure (share of family displaced). 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 identifies the first-stage equation. This finding is robust to the valid critical values calculated by Lee et al. (2022). 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.

In Panel B the IV estimates reveal a higher magnitude of the effect than the OLS estimates. After correcting for the potential endogeneity, the point estimate increases in absolute terms from 0.22% to 0.54%. A 1-percentage point increase in families displaced by the typhoon now results in 0.54% lower debt payments, which translates to a 17% reduction in debt payments.

Finally, the typhoon had a quantitatively small but significant positive effect on labor and employment. A 1-percentage point increase in the proportion of families displaced by the typhoon results in 0.02% higher labor and employment expenditures. With the 2SLS estimation, the coefficient estimate on labor and employment is similar but the effect loses statistical significance.

Another way to assess our results is to compare our estimates to prior studies. Noy, Okubo, et al. (2021) show that natural disasters in Japan tend to increase total expenditures through higher disaster relief while all other spending categories remained unchanged. In a related study on the effect of hurricane shocks on local public finances, Jerch et al. (2023) find that public expenditures decrease mostly through public works (water, sewer, trash and public transit), which are encompassed in our definition of general public services (Table A1 in the online Appendix). These findings, although from higher economies than the Philippines, tend to corroborate our results. The notable exception is the significant reduction in debt payments that followed Typhoon Haiyan. Whereas Jerch et al. (2023) find that local US government's debt tends to increase in the decade following a strong storm (from 19% to 26%), our results suggest that debt payments by affected LGUs decreased in the short and medium-run (from 7% to 17%). We discuss this result in Section 7 and the role played by the national government in the aftermath of the typhoon.

## 6.2 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 IV estimates are nearly the same as the DID estimates, but none have remained statistically significant.[19]

Furthermore, the estimated coefficient on inter-local transfers is statistically insignificant, which presents suggestive evidence that there might be limited concerns about fiscal spillover to municipalities belonging to the control group: funds transferred from unaffected municipalities to the affected ones do not systematically differ from local funds transferred to non-affected municipalities. Once again, the results are robust to using wind speed estimates as an alternative measure, although the coefficients on business tax, business income and inter-local transfers have a reduced magnitude, as compared to the DID coefficients with the share of family affected. As expected, in each case, the direction of the change is towards the IV estimates, which confirms that the latter measure might be less prone to endogeneity.

[19] The results with other taxes are inconsistent. The coefficient on other taxes is positive and statistically significant in the 2SLS estimation, but this coefficient is not statistically significant in the DID estimation.

Interestingly, our results corroborate those of Jerch et al. (2023) where US local government income is also found to be unaffected by hurricanes in the short-run, but in the medium-run (after 6 years), local tax revenues decrease. Since our study sample spans a 12-year horizon (2007-2018) with only 5 years after Typhoon Haiyan, we cannot explore the effects on a similar medium-run period. However, the dynamic effects presented below tend to indicate that the medium-run effect on local government income (and local tax revenue) might have remained unchanged.

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

## 6.3 Dynamic effects and internal validity

So far, we have documented the average effect of the typhoon over the sample period (2007 to 2018). However, the effects 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. Specifically, 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.

Figure 1 shows the dynamic effects of Typhoon Haiyan on local expenditures, and Figures 2 and 3 present the dynamic effects on local income. The graphs plot the coefficient estimates of interaction terms between *Family* and year dummies, including the baseline set of controls as in equation 2, and with corresponding 95% confidence intervals in dashed lines.[20]

While we find that most of the coefficient estimates are statistically insignificant before Typhoon Haiyan, some trends in pre-typhoon periods might affect the outcome in post-typhoon periods, such as general and total expenditures, business income and total income. To accommodate for such potential pre-trends and account for the dynamic effects post-Haiyan, we implement the procedure developed by Freyaldenhoven et al. (2021) and where we estimate a linear pre-trend from exploiting possibly unaffected covariates that relate to confounding factors and identify the Typhoon effect from the counterfactual pre-trend.[21] Figures A5, A6 and A7 in the Online Appendix provide evidence that our baseline estimates are not driven by confounding time trends.

In addition, our measure of typhoon exposure using the share of families displaced implies a heterogenous treatment, which could lead to negative weights in a standard two-way fixed effect model. We first use the diagnostic approach proposed by De Chaisemartin and d'Haultfoeuille (2020) that estimates the weights and the number of group-time Aver-

[20]We also checked that our baseline covariates are not overfitting the model; once excluded, all graphs show significant pre-trends, confirming that we are controlling for municipality characteristics that could systematically differ between control and treated municipalities. Figures without controlling for our baseline covariates are available upon request.

[21]Our assumption imposes that every municipality's confounding factors follow a linear trend, which might be plausible given the short period before the Typhoon.

age Treatment effect on the Treated (ATT) that receive negative weights. The diagnostic test on Debt, one of the outcomes with a significant effect, the estimated weights attached to $\hat{\delta}$ lead to 755 positive and 75 negative weights, with the negative weights summing to only -.00523 (vs. 1.005 for the positive weights). This result suggests that the issue related to the negative weights introduced by the heterogenous treatment with our conventional TWFE approach may be limited. Still, in order to allow for treatment effect heterogeneity across unit, we implement the estimator robust to treatment effect heterogeneity proposed by De Chaisemartin and d'Haultfoeuille (2020). Figures A8, A9, and A10 in the Online Appendix present the event study graphs generated by the new estimator, and establish robustness of our baseline results.

Likewise, Tables 4 and 5 provide further evidence to support the validity of our strategy: using a dynamic analogue of equation (4) estimated on yearly data for each outcome, the Tables show the IV estimates for the expenditure and income outcomes respectively. Both general and total expenditures on one side, and business income and total income on the other side, exhibit no trend prior to the 2013 Typhoon. In Figures A11, A12, and A12 we further show that changing the reference year from 2013 to 2012 does not invalidate the validity of our strategy, as all results remain qualitatively unchanged: during the pre-typhoon period, the point estimates are close to zero and statistically insignificant.

Overall, we document a strong decline in debt payments for the first three years after the Typhoon, from 2014 to 2016. Adjusting for the potential endogeneity of the number of displaced families, the IV estimations (Table 4) show that the decline in debt further increased towards the end of the sample period. This result suggests that the effect on debt payments was immediate and relatively persistent.

In the first two years following the typhoon, the effect on user charges, business income, and business tax become statistically significant and negative, although only the user charges result is robust to the IV estimation.In any case, this temporary effect fades away after the second year of the typhoon. As expected, the typhoon was followed by a massive surge in extraordinary receipts (which include foreign aid and other typhoon-relief assistance) for the first two years. However, the high variability of the point estimates might indicate that aid was concentrated on a specific set of affected cities/municipalities, especially in the years following the first year after the Typhoon. Overall, the different estimations and robustness checks 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.

# 7 Robustness

In this section, we report a series of additional robustness checks. We first explore how our results change as we broaden our definition of control cities/municipalities. We then consider the effects of the typhoon on the outcomes of interest when the latter are taken as a share in total expenditures.

## 7.1 Extended sample

We extend our data sample to all cities/municipalities that belong to a region (instead of a province) that was affected by the typhoon. This new definition almost double the sample size (606 cities/municipalities over the sample period compared to 352) but also increases heterogeneity. Tables A3 and A4 in the Online Appendix replicate our baseline results on the effects of the typhoon on local public fiscal responses with the extended sample. The results are similar to those presented in Tables 2 and 3.

## 7.2 Relative importance

In the Online Appendix, we study the relative importance of our outcome variables in the total local expenditures and total local income net of PIRA in Tables A5 and A6. Our previous results reveal a negative and significant effect of the typhoon on debt payment. The results remain the same. We study whether this effect persists when debt payment is considered as a share in total expenditures. Figure A14 in the Online Appendix presents the average debt share between the treatment and control groups. Since the definition of total expenditures changed after 2008, we restrict the sample period to 2009-2018.[22] Figure A15 in the Online Appendix illustrates the dynamics effect of Typhoon Haiyan on debt share in total expenditures. The first figure indicates a downward trend in the average debt payment in the share of total expenditures for both affected and unaffected cities/municipalities. However, Figure A15 in the Online Appendix provides visual evi-

[22]This information was accessed from https://blgf.gov.ph/lgu-fiscal-data on 7 July 2022.

dence that cities/municipalities ravaged by the typhoon experienced a stronger reduction of debt both in level and in share of total expenditures after the occurrence of the typhoon. One possible explanation for this result is that while all cities/municipalities were generally attempting to reduce their level of debt payment, ravaged cities/municipalities with contractual loan obligations may have been more financially constrained and thereby less able to prioritise their fiscal resources to other items such as health or education relative to unaffected cities/municipalities. Another explanation is that affected cities/municipalities, which borrow money mostly from nationally owned institutions and banks in the Philippines, may have benefited from short-term lending arrangements in debt payment set by the national government in the aftermath of the typhoon, such as an extension of period to pay loans by LGUs to the lending institutions. Indeed, the rules governing the loan application process and debt service ceiling were eased for Haiyan-affected cities/municipalities by the Department of Finance (DOF), although it did not entail a reduction in debt payment (Alvina, 2019). In any case, our results demonstrate that debt reduction does not correlate with any increase in public expenditures. Instead of reallocating resources elsewhere, the reduction in debt payments might have primarily been caused by debt relief policies that allowed for restructuring financial debts on a staggered basis.

Transaction-based incomes, such as regulatory fees and user charges, become statistically significant and positive, highlighting their relative importance in the share of total expenditures. One possible explanation is that this category of expenditures is more flexible for short-term readjustments: the main income sources – property-based, business income - have reduced in a mechanical sense due to the devastating effects of the typhoon, increasing thereby the share of transaction-based income.

# 8 Heterogeneous effects

We attempt in this section to understand the potential mechanisms through which Typhoon Haiyan may have affected local public fiscal response. In particular, a shift in local public finances could be due to either a surge in external or foreign aid, or an increase in displaced populations. We further present a heterogeneity effect analysis, where we study whether the distribution of city/municipality income differently affects local public finances.

We establish causality by instrumenting $H_{ip}$ and $Family_{ip} \times H_{ip}$ with the triple interaction $Distance_{ip} \times Haiyan_t \times H_{ip}$, our baseline instrument $Distance_{ip} \times Haiyan_t$ and $Haiyan_t \times H_{ip}$.

## 8.1 Aid

The typhoon sparked an important mobilisation of resources, both nationally and internationally. According to data collected from the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) Financial Tracking Service, in total, an estimated US$865 million was spent by the international community on food security and agriculture, emergency shelter, and early recovery and livelihoods.[23] How did national and foreign aid affect local fiscal response? As discussed in Section 3, external aid can incentivise local authorities to mobilise more local resources and trigger an increase in local expenditures for the rehabilitation of damaged public infrastructures, and relief operations. On the other hand, local governments may overly depend on external assistance and be discouraged from collecting local taxes or generating their own revenues. To examine these mechanisms, we first allow the effect of the typhoon to differ across cities/municipalities according to the received aid support. $Aid_{ipt}$ is extraordinary receipts, including national and foreign aid, grants, and donations that transit through the central government budget, and which can subsequently be requested by local government, in city or municipality $i$ in province $p$ at time $t$.[24]

With the triple interaction term, we effectively compare cities or municipalities affected by the typhoon in the post-2013 period with those that were also affected but received aid, grants, and donations.[25] The IV estimates of the triple interaction terms are reported in Tables 6 and 7. As discussed above, aid may be associated with changes in local 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

[23]Total emergency funding for the 2013 Typhoon Haiyan was accessed from the OCHA Financial Tracking System at `https://fts.unocha.org/appeals/441/summary`.

[24]As mentioned in Section 3, we only have data on aid that transit to the government's budget; yet, this should be of limited concern since off-budget aid has little effect on local fiscal's response (Van de Sijpe, 2013).

[25]Importantly, displaced families cannot be confounded by the level of aid since aid came as a response to the damages left by the Typhoon.

resulting in diminished efforts to collect local taxes. The results support the former view. Aid led to higher local expenditures, including general public services, education, social, economic services, and debt payments. Debt payments are higher by 0.09% per family affected, or 2.79% on average when we consider the average number of families affected, which is 31%. Social and economic services are higher by 0.07% per family affected, or 2.17% on average. There is a 0.06% change in expenditure related to education, culture and sports, which 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.

Aid did not lead to lower tax collection efforts, and hence a moral hazard story is less likely. If anything, external resources led to higher income from local sources, particularly non-tax revenues and other general income.

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 is 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 program, topped up with additional cash from international agencies.[26] 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,[27] economic services and debt payments.

However, some endogeneity concerns about aid remain. First we assess the concern on the income side. What is the direction of the bias? The effort to collect taxes and other sources of income is unobservable, but we can further discuss the direction of the bias. If the moral hazard story is true then, the bias is more likely to be in the negative direction: the lower the effort to collect taxes, the lower the income, but the higher the aid. However, this story is less likely since the estimated coefficients in Table 7 are all in the positive direction (except user charges), albeit statistically insignificant. If there is a negative bias, then the coefficients are underestimated, and could have been greater in magnitudes, moving farther away from the moral hazard story.

We further explore the possibility of a selection bias on the expenditure side. Although our instrument should provide causal estimates, there might remain some endogeneity concerns regarding the use of aid. In particular, since the aid allocation starts with a request by local authorities to the central government, the process might create a self-selection bias: requests for external resources could be endogenous to the local resources of local governments.

[26] 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.

[27] 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 BLGF Glossary of Terms, which was accessed on 18 March 2022 from https://blgf.gov.ph/wp-content/uploads/2016/08/Metadata.docx.

Notice first that all coefficients on the triple interaction term with *Aid* are positive: if the coefficients are downward biased, the results would provide some lower bound estimates and the bias would then qualitatively affect our findings. Hence, the endogeneity concern is more problematic in cases of upward bias. The coefficients would be overestimated if municipalities with higher financial capacity would systematically request (and receive) external aid: affected cities or municipalities with lower capacity could be comparatively less able to establish a budget plan and detail how additional resources would be used for public purposes, as required by the central government. We find suggestive evidence for this channel: Table A7 in the Online Appendix shows that cities or municipalities with lower resources (i.e. below-median incomes) are less likely to receive aid. Then in Table A8 in the Online Appendix further explores the possibility that municipalities that receive aid but with lower local resources reduce public spending, by interacting the triple interaction $family_{ip} \times Haiyan_t \times Aid_{ip}$ with an indicator variable that equals to one if the total income of municipality $i$ in province $p$ is below the sample median. The results confirm our expectations: accounting for the limited income of the poorest municipalities reduces all (joint) coefficient estimates. Hence, the findings suggest that the effect of aid on local public spending is higher only for affected municipalities with relatively higher fiscal constraint. For the other municipalities, aid did not trigger any statistically significant response on public expenditures.

Overall, our analysis of the local income and expenditures show strong evidence that the moral hazard story is less likely in our case, since local governments who received aid tend to have higher income and at the same time spend more with aid, particularly those who have higher local resources, as shown by Table A8. Our estimates of the effect of Typhoon Haiyan on local income and expenditures are inconsistent with moral hazard discussed above.

## 8.2 Displaced populations and evacuation centers

Likewise, the effect of evacuation centers on local resources is also unclear, at least theoretically. A permanent or long-run 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 centers, 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 centers may have inadvertently attracted or willingly accommodated displaced populations from other areas. Are local finances higher or lower in local areas with more evacuation centers? 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 evacuation centers, and conducting drills to better prepare for natural disasters. However, the presence of evacuation centers can also be a symptom of being in a natural-prone area.[28] This case may lower some local sources, such as tax on business, as a natural disaster like Typhoon Haiyan may disrupt local businesses. This case is consistent with national government reports stating, for example, that "90 percent of total damage and loss from Typhoon Haiyan were private assets and income, mostly from businesses" (NDRRMC, 2014, p. 87). Thousands of small and medium enterprises in Eastern Visayas were totally damaged by the Typhoon.[29] We examine whether the effects are differently adverse in cities or municipalities that hosted evacuation centers, $Evacuation_{ipt}$. In total, an estimated 161,973 families were pre-emptively relocated to 812 evacuation centers (NDRRMC, 2013, p. 3), which included public hospitals, schools, gymnasiums (NDRRMC, 2014). The regression model that we run is as follows:

$$y_{ipt} = \delta_3(\hat{Family}_{ip} \times Haiyan_t \times Evacuation_{ip}) + X'_{ipt}\Gamma + \mu_{ip} + \lambda_t + \iota_{ipt} \tag{5}$$

Tables 6 and 7 present the coefficient estimates on the triple interaction with *Evacuation* from equation 5. The results show that evacuation centers are not a symptom of higher population and higher local expenditure. The triple interaction with evacuation centers has no effect on local expenditures. Evacuation centers do not affect local income either, except for business tax. Overall, the results suggest that evacuation centers and the pop-

[28]Note that these are different from the transitory emergency shelters that were installed in most affected municipalities.

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

ulation who temporarily use them have no significant short-run effects on local public finance.

### 8.3 City or municipality income-class distribution

Finally, we explore the possibility that local finances are collected and allocated differently in cities/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 if they have higher access to local resources such as savings. For example, richer cities/municipalities may be able to borrow more easily from banks than poorer cities/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.[30] The equation is presented by:

[30] 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. This information was accessed from https://psa.gov.ph/classification/psgc on 29 March 2022.

$$y_{ipt} = \delta_4(\hat{Family}_{ip} \times Haiyan_t \times IncomeClass_{ip}) + X'_{ipt}\Gamma + \mu_i + \lambda_{pt} + \kappa_{ipt} \tag{6}$$

Figures 4 and 5 present the coefficient estimates of the triple interaction at each quantile of the income distribution along with the associated 95% confidence intervals. These figures show that on average local public finances are not consistently more (or less) affected by the typhoon in comparatively poorer cities/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 6. 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% on average).

Local governments may be unable to generate as many local revenues as before Typhoon Haiyan due to the resulting losses to local businesses and reductions in local market activities on which business and real property taxes are imposed.[31] For humanitarian and political considerations, the local governments in the affected areas also may have levied lower taxes on their constituents. For instance, the city government of Bogo in the province of Cebu imposed reduced taxes on local real property owners in March 2014 following Typhoon Haiyan.[32]

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. In normal times, local government spending tends to increase higher with local tax revenue collection than with intergovernmental transfers (Gadenne, 2017). However, in difficult times such as the aftermath of a natural disaster, the loss in local revenues, particularly income from businesses and

[31]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 central fiscal transfers (Manasan et al., 2005; Llanto, 2012).

[32]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.

economic enterprises, suggests that increasing transfer revenues to local governments may have a higher direct effect on public good provision than technical support for local tax capacity building. When a typhoon as powerful as Haiyan affects the generating revenue capacity of local governments, central government transfers and foreign aid are crucial to maintaining public expenditures that benefit citizens.

# 9 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 have compiled city and municipal-level data for the Philippines, covering the periods before and after Typhoon Haiyan devastated the central part of the country in November 2013, to investigate how natural disasters affect local public finances. We have found no evidence that local public income or expenditures have changed in the immediate aftermath of Typhoon Haiyan, except for debt payments which significantly decreased. Although our data does not allow to further explore its source of variations, the observed effect on debt may have been caused by short-term lending arrangements in debt payment set by the national government for the affected cities and municipalities. Our results suggest that local governments may not have been able to fully use their taxing powers (such as fees, charges, and real estate property taxes) to mitigate the adverse effects of the external shock on local infrastructures and the provision of public services, and address its fiscal imbalances. Our evidence further suggests that affected local authorities that were comparatively more financially constrained had lower access to external resources such as aid.

Beyond the absence of local government fiscal response, this paper demonstrates the importance of accounting for local external funding and regional heterogeneity in predicting local fiscal response. First, we have documented that aid results in higher local expenditures, particularly general public services, education, social services and welfare, economic services, and debt payments. These results provide no support for moral hazard behaviour whereby foreign aid would crowd out local public financing. One possible explanation is that the marginal benefit of spending on items targeted or partially supported by donors might be comparatively higher. Alternatively, aligning with the international community might be more rewarding for local decision-makers (Inman, 2008). Second, evacuation centers which we use as a 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 the host local governments, and diminished in turn their capacity to further support the displaced families. The displaced families in the evacuation centers may instead have been directly supported by NGOs, private donors, or international organizations through in-kind transfer programs. Third, we have found that affected lower-income class cities or municipalities have lower local income from tax and non-tax revenues in the aftermath of the typhoon. This last result highlights the heterogeneity in the response of local fiscal finances in the aftermath of exogenous shocks and the importance of the initial conditions of local public finances to cope with the revenue loss. Although decentralisation may bring more accountability and efficient public spending, our findings underline the role of the central government financing's support in addressing those local inequalities and mitigating the adverse effects of exogenous shocks on the provision of local public services, particularly among the poorest cities/municipalities (Capuno, 2001; Troland, 2016).

Altogether, our findings suggest that local governments exposed to common nationwide shocks might have limited capacity to reallocate or mobilise additional resources that would address the increased demand for local public spending. 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. 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 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 (off-budget) foreign aid and whether these overall funds are effectively targeting the most vulnerable communities.

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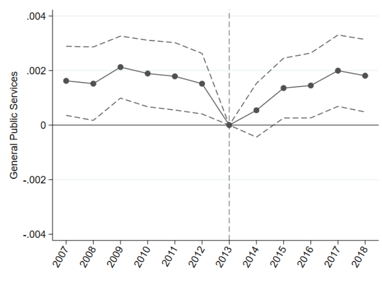
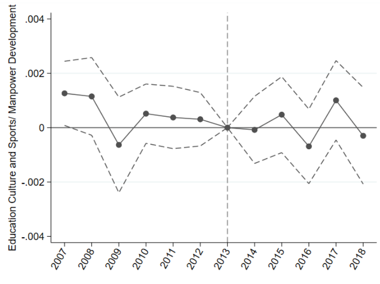
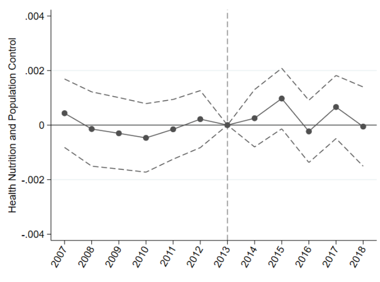
Figure 1: Dynamic effects of the typhoon on local expenditures



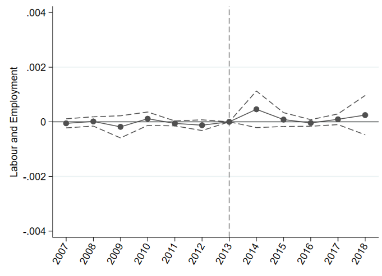

(a) General



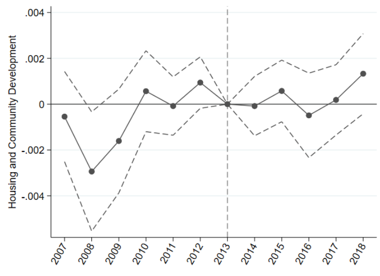

(b) Education



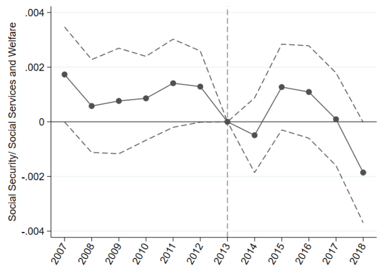

(c) Health



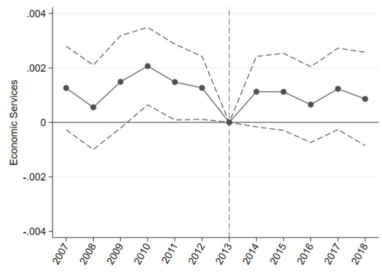

(d) Labor



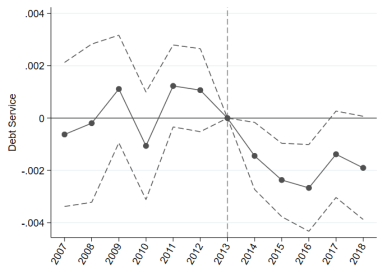

(e) Housing



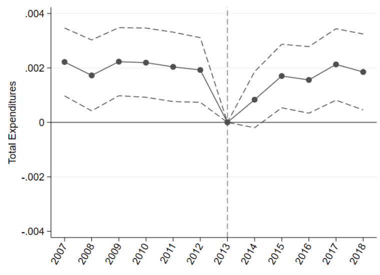

(f) Social services




(g) Economic services



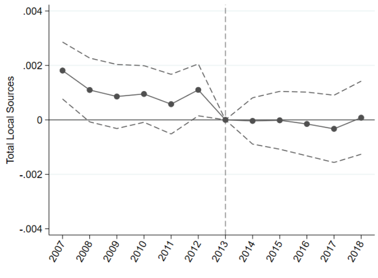

(h) Debt



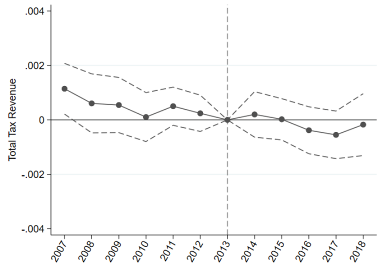

(i) Total

**Notes:** Each graph plots the coefficient estimates of equation (2) along with their 95% confidence intervals, with 2013 as the reference year. Each graph presents the $\delta_t$ coefficients on the interaction of a yearly indicator and the variable $Family$. Robust standard errors are adjusted for clustering at the city/municipality level.

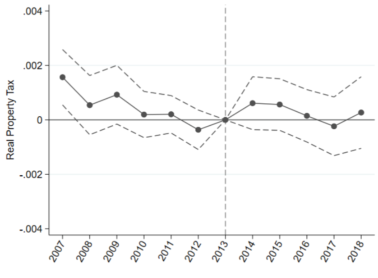
FIGURE 2: DYNAMIC EFFECTS OF HAIYAN ON LOCAL INCOME (I)



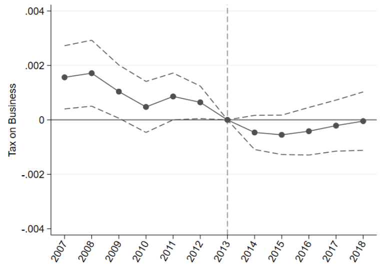

(A) Local sources



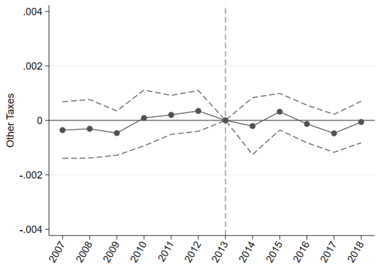

(B) Tax revenue



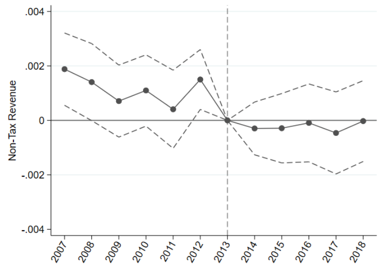

(C) Real-property tax



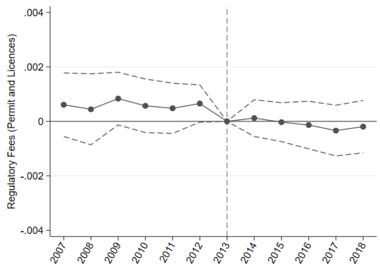

(D) Business tax



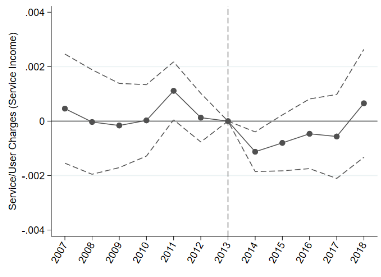

(E) Other taxes




(F) Non-tax revenue




(G) Regulatory fees

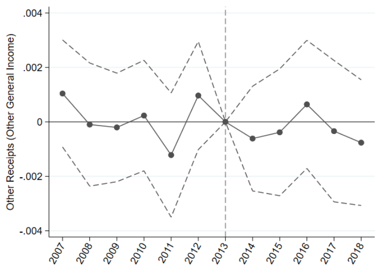



(H) User charges

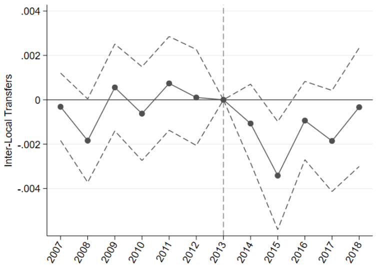
**Notes:** Each graph plots the coefficient estimates of equation (2) along with their 95% confidence intervals, with 2013 as the reference year. Each graph presents the $\delta_t$ coefficients on the interaction of a yearly indicator and the variable *Family*. Robust standard errors are adjusted for clustering at the city/municipality level.

Figure 3: Dynamic effects of Haiyan on local income (II)

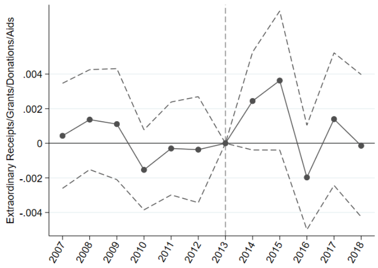

(A) Business income



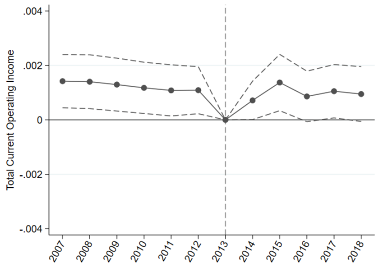

(B) Other general income




(C) Inter-local transfers



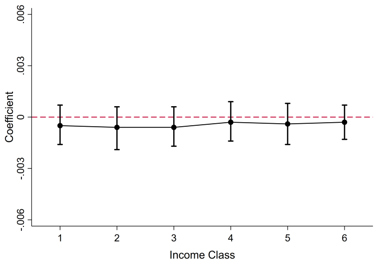

(D) Extraordinary receipts



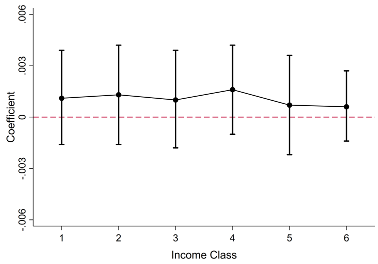

(E) Total

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

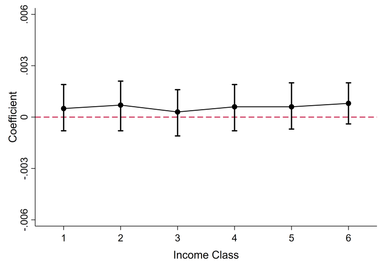
Figure 4: Effects of the typhoon on local expenditures by City or Municipality income quantiles



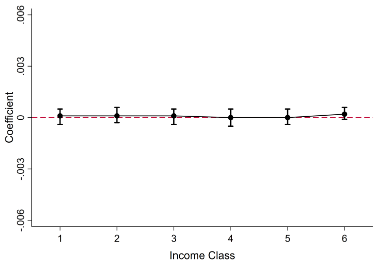

(a) General



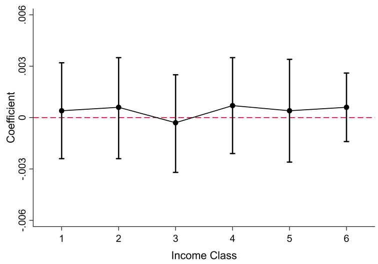

(b) Education



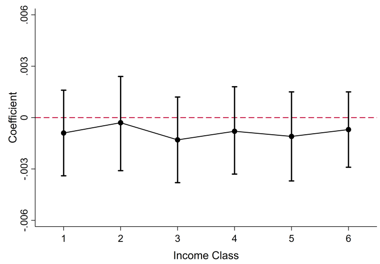

(c) Health



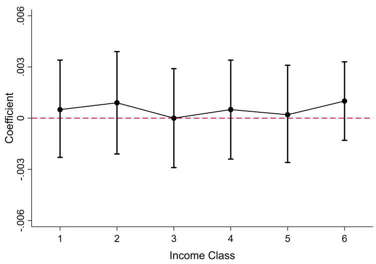

(d) Labor



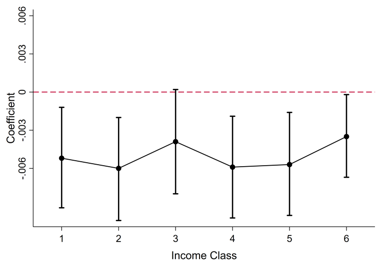

(e) Housing



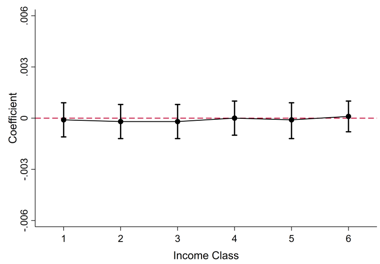

(f) Social services




(g) Economic services



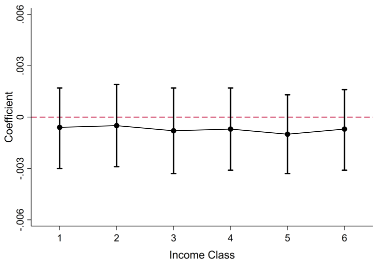

(h) Debt



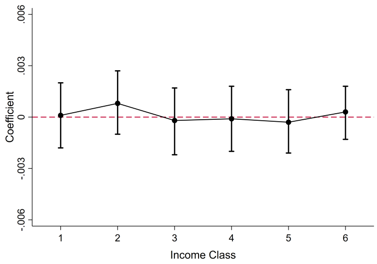

(i) Total

**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 city/municipality income distribution. All regressions include all baseline controls and standard errors are adjusted for clustering at the city/municipality level.

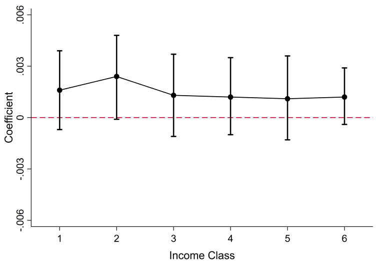
Figure 5: Effects of the typhoon on local income by City or Municipality income quantiles



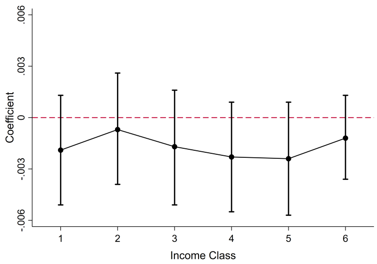

(a) Local sources



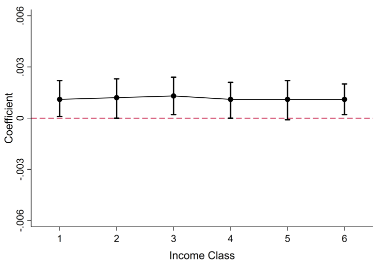

(b) Tax revenue



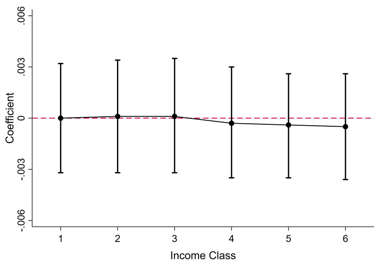

(c) Real-property tax



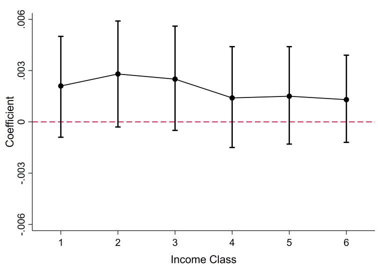

(d) Business tax



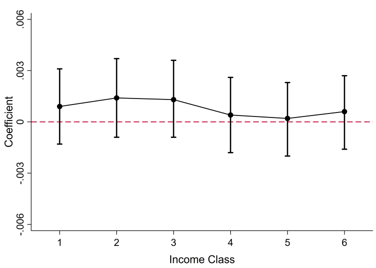

(e) Other taxes




(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 city/municipality income distribution. All regressions include all baseline controls and standard errors are adjusted for clustering at the city/municipality level.

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

| | Outside Haiyan path | | | Inside Haiyan path | | | Inside-Outside 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 | 53.59 | 224.63 | 993 | 18.48 | 52.83 | -35.11 | 7.02 | 0.00 |
| Total tax revenue | 1,086 | 35.61 | 157.68 | 993 | 10.27 | 36.53 | -25.33 | 4.92 | 0.00 |
| Real property tax | 1,086 | 16.68 | 68.21 | 993 | 6.09 | 27.19 | -10.58 | 2.24 | 0.00 |
| Tax on business | 1,086 | 16.58 | 82.84 | 993 | 3.54 | 12.34 | -13.04 | 2.54 | 0.00 |
| Other taxes | 1,086 | 2.35 | 11.10 | 993 | 0.64 | 1.40 | -1.71 | 0.34 | 0.00 |
| Total non-tax revenue | 1,086 | 17.98 | 72.37 | 993 | 8.21 | 20.39 | -9.78 | 2.29 | 0.00 |
| Regulatory fees | 1,086 | 3.36 | 11.95 | 993 | 1.59 | 4.15 | -1.77 | 0.39 | 0.00 |
| User charges | 1,086 | 3.65 | 21.12 | 993 | 1.39 | 6.35 | -2.26 | 0.67 | 0.00 |
| Income from business | 1,086 | 6.28 | 14.61 | 993 | 3.96 | 9.52 | -2.32 | 0.54 | 0.00 |
| Other general income | 1,086 | 4.67 | 36.36 | 993 | 1.24 | 5.88 | -3.43 | 1.12 | 0.00 |
| Inter-Local transfers | 1,086 | 0.50 | 4.78 | 993 | 0.40 | 2.58 | -0.10 | 0.17 | 0.54 |
| Extraordinary receipts | 1,086 | 1.25 | 5.33 | 993 | 0.91 | 4.10 | -0.34 | 0.21 | 0.10 |
| Total current operating income | 1,086 | 183.72 | 410.15 | 993 | 104.06 | 143.93 | -79.66 | 13.26 | 0.00 |
| **Expenditures** | | | | | | | | | |
| Total local expenditure | 1,086 | 143.53 | 323.94 | 993 | 84.75 | 104.93 | -58.78 | 10.38 | 0.00 |
| General public services | 1,086 | 80.63 | 171.86 | 993 | 52.42 | 62.28 | -28.20 | 5.58 | 0.00 |
| Education | 1,086 | 5.95 | 21.66 | 993 | 2.20 | 5.49 | -3.75 | 0.68 | 0.00 |
| Health | 1,086 | 12.54 | 31.71 | 993 | 7.27 | 9.10 | -5.28 | 1.01 | 0.00 |
| Labour | 1,086 | 0.03 | 0.40 | 993 | 0.02 | 0.26 | -0.01 | 0.01 | 0.35 |
| Housing | 1,086 | 3.36 | 17.76 | 993 | 0.76 | 2.83 | -2.60 | 0.55 | 0.00 |
| Social services | 1,086 | 6.19 | 15.79 | 993 | 3.66 | 4.54 | -2.53 | 0.50 | 0.00 |
| Economic services | 1,086 | 21.03 | 46.93 | 993 | 12.36 | 20.66 | -8.67 | 1.57 | 0.00 |
| Debt | 1,086 | 13.80 | 66.06 | 993 | 6.07 | 22.02 | -7.73 | 2.12 | 0.00 |
| **Municipality characteristics** | | | | | | | | | |
| PIRA | 1,086 | 126.44 | 225.09 | 993 | 82.26 | 94.92 | -44.18 | 7.46 | 0.00 |
| No. Evacuation centres | 1,086 | 0.67 | 5.25 | 993 | 0.59 | 2.21 | -0.07 | 0.17 | 0.67 |
| Income Class | 1,086 | 3.22 | 1.49 | 993 | 3.45 | 1.29 | 0.24 | 0.06 | 0.00 |
| Poverty | 1,086 | 31.89 | 13.47 | 993 | 30.78 | 10.23 | -1.11 | 0.52 | 0.03 |
| Population | 1,086 | 55.21 | 88.89 | 993 | 41.42 | 48.99 | -13.79 | 3.11 | 0.00 |
| **Instrument** | | | | | | | | | |
| Distance to Yolanda path (in km) | 1,086 | 1.07 | 0.62 | 993 | 0.26 | 0.18 | -0.81 | 0.02 | 0.00 |

**Source:** Philippine Bureau of Local Government Finance. **Notes:** Population is expressed in thousands of inhabitants from the 2010 Population Census. All income, expenditures and central government transfers (PIRA) are expressed in millions of 2018 PhP.

Table 2: Effect of the typhoon on local government expenditures

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | General | Education | Health | Labor | Housing | Social | Economic | Debt | Total |
| Panel A: Difference-In-Difference | | | | | | | | | |
| Share family affected × Post2013 | -0.0001 | -0.0002 | 0.0004 | 0.0002* | 0.0008 | -0.0008 | -0.0001 | -0.0022** | -0.0001 |
| | (0.0003) | (0.0006) | (0.0004) | (0.0001) | (0.0009) | (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 |
| Mean Dep. (pre-2013) | 4.46 | .989 | 2.49 | .0127 | .376 | 1.76 | 2.76 | 1.26 | 4.94 |
| Panel B: 2SLS Estimates | | | | | | | | | |
| Share family affected × Post2013 | -0.0005 | 0.0012 | 0.0006 | 0.0001 | 0.0005 | -0.0009 | 0.0005 | -0.0054** | -0.0001 |
| | (0.0006) | (0.0015) | (0.0007) | (0.0002) | (0.0014) | (0.0014) | (0.0014) | (0.0022) | (0.0005) |
| Observations | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 |
| Municipalities | 351 | 351 | 351 | 351 | 351 | 351 | 351 | 351 | 351 |
| Panel C: First-stage of the corresponding 2SLS panel regressions | | | | | | | | | |
| Dependent variable: | | | | | Share family affected | | | | |
| Distance to storm path × Post2013 | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** |
| | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) |
| Kleibergen-Paap $F$-statistic | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 |
| Controls as in panel A | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** All results are obtained from OLS with fixed effect estimations in panel A, 2SLS estimations in panel B and first-stage estimates in panel C. 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 and province-year levels. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

## Table 3: Effect of the typhoon on local government income

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 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 |
| Panel A: Difference-In-Difference | | | | | | | | | | | | | |
| Share family affected × Post2013 | -0.0010* | -0.0006 | -0.0001 | -0.0012** | 0.0000 | -0.0012* | -0.0006 | -0.0006 | -0.0022** | -0.0003 | -0.0014* | 0.0009 | -0.0001 |
| | (0.0005) | (0.0004) | (0.0004) | (0.0006) | (0.0003) | (0.0007) | (0.0005) | (0.0007) | (0.0009) | (0.0009) | (0.0008) | (0.0013) | (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 |
| Mean Dep. (pre-2013) | 2.77 | 2.01 | 1.47 | 1.2 | .531 | 2.16 | .952 | .734 | 1.45 | .643 | .132 | .335 | 5.13 |
| Panel B: 2SLS Estimates | | | | | | | | | | | | | |
| Share family affected × Post2013 | -0.0007 | 0.0000 | 0.0016 | -0.0020 | 0.0012** | -0.0001 | 0.0019 | 0.0006 | -0.0023 | -0.0010 | -0.0023 | 0.0014 | -0.0004 |
| | (0.0012) | (0.0009) | (0.0012) | (0.0016) | (0.0005) | (0.0017) | (0.0016) | (0.0010) | (0.0021) | (0.0018) | (0.0016) | (0.0022) | (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 C: First-stage of the corresponding 2SLS panel regressions | | | | | | | | | | | | | |
| Dependent variable: | Share family affected | | | | | | | | | | | | |
| Distance to storm path × Post2013 | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** |
| | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) |
| Kleibergen-Paap $F$-statistic | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 |
| Controls as in panel A | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** All results are obtained from OLS with fixed effect estimations in panel A, IV estimations in panel B and first-stage estimates in panel C. The intensity of Typhoon Haiyan is proxied by the share of family affected in the total city/municipality population based on the 2010 Census. All dependent variables are transformed using the inverse hyperbolic sine function. Robust standard errors in parentheses are clustered at the city/municipality and province-year levels. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

## Table 4: Effects of Haiyan on local public expenditures (IV estimation)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | General | Education | Health | Labor | Housing | Social | Economic | Debt | Total |
| Panel A: Average effect | | | | | | | | | |
| Share family affected × Post2013 | -0.0005 | 0.0012 | 0.0006 | 0.0001 | 0.0005 | -0.0009 | 0.0005 | -0.0054** | -0.0001 |
| | (0.0006) | (0.0015) | (0.0007) | (0.0002) | (0.0014) | (0.0014) | (0.0014) | (0.0022) | (0.0005) |
| Observations | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 |
| Municipalities | 351 | 351 | 351 | 351 | 351 | 351 | 351 | 351 | 351 |
| Panel B: Yearly effect | | | | | | | | | |
| Haiyan × (year = 2007) | 0.0011 | 0.0013 | -0.0022 | -0.0000 | 0.0012 | 0.0034 | 0.0003 | -0.0037 | 0.0011 |
| | (0.0015) | (0.0023) | (0.0015) | (0.0004) | (0.0042) | (0.0024) | (0.0017) | (0.0040) | (0.0015) |
| Haiyan × (year = 2008) | 0.0008 | 0.0009 | -0.0022 | 0.0001 | 0.0005 | 0.0025 | -0.0003 | -0.0018 | 0.0010 |
| | (0.0015) | (0.0024) | (0.0014) | (0.0003) | (0.0042) | (0.0024) | (0.0020) | (0.0045) | (0.0015) |
| Haiyan × (year = 2009) | 0.0014 | -0.0027 | -0.0013 | 0.0004 | 0.0008 | 0.0032 | 0.0012 | 0.0017 | 0.0012 |
| | (0.0013) | (0.0020) | (0.0016) | (0.0006) | (0.0026) | (0.0029) | (0.0023) | (0.0018) | (0.0014) |
| Haiyan × (year = 2010) | 0.0010 | -0.0004 | -0.0022* | 0.0008 | 0.0032 | 0.0017 | 0.0003 | -0.0025 | 0.0009 |
| | (0.0014) | (0.0014) | (0.0013) | (0.0006) | (0.0021) | (0.0020) | (0.0022) | (0.0023) | (0.0014) |
| Haiyan × (year = 2011) | 0.0010 | 0.0003 | -0.0012 | 0.0001 | 0.0036* | 0.0011 | 0.0005 | 0.0013 | 0.0009 |
| | (0.0013) | (0.0014) | (0.0011) | (0.0003) | (0.0021) | (0.0018) | (0.0021) | (0.0015) | (0.0014) |
| Haiyan × (year = 2012) | -0.0002 | -0.0005 | -0.0006 | 0.0004 | 0.0027 | 0.0008 | 0.0013 | 0.0009 | 0.0003 |
| | (0.0013) | (0.0012) | (0.0009) | (0.0003) | (0.0021) | (0.0017) | (0.0014) | (0.0011) | (0.0013) |
| Haiyan × (year = 2014) | -0.0006 | 0.0008 | -0.0013 | 0.0009 | 0.0013 | -0.0014 | 0.0004 | -0.0035** | -0.0004 |
| | (0.0013) | (0.0019) | (0.0010) | (0.0005) | (0.0021) | (0.0021) | (0.0016) | (0.0017) | (0.0013) |
| Haiyan × (year = 2015) | 0.0004 | -0.0003 | 0.0002 | 0.0006 | 0.0023 | 0.0037* | 0.0001 | -0.0048** | 0.0009 |
| | (0.0012) | (0.0022) | (0.0012) | (0.0004) | (0.0021) | (0.0020) | (0.0019) | (0.0019) | (0.0013) |
| Haiyan × (year = 2016) | 0.0001 | 0.0009 | -0.0009 | -0.0001 | 0.0019 | 0.0023 | 0.0018 | -0.0057*** | 0.0008 |
| | (0.0013) | (0.0023) | (0.0012) | (0.0002) | (0.0023) | (0.0020) | (0.0017) | (0.0022) | (0.0014) |
| Haiyan × (year = 2017) | 0.0011 | 0.0023 | 0.0007 | -0.0000 | 0.0016 | 0.0025 | 0.0017 | -0.0059** | 0.0016 |
| | (0.0015) | (0.0021) | (0.0012) | (0.0002) | (0.0022) | (0.0021) | (0.0017) | (0.0025) | (0.0015) |
| Haiyan × (year = 2018) | 0.0003 | 0.0015 | -0.0025* | 0.0006 | 0.0038 | -0.0027 | 0.0012 | -0.0099*** | 0.0004 |
| | (0.0015) | (0.0023) | (0.0013) | (0.0006) | (0.0026) | (0.0020) | (0.0018) | (0.0035) | (0.0016) |
| Observations | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 |
| Municipalities | 351 | 351 | 351 | 351 | 351 | 351 | 351 | 351 | 351 |

**Notes:** Panel A reports the average effect of the IV estimates, and panel B reports the results using a dynamic analogue of equation (4) estimated on yearly data. Robust standard errors in parentheses are clustered at the city/municipality and province-year levels. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

# Table 5: Effects of Haiyan on local public income (IV estimations)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 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 |
| Panel A: Average effect | | | | | | | | | | | | | |
| Share family affected × Post2013 | -0.0007 | 0.0000 | 0.0016 | -0.0020 | 0.0012** | -0.0001 | 0.0019 | 0.0006 | -0.0023 | -0.0010 | -0.0023 | 0.0014 | -0.0004 |
| | (0.0012) | (0.0009) | (0.0012) | (0.0016) | (0.0005) | (0.0017) | (0.0016) | (0.0010) | (0.0021) | (0.0018) | (0.0016) | (0.0022) | (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: Yearly effect | | | | | | | | | | | | | |
| Haiyan × (year = 2007) | 0.0023 | 0.0022 | 0.0015 | 0.0049** | -0.0017* | 0.0016 | -0.0009 | 0.0003 | 0.0009 | 0.0040 | -0.0009 | 0.0030 | 0.0011 |
| | (0.0020) | (0.0021) | (0.0020) | (0.0024) | (0.0009) | (0.0022) | (0.0019) | (0.0019) | (0.0016) | (0.0033) | (0.0016) | (0.0025) | (0.0010) |
| Haiyan × (year = 2008) | 0.0005 | 0.0006 | -0.0005 | 0.0046** | -0.0023** | 0.0004 | -0.0019 | -0.0002 | 0.0000 | 0.0029 | -0.0019 | 0.0029 | 0.0014 |
| | (0.0020) | (0.0020) | (0.0021) | (0.0023) | (0.0010) | (0.0024) | (0.0022) | (0.0019) | (0.0018) | (0.0033) | (0.0015) | (0.0025) | (0.0011) |
| Haiyan × (year = 2009) | -0.0025 | -0.0021 | -0.0022 | 0.0027 | -0.0026*** | -0.0023 | 0.0006 | -0.0031* | -0.0002 | -0.0011 | 0.0017 | -0.0002 | -0.0003 |
| | (0.0024) | (0.0024) | (0.0025) | (0.0017) | (0.0009) | (0.0022) | (0.0015) | (0.0018) | (0.0017) | (0.0031) | (0.0019) | (0.0049) | (0.0014) |
| Haiyan × (year = 2010) | 0.0002 | 0.0002 | -0.0003 | 0.0030* | -0.0017** | -0.0011 | -0.0012 | -0.0006 | 0.0010 | -0.0015 | 0.0012 | -0.0014 | 0.0005 |
| | (0.0015) | (0.0014) | (0.0011) | (0.0018) | (0.0008) | (0.0020) | (0.0016) | (0.0013) | (0.0017) | (0.0022) | (0.0018) | (0.0023) | (0.0010) |
| Haiyan × (year = 2011) | -0.0011 | -0.0003 | -0.0008 | 0.0018 | -0.0010** | -0.0029 | -0.0001 | 0.0014 | -0.0009 | -0.0063* | 0.0029 | 0.0002 | 0.0002 |
| | (0.0016) | (0.0014) | (0.0011) | (0.0015) | (0.0005) | (0.0021) | (0.0014) | (0.0012) | (0.0013) | (0.0032) | (0.0026) | (0.0031) | (0.0010) |
| Haiyan × (year = 2012) | -0.0005 | -0.0001 | -0.0009 | 0.0017 | -0.0004 | -0.0006 | 0.0014 | -0.0000 | -0.0007 | -0.0009 | 0.0007 | 0.0003 | 0.0003 |
| | (0.0014) | (0.0014) | (0.0014) | (0.0011) | (0.0006) | (0.0014) | (0.0010) | (0.0008) | (0.0012) | (0.0024) | (0.0016) | (0.0025) | (0.0009) |
| Haiyan × (year = 2014) | 0.0004 | 0.0009 | 0.0011 | 0.0012 | -0.0002 | 0.0008 | 0.0019** | -0.0013* | -0.0002 | 0.0002 | -0.0002 | 0.0055** | 0.0002 |
| | (0.0015) | (0.0015) | (0.0019) | (0.0010) | (0.0006) | (0.0015) | (0.0009) | (0.0007) | (0.0014) | (0.0026) | (0.0015) | (0.0024) | (0.0009) |
| Haiyan × (year = 2015) | -0.0016 | 0.0001 | 0.0013 | 0.0000 | 0.0003 | -0.0024 | 0.0025** | 0.0003 | -0.0010 | -0.0039 | 0.0006 | 0.0055* | 0.0008 |
| | (0.0015) | (0.0013) | (0.0021) | (0.0011) | (0.0005) | (0.0020) | (0.0012) | (0.0011) | (0.0017) | (0.0033) | (0.0017) | (0.0032) | (0.0010) |
| Haiyan × (year = 2016) | -0.0011 | 0.0003 | 0.0020 | 0.0004 | 0.0000 | -0.0019 | 0.0013 | -0.0002 | -0.0008 | -0.0027 | -0.0029* | -0.0015 | 0.0001 |
| | (0.0016) | (0.0014) | (0.0020) | (0.0012) | (0.0005) | (0.0021) | (0.0013) | (0.0015) | (0.0020) | (0.0034) | (0.0017) | (0.0030) | (0.0010) |
| Haiyan × (year = 2017) | -0.0007 | 0.0001 | 0.0016 | 0.0006 | -0.0010* | -0.0002 | 0.0012 | 0.0003 | -0.0032 | 0.0009 | -0.0050** | 0.0009 | 0.0001 |
| | (0.0017) | (0.0014) | (0.0018) | (0.0012) | (0.0005) | (0.0019) | (0.0013) | (0.0017) | (0.0023) | (0.0030) | (0.0025) | (0.0035) | (0.0011) |
| Haiyan × (year = 2018) | -0.0015 | -0.0008 | -0.0003 | 0.0010 | -0.0002 | -0.0002 | 0.0012 | 0.0025 | -0.0060* | -0.0013 | -0.0017 | 0.0003 | -0.0008 |
| | (0.0016) | (0.0016) | (0.0018) | (0.0014) | (0.0006) | (0.0021) | (0.0013) | (0.0022) | (0.0033) | (0.0035) | (0.0028) | (0.0039) | (0.0012) |
| 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:** Panel A reports the average effect of the IV estimates, and panel B reports the results using a dynamic analogue of equation (4) estimated on yearly data. Robust standard errors in parentheses are clustered at the city/municipality and province-year levels. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

# Table 6: The heterogeneous effect of Haiyan on local public expenditures (IV estimation)

| | 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 | | | | | | | | | | | | |
| $\times Aid$ | | 0.0005*** | | | | 0.0006** | | | | 0.0001 | | |
| | | (0.0002) | | | | (0.0002) | | | | (0.0002) | | |
| $\times Evacuation$ | | | 0.0001 | | | | -0.0006 | | | | 0.0003 | |
| | | | (0.0006) | | | | (0.0013) | | | | (0.0010) | |
| $\times IncomeClass$ | | | | 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 |

| | Labor | | | | 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 | | | | | | | | | | | | |
| $\times Aid$ | | 0.0002 | | | | -0.0003 | | | | 0.0007* | | |
| | | (0.0001) | | | | (0.0002) | | | | (0.0004) | | |
| $\times Evacuation$ | | | 0.0001 | | | | -0.0004 | | | | 0.0015 | |
| | | | (0.0002) | | | | (0.0017) | | | | (0.0014) | |
| $\times IncomeClass$ | | | | 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 | | | | | | | | | | | | |
| $\times Aid$ | | 0.0007*** | | | | 0.0009** | | | | 0.0005*** | | |
| | | (0.0003) | | | | (0.0004) | | | | (0.0002) | | |
| $\times Evacuation$ | | | 0.0006 | | | | -0.0005 | | | | -0.0000 | |
| | | | (0.0014) | | | | (0.0017) | | | | (0.0006) | |
| $\times IncomeClass$ | | | | -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 obtained from 2SLS estimations. The instrument used is the interaction between distance to the 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 and province-year levels.
*** p<0.01, ** p<0.05, * p<0.1

# Table 7: The heretogenous effect of Haiyan on local public income (IV estimation)

| | 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 |

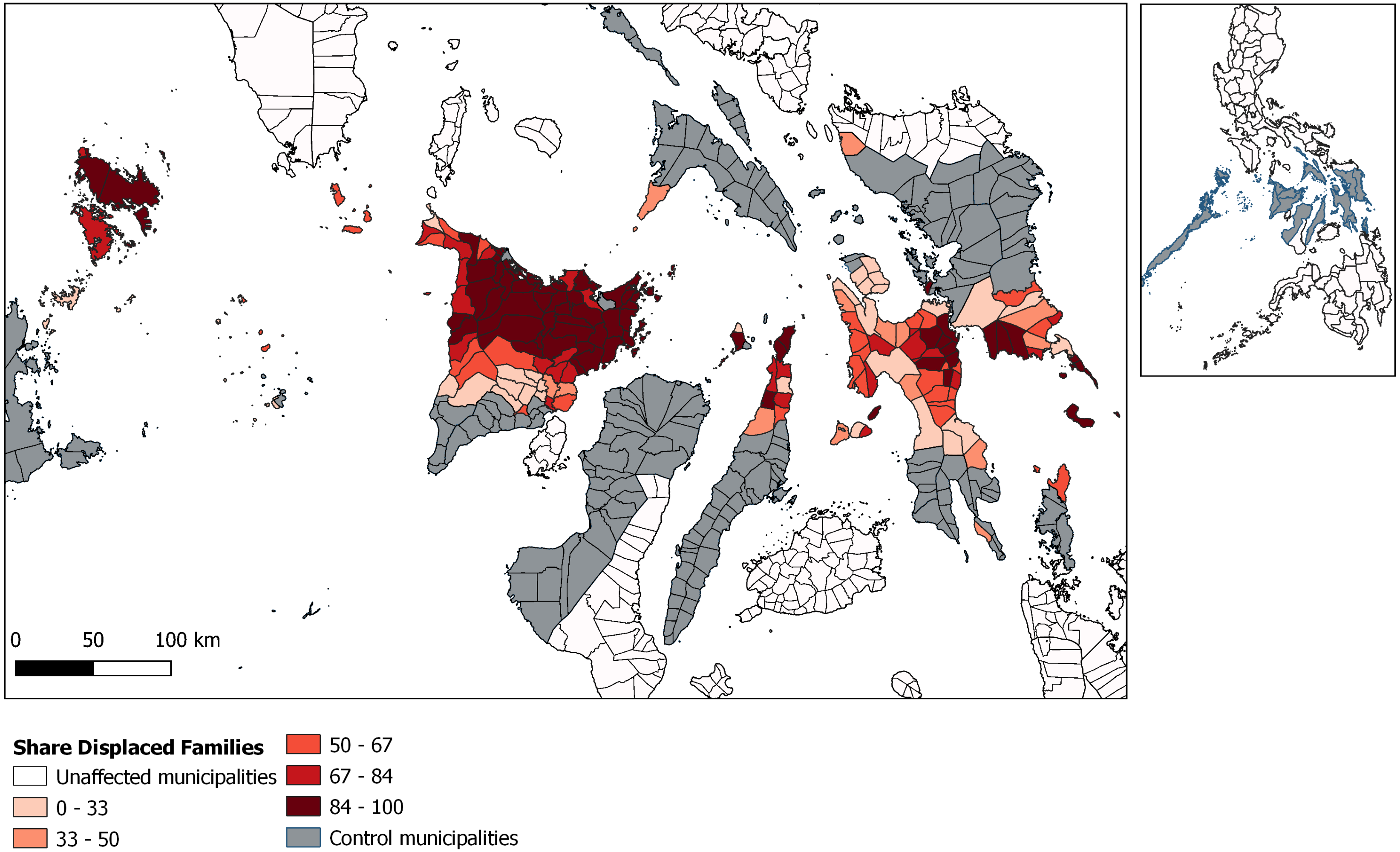
| | Other taxes | | | | Non-tax revenue | | | | Regulatory fees | | | | User charges | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (17) | (18) | (19) | (20) | (21) | (22) | (23) | (24) | (25) | (26) | (27) | (28) | (29) | (30) | (31) | (32) |
| Family × Haiyan | 0.0011** | 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 obtained from 2SLS estimations. The instrument used is the interaction between distance to the 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 and province-year levels.
*** p<0.01, ** p<0.05, * p<0.1

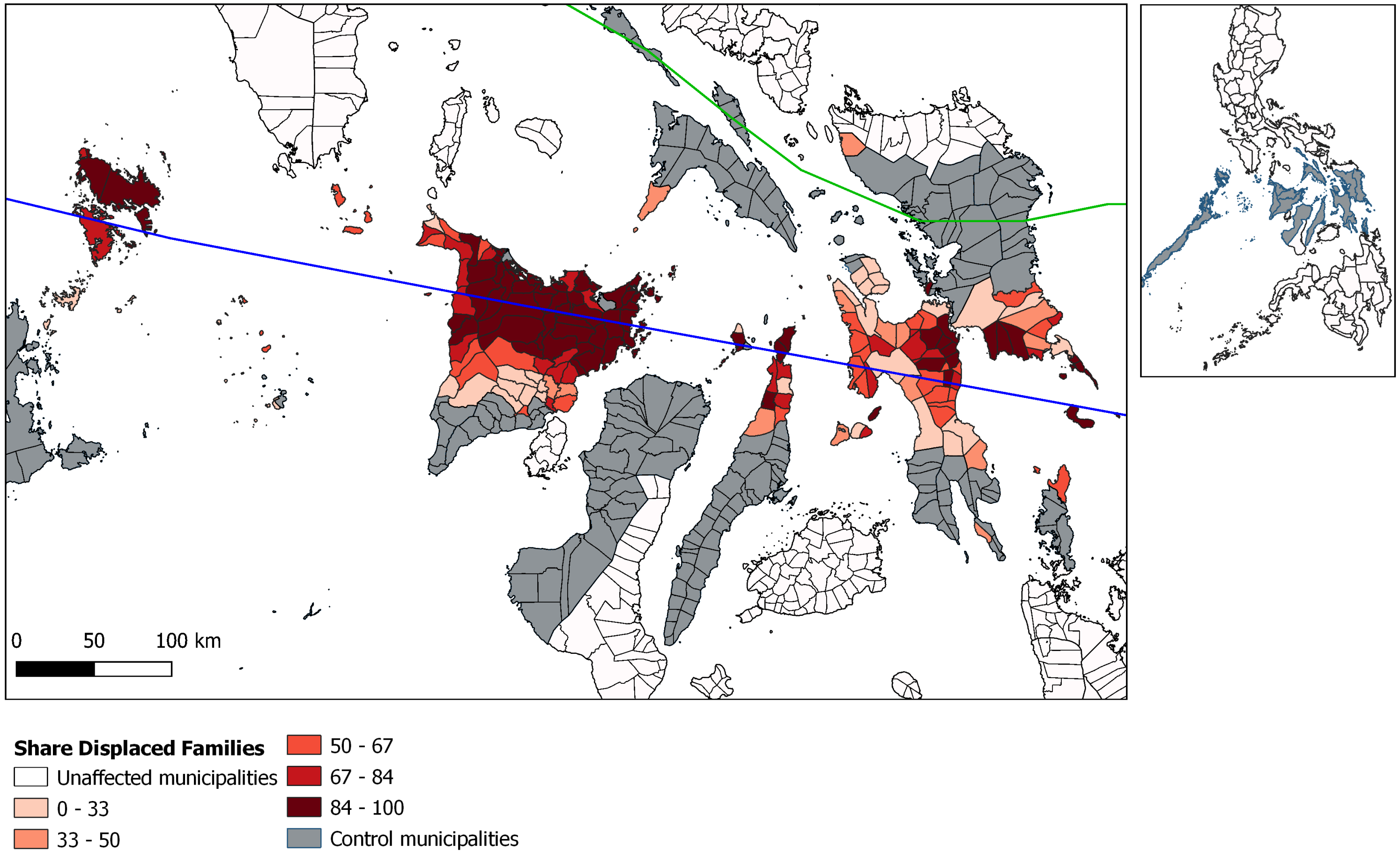
# Appendix for online publication

Figure A1: Storm path of Haiyan and affected cities and municipalities



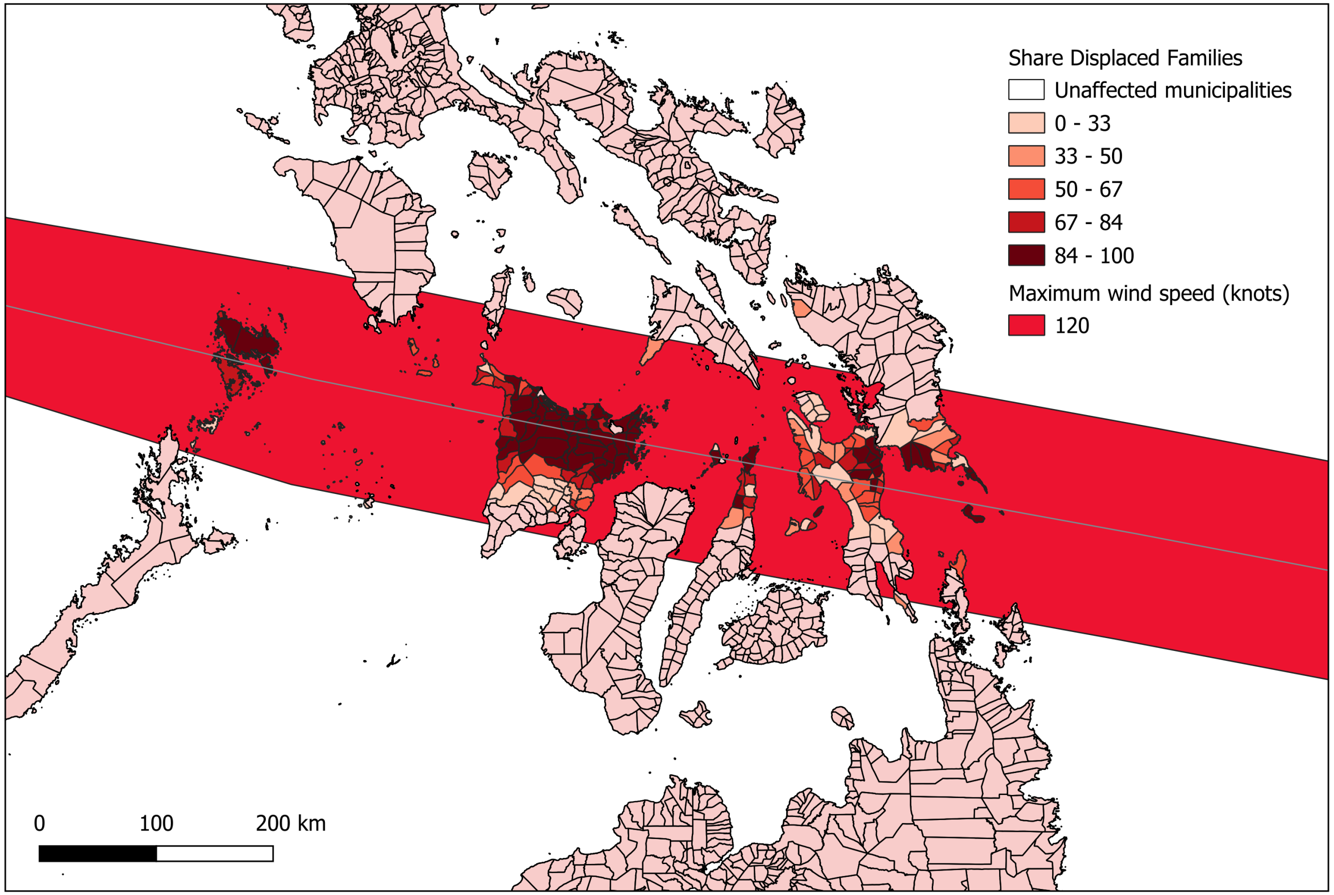

**Notes:** The map shows the cities and municipalities affected by Typhoon Haiyan in 2013, along with the share of displaced families in the total number of families affected. The map on the top right corner displays the full map of the Philippines with the Haiyan affected provinces in grey. The data was collected from the Department of Social Welfare and Development and the National Disaster Risk Reduction and Management Council of the Philippines.

Figure A2: Storm paths of typhoons between 2003 and 2018



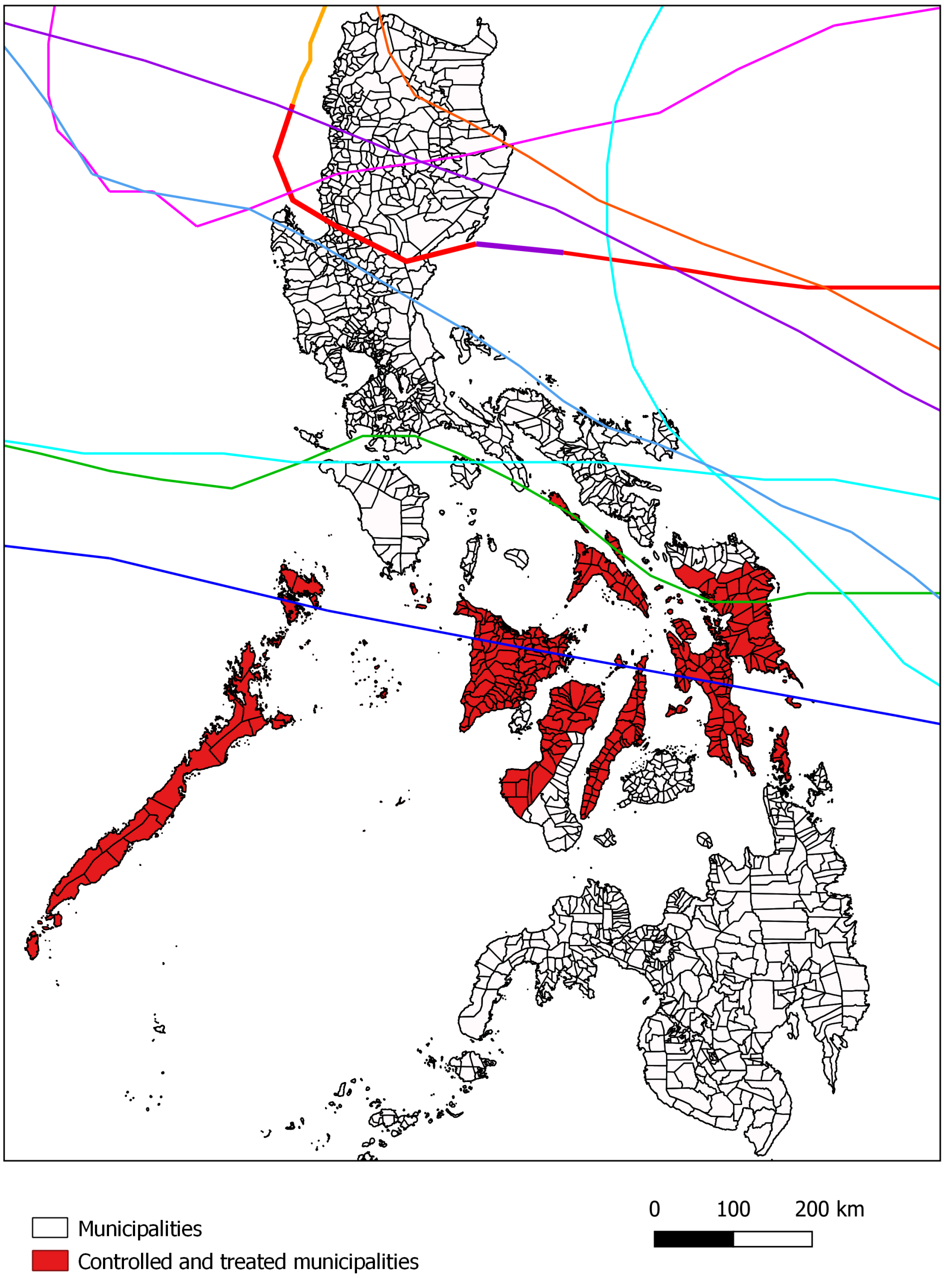

**Notes:** The map shows the cities and municipalities affected by Typhoon Haiyan in 2013 (in blue), along with all typhoon paths of category 4 and 5 between 2003 and 2018. The path of the only other typhoon during the period appears in green for the 2014 Typhoon Ruby appears . The financial effect of Typhoon Ruby is estimated to be less than 5% of the financial loss estimated for Typhoon Haiyan (NDRRMC, 2014). The map on the top right corner displays the full map of the Philippines with the Haiyan affected provinces in grey. The data was collected from the Joint Typhoon Warning Center and the U.S. National Oceanographic and Atmospheric Administration.

Figure A3: Wind speed exposure



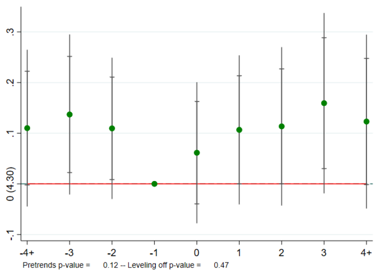

**Notes:** The map shows the cities and municipalities affected by Typhoon Haiyan in 2013, along with the swath of the typhoon with wind speed. Geo-coded data on the storm path and wind speed was obtained from the Joint Typhoon Warning Center and the U.S. National Oceanographic and Atmospheric Administration.

Figure A4: Storm paths of typhoons between 2003 and 2018 in the Philippines

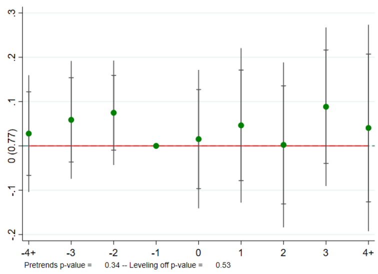



**Notes:** The map shows all typhoon track paths for typhoons of category 4 or 5 between 2003 and 2018 in the Philippines. Municipalities used in our data sample (treatment and control groups) are coloured in red. The 2013 Typhoon Haiyan appears in blue. The data was collected from the Joint Typhoon Warning Center and the U.S. National Oceanographic and Atmospheric Administration.

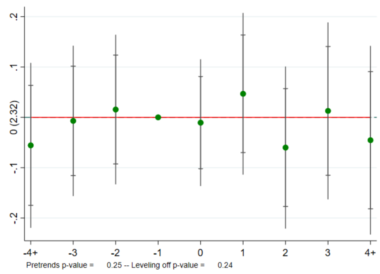
Figure A5: Dynamic effects of the typhoon on local expenditures



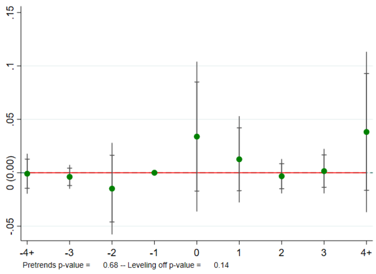

(a) General



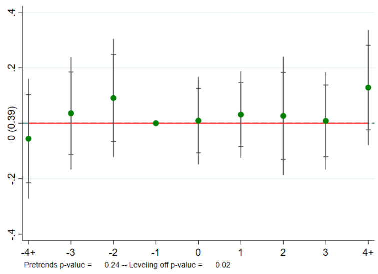

(b) Education



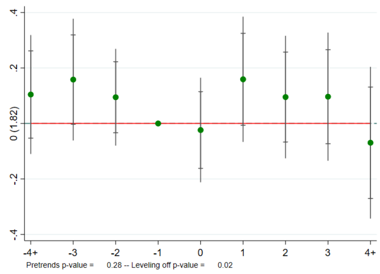

(c) Health



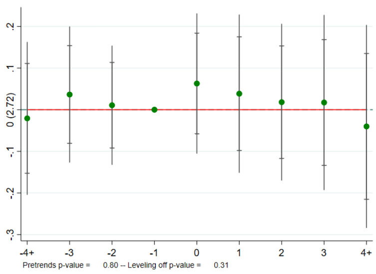

(d) Labor



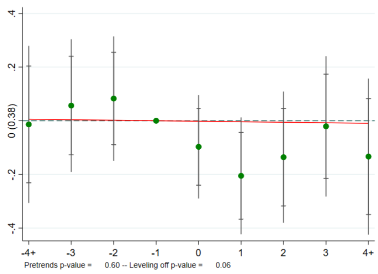

(e) Housing



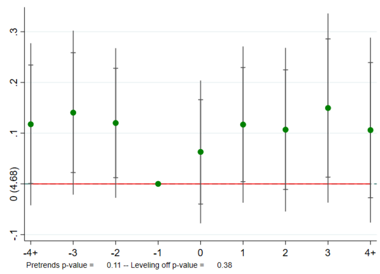

(f) Social services




(g) Economic services



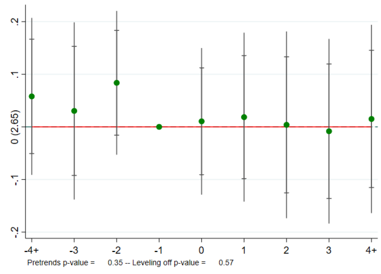

(h) Debt



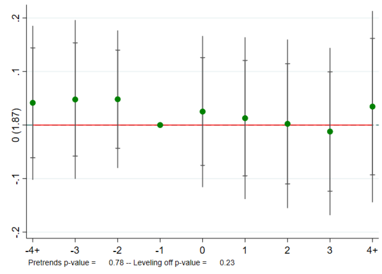

(i) Total

**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.

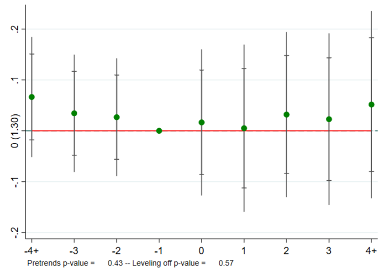
Figure A6: Dynamic effects of Haiyan on local income (I)



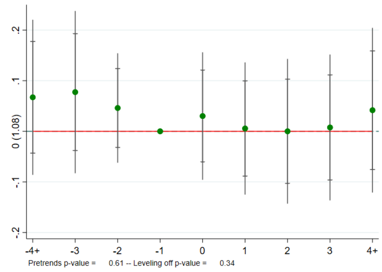

(a) Local sources



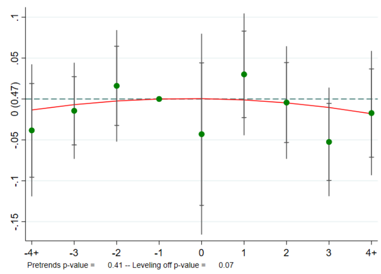

(b) Tax revenue



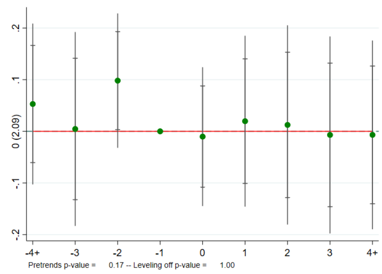

(c) Real-property tax



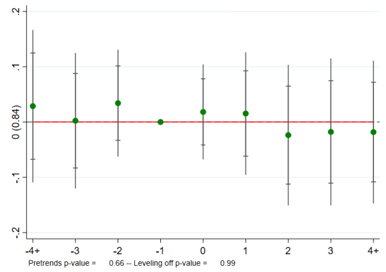

(d) Business tax



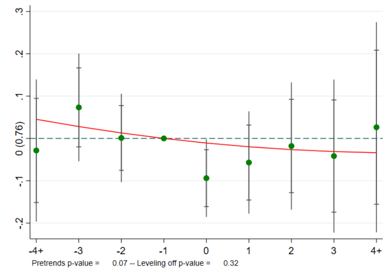

(e) Other taxes




(f) Non-tax revenue



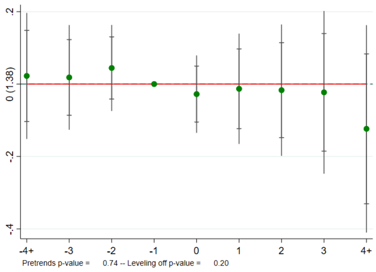

(g) Regulatory fees



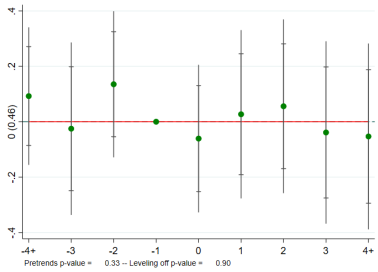

(h) User charges

**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.

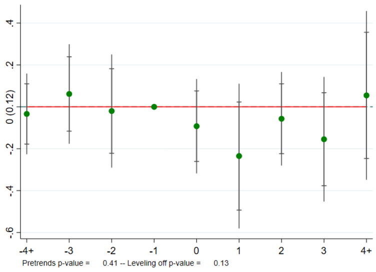
Figure A7: Dynamic effects of Haiyan on local income (II)



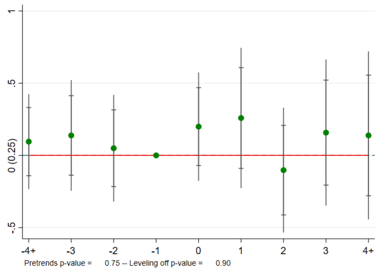

(a) Business income



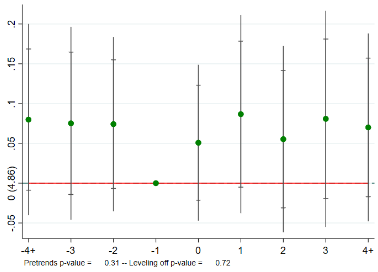

(b) Other general income




(c) Inter-local transfers



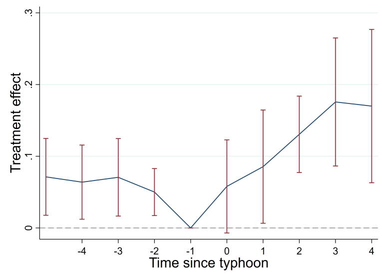

(d) Extraordinary receipts



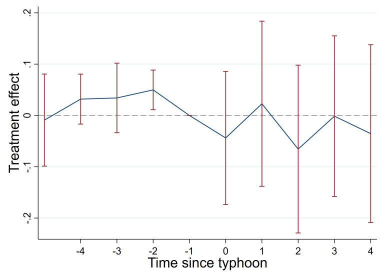

(e) Total

**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.

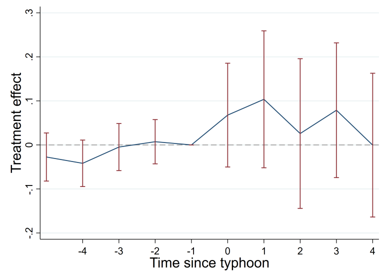
Figure A8: Dynamic effects of the typhoon on local expenditures



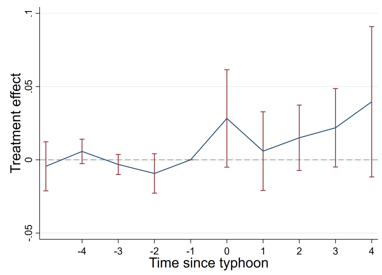

(a) General



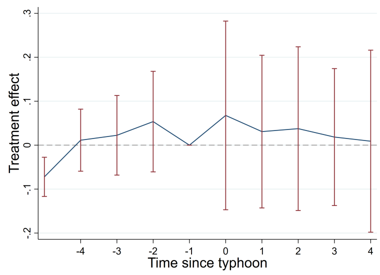

(b) Education



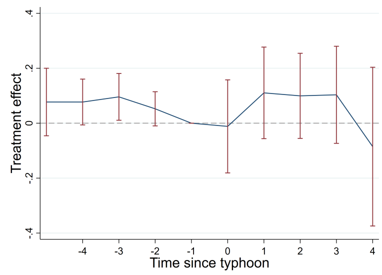

(c) Health



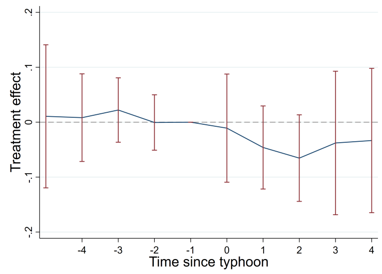

(d) Labor



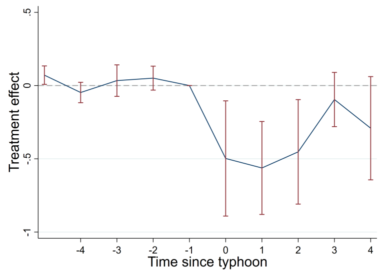

(e) Housing



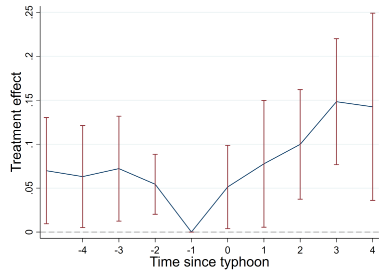

(f) Social services




(g) Economic services



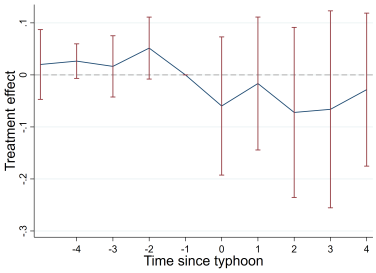

(h) Debt



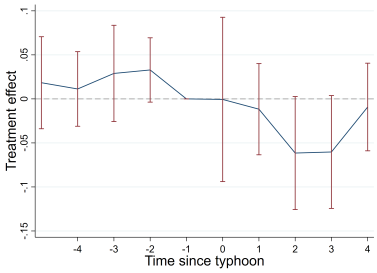

(i) Total

**Notes:** Each graph plots the coefficient estimates of equation (2) along with their 95% confidence intervals, with 2013 as the reference year. The event-study plots are constructed using the estimator proposed by De Chaisemartin and d'Haultfoeuille (2020), and include all baseline controls. Robust standard errors are adjusted for clustering at the city/municipality level.

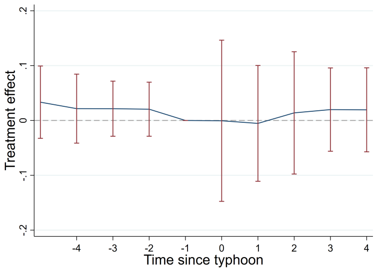
Figure A9: Dynamic effects of Haiyan on local income (I)



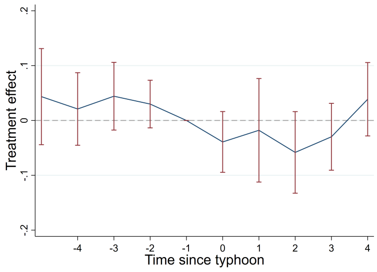

(a) Local sources



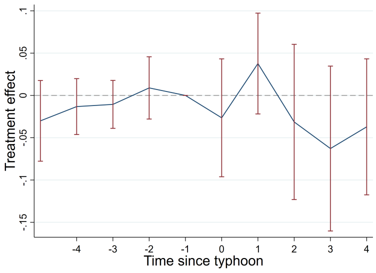

(b) Tax revenue



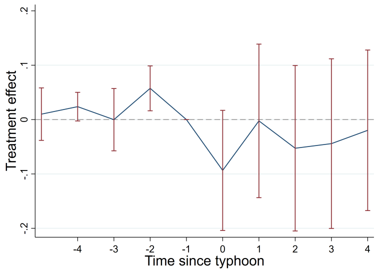

(c) Real-property tax



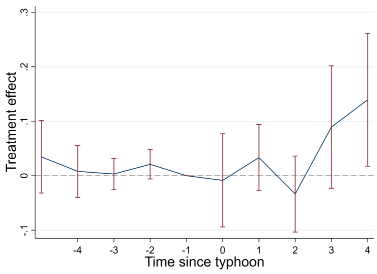

(d) Business tax



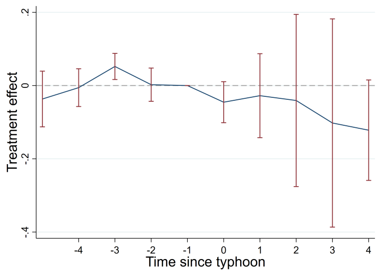

(e) Other taxes




(f) Non-tax revenue



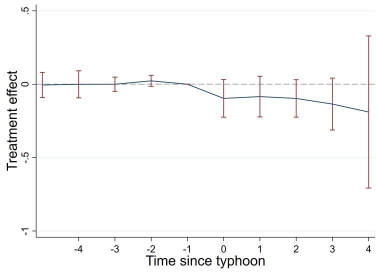

(g) Regulatory fees



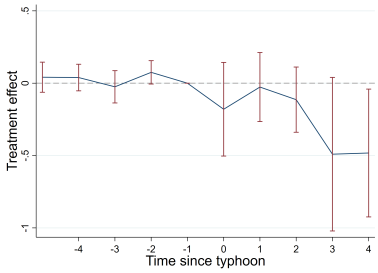

(h) User charges

**Notes:** Each graph plots the coefficient estimates along with their 95% confidence intervals, with 2013 as the reference year. The event-study plots are constructed using the estimator proposed by De Chaisemartin and d'Haultfoeuille (2020), and include all baseline controls. Robust standard errors are adjusted for clustering at the city/municipality level.

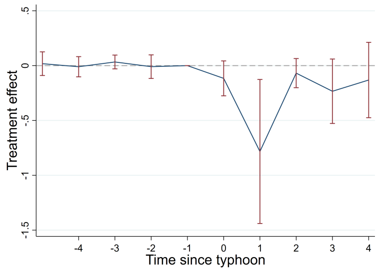
Figure A10: Dynamic effects of Haiyan on local income (II)



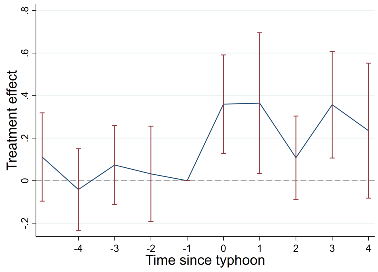

(A) Business income



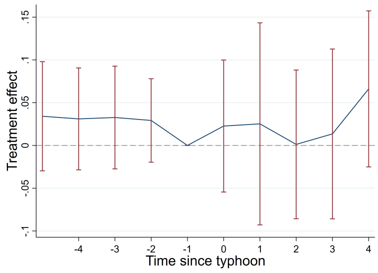

(B) Other general income




(C) Inter-local transfers



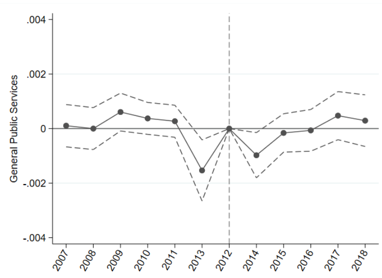

(D) Extraordinary receipts



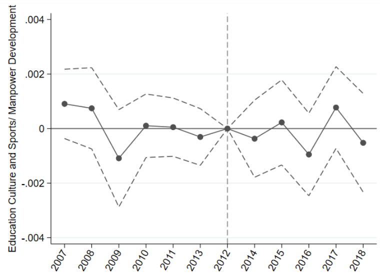

(E) Total

**Notes:** Each graph plots the coefficient estimates along with their 95% confidence intervals, with 2013 as the reference year. The event-study plots are constructed using the estimator proposed by De Chaisemartin and d'Haultfoeuille (2020), and include all baseline controls. Robust standard errors are adjusted for clustering at the city/municipality level.

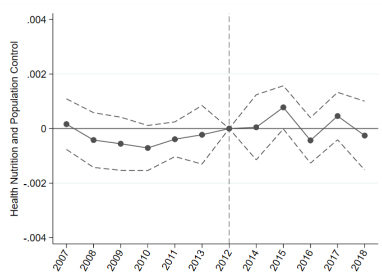
Figure A11: Dynamic effects of the typhoon on local expenditures (2012 reference year)



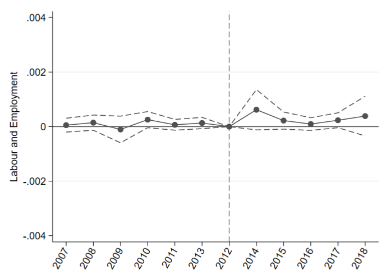

(a) General



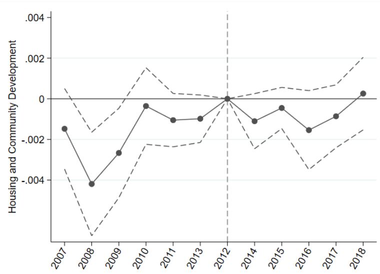

(b) Education



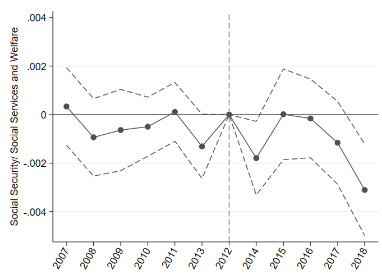

(c) Health



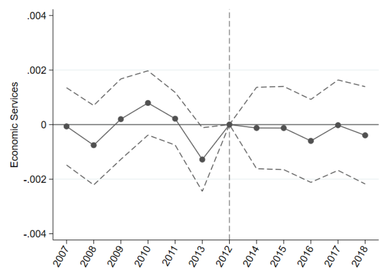

(d) Labor



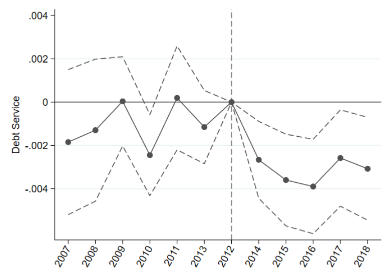

(e) Housing




(f) Social services



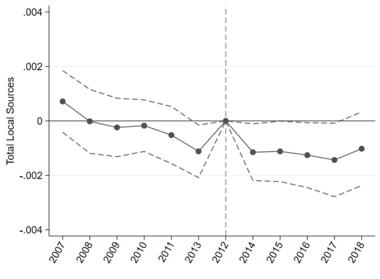

(g) Economic services



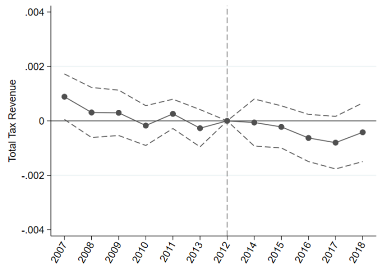

(h) Debt

**Notes:** Each graph plots the coefficient estimates of equation (2) along with their 95% confidence intervals, with 2012 as the reference year. Each graph presents the $\delta_t$ coefficients on the interaction of a yearly indicator and the variable $Family$. Robust standard errors are adjusted for clustering at the city/municipality level.

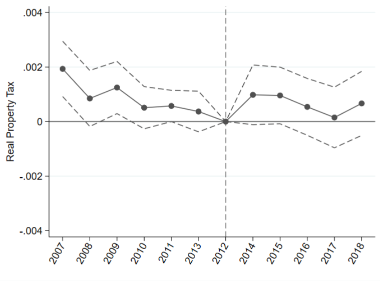
Figure A12: Dynamic effects of Haiyan on local income (I) (2012 reference year)



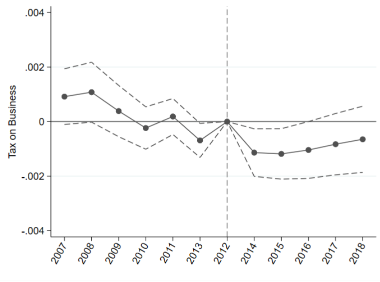

(a) Local sources



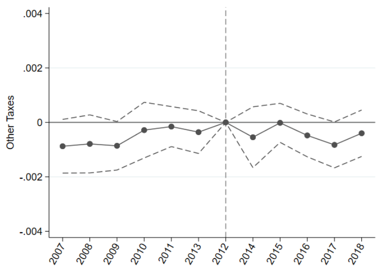

(b) Tax revenue



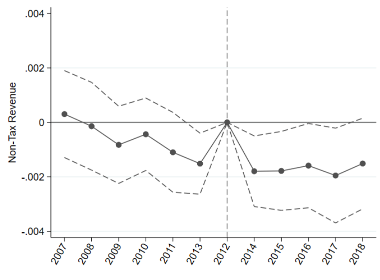

(c) Real-property tax



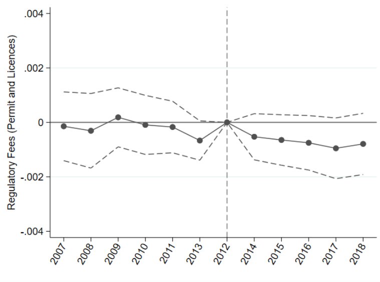

(d) Business tax



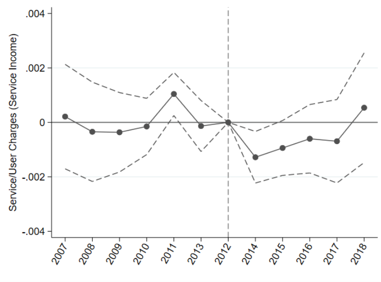

(e) Other taxes




(f) Non-tax revenue




(g) Regulatory fees

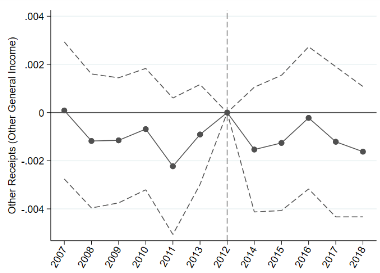



(h) User charges

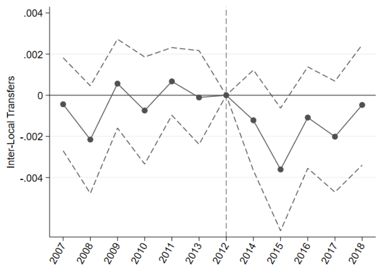
**Notes:** Each graph plots the coefficient estimates of equation (2) along with their 95% confidence intervals, with 2012 as the reference year. Each graph presents the $\delta_t$ coefficients on the interaction of a yearly indicator and the variable *Family*. Robust standard errors are adjusted for clustering at the city/municipality level.

Figure A13: Dynamic effects of Haiyan on local income (II) (2012 reference year)

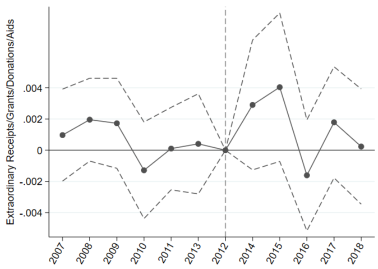

(A) Business income




(B) Other general income



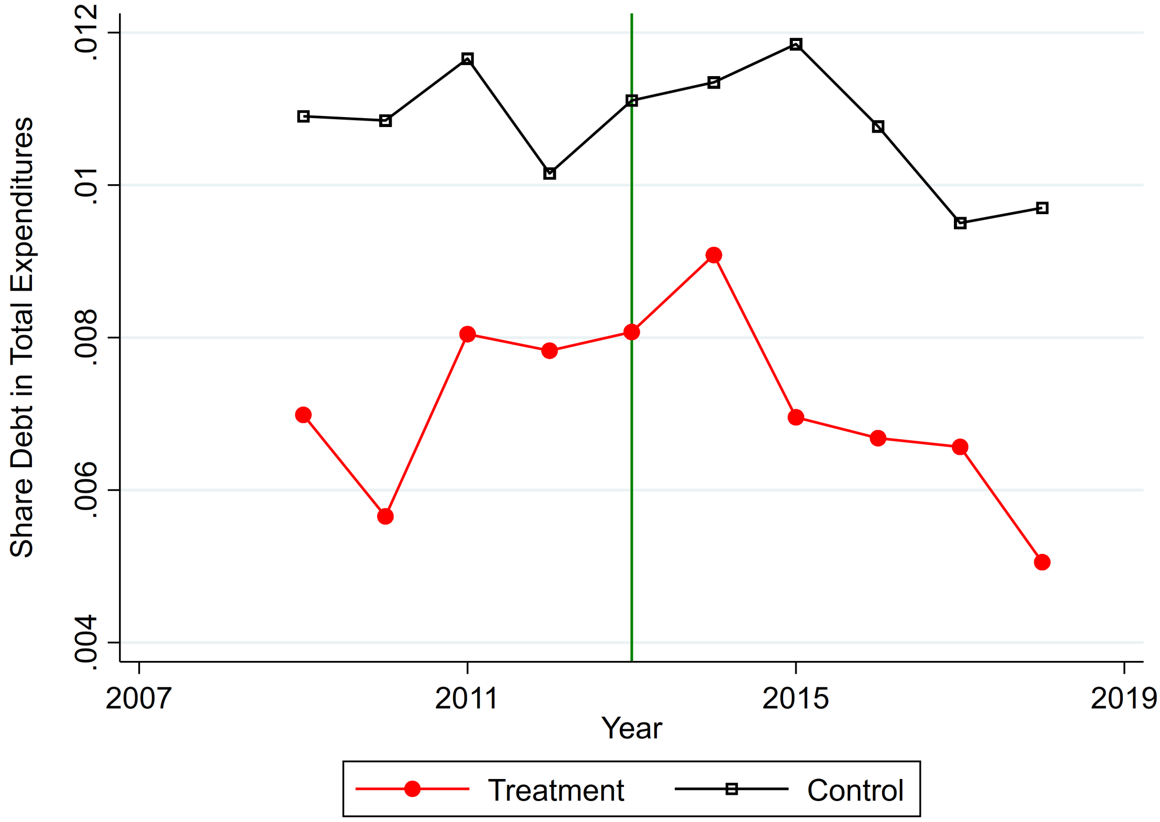

(C) Inter-local transfers




(D) Extraordinary receipts

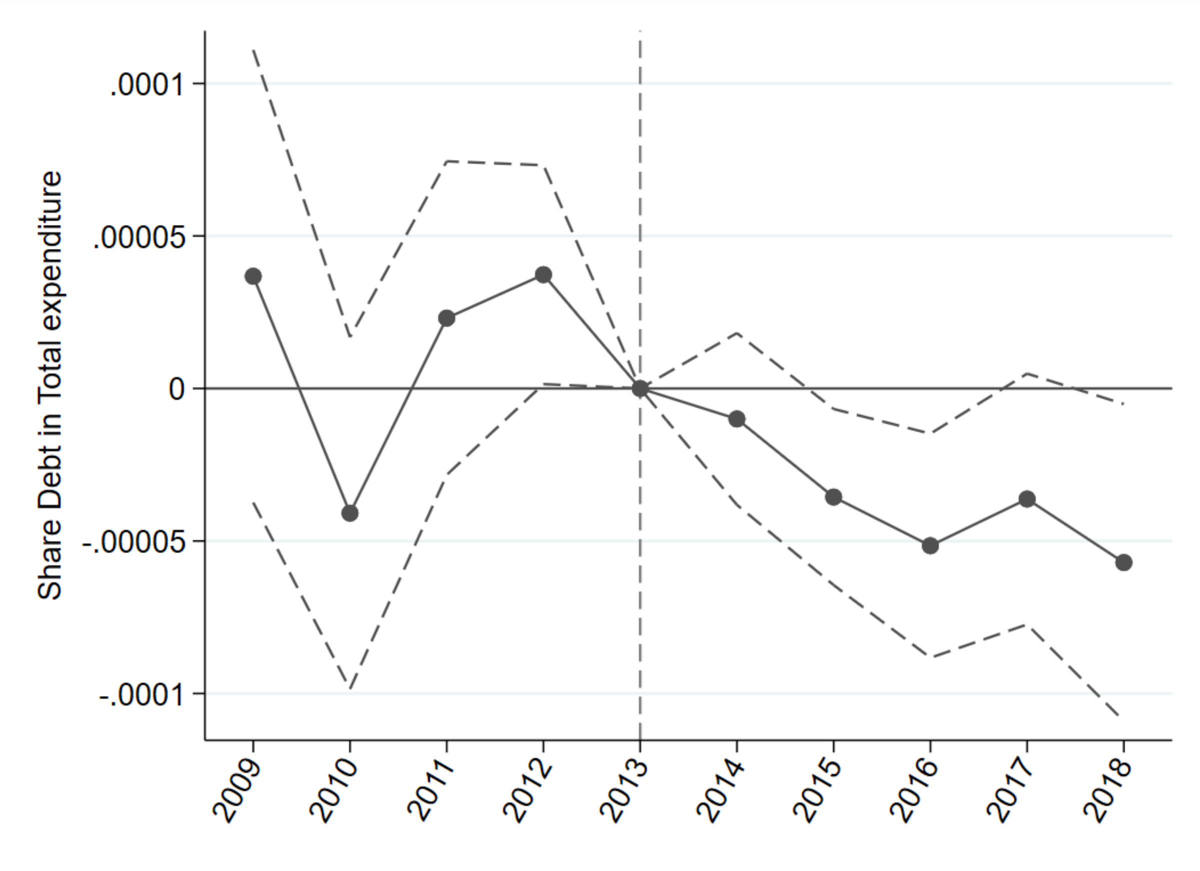
**Notes:** Each graph plots the coefficient estimates of equation (2) along with their 95% confidence intervals, with 2012 as the reference year. Each graph presents the $\delta_t$ coefficients on the interaction of a yearly indicator and the variable *Family*. Robust standard errors are adjusted for clustering at the city/municipality level.

Figure A14: Average share of debt service in total expenditures




**Notes:** The graph plots the average share of debt services in total expenditures for affected (treatment) and non-affected (control) cities/municipalities.

Figure A15: Average share of debt service in total expenditures




**Notes:** The graph plots the coefficient estimates on debt services in total expenditures (equation 2) along with their 95% confidence intervals. Robust standard errors in parentheses are clustered at the city/municipality and province-year levels.

Table A1: Variable Definitions

| Variable | Name in records |
|---|---|
| General | General public services |
| Education | Education culture and sports/manpower development |
| Health | Health nutrition and population control |
| Labor | Labor 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 + Non-tax revenue |
| **Tax revenue** | |
| Real-property tax | Real-property tax |
| Business tax | Tax on business |
| Other taxes | Annual tax imposed by the LGU not falling under the accounts mentioned in business tax |
| **Non-tax revenue** | |
| Regulatory fees | Including permit and licences |
| User charges | Including service income |
| Business income | Income from economic enterprises (business income) |
| Other general income | Other receipts not falling under any of the above categories (other general income) |
| **External sources** | |
| Inter-local transfers | Inter-local transfers |
| Extraordinary receipts | Non-recurring receipts that include grants, donations and national aids |
| Total | Total current operating income = Local sources + External sources |

**Source:** Philippine Bureau of Local Government Finance.

## Table A2: Effect of the typhoon on local government expenditures

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | General | Education | Health | Labor | Housing | Social | Economic | Debt | Total |
| Panel A: Difference-In-Difference | | | | | | | | | |
| Share family affected × Post2013 | -0.0001 | -0.0002 | 0.0004 | 0.0002* | 0.0008 | -0.0008 | -0.0001 | -0.0022** | -0.0001 |
| | (0.0003) | (0.0006) | (0.0004) | (0.0001) | (0.0009) | (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 |
| Mean Dep. (pre-2013) | 4.46 | .989 | 2.49 | .0127 | .376 | 1.76 | 2.76 | 1.26 | 4.94 |
| Panel A2: Difference-In-Difference | | | | | | | | | |
| Wind Speed × Post2013 | 0.0002 | 0.0001 | 0.0002 | 0.0002** | 0.0004 | -0.0006 | -0.0001 | -0.0015** | 0.0001 |
| | (0.0002) | (0.0004) | (0.0003) | (0.0001) | (0.0004) | (0.0005) | (0.0005) | (0.0006) | (0.0002) |
| Observations | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 |
| Municipalities | 351 | 351 | 351 | 351 | 351 | 351 | 351 | 351 | 351 |
| Mean Dep. (pre-2013) | 4.46 | .989 | 2.49 | .0127 | .376 | 1.76 | 2.76 | 1.26 | 4.94 |
| Panel B: 2SLS Estimates | | | | | | | | | |
| Share family affected × Post2013 | -0.0005 | 0.0012 | 0.0006 | 0.0001 | 0.0005 | -0.0009 | 0.0005 | -0.0054** | -0.0001 |
| | (0.0006) | (0.0015) | (0.0007) | (0.0002) | (0.0014) | (0.0014) | (0.0014) | (0.0022) | (0.0005) |
| Observations | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 |
| Municipalities | 351 | 351 | 351 | 351 | 351 | 351 | 351 | 351 | 351 |
| Panel C: First-stage of the corresponding 2SLS panel regressions | | | | | | | | | |
| Dependent variable: | Share family affected | | | | | | | | |
| Distance to storm path × Post2013 | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** | -0.345*** |
| | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) | (0.053) |
| Kleibergen-Paap $F$-statistic | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 | 42.04 |
| Controls as in panel A | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** All results are obtained from OLS with fixed effect estimations in panel A, 2SLS estimations in panel B and first-stage estimates in panel C. 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 and province-year levels. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

## Table A3: Extended sample - Effect of the typhoon on local government expenditures

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | General | Education | Health | Labor | Housing | Social | Economic | Debt | Total |
| Panel A: Difference-In-Difference | | | | | | | | | |
| Family × Haiyan | 0.0001 | -0.0003 | 0.0005 | -0.0001 | 0.0008 | -0.0007 | 0.0003 | -0.0011 | 0.0001 |
| | (0.0004) | (0.0006) | (0.0004) | (0.0001) | (0.0009) | (0.0007) | (0.0008) | (0.0010) | (0.0003) |
| Observations | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 |
| Municipalities | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 |
| Mean of Dependent Variable | | | | | | | | | |
| Panel B: 2SLS Estimates | | | | | | | | | |
| Family × Haiyan | -0.0000 | 0.0021 | 0.0005 | -0.0001 | 0.0007 | 0.0000 | 0.0006 | -0.0046* | 0.0003 |
| | (0.0007) | (0.0017) | (0.0009) | (0.0003) | (0.0017) | (0.0016) | (0.0017) | (0.0024) | (0.0006) |
| Observations | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 |
| Municipalities | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 |
| Panel C: First-stage of the corresponding 2SLS panel regressions | | | | | | | | | |
| Dependent variable: | Share family affected | | | | | | | | |
| Distance to storm path × Haiyan | -0.260*** | -0.260*** | -0.260*** | -0.260*** | -0.260*** | -0.260*** | -0.260*** | -0.260*** | -0.260*** |
| | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) |
| Kleibergen-Paap $F$-statistic | 69.8 | 69.8 | 69.8 | 69.8 | 69.8 | 69.8 | 69.8 | 69.8 | 69.8 |
| Controls as in panel A | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** All results are obtained from OLS with fixed effect estimations in panel A, 2SLS estimations in panel B and first-stage estimates in panel C. 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 and province-year levels. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

## Table A4: Extended sample - Effect of the typhoon on local government income

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 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 |
| Panel A: Difference-In-Difference | | | | | | | | | | | | | |
| Family × Haiyan | -0.0008 | -0.0005 | -0.0002 | -0.0015** | -0.0004 | -0.0011 | -0.0010* | -0.0012 | -0.0025*** | 0.0000 | -0.0021*** | 0.0021* | -0.0000 |
| | (0.0006) | (0.0005) | (0.0004) | (0.0006) | (0.0004) | (0.0007) | (0.0006) | (0.0007) | (0.0009) | (0.0009) | (0.0008) | (0.0012) | (0.0002) |
| Observations | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 |
| Municipalities | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 |
| Mean of Dependent Variable | | | | | | | | | | | | | |
| Panel B: 2SLS Estimates | | | | | | | | | | | | | |
| Family × Haiyan | 0.0000 | 0.0004 | 0.0022 | -0.0022 | 0.0013* | 0.0007 | 0.0022 | 0.0010 | -0.0028 | 0.0000 | -0.0037* | 0.0022 | -0.0003 |
| | (0.0014) | (0.0012) | (0.0014) | (0.0021) | (0.0007) | (0.0020) | (0.0018) | (0.0014) | (0.0025) | (0.0019) | (0.0020) | (0.0023) | (0.0005) |
| Observations | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 | 7148 |
| Municipalities | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 | 601 |
| Panel C: First-stage of the corresponding 2SLS panel regressions | | | | | | | | | | | | | |
| Dependent variable: | Share family affected | | | | | | | | | | | | |
| Distance to storm path × Haiyan | -0.260*** | -0.260*** | -0.260*** | -0.260*** | -0.260*** | -0.260*** | -0.260*** | -0.260*** | -0.260*** | -0.260*** | -0.260*** | -0.260*** | -0.260*** |
| | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) | (0.031) |
| Kleibergen-Paap $F$-statistic | 69.8 | 69.8 | 69.8 | 69.8 | 69.8 | 69.8 | 69.8 | 69.8 | 69.8 | 69.8 | 69.8 | 69.8 | 69.8 |
| Controls as in panel A | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** All results are obtained from OLS with fixed effect estimations in panel A, 2SLS estimations in panel B and first-stage estimates in panel C. The intensity of Typhoon Haiyan is proxied by the share of family affected in the total city/municipality population based on the 2010 Census. All dependent variables are transformed using the inverse hyperbolic sine function. Robust standard errors in parentheses are clustered at the city/municipality and province-year levels. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

## Table A5: IV estimation - Effect of the typhoon on the share of local government expenditures

| Panel A: Panel data estimation | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | General | Education | Health | Labor | Housing | Social | Economic | Debt |
| Family × Haiyan | -0.0002 | 0.0000 | 0.0001 | 0.0000 | 0.0001 | -0.0000 | 0.0002 | -0.0002* |
| | (0.0002) | (0.0000) | (0.0001) | (0.0000) | (0.0001) | (0.0001) | (0.0002) | (0.0001) |
| Observations | 4160 | 4160 | 4160 | 4160 | 4160 | 4160 | 4160 | 4160 |
| Municipalities | 351 | 351 | 351 | 351 | 351 | 351 | 351 | 351 |

| Panel B: First-stage of the corresponding 2SLS panel regressions | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Dependent variable: | Share family affected | | | | | | | |
| Distance to storm path × Haiyan | -38.272*** | -38.272*** | -38.272*** | -38.272*** | -38.272*** | -38.272*** | -38.272*** | -38.272*** |
| | (4.475) | (4.475) | (4.475) | (4.475) | (4.475) | (4.475) | (4.475) | (4.475) |
| Kleibergen-Paap $F$-statistic | 73.15 | 73.15 | 73.15 | 73.15 | 73.15 | 73.15 | 73.15 | 73.15 |
| Controls as in panel A | 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 and expressed as the share of total expenditures. Robust standard errors in parentheses are clustered at the city/municipality and province-year levels. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

## Table A6: IV estimation - Effect of the typhoon on the relative importance of local income sources

| Panel A: Panel data estimation | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 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 |
| Family × Haiyan | 0.0004 | 0.0002 | 0.0004 | -0.0003 | 0.0001** | 0.0004 | 0.0006** | 0.0004*** | -0.0001 | -0.0004 | -0.0003* | 0.0002 |
| | (0.0004) | (0.0004) | (0.0004) | (0.0002) | (0.0001) | (0.0003) | (0.0003) | (0.0001) | (0.0003) | (0.0003) | (0.0002) | (0.0003) |
| Observations | 4161 | 4161 | 4161 | 4161 | 4161 | 4161 | 4161 | 4161 | 4161 | 4161 | 4161 | 4161 |
| Municipalities | 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 | -38.279*** | -38.279*** | -38.279*** | -38.279*** | -38.279*** | -38.279*** | -38.279*** | -38.279*** | -38.279*** | -38.279*** | -38.279*** | -38.279*** |
| | (4.473) | (4.473) | (4.473) | (4.473) | (4.473) | (4.473) | (4.473) | (4.473) | (4.473) | (4.473) | (4.473) | (4.473) |
| Kleibergen-Paap $F$-statistic | 73.24 | 73.24 | 73.24 | 73.24 | 73.24 | 73.24 | 73.24 | 73.24 | 73.24 | 73.24 | 73.24 | 73.24 |
| Controls as in panel A | 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 city/municipality population based on the 2010 Census. All dependent variables are transformed using the inverse hyperbolic sine function and expressed as the share in the total local income subtracted from central government transfers PIRA. Robust standard errors in parentheses are clustered at the city/municipality and province-year levels. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table A7: The heterogeneous effect of Haiyan on aid (IV estimation)

| | Aid | |
|---|---|---|
| | (1) | (2) |
| Haiyan × Family | 0.0014 | 0.0030 |
| | (0.0021) | (0.0023) |
| Haiyan × Family | | |
| × Below median income | | -0.0032* |
| | | (0.0017) |
| Joint p-value | | 0.92 |
| Municipality FE | ✓ | ✓ |
| Department-year FE | ✓ | ✓ |
| Baseline controls | ✓ | ✓ |
| Observations | 4173 | 4173 |
| Municipalities | 351 | 351 |
| Kleibergen-Paap $F$-statistic | 73.08 | 38.86 |

**Notes:** All results are obtained from 2SLS estimations. The instrument used is the interaction between distance to the 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 and province-year levels.
*** p<0.01, ** p<0.05, * p<0.1

Table A8: The heterogeneous effect of Haiyan and aid (IV estimation)

| | General | | Education | | Health | | Labor | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Haiyan × Family × Aid | 0.0005** | 0.0034* | 0.0006** | 0.0065*** | 0.0000 | 0.0016 | 0.0002 | 0.0021* |
| | (0.0002) | (0.0020) | (0.0003) | (0.0022) | (0.0002) | (0.0014) | (0.0001) | (0.0012) |
| Haiyan × Family × Aid | | | | | | | | |
| × below median income | | -0.0032* | | -0.0060*** | | -0.0012 | | -0.0020* |
| | | (0.0018) | | (0.0021) | | (0.0012) | | (0.0011) |
| Joint p-value | | 0.61 | | 0.13 | | 0.14 | | 0.55 |
| Municipality FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Department-year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Baseline controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 |
| Municipalities | 351 | 351 | 351 | 351 | 351 | 351 | 351 | 351 |
| Kleibergen-Paap $F$-statistic | 27.54 | 3.65 | 27.54 | 3.65 | 27.54 | 3.65 | 27.54 | 3.65 |

| | Housing | | Social | | Economic | | Debt | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Haiyan × Family × Aid | -0.0003 | 0.0010 | 0.0007* | 0.0041* | 0.0007*** | 0.0021 | 0.0009** | -0.0006 |
| | (0.0002) | (0.0023) | (0.0004) | (0.0021) | (0.0003) | (0.0020) | (0.0004) | (0.0032) |
| Haiyan × Family × Aid | | | | | | | | |
| × below median income | | -0.0010 | | -0.0032 | | -0.0015 | | 0.0005 |
| | | (0.0021) | | (0.0020) | | (0.0018) | | (0.0028) |
| Joint p-value | | 0.95 | | 0.26 | | 0.17 | | 0.81 |
| Municipality FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Department-year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Baseline controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 | 4173 |
| Municipalities | 351 | 351 | 351 | 351 | 351 | 351 | 351 | 351 |
| Kleibergen-Paap $F$-statistic | 27.54 | 3.65 | 27.54 | 3.65 | 27.54 | 3.65 | 27.54 | 3.65 |

**Notes:** All results are obtained from 2SLS estimations. The instrument is the triple interaction $Distance_{ip} \times Haiyan_t \times Aid_{ip}$, our baseline instrument $Distance_{ip} \times Haiyan_t$ and $Haiyan_t \times Aid_{ip}$. The indicator variable Below median income is equal to 1 if the total income of municipality $i$ in province $p$ is below the sample median. 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 and province-year levels.
*** p<0.01, ** p<0.05, * p<0.1