Destruction, Disinvestment, and Death: Economic and Human Losses Following Environmental Disaster*

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Abstract

The direct physical damage caused by environmental disasters is straightforward to document and often the focus of media and government attention, but addressing disasters' indirect effects remains difficult because they are challenging to observe. We exploit annual variation in the incidence of typhoons (West-Pacific hurricanes) to identify the effect of environmental disaster on economic and health outcomes in Filipino households. We find that the Philippines' typhoon climate causes large losses to households' economic well being, destroying durable assets and depressing incomes in the wake of storms. Household income losses translate directly into expenditure reductions, which are achieved in part through disinvestments in health and human capital. Examining infant mortality rates, we observe substantially increased female infant mortality in the years following storm exposure. Striking similarities in the structure of these mortality and economic responses, along multiple dimensions, implicates the deterioration of economic conditions and subsequent disinvestments as the cause of mortality among female infants. Bolstering this hypothesis, we find that mortality is highest in households where infant daughters face the greatest competition with other children for resources, particularly older brothers. We estimate that these delayed deaths among female infants outnumber officially reported typhoon deaths in the general populace by a factor of fifteen.

1 Introduction

It is obvious that natural disasters cause immediate destruction and death. In theory, documenting the direct physical damages caused by hurricanes, earthquakes, and other catastrophes is straightforward, although the logisitics of doing so are often difficult. At the same time, even our theoretical understanding of disasters' aftereffects, particularly on economic outcomes, remains limited by a paucity of empirical observations. The few facts we have about post-disaster economics come primarily from studies that link macroeconomic data with country-level estimates of disaster impacts (see Strömberg (2007) and Cavallo and Noy (2009) for reviews of the literature). Thus even fairly basic questions about disasters' economic effects, such as whether household incomes rise or fall in a disaster's wake, remain unsettled (Albala-Bertrand (1993); Benson and Clay (2004); Caselli and Malhotra (2004); Hallegatte and Ghil (2008); Horchrainer (2009); Loayza et al. (2009); Dercon and Outes (2009); Noy (2009); Fomby, Ikeda and Loayza (2009); Hsiang (2010); Strobl (2011); Deryugina (2011)).

Improving our understanding of post-disaster economic outcomes is important for several reasons. Designing effective disaster management policies and institutions requires that we understand the full cost of disasters (Kunreuther et al. (2009); United Nations (2009)); if a sizeable portion of a disaster's costs manifest after the event itself, then models of humanitarian intervention which focus on immediate damages may need to be reassessed or expanded. Secondly, the wealth of evidence suggesting that disasters' immediate death and destruction is most acute in low-income countries (Kahn (2005), Mutter (2005), Yang (2008), Hsiang and Narita (forthcoming)) indicates that disasters might plausibly influence economic development. Of particular concern is disasters' potential to alter long-run outcomes due to short-run losses: if poor households have a limited ability to mitigate disaster-induced losses, disaster incidence may cause them to sacrifice valuable investment (Udry (1994); Jacoby and Skoufias (1997);

Duflo (2000); Maccini and Yang (2009); Banerjee and Mullainathan (2010)) for short-run needs. Lastly, recent evidence suggests that global climate change is expected to increase the frequency of certain types of environmental disaster, (IPCC 2007; Knutson et al. (2010)). This implies that any improvement in estimates of disasters' costs will necessarily inform estimates of climate change's anticipated damages (Narita, Tol and Anthoff (2009); Mendelsohn, Emanuel and Chonobayashi (2010)), and in turn the formulation of climate change policy in general (Stern (2006); Nordhaus (2008); Tol (2009); Weitzman (2009); Pindyck (2011)).

In this paper we measure the post-disaster economic and health effects of a specific type of environmental disaster: typhoons. Typhoons, or tropical cyclones[1], are large, fast-moving storms which form over the oceans and cause physical damage via intense winds, heavy rainfall, and ocean surges. We focus on typhoons both because they are one of the most common and costly types of natural disaster (Bevere, Rogers and Grollimund (2011)) and because their variation in timing and spatial distribution allow us to identify their effects using quasi-experimental techniques (Holland (1986)). Typhoons are relatively brief, usually affecting a given location for at most 1- 2 days. They are also sharply defined in space, being 100-200 kilometers across and traveling distances ranging from a few hundred to a few thousand kilometers in length. The intensity of a location's typhoon exposure is also variable, both because the storms themselves vary in frequency and intensity and because different locations are exposed to different parts of the same storm, another feature that we exploit in our econometric analysis.

The Philippines is situated in one of the most intense typhoon climatologies on the planet (see Figure 1), a fact that both improves our identification strategy and differentiates this study from analyses of one-off or infrequent natural disasters. In order to capture spatial and temporal variations in typhoon exposure within the Philippines

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[1] "Typhoon" is the name for a tropical cyclone that occurs in the western Pacific Ocean. The same storms are called "hurricanes" in the Atlantic Ocean and simply "cyclones" in the Indian Ocean.

we use a physical model of typhoon winds developed in Hsiang (2010) to create a unique panel dataset of province-level incidence. This dataset allows us to adopt a difference-in-differences approach which takes advantage of each province's year-to-year variation in typhoon exposure.

We combine physical storm data with two household survey files: the Family Income and Expenditure Survey (FIES), a repeated cross sectional survey of household economic outcomes conducted by the Filipino government every three years; and the Demographic and Health Survey (DHS), a suite of cross sectional household-level health and fertility surveys. The FIES data allow us to identify the impact of storms on households' physical assets, income, and consumption[2], while the DHS's retrospective data on mothers' fertility allow us to reconstruct a mother-by-year panel dataset of infant births and mortality. Infant mortality constitutes a sensitive[3] measure of health itself as well as an indicator of general household well being. When linked together, these three datasets allow us to characterize the multidimensional response of households to typhoons.

We begin by demonstrating that our empirical model indeed captures typhoons' direct destructive impact. We verify that our measure of typhoon exposure, spatially-weighted maximum typhoon wind speed (henceforth "wind speed"), is a good predictor of damages and deaths at the national level. We demonstrate that these nationally-aggregated losses are also apparent at the household-level in the form of lost capital assets, such as televisions, toilets, and walls.

Turning next to household income, we find that typhoons reduce average income the year after they strike, presumably due to storms' direct physical damages as well

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[2]We note that expenditures alone do not infer quantity of consumption in the absence of prices, and thus perform a variety of checks on storms' impact on prices, which we find to be negligible; see Section 5 for details.

[3]As Chay and Greenstone (2003) point out, infant mortality minimizes problems of cumulative exposure and a host of other potentially confounding identification concerns that emerge when examining other human capital measures.

as their more indirect disruption of economic activity. We find that household income drops linearly by 0.39% per meter per second of wind speed exposure. Given the average annual exposure at the province level of 16.9 m/s during our sample period, we estimate that the average short-run effect of the country's typhoon climate is to depress incomes by 6.7%. This effect occurs across a variety of income sources, affects both richer and poorer households, and is net of public and private transfers.

The income losses we measure translate nearly one-for-one into a reduction of household expenditures, which decrease 7.1% for the average household in the average year. These expenditure reductions track total income losses closely when they are examined across years (relative to the storm), across space, across typhoon intensities, and across income groups. This tight relationship suggests that households do not mitigate storm-induced losses via consumption-smoothing strategies, such as in-kind transfers, savings, or borrowing. Instead, we observe that households make large adjustments to their *relative* spending on different types of consumption and investment. In general, households reduce their spending the most on expenditures that most closely resemble human capital investments, such as medicine, education and high nutrient foods that include meat, dairy, eggs and fruit. In contrast, expenditures decline much less on pure consumption goods, such as recreation, alcohol and tobacco.

We next examine whether typhoons impact household health outcomes by examining infant mortality rates. We find no evidence that infant mortality rises during or immediately following typhoon exposure, implying that deaths from physical exposure to the storm itself, which we term 'trauma deaths', are few. However, we find that typhoons cause infant mortality to rise the calendar year *after* the storm itself has passed. This is illustrated in Figure 2, which shows the cumulative monthly mortality impact of typhoons. The vast majority of infant female deaths (grey line) manifest well after the typhoon event; moreover, many of the infants who die in the aftermath of

5

the storm were not even conceived until after the storms are gone (dotted black line), implying that the direct mortality impact of the storm is minimal. We estimate that in our sample of mothers who never migrate, these typhoon-associated deaths amount to an annual average of 1,130 female infant deaths per million households, corresponding to 55% of the baseline infant female mortality rate.

Multiple aspects of our findings suggest that deteriorating economic conditions and disinvestments in human capital are responsible for these female infant deaths. We "fingerprint" patterns of economic contraction and disinvestment across many dimensions by looking at their timing relative to storms, their nonlinear response to storm intensity, their short and medium-run lag structure at different locations in the income distribution, and their spatial patterns. We then demonstrate that patterns of female infant mortality exhibit an almost identical "fingerprint" across these same dimensions. Furthermore, we find that mortality is highest in households where infant daughters face competition from other children over resources, particularly if those siblings are male. These findings together suggest that female infant deaths following typhoon events are 'economic deaths' resulting from economic losses and the resulting household decisions regarding human capital investments and within-household resource allocation. This conclusion that female infants bear a differentially large share of the burden from income loss is consistent with findings from a variety of other contexts (Rosenzweig and Schultz (1982); Rose (1999); Duflo (2000); Duflo (2005); Bhalotra (2010)). Extrapolating these estimates to the entire non-migrant population suggests that approximately 11,000 female infants suffer 'economic deaths' in the Philippines every year due to the previous year's storm season. In contrast, there was an average of 743 'trauma deaths' per year according to official reports for the same period (OFDA/CRED 2009). This suggests that mortality attributable to Filipino typhoons is roughly 1500% of previous estimates.

6

The remainder of the paper is structured as follows. Section 2 presents background on typhoons and disaster impacts. Section 3 presents the data and Section 4 presents the identification strategy. Section 5 presents our results. We conclude in Section 6, which discusses our findings and some of their implications for policy.

2   Background

The Typhoon Climate of the Philippines

Figure 1 shows a map of the Philippines' annual expected typhoon exposure, or its typhoon climate. The Philippines possesses one of the most active cyclone climatologies in the world, on average experiencing over ten typhoons each year ranging in intensity from mild to severe. Because the Philippines is large compared to typhoons[4], different regions within the country may experience entirely different levels of storm exposure in the same year.

The Philippines' active typhoon climate provides additional benefits for analysis compared to other idiosyncratic destructive events such as earthquakes[5] or wars, in that typhoons in the Philippines are a regular and expected occurrence. This can be seen in Figure 4, which shows the distribution of typhoon exposure for each Filipino province; we note that median exposure (white bars at the center of each box) is non-zero for all but a handful of provinces. While destructive and unpredictable, typhoon exposure itself is thus not surprising, and households almost certainly incorporate typhoon risk into their economic decisions. We can thus plausibly infer that any impacts that we observe occur in spite of all the adaptive responses that households employ to mitigate

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[4]See, for example, Appendix Figure C.1 showing a satellite photo of Typhoon Nanmadol.

[5]Note that while earthquakes certainly have a spatial and temporal incidence structure similar to typhoons the interarrival time of destructive earthquakes is orders of magnitude longer than for destructive typhoons. See, for example, Triep and Sykes (1997).

typhoon impacts.

Our estimate of typhoons' costs adds to the rapidly growing literature on the natural environment's impact on health outcomes (Deschênes and Moretti (2009); Maccini and Yang (2009); Deschênes and Greenstone (2011)), as well as the literature on the economic and health impacts of disasters (Toya and Skidmore (2007); Strömberg (2007); Cavallo and Noy (2009); Simeonova (2011); Hsiang (2010); Deryugina (2011)) as well as the more general literature exploring climatic influence on economic outcomes (Gallup, Sachs and Mellinger (1999); Acemoglu, Johnson and Robinson (2002); Bloom, Canning and Sevilla (2003); Easterly and Levine (2003); Miguel, Satyanath, and Sergenti (2004); Nordhaus (2006b); Schlenker and Roberts (2009); Dell, Jones, and Olken (2009); Hsiang (2010); Graff Zivin and Neidell (2010)). It also augments the literature on the economic consequences of physically destructive shocks (Davis and Weinstein (2002); Vigdor (2008); Miguel and Roland (2011)) though it differs from much of that literature in that typhoons, rather than being idiosyncratic events like bombings, are a persistent and common state of the climate.

Household Adjustments to Income Loss

Reductions in household income have the obvious potential to cause deleterious effects: consumption of goods and services, investments in health and education, and savings for future use are all potential margins of adjustment which may suffer following income loss. There are a variety of means by which households seek to minimize these costs. Firstly, households may attempt to smooth their income or consumption over time, thereby spreading costs out and attenuating the immediate impact of income loss. This smoothing can come in the form of within-household adjustments such as accumulating precautionary savings (Paxson (1992); Kazarosian (1997)), directly supplanting income through adaptive labor market activity (Kochar (1995); Jacoby and Skoufias (1998);

Kochar (1999)), or selling assets during times of duress (Rosenzweig and Wolpin (1993). It may also come in the form of extra-household adjustments such as accessing credit markets (Rosenzweig(1988); Cochrane (1991); Morduch (1995)) or relying on transfers (Foster and Rosenzweig (2001); Fafchamps and Lund (2003); Yang and Choi (2007)). It is important to note that the income and consumption smoothing literature differentiates between relatively easily insured-against idiosyncratic shocks (i.e., income losses affecting different households at different times) and less easily mitigated aggregate shocks affecting many houses (Cochrane (1991); Townsend (1995)). One might thus expect that income losses due to typhoons, which are particularly large and common aggregate shocks, might be particularly difficult to smooth over time.

If income losses cannot be smoothed then households may adjust by altering their expenditure patterns. This adjustment may manifest in altered consumption, e.g., via changes in eating habits (Subramanian and Deaton (1996); Jensen and Miller (2008)), or it may manifest as a reduction in investments, such as to human capital (Mincer (1958); Jensen (2000); Banerjee and Mullainathan (2010))[6]. If losses to income result in disinvestment in human capital, particularly among children, then the potential costs of a shock may far exceed its immediately observable effects in the long run via worsened later-life outcomes (Strauss and Thomas (1998); Maccini and Yang (2009); Banerjee et al. (2010)). Moreover these losses may become compounded if households differentially disinvest in children by type, for example due to gender biases (Sen (1990); Duflo (2005)).

This paper expands upon the literature documenting household disinvestments in children's human capital following income loss (Jacoby and Skoufias (1998); Strauss and Thomas (1998); Jensen (2000)), particularly disinvestments in girls' human capital

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[6]Note that in many instances consumption and investment cannot be disentangled; expenditures on nutritious food, for example, can be equally viewed as consumption as well as investment in future human capital.

(Rose (1999); Bhalotra and Heady (2003); Maccini and Yang (2009); Chen (2011)). More broadly, this paper adds to the growing body of research documenting the excess risk burden born by female household members in developing contexts (Horton (1986); Sen (1990); Duflo (2005); Qian (2008); Robinson and Yeh (2011)).

3 Data

Our analysis requires data describing household assets, income, expenditures, health outcomes, and typhoon exposure. Summary statistics of these data are presented in Tables 1, 2, and 3. For reference, Appendix Figure C.2 displays an administrative map of the 82 provinces (smaller units) and 17 regions (larger units) we include in our data.

Typhoon data

A central innovation of our analysis is the development of a comprehensive data file describing a physical measure of typhoon incidence over time. We develop this measure to ensure that our typhoon data are sufficiently precise to describe meaningful variations in typhoon exposure in a climate where typhoons are common. We begin by reconstructing the wind field for every West Pacific cyclone in the International Best Track Archive for Climate Stewardship (IBTrACS) database (Knapp (2009)) using the Limited Information Cyclone Reconstruction and Integration for Climate and Economics (LICRICE) model (see Hsiang (2010) for a detailed description of the model[7]). LICRICE only reconstructs wind fields and does not explicitly account for rains, flooding, or storm surges because wind fields are less influenced by topography and are thus more generalizable. However, our wind field measures describes these other typhoon

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[7]Since Hsiang (2010), version 2 of LICRICE was built (used in this study), substantially improving upon the model's original accuracy. However these improvements were focused on numerical methods and the heuristic description in Hsiang (2010) remains accurate.

impacts to the extent that they are correlated with wind speed.

We use LICRICE to reconstruct the wind field as a translating vortex for all 2,246 storms recorded in the West Pacific Basin between 1950-2008 by interpolating among 72,901 6-hour observations over every $1/34° \times 1/34°$ pixel of the Philippines ($1/34° \approx 0.0294° \approx 2.02$ miles ≈ 3.26 kilometers). Figure 3 illustrates a snapshot of a storm's wind field for an example storm, with the height of the surface depicting the speed of the surface winds. Using this approach, we find that 837 storms affected the Philippines[8] between 1950-2008 (13.72 storms per year). Of these storms, 411 occurred during 1979-2008 (13.70 storms per year), the period for which we have overlapping economic and health data. For reference, annual maps of raw LICRICE output for the period 1979-2008 are presented in Appendix Figures C.3 and C.4

To match typhoon exposure with annualized socioeconomic data files, our continuous physical measure of typhoons must be summarized to form a single observation for each location in every year. We summarize annual typhoon exposure for provinces and regions by computing the maximum wind speed achieved at each pixel and then taking the average across pixels within an administrative unit. We opt for this measure because it allows us to capture storm intensity while controlling for variations in the physical size of regions and provinces[9]; a storm that passes over the entirety of a geographic area would thus register as stronger treatment than one that merely passed

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[8]That is, 837 storms registered non-zero wind speeds over at least one $1/34° \times 1/34°$ pixel.

[9]Hsiang and Narita (forthcoming) discuss the variety of tropical cyclone measures that have been employed in previous econometric studies, such as windspeed at landfall, minimum central pressure and total energy dissipated. As Hsiang and Narita demonstrate, the spatially-weighted maximum wind speed measure that is employed in this study is well-supported by theory and outperforms alternative measures in a country-by-year panel analysis. Briefly, the theoretical basis for this measure rests on two observations. First, the stress-strain relationship for most materials is highly non-linear, with catastrophic failure occurring at a critical level of stress (Nordhaus (2006a)). Thus, for a given material, only the maximum level of stress that the material is exposed to, i.e. the maximum wind speed, is relevant for determining whether failure is expected. Secondly, people and capital are distributed across space within a province, making it necessary to construct some sort of spatial average for wind exposure. We follow Hsiang (2010) and Hsiang and Narita (forthcoming) and adopt area-weights for our averages because they cannot be endogenous in the same ways that population, capital or income weights might be. For further discussion see section A in the appendix.

over a small portion of it. For succinctness, we refer to this statistic as 'wind speed' and it is presented in the units of meters per second (1 m/s = 3.6 km per hour ≈ 2.24 miles per hour)[10].

Figure 4 displays medians, inter-quartile ranges and extreme values of typhoon exposure for each of the 82 provinces in our sample during 1950-2008. The figure illustrates that there is strong variation in typhoon exposure between provinces as well as strong year-to-year variations in exposure at the level of an individual province. Note that no province completely escapes typhoon exposure in the period of observation and there are many provinces that are exposed to typhoons every year. Approximately half of the provinces have median annual exposures in excess of 20 m/s and many provinces are exposed to events exceeding 50 m/s. As shown in Table 1, the average province was exposed to wind speeds of 17.6 m/s (s.d. = 12.0 m/s) between 1950 and 2008, or 16.9 m/s (s.d. = 11.6 m/s) between 1979 and 2008.

Household Asset, Income and Expenditure Data

Information on household assets, income and consumption are obtained from the cross-sectional Family Income and Expenditure Survey (FIES) conducted by the National Statistics Office (NSO) of the Philippines (Ericta and Fabian (2009)). In 1957, the government of the Philippines began conducting the FIES irregularly (approximately every five years) to understand the distribution of income, spending patterns and the prevalence of poverty, as well as to benchmark consumer price indices. In 1985, the survey was completely restructured and the NSO began conducting it at regular three year intervals. In this analysis, we obtain and use FIES Public Use Files for the years 1985, 1988, 1991, 1994, 1997, 2000, 2003 and 2006.

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[10]It is important to note that because reported wind speed values are area-averages, actual wind speeds at the center of storms are substantially greater than the values we report and cannot be directly compared.

The FIES provide us with data on each household's assets across several different categories, household income by source, total income *net* of any transfers and subsidies, and household expenditures on different goods and services.

We note that there are important timing issues to contend with in analyzing the FIES data that arise from the manner in which the survey is administered. FIES data are collected twice for each household, just after the middle of the year (July) and just following the end of the year (the following January), with responses for each survey reflecting economic behaviors over the preceding six months. Responses for each household are then averaged between the two surveys to construct annual estimates; however, if a household cannot be found in either round of the survey they are dropped from the sample[11]. Figure 5 shows the FIES survey timeline overlaid with mean monthly typhoon strikes to indicate why this is a potential concern. Typhoon activity in the Philippines is concentrated late in the year, so estimates of typhoon impacts during the year of exposure may be somewhat attenuated because first phase responses are recorded prior to the bulk of typhoon events. This motivates us to focus on capital losses the year following typhoon exposure, since it seems unlikely that capital can be replaced immediately following a storm[12].

Also concerning is the NSO's policy of dropping second round non-respondents, since typhoons may cause households to migrate, the obliteration of participants' physical homes, or villages becoming inaccessible due to flooding or infrastructure damage[13]. This results in observations being dropped from our sample based on extreme values

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[11]Surveyors attempt to revisit households two additional times if the household head cannot be located in the first visit. Only after three unsuccessful interview attempts is a household dropped.

[12]We note that a typhoon's contemporaneous effect on capital is roughly 53% of its effect in the following year. This is consistent with our concern that contemporaneous effects will be smaller because phase 1 responses occur before roughly 65% of storm events.

[13]The NSO explicitly states that a major cause of second phase survey attrition is the inability to locate households when the physical structure they inhabited during the first phase interview is destroyed by a typhoon before the second phase. When areas become inaccessible due to flooding or infrastructure damage, the NSO generally tries to postpone surveys within the affected region. Unfortunately, the NSO does not provide statistics on these types of attrition.

of the treatment effect we are interested in, a fact that probably biases our estimate of treatment effects towards zero. We attempt to minimize this attenuation by including a vector of observable household covariates in all our models. In addition, we explicitly test for balance on treatment in Section 4.

Lastly, we note that the lowest unit of geographic designation in the FIES surveys changed between the 2000 and 2003 waves; early years include province level identifiers (more detailed) while later years only report regional identifiers (less detailed). Thus, our baseline models analyze outcomes at the province level but omit 2003 and 2006. We then reintroduce these years in region level estimates as a check on our main results. For province level models we are able to match 142,789 household observations contained in the period 1985-2000, whereas our sample expands to 174,896 observations in regional level models that span the period 1985-2006.

Infant Mortality Data

Our infant mortality data are taken from the 1993, 1998, 2003, and 2008 waves of the Demographic and Health Surveys (DHS)[14] for the Philippines. The DHS are cross-sectional surveys with questions related to population, health, and nutrition, particularly pertaining to maternal and child health. The DHS program is highly standardized with changes between surveys documented and propagated, allowing for comparison of surveys both across countries and within countries across time. Samples are designed to be representative at the national and regional levels. Within the Philippines, each household's location is identified according to its administrative region and provincial identifiers are not available.

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[14]The DHS are administered by the Measure DHS project (funded largely by USAID) and are available for free download online at http://www.measuredhs.com/. Started in 1984, the DHS program has collected survey data on 84 countries as of late 2011, with many of those countries having been subject to multiple survey waves.

The primary interview targets of the DHS are women between the ages of 15 and 49. A wide suite of questions are asked on topics ranging from HIV awareness to nutritional practices to each woman's full fertility history. The latter provides us with a source of our infant mortality data, as each woman is asked to provide detailed information about every child she has ever born, including any children who have died. We are thus able to construct a time series for each woman's fertility and mortality events over the duration of her life up until the survey, echoing recent research that uses the DHS in a similar way (Kudamatsu (2011); Kudamatsu, Persson, and Strömberg (2011); Chakravarty (2011)). We follow these authors in excluding migrant mothers from our sample, thereby minimizing the sorting and migration concerns that arise in the FIES. The 24,841 non-migrant mothers in our sample yield 265,430 mother-by-year observations, or nearly 11 years of longitudinal data per woman. Table 3 shows summary statistics.

The DHS data include several variables aside from infant mortality events which are particularly useful for this analysis. Of particular note are: a measure of each woman's prior migration history, captured by whether she has ever lived anywhere else and, if so, when she moved to her current location of residence; educational attainment of both the woman and her husband, if any; the geographical region in which the woman resides; and the woman's age at time of survey. While there is no direct questioning on each woman's or household's income, a variety of socioeconomic status (SES) indicators are collected, ranging from whether the household has electricity to whether anyone in the househole owns a car. We construct a proxy for socioeconomic status from these data for comparison of distributional impacts in a process detailed in Section B.

Other Data

Emergency Events Database (EM-DAT) Nationally aggregated data on economic losses and deaths from tropical cyclones are obtained from the Emergency Events Database data file commonly referred to as "EM-DAT" (OFDA/CRED 2009). The EM-DAT data file contains information provided by national governments, international organizations, NGOs, and private companies (e.g., re-insurance companies) on a self-reporting basis[15]. EM-DAT data of economic losses are an estimate of negative economic impacts that may include lost consumption goods, lost productive capital or cost of business interruption, depending on the protocols of the reporting institution. EM-DAT is the database used in most previous cross-country studies of post-disaster economics, with some of its limitations discussed in the review by Cavallo and Noy (2009).

Temperature and Rainfall We control for mean annual temperature and rainfall in all of our analyses to minimize potentially confounding climate behaviors that might be correlated with typhoon incidence (Auffhammer et al. 2010). Temperature observations are extracted from the gridded reanalysis of the Climate Data Assimilation System I (CDAS1) produced by the National Center for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR) (Kalnay et al. (1996). Rainfall estimates are obtained from the Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP) which merges station readings on the ground with available satellite data (Xie and Arkin 1996). Both temperature and precipitation data are spatially averaged over each region or province.

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[15]EM-DAT is provided for free by the Centre for Research on the Epidemiology of Disasters (CRED) at `www.emdat.be`, Universite Catholique de Louvain, Belgium.

Crop Prices and Wage Rates Province-level data on annual farm worker wage rates and commodity retail prices are obtained from the Bureau of Agricultural in the Philippines[16]. Data are available for the period 1985-2008.

4 Identification

To empirically identify the impact of typhoons on household outcomes we use a difference-in-differences approach that exploits random variations in each location's typhoon incidence. Identifying the treatment effect of typhoons requires that we must only utilize variations in typhoon exposure that are randomly assigned to households (Holland (1986); Freedman (1991)). Because the formation of typhoons and their trajectories have strong spatial patterns, some locations have relatively higher or lower levels of average typhoon exposure (recall Figure 1). However, these cross-sectional variations in mean exposure might be correlated with cross-sectional differences in the unobservable characteristics of different locations, for example culture. For this reason, we do not utilize the cross-sectional variation in average exposure and instead rely only on random year-to-year variations in exposure at each specific location. To achieve this, we include province (or region) fixed-effects in all of our regressions to absorb any cross-sectional variation in typhoons exposure or losses. If there are unobservable reasons why some locations have higher (or lower) incomes or infant mortality on average, these fixed-effects will non-parametrically account for this difference and it will not contaminate our estimates of the typhoon treatment effect (Greene (2003)).

Randomness in typhoon exposure arises because both the location and timing of storm formation as well as storm trajectories themselves are stochastic. One might be concerned that annual variations in storm exposure might not be entirely random

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[16]Details and data are available at http://countrystat.bas.gov.ph

because households could make location choices based on seasonal typhoon forecasts. Yet, while it is now possible to predict average storm frequencies for each storm season in a given basin with moderate skill (Heming and Goerss (2010); Smith et al. (2010)), these forecasts have almost no predictive power if one were to try forecasting *location-specific* seasonal risk. Thus, it is reasonable to assume that annually varying risk differentials are imperceptible for individuals on the ground, since these differentials still cannot be predicted by scientists. In contrast to seasonal prediction, it is possible to forecast typhoon exposure a few days before a storm strikes[17] (Heming and Goerss (2010)), a fact that often allows individuals to evacuate and protect some of their assets. This is important for interpreting our results, because the treatment effect that we estimate is the effect of typhoons after households have employed the full range of adaptive behaviors available to them, such as evacuation. But it does not seem plausible that short-term evacuations based on short-term forecasts lead to the reorganization of populations on annual time-scales, so it is unlikely that forecast-based sorting affects our annualized estimates.

We wish to avoid spurious correlations, so we must avoid correlating trends in typhoon incidence and our outcomes of interest. To do this, we flexibly account for common trend behaviors by including year fixed-effects in all of our models (Greene (2003)). These fixed effects also account for any unobservable common climatic shocks, such as the El-Niño-Southern Oscillation, which could be correlated with typhoon exposure (Camargo and Sobel (2005)) as well as socio-economic outcomes (Hsiang, Meng and Cane (2011)).

The primary threat to the validity of our study is the potential for household sorting in the wake of typhoon exposure. As we explained, sorting due to typhoon *risk* should

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[17]For example, Willoughby et al. (2007) note: "In the past, a forecast was considered successful if it predicted the hurricanes position and intensity 12 - 72 h into the future. By the 1990s, forecast users came to expect more specific details such as spatial distributions of rainfall, winds, flooding, and high seas. In the early 21st century, forecasters extended their time horizons to 120 h."

not be a major concern since we include location fixed-effects and annual changes in risk are imperceptible to households. Sorting on typhoon *incidence*, however, could be problematic if the passage of a storm causes families to migrate away for long periods, altering the household composition of different locations. This is of particular concern for the FIES data given their survey methodology (discussed in Section 3).

To address this concern, we test for balance in the FIES data by regressing observable household characteristics on typhoon exposure, presenting results in Table 4. This approach checks whether observable household characteristics vary with the intensity of the previous years' typhoon exposure. We allow household composition to vary nonlinearly in response to typhoon exposure by including indicator variables for prior year's maximum wind speed[18]. In support of our approach, we find almost no evidence of sorting. Out of 49 parameters estimated, six are statistically significant at the 10% level and one is significant at the 5% level; this is very close to what we would expect if household composition were random (five and two respectively). If one interprets these coefficients literally, they might provide suggestive evidence that typhoon exposure is positively associated with total family size and negatively with the probability that the household head has finished primary school. However, in neither case does the intensity of cyclone exposure matter in a systematic way, suggesting that these correlations are probably random[19]. Nonetheless, to be certain that bias from sorting along these covariates is minimized, we control for all of these all of them in our main regression models.

We are less concerned about sorting in the DHS data for two reasons. First, households in the DHS are asked whether they have ever lived anywhere other than their current location. This allows us to directly avoid sorting behavior by restricting our

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[18]This exact model is used throughout the paper to identify the effect of typhoons on time-varying outcomes. It is explained in greater detail in the next section.

[19]See Appendix Section A for additional discussion.

sample to non-migrant mothers. The second reason is that, unlike FIES data, the DHS data are a true panel that allows us to follow specific women over time. Thus, there are no compositional changes in the DHS panel that can be driven by typhoon exposure during the mother's adult life.

5   Results

We structure the presentation of our results as follows: We first demonstrate that our measure of typhoon incidence accurately predicts physical damage at both the macro and micro level in Section 5.1. We then demonstrate in Section 5.2 that the legacy of this physical destruction leads to losses to income the year following storms, which are closely matched by expenditure and consumption losses as detailed in Section 5.3. We then demonstrate the infant mortality impacts of typhoons in Section 5.4 and provide evidence supporting the argument that they stem from economic losses in Section 5.4.2. Lastly we explore cross-sectional evidence of adaptation in Section 5.5.

5.1   Physical damages

It may seem obvious that typhoons are physically destructive, but measuring the economic importance of this destruction is not trivial. The first studies that used aggregate measures of tropical cyclone (including typhoon) losses were unable to detect any effect of storm intensity on losses (Kahn (2005); Noy (2009)). If this result were accepted at face value, it would imply that variations in the intensity of cyclone climates have no effect on economies. In this section we show evidence that our measure of typhoon incidence predicts physical damages using both national data from EM-DAT as well as asset loss data from FIES.

5.1.1 *Prima Facie* Evidence from National Data

We begin by presenting *prima facie* evidence that aggregate losses scale with typhoon intensity in the Philippines. Using "standard" EM-DAT estimates for all the economic losses and deaths attributed to typhoons in each year, we estimate whether national losses increase with wind speed exposure, averaged over the entire country. National losses and their bivariate dependance on wind speed are shown in Figure 6. In Table 5 we present several ordinary least-squares estimates for the time-series regression

$$Z_t = \alpha W_t + \mu + \theta_1 t + \theta_2 t^2 + \epsilon_t \tag{1}$$

where Z is the log of total deaths or total economic losses, W is typhoon wind speed, μ is a constant, θ_1 and θ_2 are trend terms and ϵ is variation that we do not explain. Following Pielke et al. (2003) and Hsiang and Narita (2011), we also present models where the dependent variable Z is normalized by the size of the economy (GDP) or the country's population.

We find that national average typhoon exposure explains about a third of the variation in EM-DAT's estimates for both total typhoon damages and total typhoon deaths. In all models, the intensity of wind exposure is highly significant, with an increase in wind exposure by one meter per second increasing losses roughly 22%. We note that the economic damages estimated by EM-DAT include capital losses, lost revenue and any other "economic cost" that is associated with a storm, but it is impossible with these data to uncover finely-grained structure that might indicate the mechanism by which either damages or, for that matter, deaths occur.

21

5.1.2 Household asset losses

To estimate typhoons' impact on household assets, we use ordinary least-squares regression to estimate the linear probability that a household has each of several different types of physical capital recorded in the FIES data. We control for unobserved household attributes common across households in a given year or province by including province and year fixed effects. We further augment the model with controls for households' observable characteristics, namely: the total number of household members; the number of members above fourteen years old; and age, gender and education level of the household head. Finally, we control for the annual mean temperature and rainfall observed in each province in each year, since these variables are known to affect economic conditions (Miguel, Satyanath, and Sergenti (2004); Nordhaus (2006b); Schlenker and Roberts (2009); Dell, Jones, and Olken (2009); Hsiang (2010)) and they are driven by many of the same climatological factors that affect typhoon incidence[20]. Thus our complete regression model is

$$Z_{hprt} = \sum_{L=0}^{5} [\alpha_L W_{p,t-L} + \beta_L T_{p,t-L} + \gamma_L R_{p,t-L}] + \tau_t + \mu_p + \zeta X_h + \epsilon_{rt} + \epsilon_{ht} \qquad (2)$$

where h indexes households, p indexes provinces, r indexes regions and t indexes years. Z is a one if a household has an asset and zero otherwise while W is typhoon wind speed, T is temperature, R is rainfall, τ is a year fixed-effect, μ is a province fixed-effect, X is the vector of observable household characteristics, ϵ_{rt} is a shock affecting all households in a region and ϵ_{ht} is a household level disturbance. We employ a distributed lag model to examine the effect of typhoon exposure for the five years prior to the survey, with lags indexed by L. In addition, because region-level shocks may exhibit unknown patterns of serial correlation and household-level shocks may exhibit spatial correlations at a

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[20]For example, typhoon activity in the West Pacific is affected by the El Niño-Southern Oscillation (Camargo and Sobel (2005)), which also influences temperatures and rainfalls in the Philippines .

sub-regional but supra-provincial scale, we cluster our estimated standard errors at the region level following Bertrand, Duflo, and Mullainathan (2004)[21] and Conley (1999).

Table 6 presents estimates of α for four of the most general and widely owned household assets: a closed toilet (eg. not a pail or open pit), a television, walls constructed with primarily strong materials (compared to light or salvaged materials) and access to electricity. We find that for all these assets response to previous year's typhoon treatment is negative and significant, varying between a 0.11% and 0.16% probability of loss per m/s of typhoon treatment, or 1.9 - 2.7 % given the average annual provincial treatment of 16.9 m/s. Cars, which we also show, do not respond at all, possibly because they are a valuable asset that can easily be moved quickly when typhoon forecasters warn populations about an impending storm[22]. We show additional results of typhoon treatment for an array of other household assets in appendix table C.2. We note that the average coefficient across all 14 assets in year zero is -0.036, versus an average coefficient in the first year lag of -.069. We estimate that the asset response in year 0 is thus 52.5% of the response in year 1, consistent with our observation that year-of typhoon impacts estimated using FIES data will be biased downwards due to averaging across the two waves of the survey and possible attrition.

Non-Linear Estimates of Asset Losses   We now relax, and test, the assumption that physical damages, and hence asset losses, are linear in windspeed. It is plausible that damage is highly non-linear in windspeed; for example, Nordhaus (2010) and Mendelsohn et al. (2010) argue that losses are a power function of windspeed at landfall. However, these papers examine aggregate storm damages, similar to Equation 1, so it

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[21]Because regions are aggregations of provinces and provinces are the level of treatment, clustering by region means we are also clustering at the level of treatment. Clustering at the province level does not appreciably change our results.

[22]It is also possible that the coefficients for cars is small because there are a limited number of households in our sample that ever possess a car.

is not obvious whether estimates using our micro-data should have similar functional forms. Thus, we estimate the losses to wind speed non-parametrically, allowing the response function to have an arbitrary functional form, and examine whether it is approximately linear or not. To do this, we construct dummy variables that are one if exposure falls within a five meter per second range and zero otherwise

$$\tilde{W}_{p,t-1}^{[x,x+5)} = \mathbf{1}\left[W_{p,t-1} \in [x, x+5)\right]$$

leaving events with 0-5 meters per second as the dropped bin. We then run the regression from Equation 2 where the inner product of these dummy variables and their coefficients replace the linear term $\alpha_1 W_{p,t-1}$. To limit the number of estimated parameters, we keep the remaining terms unchanged and focus our attention on the coefficients of these dummy variables. The full nonlinear model that we estimate is

$$
\begin{aligned}
Z_{hprt} =& \alpha_1^{[5,10)}\tilde{W}_{p,t-1}^{[5,10)} + \alpha_1^{[10,15)}\tilde{W}_{p,t-1}^{[10,15)} + \alpha_1^{[15,20)}\tilde{W}_{p,t-1}^{[15,20)} + \alpha_1^{[20,25)}\tilde{W}_{p,t-1}^{[20,25)} + \\
& \alpha_1^{[25,30)}\tilde{W}_{p,t-1}^{[25,30)} + \alpha_1^{[30,35)}\tilde{W}_{p,t-1}^{[30,35)} + \alpha_1^{[35,\infty)}\tilde{W}_{p,t-1}^{[35,\infty)} + \\
& \sum_{L\in\{0,[2,5]\}} \alpha_L W_{p,t-L} + \sum_{L=0}^{5} \left[\beta_L T_{p,t-L} + \gamma_L P_{p,t-L}\right] + \\
& \tau_t + \mu_p + \zeta X_h + \epsilon_{rt} + \epsilon_{ht}
\end{aligned}
\tag{3}
$$

and it is estimated using the same method and sample as Equation 2. Panel A of Figure 7 displays these coefficients for six of the main asset types. The probability that households lose electricity, a closed toilet, walls made of strong materials, their television or their refrigerator increase approximately linearly with typhoon wind speed exposure. In contrast, the probability that a household loses a car to typhoon exposure remains near zero.

The linearity of these response functions indicates that our earlier estimate for the

24

average number of households missing an asset due to typhoons was a good approximation. Furthermore, the coefficient for the 15-20 meter per second bin is generally in the range of 1.5-3%, matching our earlier linearized estimates. Finally, it is worth noting that exposures exceeding 35 meters per second (spatially-averaged) are not uncommon, recall Figure 4, and these stronger events cause 4-7% of households to lose their immobile assets.

5.2 Income Losses

Our approach to estimating income losses mirrors our approach to estimating physical damages. We focus our attention on income earned by households the year following storm exposure, partly to minimize the aforementioned attenuation risk in the FIES data and partly because that is where the result manifests most strongly. We again note that the measures of total household income collected by FIES include all reported transfers from other households and the government. Prior work by Yang (2008) demonstrated that tropical cyclone strikes increased remittances to some countries, suggesting that transfers provided a mechanism for income insurance. In addition, Fafchamps (2003) used Filipino micro data to show that some income shocks lead to inter-household transfers that partially compensate for losses[23]. These previous studies suggest that transfers might be important for mitigating household income losses, so it is fortunate that our measures of total income account for them.

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[23]Deryugina (2011) finds similar results for Federal transfers in response to hurricanes in the United States.

5.2.1 Household Income Losses

To estimate the effect of typhoons on income, we estimate Equation 2 replacing Z with the natural logarithm of household income. Table 7 presents these results[24] in in columns 1-4. Including all all our control variables, we find that household income falls by 0.39% for each additional meter per second of windspeed exposure the year prior. This implies that under average exposure levels (16.9 m/s), average household income is depressed 6.6%. In column 5 we estimate the same model except we match households to the average exposure of its region (the larger administrative unit) rather than its province. Doing this allows us to include the 2000 and 2006 waves of the FIES which we could not do otherwise because households in these waves lack province identifiers. Using this longer sample with coarser measures of exposure, we continue to find a large effect of typhoon exposure on household income. In a final specification check presented in column 6, we collapse our household data to the province level, dramatically reducing our number of observations from 142,779 to 367. This allows us to conduct two additional checks: (1) whether we are over-estimating our true number of independent observations (Bertrand, Duflo, and Mullainathan (2004)) and (2) whether spatial correlations in ϵ cause us to underestimate our standard errors[25] (Conley (2008)). Estimating an analog[26] of Equation 2 using this collapsed data set and estimating spatially-robust standard errors[27] we find our coefficient of interest unchanged and that our standard errors increase only slightly.

In Table 8, we examine whether wage or entrepreneurial income responds more

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[24]Similar to our results for capital losses, province fixed-effects are the most important control for limiting bias.

[25]In theory, we could explicitly account for spatial correlation in errors using our micro-data, however it is not computationally cost effective.

[26]Using our collapsed data set requires that we introduce a lagged dependent variable into Equation 2 because aggregated output measures are highly correlated over time. We do not do this in the model with household data because that data set is not a true panel, so we do not know what household incomes were in the last period of observation.

[27]For technical reference, see Conley (1999).

strongly to cyclone exposure. Entrepreneurial income is income from self-employed activities, including own agricultural cultivation, whereas wage income is income earned by selling labor to firms or other households. We find that self-employed entrepreneurial income responds strongly and negatively in the year following storms, falling -0.28% per m/s or 4.7% for average treatment. Non-agricultural wages also fall by an average of 3.2% per year, although the effect is not significant, and it is worth noting that both coefficients are negative, but not significant, in the second lagged year as well. This is in stark contrast to agricultural wages, which do not respond negatively in the first lag and exhibit little systematic variation in response to typhoon exposure.

Table 9 presents the estimated value of α_1 for different categories of entrepreneurial income ranked by the number of respondents claiming any income from that source. None of these estimates are statistically different from zero, probably because the sample size declines rapidly for each subcategory. However, we find that the point estimates for lost income are consistently negative with only two exceptions: earnings from gambling and income in the transport and storage industry. We thus are confident in stating that income losses seem to not be driven by losses confined to a single sector.

Non-Linear Estimates of Income Losses   We verify that our linear approximation of the income response is reasonable by estimating Equation 3 for household income. Panel B in Figure 8 plots the coefficient for each wind speed bin along with its confidence interval, and panel B of Figure 7 presents coefficients for the entrepreneurial and non-agricultural wage components of income. All of theses measures of household income loss are approximately linear in wind speed exposure. This linearity suggests that Equation 2 is a good approximation of the response function and it agrees with previously measured GDP responses to tropical cyclone exposure (Hsiang (2010)).

5.2.2 Income Losses at Different Locations of the Income Distribution

Kahn (2005), Skidmore and Toya (2007), Noy (2009), Hsiang (2010), Hsiang and Narita (2011), the United Nations (2009) and the World Bank (2010) have all suggested that poor populations experience larger relative losses to natural disasters, including tropical cyclones. Though compelling, these analyses have been based on country-level comparisons of income which may be tainted by an array of confounding factors as well as subject to omitted variable bias. We explore whether this relationship is plausible within-country by comparing losses for high and low-income households that inhabit the same Filipino province and are subject to the same institutional environment.

The FIES are not a true panel, so we cannot condition household income (or capital) losses on income in the previous period. We overcome this limitation by comparing how the *income distribution* in each province responds to typhoon exposure. To do this, we first collapse the data by province-year, retaining estimates of Y_{pt}^q, the household income at the q-quantile of the income distribution for province p in year t. Thus, for each value of q we have a panel of province by year observations that we use to estimate the model

$$Y_{pt}^q = \rho^q Y_{p,t-1}^q + \sum_{L=0}^{5} [\alpha_L^q W_{p,t-L} + \beta_L^q T_{p,t-L} + \gamma_L^q R_{p,t-L}] + \tau_t^q + \mu_p^q + \epsilon_{pt}^q \qquad (4)$$

where all coefficients are q-quantile specific versions of those described in Equation 2 and ρ^q is a q-quantile specific autocorrelation coefficient that we introduce because our collapse of the dataset generates substantial autocorrelation (recall column 6 of Table 7). Similar to before, our variable of interest is α_1^q, the relative shift of income observed at the q-quantile following the previous year's typhoon exposure.

Panel A of Figure 9 presents OLS estimates of α_1^q for $q \in \{10, 20, ...90\}$ along with confidence intervals. Strikingly, the semi-elasticity of income to wind speed is practically

28

constant at all points along the income distribution, with the response always near the average household response (horizontal line). These results seem at odds with earlier cross-country studies that found different short-run responses for high and low-income populations. Yet, a completely different picture emerges when we examine the cumulative impact of typhoons on the shape of the income distribution. Panel B shows estimates for the cumulative effect of one additional meter per second in wind: $\sum_{L=0}^{5} \alpha_L^q$. When we sum coefficients for all the years following a storm, we see that incomes below the median suffer much larger cumulative losses than income above the median, which actually exhibit no cumulative losses. This occurs because losses at low ends of the income distribution persist for several years after the storm, whereas incomes at the high end of the distribution actually rise slightly above average a few years after the storm, allowing these groups to recover previously unearned income. Thus, when we look at typhoon-induced income losses beyond the first year we find strong evidence that the income distribution widens, with low-income households suffering differentially larger cumulative losses when compared to high-income households.

5.3 Consumption and Investment Effects

Having found strong evidence that household incomes respond negatively to typhoon-induced economic losses, we examine whether consumption and investment expenditures also adjust. To determine whether expenditures fall, we implement the same analysis that we conducted for income, but instead examine the consumption and investment variables available in FIES. Broadly, these variables are all "expenditures," although it is not always possible to clearly distinguish whether a specific variable represents "consumption" or "investment," since many expenditures represent a combination of the two. For example, "recreation" is clearly a consumption good, while "education" is mostly an investment in human capital, but "food" is probably some combination

29

since food consumption increases immediate utility but also augments health, a specific dimension of human capital.

We note that a change in expenditures absent information about a potential change in prices does not allow one to infer changes in consumption. We check for and find little evidence that typhoons affect regional prices for food in Section B of the Appendix.

5.3.1   Household Losses to Consumption and Investment

We estimate Equation 2, replacing Z with the logarithm of household expenditures, and present the results in Table 10. In column 1 we show that household expenditures fall 0.42% for each additional meter per second in the prior year's typhoon wind speed. This implies that under the average level of exposure (16.9 m/s), total expenditures are 7.1% lower than they would otherwise be due to the transient impact of the typhoon climate, mirroring the average income loss of 6.6%. In columns 2-11, we estimate Equation 2 for different expenditure subcategories. For eight out of ten subcategories we observe similar patterns of losses with the exceptions being recreational expenditures, which declines insignificantly, and repairs to the household's capital assets, which rise slightly. Notably, some of the largest relative declines in spending occur in categories related to human capital investments: personal care (-0.74% per m/s), medical services (-0.85% per m/s), and education (-0.79% per m/s). Food expenditures, another type of investment in human capital, do not decline as strongly. However, clear reductions in food expenditure seem to extend over a longer period of time, beginning immediately in the year of storm exposure and continuing for three years afterwards.

In Table 11 we decompose the response of food expenditures into its different subcategories. The strongest declines are clearly in the purchase of meat, with strong responses also appearing in the fish, dairy & eggs and fruit categories. Purchases of cereal also decline, but much less than the more nutritious foods. The overall structure

30

of this response is consistent with previous observations by Subramainian and Deaton (1996) and Jensen and Miller (2008) that real income losses lead to a shift in food consumption that protects overall calorie intake at the expense of nutrients.

The last three columns of Table 11 present the expenditure response for nonalcoholic beverages, alcoholic beverages and tobacco. All three types of purchases decline in the year of typhoon exposure, however their responses after that year diverge: nonalcoholic purchase remain low for up to three more years, alcoholic purchases mostly recover but also have long but statistically insignificant declines, while tobacco purchases become insignificantly positive in the year following exposure but then return to their original level. This relatively lower income elasticity of alcohol and tobacco, pure consumption goods, relative to more nutritious foods, partially human-capital investments, agrees with our earlier observation that other non-food varieties of human capital investments decline more rapidly than expenditures that more closely resemble pure consumption goods (Table 10). This finding is consistent with the hypothesis that wealth shocks directly alter the utility function of household members by increasing the marginal utility of immediate consumption (e.g., Banerjee and Mullainathan (2010)).

Non-Linear Estimates of Consumption and Investment Losses   Following our earlier estimates, we verify that our linear model is a good approximation of the expenditure response by non-parametrically estimating the impact to typhoon exposure. We estimate Equation 3 for total expenditures and present our coefficients in Panel D of Figure 8. We find that the response of expenditures is almost exactly linear and mirrors the response to income, which we illustrate by overlaying the two responses in Panel C of Figure 7. When we examine the various subcategories of expenditures, which we show in Panel D of Figure 7, we continue to observe responses that are linear in typhoon wind speed. Inspecting subcategories of food purchases, displayed in Panel

E, we see the same linear structure.

5.3.2 Expenditure Losses at Different Locations of the Expenditure Distribution

We next examine how the expenditure distribution responds to typhoon incidence, demonstrating that it mirrors the response of in the income distribution. We estimate Equation 4 for both total expenditures and food expenditures, displaying our results in panels C-F of Figure 9. Identical to our results for the income distribution, the total expenditure and food expenditure distributions shift coherently the year after typhoon exposure. This shift persists for the following years at q-quantiles below the median, generating large cumulative impacts. In contrast, total expenditure actually rises in later years for households above median expenditure, leading to a cumulative impact near zero. Households above median food expenditure do not consume extra food in later years, however, so cumulative effects are observable throughout the distribution. It is plausible that this occurs because the benefits or utility from food consumption are not substitutable over time periods longer than a year.

5.4 Infant deaths

Our final analysis of household outcomes centers around estimating infant mortality. We first show that the entirety of the child and infant mortality response is driven by infant female deaths, and then provide evidence suggesting that these deaths are attributable to typhoon-induced economic losses and the resulting household decisions.

5.4.1 The Response of Infant Mortality

We estimate the effect of typhoons on child mortality by altering Equation 2 to reflect the structure of the DHS data. We arrive at the model

$$Z_{wrt} = \sum_{L=0}^{5} [\alpha_L W_{r,t-L} + \beta_L T_{r,t-L} + \gamma_L R_{r,t-L}] + \tau_t + \mu_w + \zeta X_{wt} + \epsilon_{rt} + \epsilon_{wt} \qquad (5)$$

where w indexes a woman. Here, Z is one if a woman reports that a child of the relevant demographic category died in year t and zero otherwise. X_{wt} are the time-varying traits of a woman's age and age-squared. μ_w is a woman-specific fixed-effect that controls for any time-invariant woman-specific traits. Estimates with this model benefit from the fact that our reconstructed panel contains more years (24) than the FIES data (6); they suffer, however, in that DHS reports only the region a woman lives in and not her province, substantially shrinking the number of distinct treatment groups that we have in any given year (13). To account for the fact that all women in a region are coded as receiving the same typhoon exposure, as well as to account for any serial correlation within or between women that in same region, we cluster our standard errors at the region-level.

We present estimates for our parameter of interest, α, in Table 12. The coefficients report the number of additional women, out of one-million, who report the death of a child in association with an increase in wind speed of one meter per second. The first column shows that there is a detectable increase in child mortality the year following a typhoon, with roughly 80 additional deaths (per one-million women) for an increase in exposure by one meter per second. For the period of observation, regional mean exposure was 15.3 meters per second. This suggests that in an average year roughly 1,220 women out of one-million would report a child dying due to typhoon exposure the prior year. Columns 2 and 3 decompose this response into deaths of male and female

33

children, revealing that the bulk of these deaths are among females. Columns 4 and 5 examines whether theses female deaths are from young children and infants, and we see that almost all of the additional deaths are infant females: of the 80 child deaths per m/s, 73 of them are female infants. In contrast, examination of infant males in column 6 reveals that they do not contribute to the observed mortality response in the first lagged year at all.

5.4.2 Attributing Infant Mortality to Economic Conditions and Household Decisions

We chose to examine child mortality partly because we claimed that they reflect human capital stocks, and we interpret these female infant deaths as evidence that households are disinvesting in the health of their female infant children. However, it is possible that these deaths are not a result of disinvestment, but instead result from the physical trauma of exposure to the typhoon itself or the typhoon's aftereffects on the ambient environment, e.g., disease ecology. We lack data on the proximate cause of death, so we cannot completely rule out these hypotheses. However, we are able to demonstrate that this mortality response mirrors the economic response across multiple dimensions, strongly suggesting that economic conditions are causing these infant deaths. Further, we are able to demonstrate that the patterns of infant mortality are consistent with our understanding of how households reallocate resources in response to a wealth shock.

Temporal Structure　The timing of female infant deaths does not suggest that they are a result of direct exposure to typhoons. We illustrate this point in Figure 2, where we estimate a version of Equation 5 at the region-month, rather than woman-year, level. The black line shows cumulative monthly infant female mortality impact of typhoon exposure, normalized such that the cumulative effect evaluated at the month

34

preceeding typhoon impact is 0. We see that the coefficient of typhoon impact on month-of mortality is near zero, and the increase in mortality rates does not manifest until nearly a year after the storm has hit. Deaths continue to accumulate past the 12 month mark, beyond which all infants in the sample have been born after typhoon exposure. We can thus conclude that the bulk of deaths occur significantly later than any immediate traumatic impact of the storm could plausibly be acting.

It is reasonable to question whether fetal exposure to typhoons may be partly driving our results. The recent explosion of literature in fetal origins[28], including natural disasters' impacts on them (Simeonova (2011)), suggests that exposure to shocks while in utero can have serious deleterious effects on later health. One might thus posit that in utero weakening contributes to or perhaps even drives the increase in death rates. We explore this claim in Figure 2 where the dotted grey line shows the number of female births *resulting in an infant deaths* per million households. We see that in utero effects may be contributing somewhat to the increase in deaths, as evinced by the increase in births ending in infant death immediately after typhoon impact. We nonetheless note that a large portion of the total cumulative births resulting in deaths occur 9 or more months after typhoon exposure, when in utero effects are strictly impossible. We conclude that while in utero impacts may be accelerating the increase in infant deaths, they can at most be an auxiliary. This observation is further supported by the lack of a similar death pattern among infant males as detailed in Appendix Section B.

Returning to the annual data, we note that there is a striking agreement between the timing of depressed economic conditions and female infant mortality. The left panels of Figure 8 display the timing of income losses, expenditure reductions and female infant mortality. The spike in mortality coincides with the sharp reductions in income and expenditure described earlier. Both mortality and economic conditions

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[28]For a detailed overview see Almond and Currie (2011).

remain abnormal two years after a typhoon, although effects are smaller and are only marginally significant. Differences only arise three and four years after the storm, when mortality remains slightly elevated but average income and expenditure return to their baseline values.

Non-linear Structure We look for nonlinear structure of the mortality response by altering Equation 5 so that α_1 is decomposed following Equation 3. Panel F of Figure 7 displays the response function for all children, all infants and female infants. The responses of the larger samples are noisy but approximately linear, but when we isolate the infant female deaths that are driving the pooled response we see an almost exactly linear response. Presenting the income, expenditure and female infant mortality responses in the right panels of Figure 8, we see that all three all three match in their linear responses to typhoon wind speed exposure.

Distributional Structure The DHS data lack income information, so to examine distributional aspects of our results we instead examine the mortality response at different locations in the *wealth* distribution. We outline our method for inferring household wealth in Appendix Section B. In Table 13 we present the response of female infant mortality for women above and below the median for assets, as well as for the bottom and top deciles. We find that in the year immediately following storm exposure, mortality is slightly higher in the lowest wealth groups, and moreover remains elevated for several years. This pattern of relative uniformity in the year after the storm, with a slower recovery for poor households, matches the response of income, expenditures and human capital investments, as we illustrate in Figure 4.

Spatial Structure Up to this point, we have only estimated response functions that pool all Filipino observations, however it is possible that some regions are more or

less susceptible to typhoon-induced economic losses. If this is true, and if economic losses are the mechanism through which typhoons increase female infant mortality, then regions suffering larger typhoon-induced economic losses should also exhibit larger typhoon-induced infant mortality. To examine whether this is the case, we estimate region-specific versions of the coefficient α_1. We do this by modifying Equations 2 and 5 so that α_1 is interacted with a vector of region dummies. In the top panel of Figure 10, we plot $-\alpha_1^{food\,expenditure}$ against $-\alpha_1^{income}$ for each region. The strong positive correlation verifies that locations with larger typhoon-induced income losses are also the regions with larger reductions in typhoon-induced food purchases, one of the most important inputs to human capital. In the bottom panel, we plot $\alpha_1^{infant\,mortality}$ against the coefficient for income, finding that the regions with stronger economic responses to typhoons are also the regions with stronger mortality responses.

Gender Bias A striking feature of the response is that it is completely restricted to female infants, with no similar response in male infants, as can be seen in Table 12. Differentially worse health outcomes for female children in times of economic duress are a common result in the development literature, see e.g., Rose (1999) for a specific case and Duflo (2005) for an overview. This pattern is generally thought to arise because parents give less weight to girls' outcomes when making decisions about intrahousehold resource allocations. Maccini and Yang (2009) and Senauer, Garcia, and Jacinto (1988) both provide evidence that this dismal situation applies to the Philippines as well. Thus, our finding that typhoon-induced infant mortality is a strictly female phenomenon is consistent with previous work on the within-household allocation of resources following income shocks.

We note that it is possible that the gender differential in mortality could be partly driven, at least shortly after impact, by the commonly documented tendency of males

to die in utero at higher rates than females (Almond and Currie (2011); Sanders and Stoecker (2011)). We examine this claim in section B in the appendix and note that while it may be occurring in our data, it cannot explain more than a portion of unobserved male deaths in the first year.

Resource Competition Among Siblings   If the female infant mortality that we observe occurs because of disinvestment in female children, it is plausible that this disinvestment will be larger if the female infant faces greater competition for resources via older siblings, particularly older brothers[29]. We look for evidence that female children who must compete for resources with other children are more likely to die in the year following a typhoon by estimating the mortality response of four subsamples of female infants: those who are the first born to their mother, those who have only older sisters, those who have only older brothers, and those who have both older sisters and brothers. Table 14 presents our results. We find that mortality among first born females is moderate, but it doubles when infants have older sisters and nearly doubles again if there are any older brothers. We interpret these findings as strong evidence that female infant mortality is driven by resource scarcity within households and not by physical exposure to typhoons themselves.

5.4.3 "Economic Deaths" Exceed "Trauma Deaths"

Our finding that infant mortality mirrors the structure of economic losses (in time, space, income/wealth, and storm intensity) combined with our finding that it is both gendered and enhanced by sibling competition, strongly suggests that these infant deaths are caused by economic conditions that deteriorate in the wake of typhoons and not by physical exposure to the typhoons themselves. We thus term the lagged mortality we observe in our data "economic deaths" to distinguish it from the "trauma

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[29]See, for example, Butcher and Case (1994).

deaths" resulting from direct physical exposure to the storm itself, e.g., via drowning or blunt injuries. We estimate that in the average year, the prior year's typhoon climate causes 1,130 additional female infant deaths in every one-million households, roughly 55% of female infant mortality in our sample. A back-of-the-envelope calculation[30] suggests that across the entire country this amounts to approximately 11,300 "economic deaths" annually. This number exceeds 721, the annual average[31] number of "trauma deaths" reported by EM-DAT across the entire population, by more than a factor of 15. These findings indicate that most of the Filipino mortality from typhoons does not result from physical exposure to the storm. Rather, the bulk of mortality occurs due to deterioration of economic conditions and subsequent disinvestment in health and human capital.

5.5 Evidence of Adaptation to Typhoon Climates

Households should suffer positive typhoon loses only if adaptation to their typhoon climate is costly. Here, we briefly examine whether there is evidence of adaptation to typhoons using cross-sectional variation in typhoon climates (recall Figures 1 and 4).

5.5.1 Optimal Adaptation in Theory

We imagine that households can exert costly adaptive effort e to reduce their losses if a typhoon strikes[32]. If the cost function over e is convex, then households will exert adaptive efforts only until their marginal costs of effort equal the expected marginal benefits. Because adaptive efforts only provide benefits when a typhoon actually strikes, loca-

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[30]We observe a death rate per woman-household of 1,130 deaths per million; 44.8% of women in the sample are non-migrants; and there were 22.3 million women aged 15-49 (the DHS age range) in 2007 according to the Philippine National Statistics Office as detailed at http://www.census.gov.ph/data/pressrelease/2010/pr10162tx.html.

[31]Between 1985-2006.

[32]For example, households could reinforce the walls of their home.

tions that have more frequent or more intense typhoons should have greater returns to adaptation. Thus, theory predicts that households located in relatively intense typhoon climates will invest more in costly adaptation, reducing their marginal losses when a typhoon actually strikes. Denoting a household's optimal level of adaptive effort e^*, we expect

$$\frac{\partial e^*}{\partial \bar{W}} > 0 \tag{6}$$

where $\bar{W}$ is expected typhoon wind exposure, a summary statistic for a location's typhoon-climate. Unfortunately, we cannot directly observe whether this is true because we do not observe e^*. However, increasing effort reduces marginal losses $(-\partial Y/\partial W)$ to a fixed level of actual typhoon exposure

$$-\frac{\partial}{\partial e}\frac{\partial Y(e)}{\partial W} < 0. \tag{7}$$

This enables us to infer that adaptation is occurring if we see that marginal losses decline as climates intensify. Assuming households optimize, we multiply equations 6 and 7 to obtain

$$-\frac{\partial}{\partial \bar{W}}\frac{\partial Y(e^*)}{\partial W} < 0 \tag{8}$$

a result that we now investigate empirically. For a more complete treatment of optimal adaptation to tropical cyclone climates, as well as empirical evidence from around the world, we refer readers to Hsiang and Narita (2011).

5.5.2 Cross-Sectional Evidence of Adaptation

We test Equation 8 by examining whether typhoon-induced losses vary with the typhoon climatologies of different Philippine regions. In the top panel of Figure 11, we plot the negative semi-elasticity of income $(-\partial Y/\partial W)$ for each region against its average typhoon exposure $(\bar{W})$. Consistent with Equation 8, the marginal effect of typhoon exposure declines with increasingly intense typhoon climates. This suggests that populations do invest adaptive effort in response to their typhoon climate. However, we note that all regions have positive marginal losses, indicating that no region undertakes "complete adaptation" by driving their marginal damages to zero. In the lower panel we provide suggestive evidence that this adaptive response can also be observed in female infant mortality responses.

Two points regarding the top panel of Figure 11 are worth noting. First, the average losses due to cyclones remain high even for regions that exhibit high levels of adaptation. This occurs because average exposure necessarily increases with the climatological wind speed, so more intense average exposure counteracts falling marginal losses. In Figure 12 we plot estimates for average annual losses and find that average total losses are almost constant across all climatologies[33]. The second point of note is that the slope of the OLS fit, representing the response of adaptive effort to climatological conditions, is -0.04. This implies that marginal losses decline by roughly 2.8% with each one meter per second increase in climatological wind speed. This number, estimated using only the within-Philippines cross-section, almost exactly matches Hsiang and Narita's (2011) earlier estimate (3%) which used the cross section of all countries in the world[34].

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[33]We fit a quadratic curve because total average cost should be quadratic if the response in Figure 11 is linear.

[34]Using the same measure of cyclones exposure (spatially averaged maximum wind speed), Hsiang and Narita (forthcoming) found that increasing average exposure by 1 m/s led to adaptive adjustments which reduced marginal damages by approximately 3% of their baseline value (when average exposure was 0 m/s). Our results, presented in Figure 11, indicate that increasing average exposure by 1 m/s reduces marginal income losses by roughly 2.8% of the analogous baseline value (marginal income

6   Summary and Discussion

We have shown that the typhoon climate of the Western Pacific imposes major economic and human costs on Filipino households. We observe this impact directly in the form of lost physical assets; measure its economic effect of depressing household income and reducing consumption and human capital investments; and lastly show evidence that these disinvestments have irreversible consequences, which we demonstrate by examining infant mortality. We discuss some implications of these results and policy options below.

The Magnitude of Typhoon Losses   We summarize the magnitude of typhoon-induced losses in Table 15, where we estimate average annual losses attributable to the typhoon climate of the Philippines. We estimate that an average household's income was 6.57% lower in an average year due to the previous year's typhoon exposure. To place this in context, the Philippines' National Statistical Office estimates that the average family's savings rate was 14.7% in 2009[35]. These income losses are closely tracked by a 7.08% reduction in expenditures, with particularly large reductions to human capital investments such as education (13.3%) and medicine (14.3%). Food consumption is less elastic, falling 5.9% in the average year, but this masks large substitutions away from expensive and higher nutrient foods, such as meat and dairy, and towards cheaper calories, such as grains. We find that average levels of typhoon exposure raise female infant mortality rates by 1,130 deaths per million households per year. Accounting for the fact that a child is not born in every household in every year, this translates into 18.1 deaths per thousand live births. This amounts to 55.0% of the observed female

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losses are 0.0143 log points per m/s when average exposure is set to 0 m/s in Figure 11).

[35]Calculated using an average family income of 129,000 pesos and savings of 19,000 pesos for 2009. Data available at http://www.nscb.gov.ph/secstat/d_income.asp

infant mortality rate in our sample[36].

These results are large, and it is important to be clear when interpreting them. We calculate these losses based on mean typhoon incidence in the average province/region; so we interpret them as capturing the expected difference in outcomes between a typhoon-free year and a year experiencing average typhoon exposure (16.9 m/s). They can thus be thought of as mean losses conditional on the Philippines having the typhoon climate that it has; any major shift in that typhoon climate would necessarily lead to a host of adaptive responses that are impossible to estimate given lack of an observable counterfactual.

Implications for Economic Development Our results indicate that typhoons destroy existing capital and reduce investments in new capital. Both of these effects are a concern for economic development. As discussed in Hsiang (2010), Dell, Jones, and Olken (2011), and Pindyck (2011), climatic conditions that interfere with capital accumulation and economic growth are particularly pernicious because their effects are compounded over time. The repeated exposure of populations to tropical cyclones, both in the Philippines and elsewhere, probably slows the accumulation of capital stocks at the household level. Unfortunately, such long run effects are difficult to identify empirically because cross-sectional variations in cyclone-climates are correlated with unobservable omitted variables; hopefully, future research will address this challenge. Nonetheless, given our evidence, tropical cyclones should be added to the list of geographically-varying factors which may be contributing to spatial patterns in global economic development (Gallup, Sachs and Mellinger (1999); Nordhaus (2006b)).

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[36]We calculate the ratio of deaths per million households per year to deaths per thousand infants in our sample to be 61.92. Note that the observed female infant mortality rate is our sample of 33.0 per thousand is close to the mean UN estimate for female infant mortality in the Philippines between 1985 and 2005 of 28.3 per thousand (data available from `http://data.un.org/`)

Implications for Climate Change   As previously discussed and shown in Figure 1, the Philippines has one of the most active typhoon climatologies in the world. The frequency with which typhoons impact the Philippines suggests that households must understand and incorporate typhoon risk into their economic decisions (Mendelsohn (2000); Hsiang and Narita (forthcoming)). Thus, we interpret our estimates as conditional on households having already exploited the full range of adaptive behaviors available to them. This assumption is supported by our cross-sectional evidence that levels of adaptation vary across typhoon-climates, results that match the cross-country findings of Hsiang and Narita (forthcoming) with striking precision. The fact that we continue to observe large typhoon impacts in one of the world's most intense typhoon climates, where populations have already adapted optimally, suggests that adaptation costs are so high that populations find they are better off suffering typhoon losses rather than investing in additional adaption. This has unsettling implications for future climate change policy.

In the design of climate change policy, adaptation to climatic changes is viewed as a substitute for efforts to mitigate climate changes directly (Stern (2006); Nordhaus (2008); de Bruin, Dellink and Tol (2009); Aldy et al. (2010); Patt et al. (2010)). If adaptation is generally inexpensive compared to mitigation, then the cost-minimizing strategy is to not invest heavily in mitigation and instead to rely primarily on adaptation. However, if adaptation is very costly, then mitigation should be utilized more vigorously. Our findings suggest that adaptation to tropical cyclones is extremely costly; thus policies cannot assume that adaption to changes in the future cyclone climate[37]

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[37]Knutson et al. (2010), a recent review of this topic, conclude

> [F]uture projections based on theory and high-resolution dynamical models consistently indicate that greenhouse warming will cause the globally averaged intensity of tropical cyclones to shift towards stronger storms, with intensity increases of 211% by 2100. Existing modeling studies also consistently project decreases in the globally averaged frequency of tropical cyclones, by 634%. Balanced against this, higher resolution modelling studies typically project substantial increases in the frequency of the most intense cyclones, and

will be cheap. This should increase the estimated social cost of greenhouse gas emissions, and concomitantly the value of mitigating these emissions. We may speculate that technological advances will reduce the future cost of adaptation, but until further evidence is martialled this remains an assumption. Moreover, if adaptation costs to tropical cyclones are representative of adaptation costs to a broader class of climatological phenomena, this would suggest that current models of future adaptation are too optimistic (de Bruin, Dellink and Tol (2009)).

Policy Options in the Current Climate

Setting aside issues surrounding the future climate, it is important to note that there are a variety of targeted policies that might increase the welfare of Filipino households, or other typhoon-afflicted populations, in the current climate. At present, large-scale post-disaster management is almost entirely an *ad hoc* process that is strongly influenced by political concerns and the media (Besley and Burgess (2002); Garrett and Sobel (2003); Eisensee and Strömberg (2007); Yang (2008); Kunreuther et al. (2009); United Nations (2009)). However, our findings provide insight into systematic policies that could address typhoon-induced welfare loss.

Insurance Social insurance allows Filipino households to smooth their consumption over some, but not all, income shocks (Fafchamps (2003), Yang and Choi (2007)). Our observation that consumption responds strongly to typhoons, reflecting income changes, indicates that current insurance networks are not well-diversified against these events. Perhaps this occurs because typhoons are large with respect to insurance networks, a

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increases of the order of 20% in the precipitation rate within 100 km of the storm centre. (p. 157)

Thus the entire distribution of tropical cyclone events is expected to shift on average, with fewer low intensity storms but more frequent high intensity storms. However, there remains extensive uncertainty and the relationship between tropical cylcones and warming is an area of active research.

fact that would reduce the idiosyncratic component of the income shock (Townsend (1995)). Expanding insurance networks over larger spatial scales should reduce the uninsurable aggregate component of typhoon shocks; however this must be done carefully as even wealthy countries have struggled to sustainably insure tropical cyclone risk (Kunreuther et al. (2009)).

Credit Without looking specifically at credit markets, we cannot say exactly how they behave in the wake of Typhoons. However, we observe that income and consumption in low income households recover more slowly than in high income households. It is plausible that this differentially slow recovery persists because poor households are credit constrained, preventing them from efficiently rebuilding their capital stocks (Duflo and Banerjee (2007); Noy (2009)). If this is true, subsidizing the development of credit markets for low-income households may increase their resilience.

Information It seems unlikely that the households in which female infants die are intentionally allowing these infants to perish. It is more plausible that parents believe their newborn can cope with higher-than-average levels of neglect, and that there will be limited permanent damage (Duflo and Banerjee (2011)). Unfortunately, for a small number of unlucky families, this assumption proves false. It may be the case that simply educating parents about the risks of post-typhoon neglect will be enough to mitigate a large portion of typhoons' effect on infant mortality.

Targeted Subsidies If household decisions were made to perfectly optimize household welfare, than post-disaster economic decisions would be efficient. Unfortunately, it seems that children's long-term welfare, which depends in part on their human capital, is differentially neglected in comparison to short-term consumption of goods like recreation, tobacco and alcohol. In this situation, it may be optimal to tax adults

46

to finance human capital subsidies that specifically target children. To avoid political manipulation of these subsidies, it might be possible that they be indexed to verifiable measures of typhoon exposure (Hellmuth (2009)).

Technology Standards Because it is difficult for consumers to verify the quality of infrastructure, construction quality may not be properly priced into markets (Olken (2007)). This could introduce additional uncertainty into households' calculation of the economic risk they bear in a particular typhoon-climate. To correct for this market imperfection, it may be optimal for governments to enforce building codes or other technology standards that mandate a specified level of robustness to typhoon exposure.

Research and Develop Adaptation Technologies We find a continuous gradient in levels of adaptation that reflects the gradient in cyclone risk. This suggests that adaptation technologies are effective, however the cost of adopting additional adaptation technology is binding throughout the Philippines (Hsiang and Narita (forthcoming)). Thus, research and development that raises the effectiveness or reduces the cost of adaptive technologies should induce households to employ greater levels of self-protection.

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7   Tables and Figures
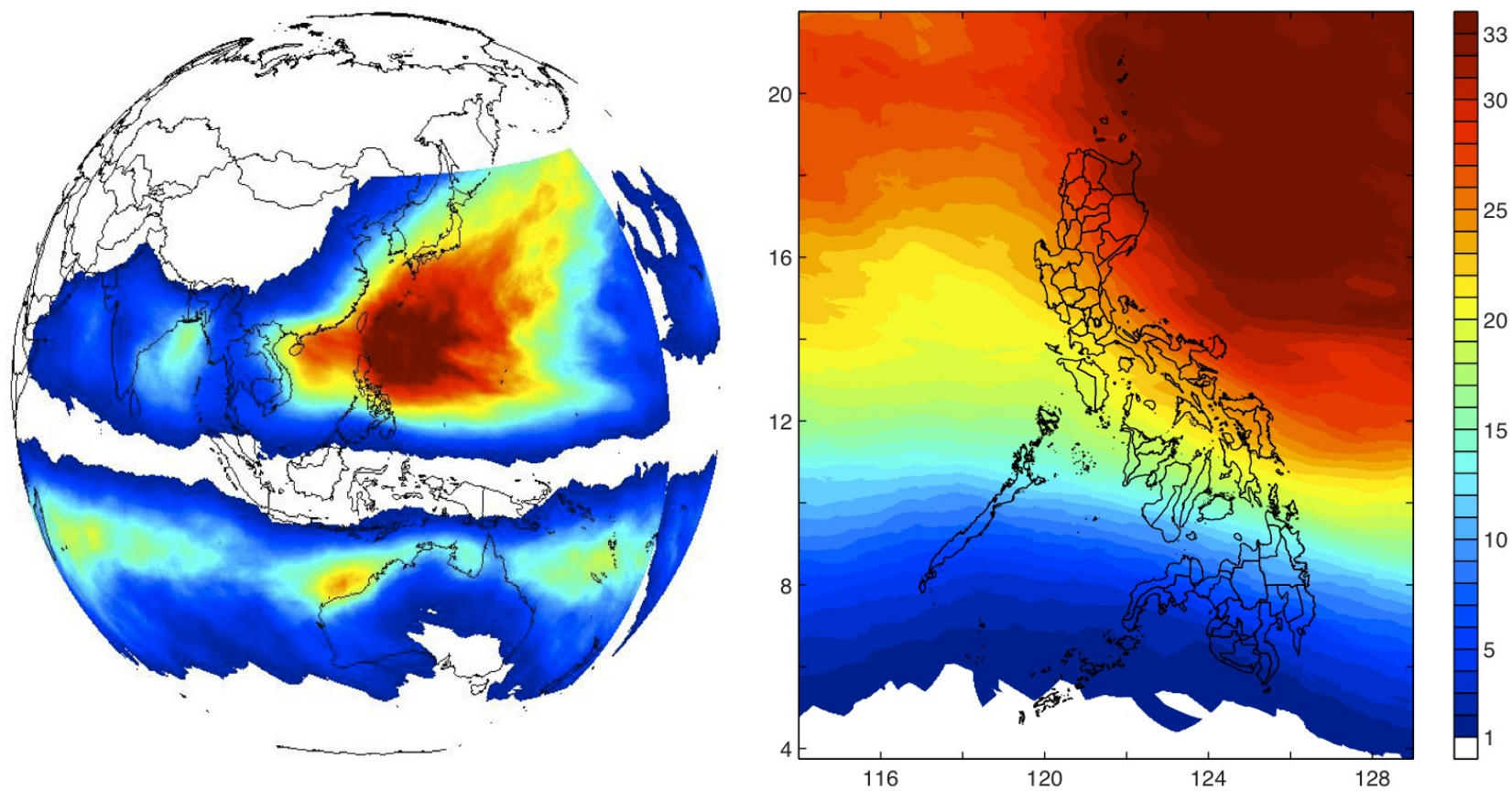
Figure 1: Annual maximum wind speed (in meters per second) averaged over 1950-2008. Data: LICRICE.

Cumulative female infant deaths (per million HH per m/s)
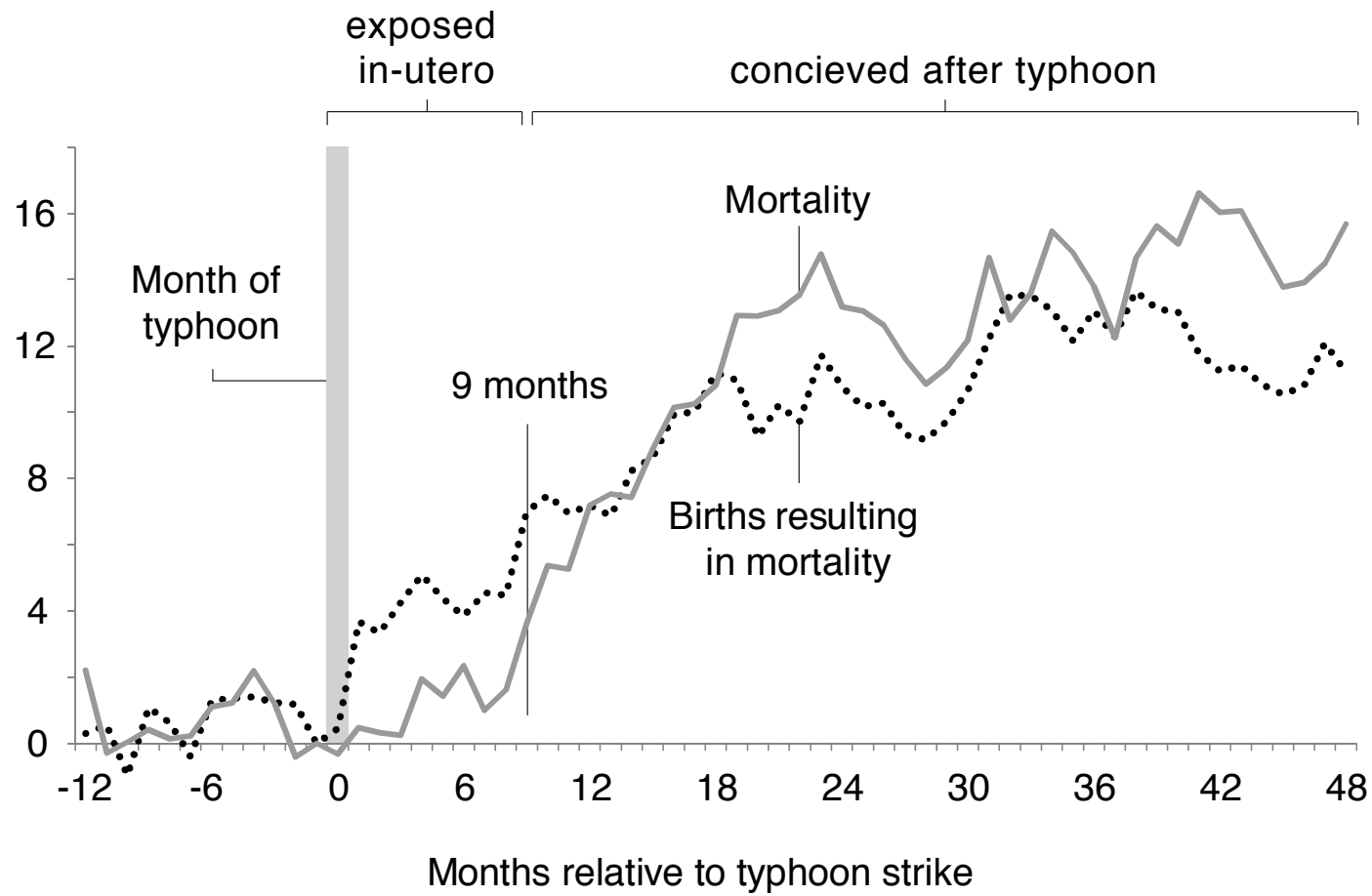
Figure 2: Cumulative impact of typhoons on number of infant female deaths (grey line) and number of female births resulting in infant deaths (dotted black line) per million households. Observation is at the regional aggregate level. Cumulative effect normalized such that month prior to typhoon impact is zero. Includes region, year, and month fixed effects, lagged temperature and precipitation controls, and lagged dependent variable.
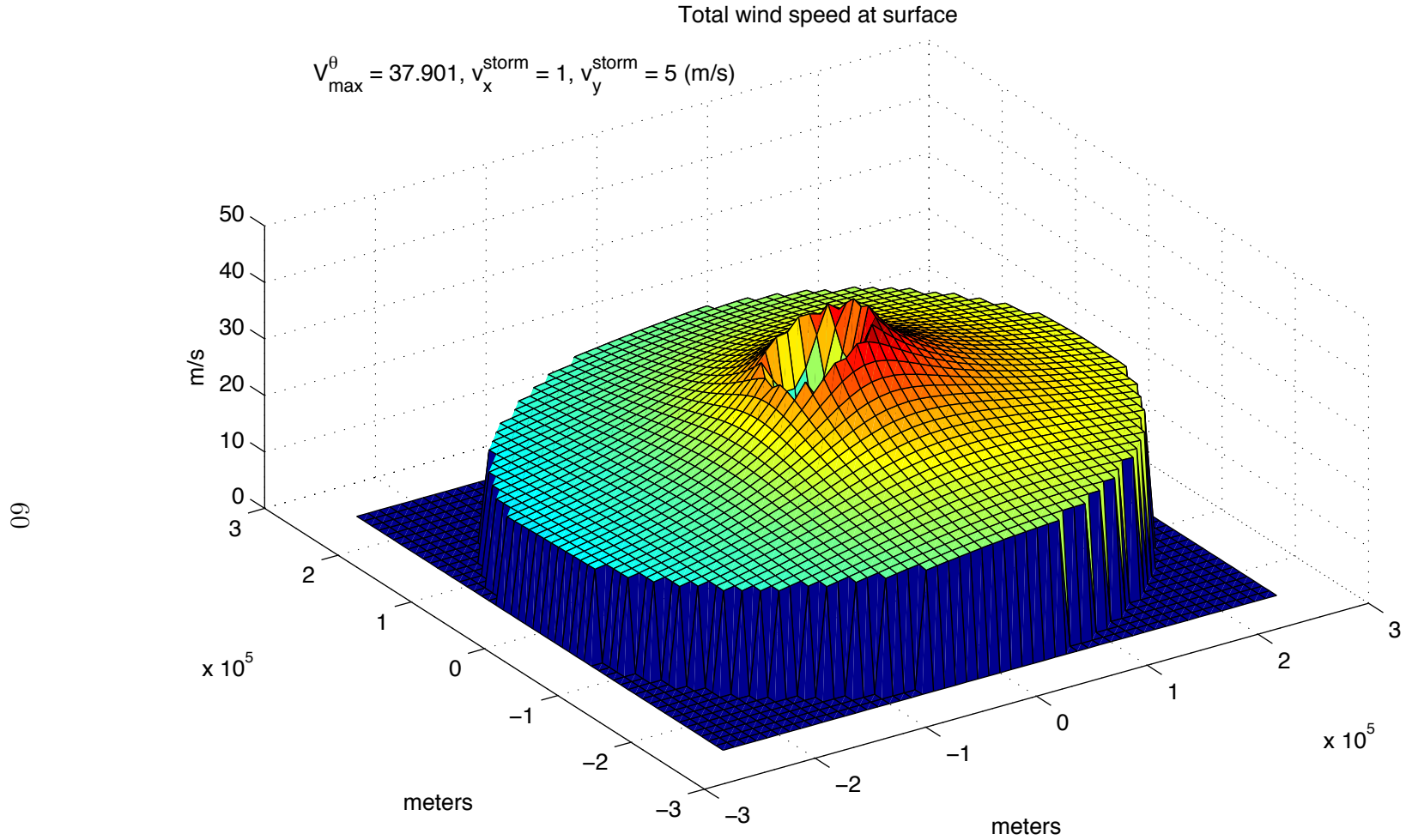
Figure 3: Snapshot of the parametrized typhoon wind field used by LICRICE to reconstruct exposure at the surface. The storm is modeled as a translating Rankine vortex, the storm pictured here is translating 1 m/s in the "x" direction (into the page and to the right) and 5 m/s in the "y" direction (into the page and to the left). The maximum windspeed on the ground (V_{max}^{θ}) is 37.901 m/s, the sum of rotational (azimuthal) winds and winds generated by the storm's translation.

Typhoons in Provinces of the Philippines: 1950–2008
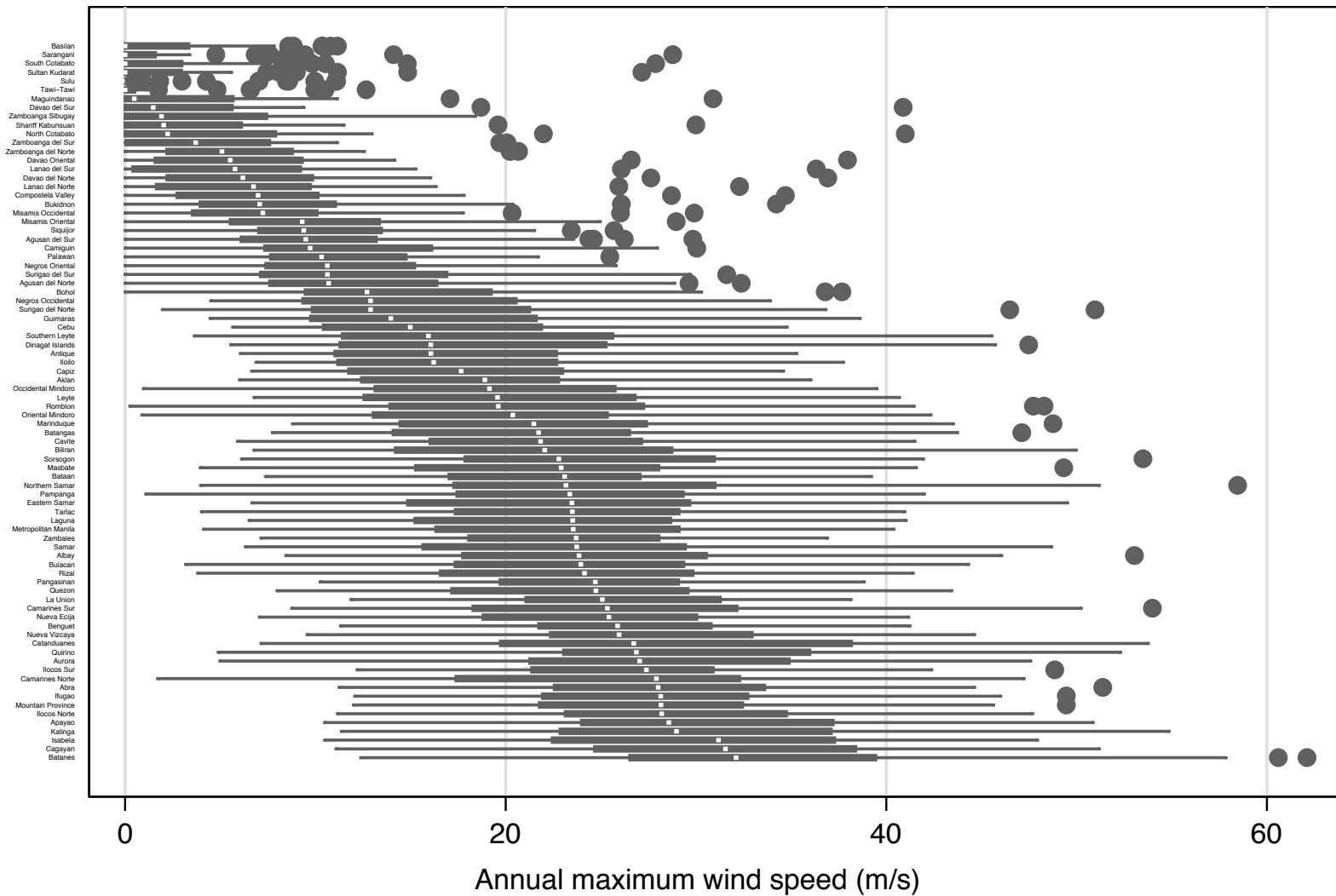
Figure 4: Box-whisker plot of provincial annual maximum wind speed measure, 1950-2008. Provinces (y axis) are ranked by median annual maximum wind speed (white dots). Shaded boxes show interquartile range of wind speed distribution; grey dots show outlier years. Data: LICRICE.
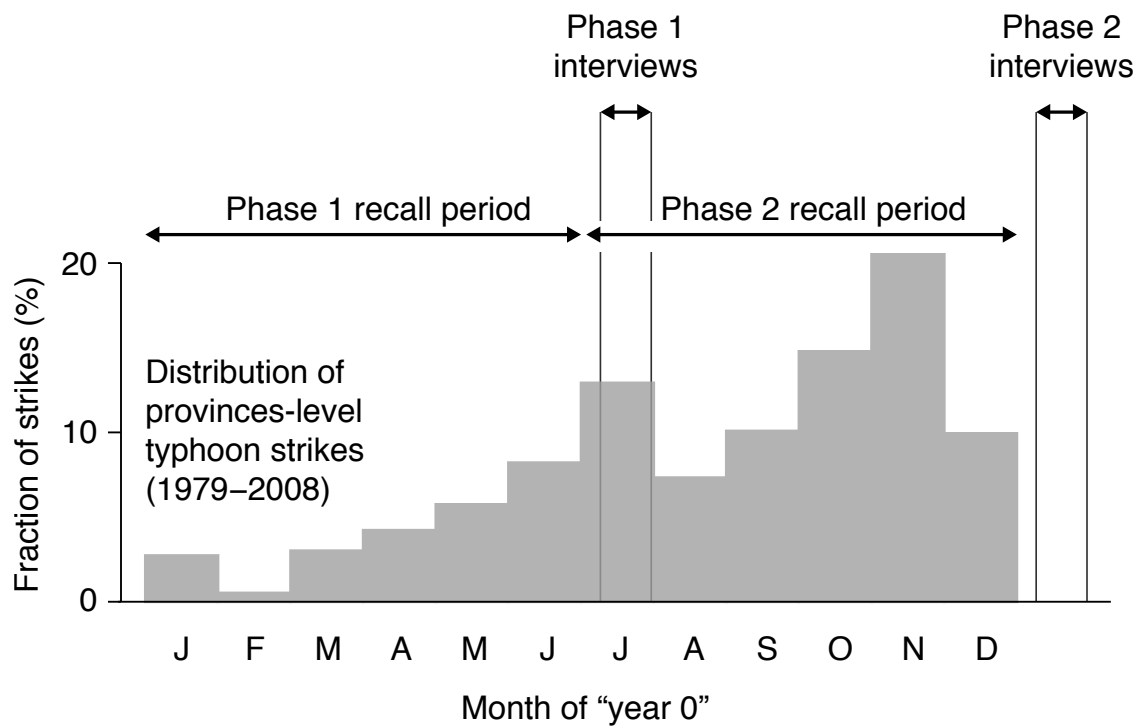
Figure 5: Timeline of FIES data collection overlaid with a histogram of typhoon events by month.
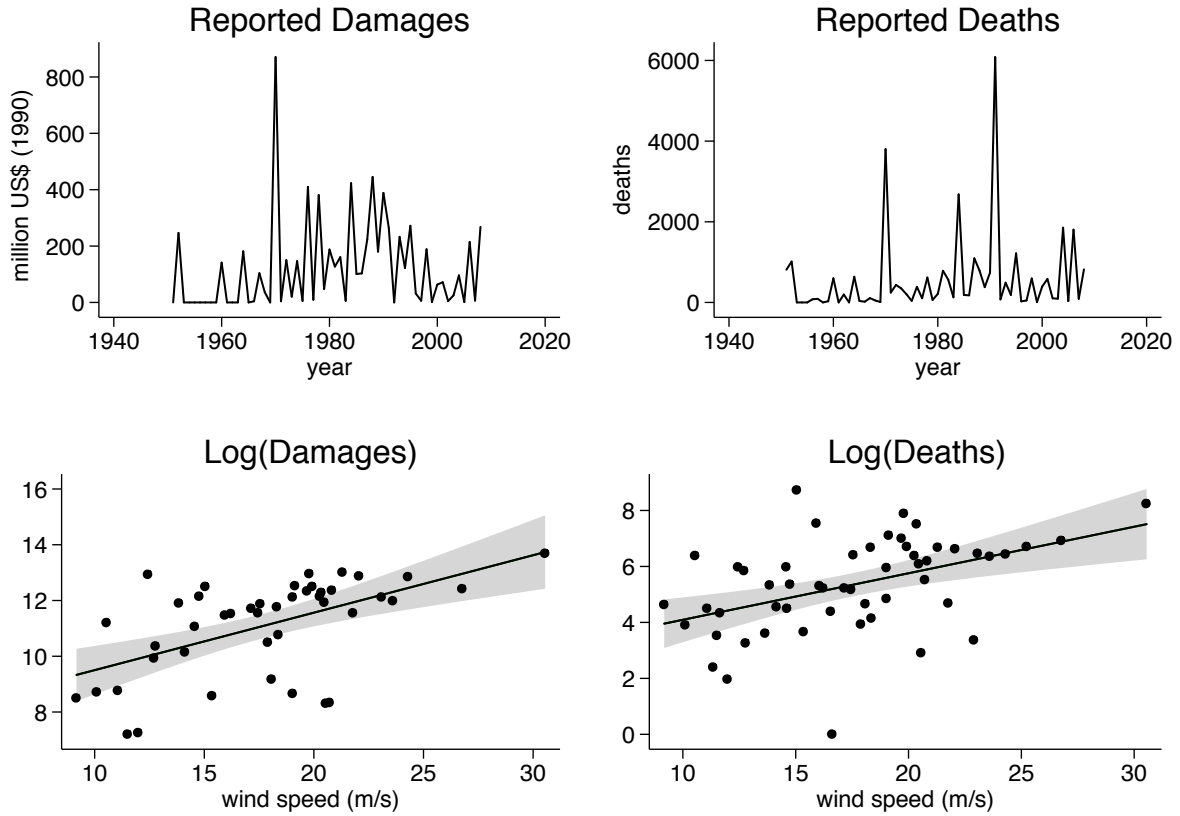
Figure 6: Country-level losses to typhoons for the Philippines. Reported damages and deaths from the EM-DAT dataset are shown as time series from 1950-2008. Scatter plots show log losses as a function of wind speed averaged nationally. Fit is OLS with confidence interval.
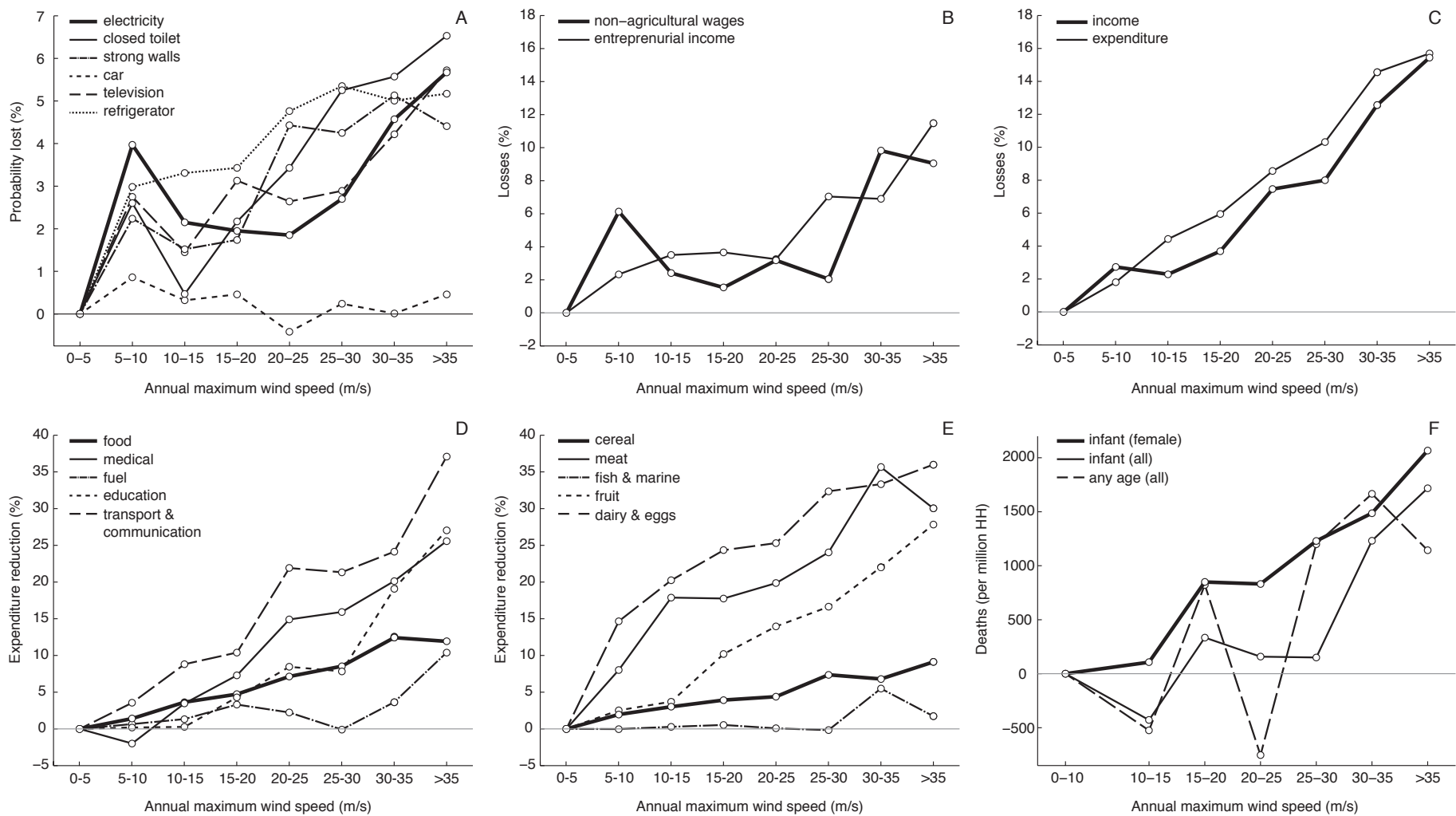
Figure 7: Household losses as a nonlinear function of previous calendar year's typhoon exposure. Losses are on the y-axis, x-axis shows coefficient on indicator variables for previous year's maximum wind speed.
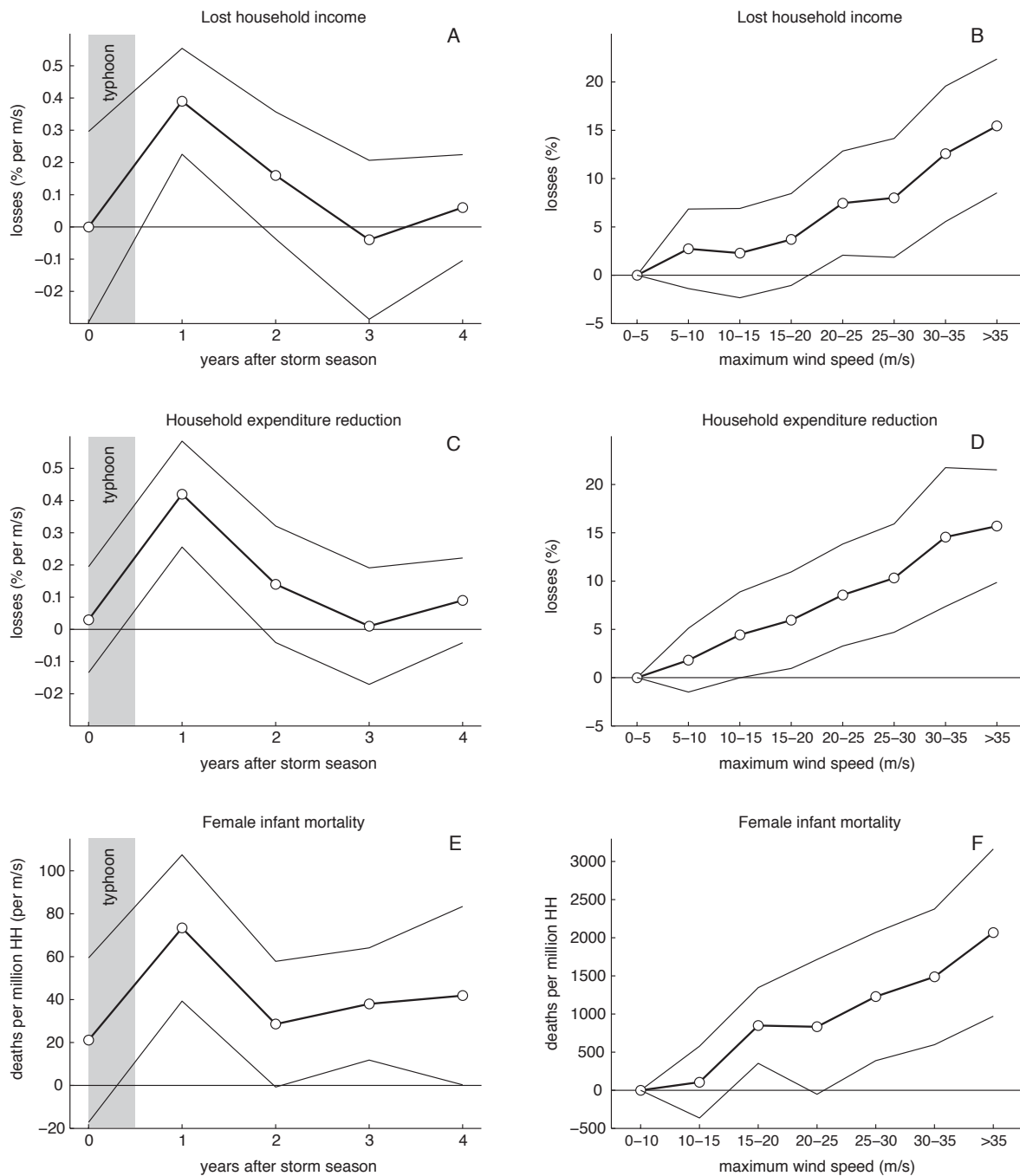
Figure 8: Similarities in the structure of typhoon losses across categories. Dynamic (left column) estimates of typhoon impacts show responses for 5 years starting in the calendar year of exposure (year 0). Nonlinear (right column) estimates show coefficients on indicator variables for previous year's (Lag=1) maximum wind speed. Thin lines are 90% CI.

65
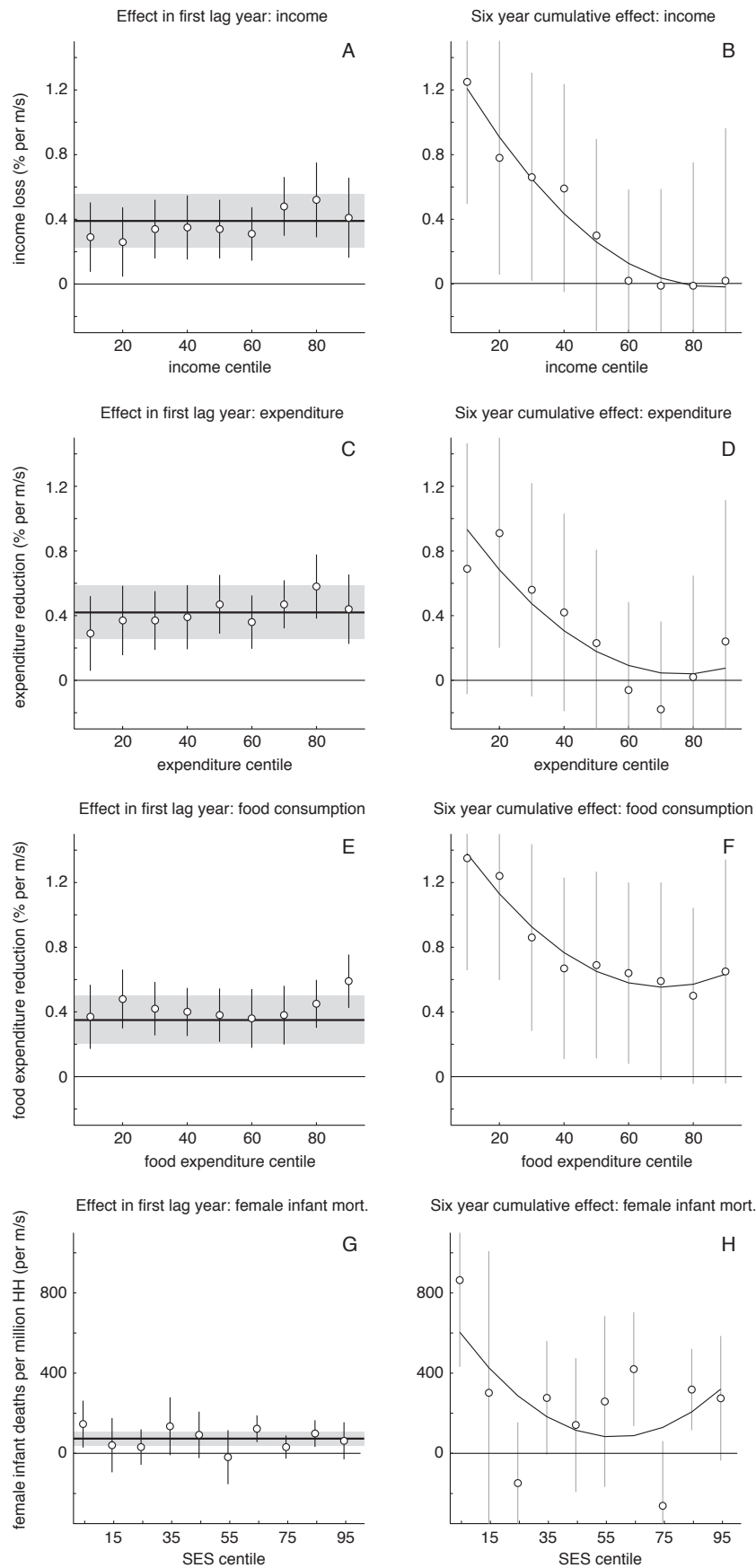
Figure 9: The effect of of typhoons on the shape of income, expenditure, and wealth distributions. Left column shows the effect of the previous year's typhoon exposure at different q-quantile cutoffs (A, C, E) and inferred socioeconomic status (G). Right column shows the cumulative impact over six years. Whiskers are 2-σ for each point-estimate. Thick horizontal lines in A, C, E, and G are the main effect from the baseline model, shaded regions are the 90% CI. Curves in B, D, F, and H are simple OLS fits to the estimated coefficients. Each coefficient is estimated in a separate province-by-year panel containing province fixed effects, year fixed effects, controls for temperature and rainfall and a lagged dependent variable.
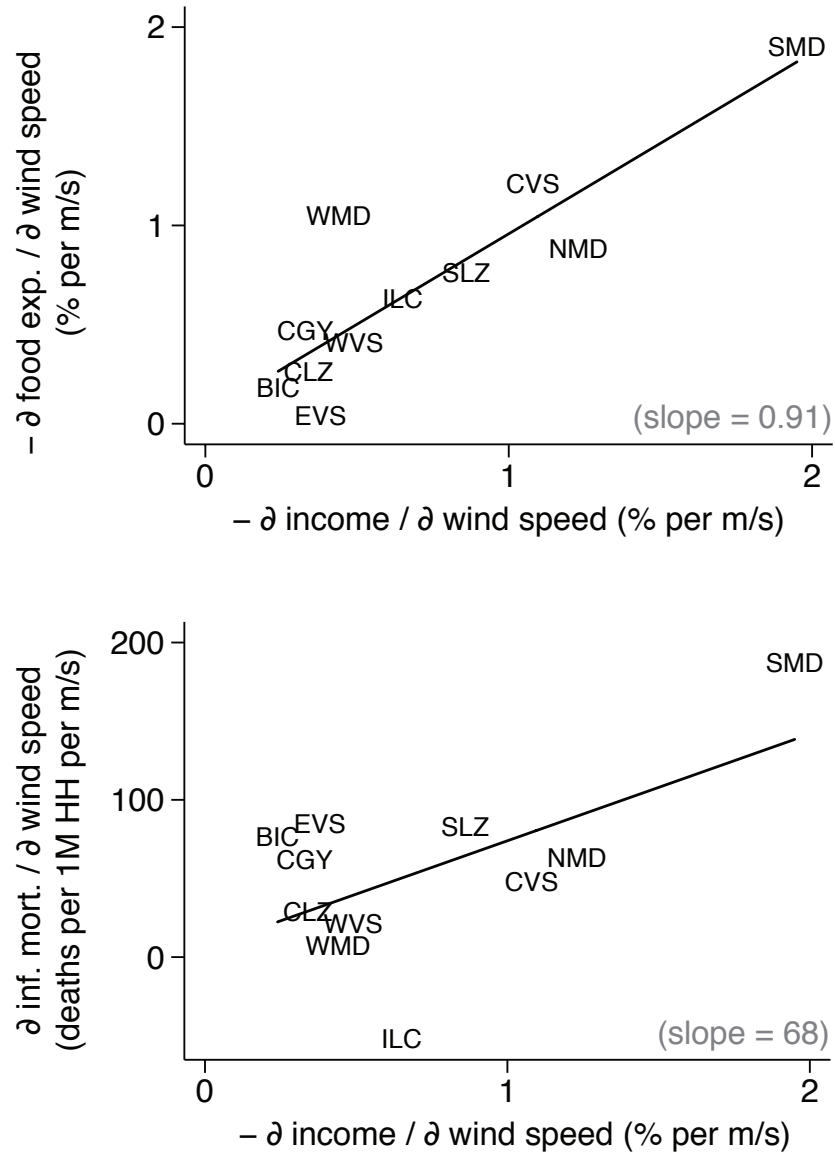
Figure 10: Cross-sectional correlation of region-specific coefficients. Regions that suffer relatively larger income losses (x-axis) also suffer larger reductions in food expenditure (top) and larger increases in infant mortality (bottom), holding the intensity of typhoon exposure fixed.
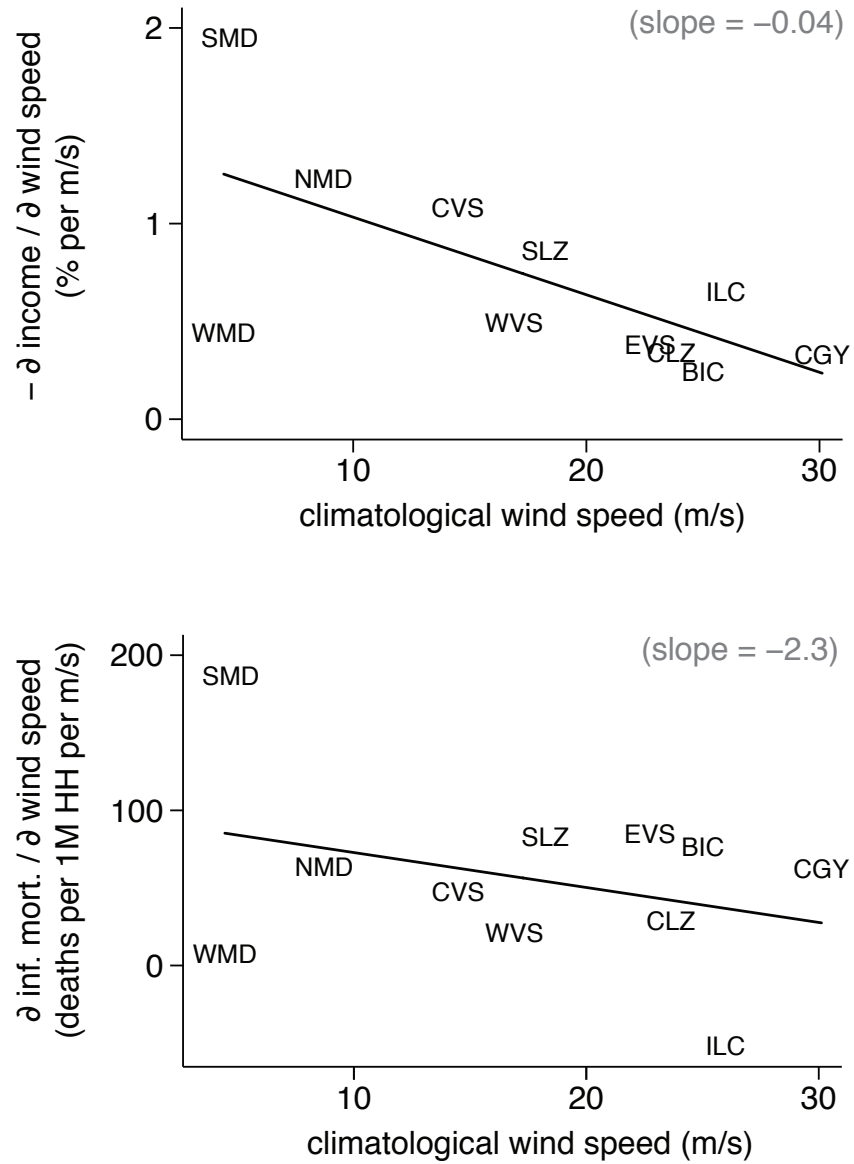
Figure 11: Cross-sectional evidence of adaptation to sub-national typhoon climates. Regions with higher mean exposure (x-axis) generally suffer smaller losses to income (top) and infant life (bottom) when the intensity of typhoon exposure is held fixed.
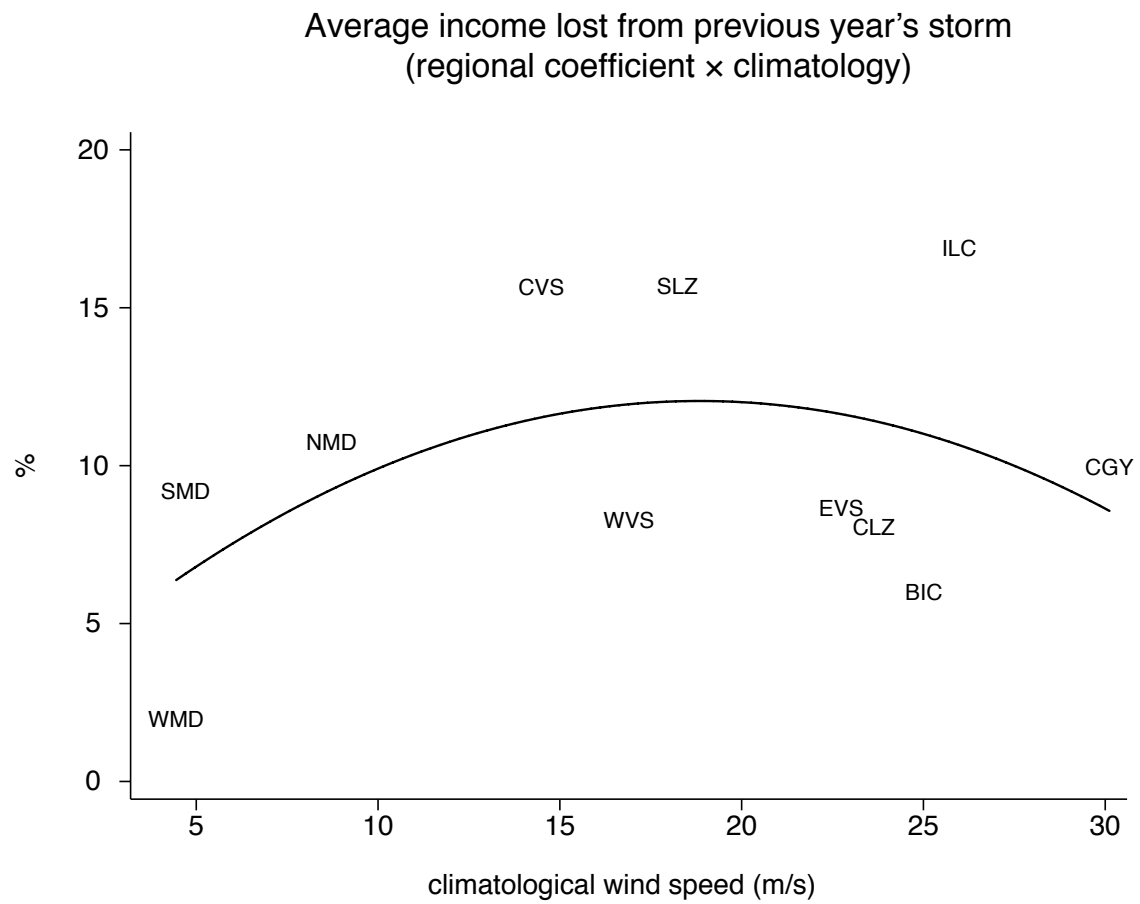
Figure 12: Average annual income loss by region. Regions exhibit marginal losses that decline as average wind speed rises (Figure 11). However, average treatment increases with average exposure, by definition. The result is an average annual loss that is quadratic in average wind speed.

Table 1: Typhoon exposure (maximum wind speed) summary statistics.

Unit of observation	Years	N	Mean	Std. Dev.	Min	Max
Province	1950 - 2008	4838	17.6	12.0	0.0	62.1
Province	1979 - 2008	2460	16.9	11.6	0.0	53.5
Region	1950 - 2008	885	16.1	11.5	0.0	47.4
Region	1979 - 2008	450	15.3	11.0	0.0	45.9
Nation	1950 - 2008	59	17.3	4.6	9.2	30.5
Nation	1979 - 2008	30	16.5	4.0	9.2	23.6

Notes: Maximum wind speed measured in meters per second.

Table 2: Summary averages for FIES households

VARIABLES	
Total number of household members	5.2
	[2.27]
Number of household members above age 15	4.1
	[1.78]
Age of household head (yr.)	47.6
	[14.16]
Household head is male (%)	85.2
	[35.5]
Household head completed no school (%)	5.7
	[23.19]
Household head completed primary school (%)	64.0
	[48.01]
Household head completed secondary school (%)	33.6
	[47.2]
Total household:	
Income (PHP)	127500
	[157600]
Expenditures (PHP)	103700
	[106000]
Food expenditures (PHP)	50500
	[33100]
Education expenditures (PHP)	4000
	[11900]
Medical expenditures (PHP)	2200
	[11300]
Observations:	142789
Household has:	
Electricity (%)	62.6
	[48.4]
Closed toilet (%)	72.2
	[44.8]
Strong walls (%)	54.5
	[49.8]
Television (%)	39.1
	[48.8]
Car (%)	6.7
	[24.9]
Observations:	107620

Notes: Standard errors shown in parentheses. Income and expenditures shown in year 2000-equivalent Philippine Pesos.

Table 3: Summary averages for DHS households

Variable	
Age	28.65
	[10.08]
Married (%)	48.32
	[49.97]
Wife has no education (%)	3.2
	[17.6]
Wife has post-secondary education (%)	28
	[44.9]
Husband has no education (%)	4.17
	[20]
Husband has post-secondary education (%)	22.5
	[41.7]
Wife's total children born	2.0
	[2.57]
Wife's total sons born	1.02
	[1.49]
Wife's total daughters born	0.95
	[1.42]
Observations	24841

Notes: Standard errors shown in parentheses. Non-migrant households only.

Table 4: Checking for balance on typhoon exposure in FIES data

VARIABLES	(1) Total family size	(2) Single family dwelling (%)	(3) Married (%)	(4) Male (%)	(5) Uneducated	(6) Only primary school	(7) Only secondary school
			Household head characteristics				
Max windspeed 5-10 m/s	0.0594	-0.81	0.30	-0.30	1.02	-3.06**	-0.45
	[0.0603]	[1.27]	[0.53]	[0.42]	[0.81]	[1.27]	[0.97]
10-15 m/s	0.1480*	-1.12	0.68	-0.17	0.67	-2.69*	-0.24
	[0.0781]	[1.60]	[0.66]	[0.65]	[0.85]	[1.55]	[1.27]
15-20 m/s	0.1205	-0.68	0.50	0.25	0.83	-3.00*	-1.04
	[0.0864]	[1.77]	[0.65]	[0.63]	[0.86]	[1.64]	[1.39]
20-25 m/s	0.1968*	-0.91	0.70	0.76	0.96	-3.26	0.40
	[0.1000]	[1.84]	[0.77]	[0.78]	[1.02]	[2.05]	[1.68]
25-30 m/s	0.0748	-0.15	0.28	0.85	0.24	-1.41	2.64
	[0.1099]	[1.87]	[0.81]	[0.81]	[1.06]	[2.20]	[1.88]
30-35 m/s	0.0808	0.81	0.44	0.53	0.97	-2.14	2.59
	[0.1139]	[2.03]	[1.05]	[1.04]	[1.11]	[2.09]	[1.82]
35+ m/s	0.1046	-0.49	0.67	1.55*	0.73	-1.21	3.13
	[0.1171]	[2.09]	[0.98]	[0.90]	[1.16]	[2.29]	[1.94]
Observations	142,789	142,789	142,789	142,789	142,789	142,789	142,789
R-squared	0.0145	0.02	0.01	0.01	0.08	0.14	0.24

Notes: Standard errors clustered at the treatment (province) level in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Lags 0 and 2-5 estimated but not shown. Includes province and year fixed effects and lagged temperature and precipitation controls.

Table 5: Country level typhoon damages.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Damages (log)	Damages (log)	Damages / GDP (log)	Damages / GDP (log)	Killed (log)	Killed (log)	Killed / pop. (log)	Killed / pop. (log)
Maximum wind speed (m/s)	20.62***	23.65***	26.34***	22.23***	16.63***	22.39***	20.62***	22.00***
	[4.24]	[5.05]	[4.89]	[5.75]	[3.54]	[3.65]	[3.53]	[3.84]
Observations	44	44	37	37	53	53	48	48
R-squared	0.31	0.34	0.41	0.48	0.21	0.35	0.30	0.34
Linear and quad trends	-	Y	-	Y	-	Y	-	Y

Notes: Typhoon treatment at national level. White standard errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Typhoon impact on assets

VARIABLES	(1) Has electricity (%)	(2) Has closed toilet (%)	(3) Strong walls (%)	(4) Has TV (%)	(5) Has car (%)
Max wind speed, T=0	-0.21*	-0.04	-0.08	-0.17*	-0.03
	[0.11]	[0.10]	[0.10]	[0.09]	[0.03]
T + 1	-0.14**	-0.16***	-0.11**	-0.12**	0.01
	[0.06]	[0.03]	[0.04]	[0.05]	[0.02]
T + 2	0.01	-0.09	-0.09	0.11*	-0.03
	[0.07]	[0.06]	[0.08]	[0.06]	[0.05]
T + 3	0.04	-0.12	0.12	-0.10*	-0.01
	[0.06]	[0.09]	[0.10]	[0.05]	[0.03]
T + 4	-0.07	-0.11	0.01	-0.15***	0.01
	[0.04]	[0.06]	[0.05]	[0.03]	[0.02]
Observations	107,620	107,620	107,620	107,620	107,620
R-squared	0.28	0.21	0.21	0.34	0.07

Notes: Notes: Standard errors clustered at the treatment (province) level in brackets. *** p<0.01, ** p<0.05, * p<0.1. Lags 0-5 estimated but only shown for 0-4. Includes province and year fixed effects, lagged temperature and precipitation controls, and household controls consisting of the number of members, working and non, in household as well as household head's gender and education level.

Table 7: Household income as a function of typhoon exposure and covariates

VARIABLES	(1) Income (%)	(2) Income (%)	(3) Income (%)	(4) Income (%)	(5) Income (%)	(6) Income (%)
Max wind speed, T=0 (m/s)	0.26	-0.10	0.02	-0.00	0.27	-0.01
	[0.26]	[0.14]	[0.15]	[0.18]	[0.16]	[0.15]
T + 1	-0.88***	-0.33***	-0.35***	-0.39***	-0.58***	-0.39***
	[0.19]	[0.09]	[0.09]	[0.10]	[0.14]	[0.14]
T + 2	1.04***	0.01	0.00	-0.16	-0.17	0.02
	[0.32]	[0.10]	[0.08]	[0.12]	[0.14]	[0.14]
T + 3	0.16	-0.14	-0.17	0.04	-0.22	0.29
	[0.17]	[0.14]	[0.13]	[0.15]	[0.15]	[0.18]
T + 4	-0.58**	-0.08	-0.09	-0.06	-0.03	-0.05
	[0.25]	[0.09]	[0.11]	[0.10]	[0.09]	[0.11]
Observations	142,789	142,789	142,779	142,779	174,896	367
R-squared	0.32	0.38	0.57	0.57	0.55	0.95
Exposure:	province	province	province	province	region	province
Province FE	-	Y	Y	Y	-	Y
Region FE	-	-	-	-	Y	-
HH controls	-	-	Y	Y	Y	-
Lagged temp, precip	-	-	-	Y	Y	Y
Lagged dependent var.	-	-	-	-	-	Y
SE clustered at region	Y	Y	Y	Y	Y	-
Years 1985 to ...	2000	2000	2000	2000	2006	2000
Conley (spatial) SE	-	-	-	-	-	Y

Notes: Percent change calculated as log points *100 per m/s of max wind speed. Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Lags 0-5 estimated but only shown for 0-4. Spatial SE calculated using a distance of 250km and uniform weights. Column 6 is collapsed to the province level. Income includes all wages, salary, and net transfers.

Table 8: Typhoon impact on income by source

VARIABLES	(1) Entrepreneurial income (%)	(2) Non-agricultural wages (%)	(3) Agricultural wages (%)
Max wind speed, T=0 (m/s)	-0.11	0.04	-0.10
	[0.22]	[0.22]	[0.35]
T + 1	-0.28**	-0.19	0.04
	[0.11]	[0.15]	[0.27]
T + 2	-0.15	-0.08	-0.29
	[0.15]	[0.18]	[0.30]
T + 3	0.02	0.35	-0.20
	[0.22]	[0.21]	[0.34]
T + 4	0.12	-0.02	0.34*
	[0.12]	[0.15]	[0.21]
Observations	96,989	77,754	30,773
R-squared	0.22	0.36	0.24

Notes: Percent change calculated as log points *100 per m/s of max wind speed. Standard errors clustered at the treatment (province) level in brackets. *** p<0.01, ** p<0.05, * p<0.1. Lags 0-5 estimated but only shown for 0-4. Includes province and year fixed effects, lagged temperature and precipitation controls, and household controls consisting of the number of members, working and non, in household as well as household head's gender and education level.

Table 9: Typhoon impact on entrepreneurial income categories

	Max wind speed, T + 1 (m/s)		
VARIABLES	% change	SE	N
Entrep. income	-0.28**	[0.11]	96,989
Crop farming / gardening income	-0.29	[0.21]	52,193
Trade income	-0.18	[0.18]	30,479
Livestock / poultry income	-0.46	[0.44]	17,158
Gambling winnings	0.28	[0.46]	10,776
Fishing income	-0.40	[0.24]	10,258
Manufact. income	0.08	[0.42]	8,715
Transport / storage income	0.15	[0.26]	7,855
Services income	-0.10	[0.45]	7,011
Forestry / hunting income	-0.44	[0.71]	2,537
N.A. / entrep. income	-1.04	[0.96]	1,454
Construct. income	-1.56	[1.24]	870

Notes: Percent change calculated as log points *100 per m/s of max wind speed. Standard errors clustered at the treatment (province) level in brackets. *** p<0.01, ** p<0.05, * p<0.1. Lags 0-5 estimated but only shown for 0-4. Includes province and year fixed effects, lagged temperature and precipitation controls, and household controls consisting of the number of members, working and non, in household as well as household head's gender and education level.

Table 10: Typhoon impact on expenditures

VARIABLES	(1) Total Exp. (%)	(2) Food (%)	(3) Fuel (%)	(4) Personal Care (%)	(5) Clothing (%)	(6) Travel / Comm. (%)	(7) Medical (%)	(8) Education (%)	(9) Special Events (%)	(10) Recreation (%)	(11) Repair (%)
Max wind speed, T=0 (m/s)	-0.03	-0.22**	0.14	-0.01	-0.18	0.06	-0.20	0.20	-0.15	-0.54*	-0.11
	[0.10]	[0.09]	[0.14]	[0.20]	[0.22]	[0.24]	[0.26]	[0.28]	[0.22]	[0.31]	[0.85]
T + 1	-0.42***	-0.35***	-0.21*	-0.74***	-0.32*	-0.84***	-0.85***	-0.79***	-0.57***	-0.11	0.09
	[0.10]	[0.09]	[0.12]	[0.15]	[0.16]	[0.17]	[0.21]	[0.16]	[0.18]	[0.23]	[0.33]
T + 2	-0.14	-0.23**	0.08	0.11	-0.18	-0.31	-0.31	-0.26	-0.34	0.79**	0.78*
	[0.11]	[0.11]	[0.13]	[0.21]	[0.22]	[0.24]	[0.29]	[0.26]	[0.24]	[0.37]	[0.46]
T + 3	-0.01	-0.12	0.19	0.13	0.20	0.17	0.10	-0.24	-0.04	0.20	-0.30
	[0.11]	[0.11]	[0.15]	[0.18]	[0.23]	[0.25]	[0.27]	[0.23]	[0.26]	[0.32]	[0.79]
T + 4	-0.09	0.03	-0.01	-0.24*	0.13	0.02	-0.10	-0.20	-0.34**	-0.36	-0.46
	[0.08]	[0.07]	[0.11]	[0.13]	[0.15]	[0.16]	[0.16]	[0.15]	[0.15]	[0.26]	[0.40]
Observations	142,779	142,779	142,757	140,384	136,030	135,077	127,364	100,268	88,440	60,893	34,923
R-squared	0.61	0.66	0.54	0.53	0.29	0.37	0.17	0.30	0.28	0.24	0.21

Notes: Percent change calculated as log points *100 per m/s of max wind speed. Standard errors clustered at the treatment (province) level in brackets. *** p<0.01, ** p<0.05, * p<0.1. Lags 0-5 estimated but only shown for 0-4. Includes province and year fixed effects, lagged temperature and precipitation controls, and household controls consisting of the number of members, working and non, in household as well as household head's gender and education level.

Table 11: Typhoon impact on food expenditures

VARIABLES	(1) Meat (%)	(2) Fish (%)	(3) Dairy (%)	(4) Fruit (%)	(5) Cereal (%)	(6) Nonalcoholic Beverages (%)	(7) Alcoholic Beverages (%)	(8) Tobacco (%)
Max wind speed, T=0 (m/s)	-0.73***	-0.49**	-0.38**	-0.03	-0.07	-0.47**	-0.64**	-0.35
	[0.22]	[0.19]	[0.18]	[0.20]	[0.07]	[0.19]	[0.29]	[0.29]
T + 1	-0.74***	-0.14	-0.75***	-0.83***	-0.22***	-0.45**	-0.17	0.32
	[0.22]	[0.13]	[0.19]	[0.15]	[0.06]	[0.18]	[0.28]	[0.23]
T + 2	-0.55**	-0.37*	-0.18	-0.37**	-0.08	-0.27	-0.21	-0.03
	[0.23]	[0.20]	[0.22]	[0.16]	[0.09]	[0.25]	[0.33]	[0.28]
T + 3	-0.52**	-0.21	-0.18	0.03	-0.01	-0.62**	-0.38	-0.25
	[0.23]	[0.20]	[0.25]	[0.20]	[0.09]	[0.27]	[0.33]	[0.30]
T + 4	-0.01	0.12	-0.08	-0.02	-0.05	0.28*	0.40*	0.34
	[0.17]	[0.12]	[0.13]	[0.12]	[0.05]	[0.16]	[0.21]	[0.21]
Observations	137,495	142,361	133,913	142,421	142,684	115,746	79,381	89,148
R-squared	0.46	0.41	0.36	0.50	0.69	0.31	0.11	0.16

Notes: Percent change calculated as log points *100 per m/s of max wind speed. Standard errors clustered at the treatment (province) level in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Lags 0-5 estimated but only shown for 0-4. Includes province and year fixed effects, lagged temperature and precipitation controls, and household controls consisting of the number of members, working and non, in household as well as household head's gender and education level.

Table 12: Typhoon impact on child mortality

VARIABLES	(1) Any age	(2) Male	(3) Female	(4) Under 5 y.o. female	(5) Infant female	(6) Infant male
Max wind speed, T=0 (m/s)	-43.16	-8.765	-36.82	-24.96	21.16	-5.697
	[30.16]	[19.39]	[32.92]	[25.76]	[23.29]	[16.44]
T + 1	79.68*	26.11	58.82**	54.46**	73.37***	1.717
	[36.61]	[29.76]	[26.03]	[22.50]	[20.71]	[16.72]
T + 2	-32.82	-21.35	-5.694	-4.821	28.54	-21.54
	[39.64]	[34.04]	[22.42]	[22.27]	[17.79]	[22.19]
T + 3	-5.614	-0.695	-4.957	12.47	37.99**	-20.31
	[32.21]	[21.82]	[24.56]	[15.39]	[15.89]	[17.46]
T + 4	63.93	43.47	26.07	30.36	41.84	23.61
	[52.90]	[35.96]	[29.56]	[26.65]	[25.27]	[22.94]
Observations	265,430	265,430	265,430	265,430	265,430	265,430
R-squared	0.106	0.090	0.086	0.083	0.082	0.084

Notes: Mortality shown per million households per year. Diarrhea expressed per million households, calculated only for survey years, and indicates that the household had a child hospitalized for diarrhea within the 2 weeks prior to survey. Standard errors clustered at the treatment (region) level in brackets. *** p<0.01, ** p<0.05, * p<0.1. Lags 0-5 estimated but only shown for 0-4. Includes region and year fixed effects and lagged temperature and precipitation controls for all models, mother's age and age squared as well as mother fixed effects in mortality models, and household controls (mother's age and education) for diarrhea model.

Table 13: Typhoon impact on child mortality by SES group

VARIABLES	(1) Poorest decile	(2) Below med.	(3) Above med.	(4) Top decile
Max wind speed, T=0 (/s)	98.33	9.214	36.08	87.85
	[62.12]	[32.81]	[25.34]	[58.01]
T + 1	146.1*	82.15**	63.44**	62.74
	[70.92]	[31.36]	[23.42]	[56.10]
T + 2	140.8*	31.53	28.99	-5.418
	[73.40]	[35.88]	[20.53]	[47.83]
T + 3	164.8*	54.30**	21.39	27.98
	[91.13]	[23.82]	[16.06]	[34.26]
T + 4	173.4**	58.67	20.27	13.61
	[74.24]	[34.35]	[22.20]	[45.81]
Observations	26,637	142,216	123,214	20,587
R-squared	0.084	0.086	0.071	0.072

Notes: Mortality shown per million households per year. Standard errors clustered at the treatment (region) level in brackets. *** p<0.01, ** p<0.05, * p<0.1. Lags 0-5 estimated but only shown for 0-4. Includes region and year fixed effects, lagged temperature and precipitation controls, and mother fixed effects.

Table 14: Typhoon impact on infant female mortality by sibling gender

VARIABLES	Max wind speed, T=1 [m/s]
First born	35.32
	[23.48]
Marginal impact of having older siblings	75.70**
	[25.35]
Only older sisters	75.80
	[78.97]
Marginal impact of having older brothers	53.18
	[67.54]
Only older brothers	121.2*
	[57.10]
Marginal impact of having older sisters	0.405
	[40.07]

Notes: Mortality shown per million households per year. Standard errors clustered at the treatment (region) level in brackets. *** p<0.01, ** p<0.05, * p<0.1. Lags 0-5 estimated but only shown for 0-4. Includes region and year fixed effects, lagged temperature and precipitation controls, and mother fixed effects.

83

Table 15: Household losses due to previous year's mean typhoon exposure

Variables	Mean typhoon impact in prev. calendar year
Income	-6.57
Expenditures	-7.08
Food exp.	-5.90
Education exp.	-13.3
Medicine exp.	-14.3
Female infant mortality rate	
deaths per million households	1130
percent of mean infant female death rate	55.0%

Notes: Losses are calculated using mean typhoon exposure between 1979 and 2008 as shown in 1 for the province level (region level for infant mortality) using coefficient on T + 1 from estimates in tables 7 (col. 4),10 (cols. 1, 2, 7, and 8) and 12 (col 5). Losses for income and expenditures are log points times 100.

Appendices

A Appendix: Data

Typhoons

The Philippines' typhoon climate Figure 1 summarizes the typhoon-climate of
the Philippines by displaying annual mean wind exposure. The globe on the left is
centered on the Philippines, displaying the country's location in the global cyclone cli-
mate, while the map on the right displays the within-country variation in that climate.
Typhoons form in the warm waters of the Pacific, generally to the east of the Philip-
pines, and are pushed westward by prevailing winds, striking the Philippine islands. As
storms move westward, they also tend to drift northward[38], causing storms to strike the
northern regions of the Philippines more often than they strike the southern regions,
generating a within-country gradient in typhoon risk that is probably the strongest
within-country gradient in the world (see figures C.3 and C.4 for trajectories of storms
during a single year).

Maximum wind speed as a measure of typhoon incidence Typhoon wind
speed is simply the maximum wind speed achieved at a location during the course
of a calendar year. If a location experiences multiple storms, the annual maximum
is the maximum of the maximum speed achieved in each storm. Pixel-specific wind
speed estimates are spatially averaged over each province[39] to aggregate exposure into

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[38]The northward drift is due both to prevailing winds as well as a phenomenon known as "beta-
drift," which results from an interaction between the storms angular momentum (vorticity) and the
angular momentum gradient of the planet. See, for example, Wang et al. (1996).

[39]It may be possible to reduce our measurement error by using population-weights, following Jones
and Olken (2010) and Hsiang et al. (2011), or capital-weights, following Nordhaus (2010), when
aggregating our exposure measure. However, we fear that if populations strategically locate themselves
or capital in response to typhoon risk, this may bias our estimated coefficients in some unknown way.

province-by-year observations. While there are other feasible measures of typhoon impact, Hsiang and Narita (2011) demonstrate in detail that spatially averaged wind speed has explanatory power of economic outcomes that is at least as good, if not better, than alternative physical measures. These alternative measures include total energy dissipated (e.g., Hsiang (2010)), wind speed at landfall (e.g., Nordhaus (2010) or Mendelsohn et al. (2010) or minimum central pressure (also in Mendelsohn et al. (2010)).

Family Income and Expenditure Survey (FIES)

FIES data collection and attrition FIES surveys are designed to be nationally representative and are conducted at the household level. For each survey wave, teams of surveyors deploy twice, the first phase from July 8-31 and the second phase from January 8-31 in the following year. Surveyors visit the same households in both phases, completely repeating the survey but asking respondents to recall income and consumption only over the last six months[40]. Annual statistics are computed by averaging responses to both the July and January phases. The survey asks detailed questions about income and expenditure, collapsing respondents estimates of both prices and quantities into summary statistics for total receipts. The NSO estimates that each surveyor samples 1.5 households per day, suggesting that the survey does not take longer than two-thirds of a working day. For each phase, the surveyor is instructed to return to the household at least twice (for three visits total) if the household head is missing or the survey cannot be completed for other reasons. In cases where a household does

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Thus, we use area-weights because populations cannot manipulate this parameter, giving us confidence that our RHS variable is fully exogenous. This conservative approach may mean that our estimation is inefficient, in the sense that it does not take advantage of all available data, but this should only make our inferences more conservative.

[40]The NSO asks respondents to describe income and consumption in an "average week" for the period of recall in an effort to limit recall biases. This method has been used consistently from 1985-2006.

not complete one of the two phases, the household is dropped from the sample. The NSO notes that this type of attrition sometimes occurs because households cannot be located in the second phase due to the passage of a typhoon, often because the physical house containing the household no longer exists. Because the NSO does not provide attrition statistics, there is little we can do to account for this attrition other than control for household characteristics and run standard tests for balance on typhoon treatment. Balance tests for our primary measure of treatment, previous year's cyclone incidence, are shown in Table 4 in section 4. We show an expanded version of our tests for balance in Table C.1. We note that even for year-of incidence, when the NSO explicitly warns of attrition bias, we find only modest evidence of sorting. Households receiving typhoon treatment the same year as they are surveyed are mildly more likely to be headed by a male household head (0.07% per m/s, or 1.2% for average treatment), an effect that seems to persist somewhat over time. They are also mildly less likely to have completed secondary school (0.23% per m/s, or 3.9% for average treatment), an effect that seems to be reversed the following year. We include both of these variables as covariates in our analysis, and note that doing so does not appreciably change our results (see, for example, the stability of our coefficient on income after the addition of household covariates during our specification search in Table 7). We conclude that they are unlikely to be driving our results.

B Appendix: Results

Income and Expenditures Losses

Prices Reductions in expenditure of course do not directly translate into reductions in consumption without knowledge of the price response. We investigate whether the expenditure losses we observe can feasibly be interpreted as losses to consumption by

testing for typhoons' impact on regional food prices for a vairety of commodities; these results are shown in appendix tables C.4, C.5 and C.6. We find little evidence to suggest that typhoon exposure materially alters food prices. The one exception to this is the price of beef, which seems to be somewhat reduced by typhoon exposure. A possible explanation for such an outcome could be shock-induced asset sales, i.e., families may be trying to smooth their income by selling off valuable assets such as cows. Regardless, our price results overall would indicate that we are not remiss in interpreting our drops in expenditures as reductions in income.

Infant Mortality

Inferring Economic Status

We follow Bollen, Glanville, and Stecklov (2002) in inferring household wealth for DHS households by tabulating the total number of asset categories present in the house, and then ranking each households' total wealth (unweighted by asset type) against other households in their region the year they were surveyed. We argue that In light of both common intuition and our results in section 5.1 it is clear that this stratification suffers from no small degree of endogeneity, since 'poorer' households with fewer assets may simply be worse hit by typhoons.

We argue that our measure of socioeconomic status is nonetheless a reasonable proxy for several reasons. First, since we rank each household against other households in its region our measure will be a poor proxy only if a household's rank *relative to other households'* is affected by typhoons nonmonotonically with wealth, and while we observe differential impacts of typhoons across by income this relationship appears to be monotonic. Second, while asset losses due to typhoons are clearly large, they are small as a proportion of total assets, implying that our potential margin for error is small.

Third, we note that due to the quasi-panel nature of DHS data our concerns about typhoon impact altering our SES metric are only relevant for very recent typhoons; for the bulk of observations we are looking at several years before the DHS surveyor arrived and observed household assets, minimizing the potential for bias.

Robustness

Table C.7 shows specification sensitivity checks of our infant female mortality result. We begin by regressing the binary variable indicating whether a household in our sample reports an infant female's death in a given year against our raw measure of typhoon intensity, maximum wind speed, with standard errors clustered at the level of treatment, the region. Even in this very limited specification we find a significant (and the 10% level) and positive association between infant female mortality and typhoon intensity in the calendar year following typhoon exposure. Controlling for year fixed effects does little to change this result, but controlling for region fixed effects does, strengthening the response and incrasing the precision with which we estimate our impacts. We find no evidence that leads in our model predict female infant mortality, or that varying the lead and lag structure of our distributed lags model appreciably alters our results.

Fetal losses

The gendered nature of infant deaths in our sample may plausibly, at least for in utero effects, reflect the widely documented gender disparity in fetal deaths (Trivers and Willard (1973); Almond, Edlund, and Palme (2009); Sanders and Stoecker (2011)). It is thus feasible that the heavily female nature of the infant mortality result is due to different timing of deaths due to fetal typhoon exposure: in utero exposure could result in immediate death for affected male fetuses but only non-mortal damage to girls. Those girls would have a higher propensity to be born preterm or low birth weight, and

be more likely to die later on.

We examine in-utero exposure in Figure C.5, showing the cumulative impact of typhoons on birth rates. We find that birth rates generally fall in the 9 months after typhoon impact, particularly for males. Since this is before possible typhoon-induced changes in conceptive behavior, we conclude that this reduction in the birth rate most likely results from the typhoon's traumatic impact on the intrauterine environment, and interpret this result as supportive of the generally higher propensity of males to die in utero. We find that female births actually increase slightly after storm impact, perhaps reflecting storms' increasing the likelihood of pre-term birth, but this effect is quickly swamped by the same downward trend. We find that after the 9 month mark has passed cumulative birth rates begin to recover, suggesting possible attempts by households to make up for lost fertility. We explore whether this effect is discernable at the annual level in Table C.8. We find that Figure C.5's reduction in birth rates is apparent in a negative, but not significant, coefficients for males.

We explore whether this differential response in fetal deaths results in material changes in gender of mortality rates in Figure C.6. We find that the large decrease in male births combined with the lack of any systematic response in male mortality makes our estimate of monthly deaths sensitive to minor changes in specification, and thus normalize gendered mortality rates by the previous period's gendered birth rates. Doing so substantially reduces noise in our estimate and reveals that while female infants experience a marked increase in birth-rate adjusted mortality, the response among male infants remains flat.

C   Appendix: Tables and Figures
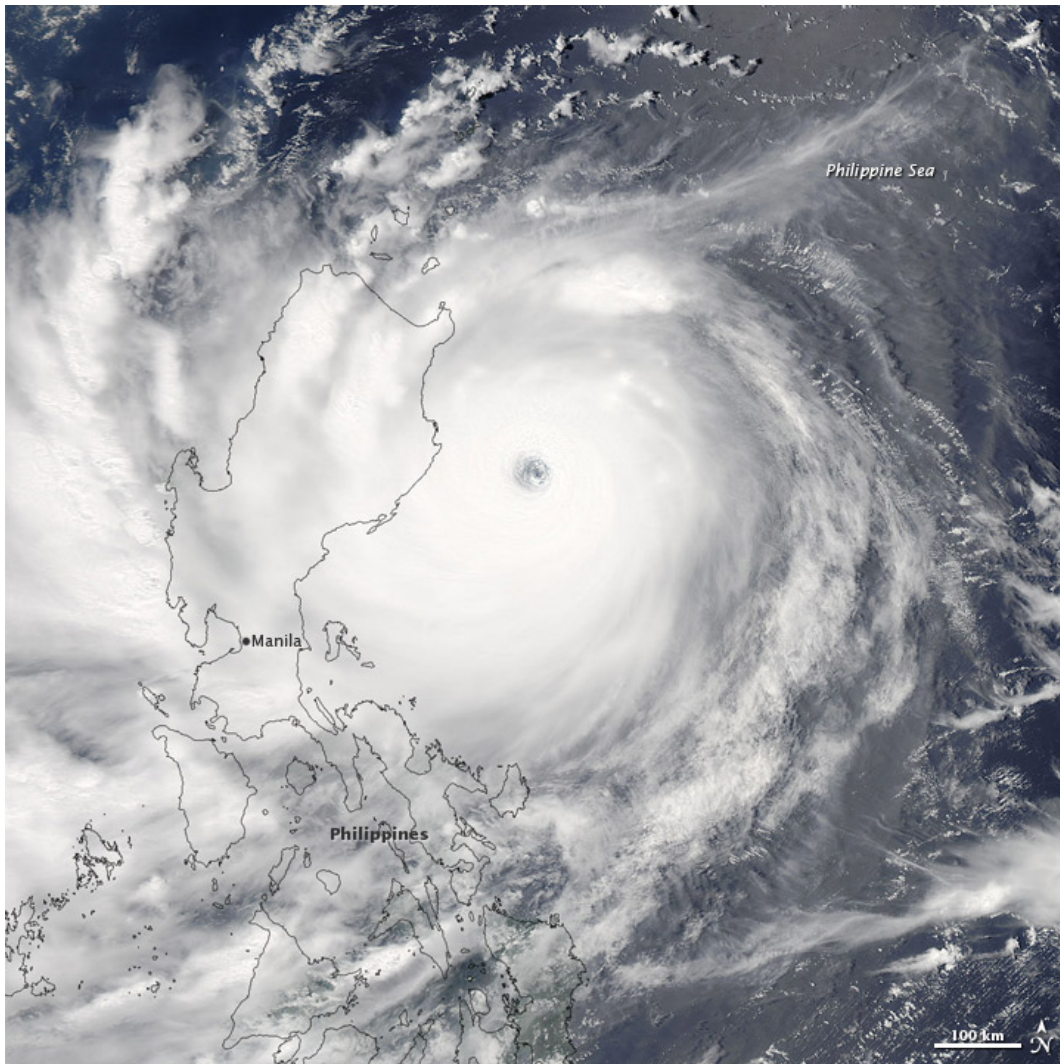
Appendix Figure C.1: Typhoon Nanmadol striking the Philippines (moving westward) in 2011.
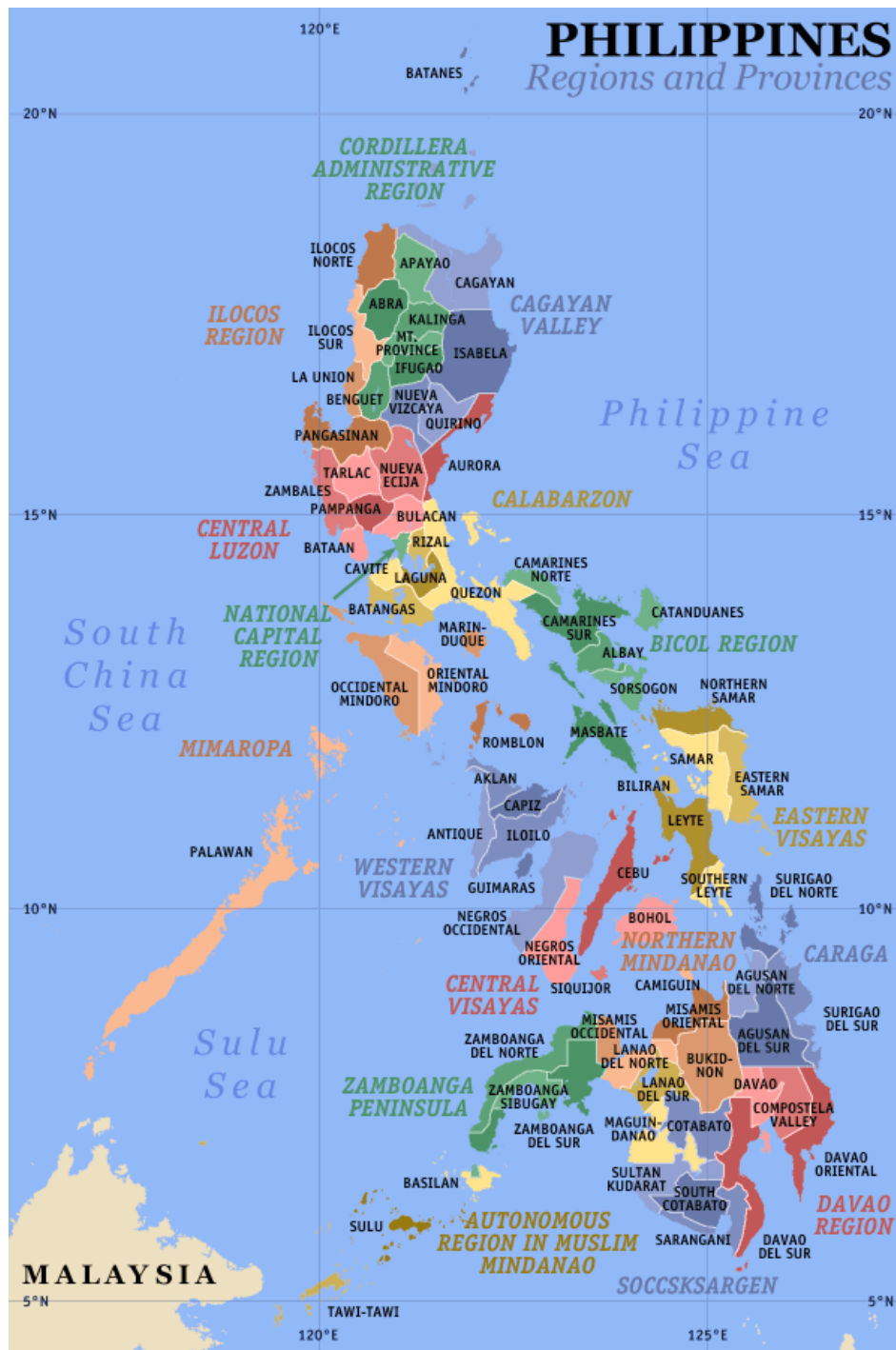
Appendix Figure C.2: Provincial map of the Philippines in 2003. Provinces are the smaller administrative unit, regions are larger and have their names in capital letters. Made by Eugene Alvin Villar and reproduced under a Creative Commons license.
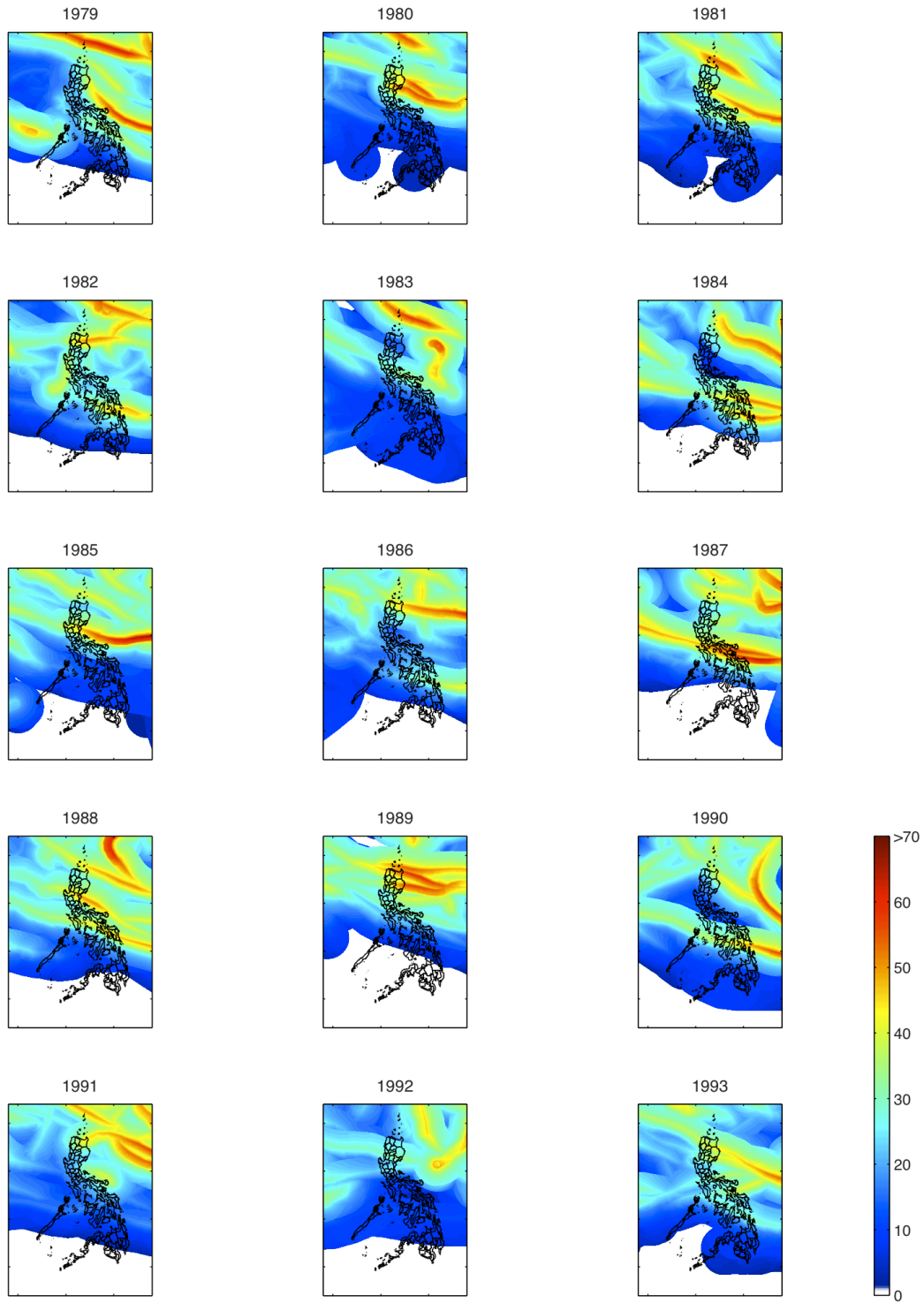
Appendix Figure C.3: LICRICE estimates of annual typhoon exposure during 1979-1993. Color indicates the maximum wind speed (m/s) experienced at the surface over the course of the year.
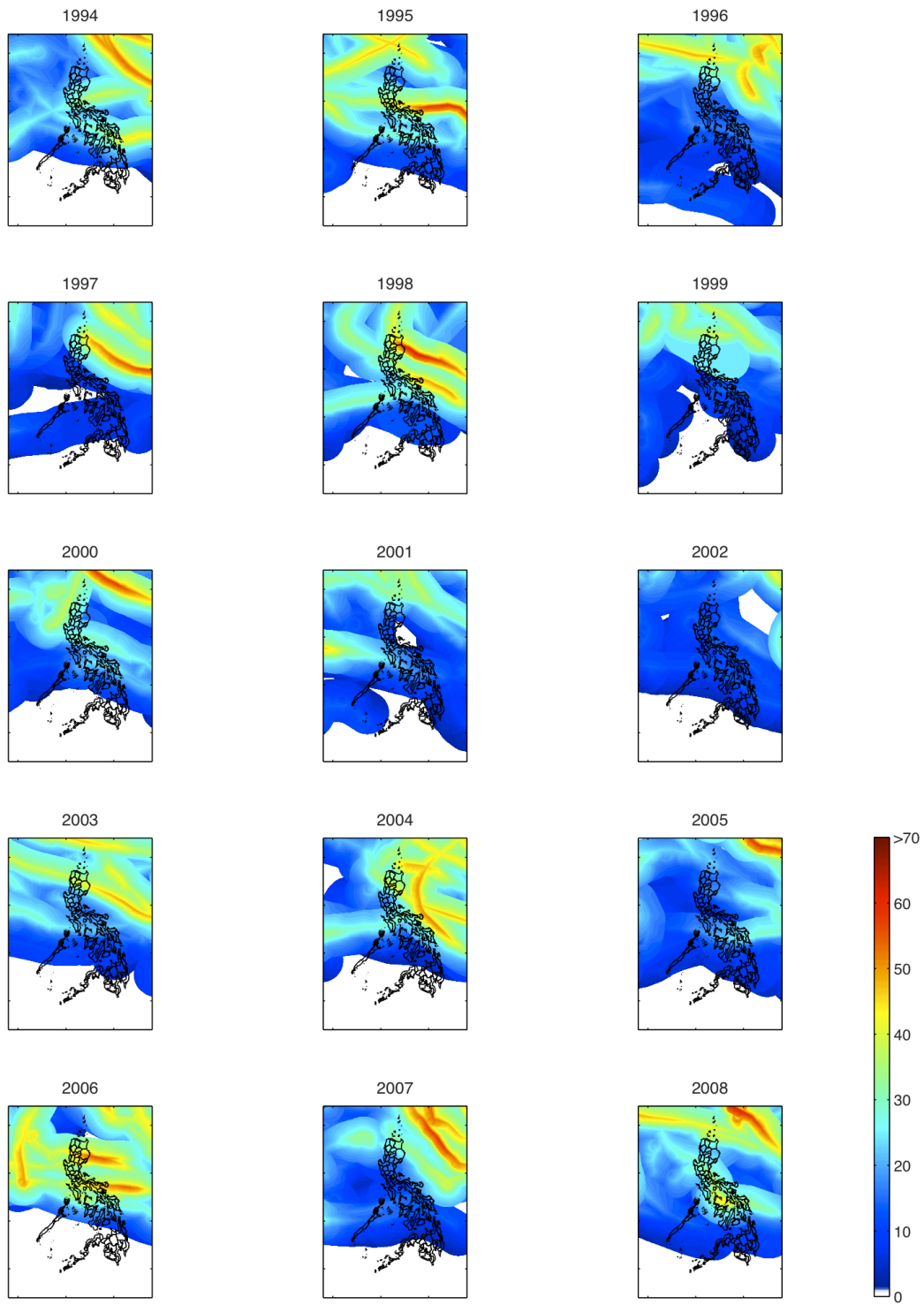
Appendix Figure C.4: LICRICE estimates of annual typhoon exposure (con't) during 1994-2008. Color indicates the maximum wind speed (m/s) experienced at the surface over the course of the year.

Typhoon impacts on birth rates
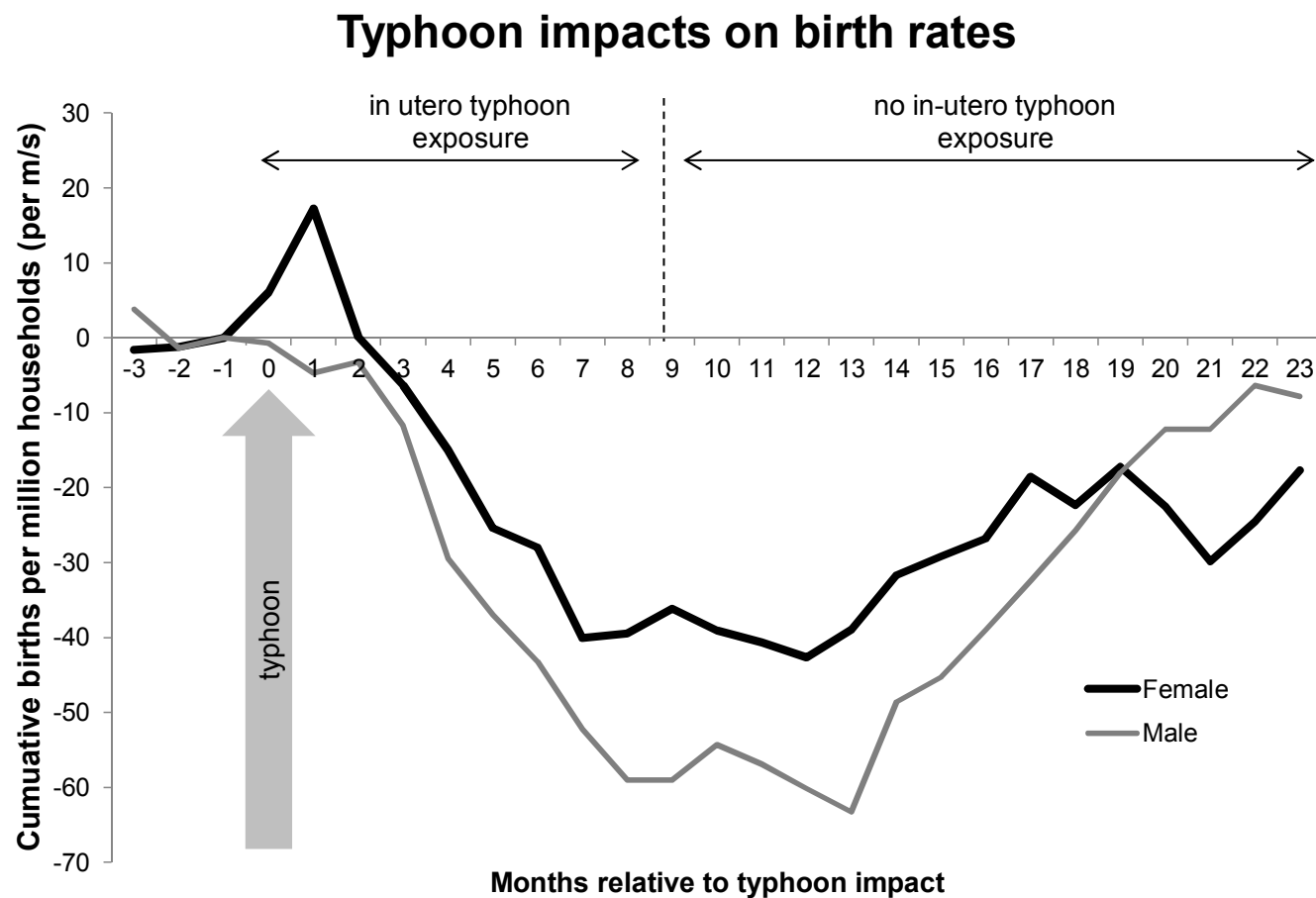
Appendix Figure C.5: Inferred cumulative impact of typhoons on female (black line) and male (grey line) fetal deaths. Births are per million households per year. Cumulative effect normalized such that month prior to typhoon impact is zero. Includes region, year, and month fixed effects, and lagged temperature and precipitation controls.

Birth-rate adjusted male vs. female infant mortality
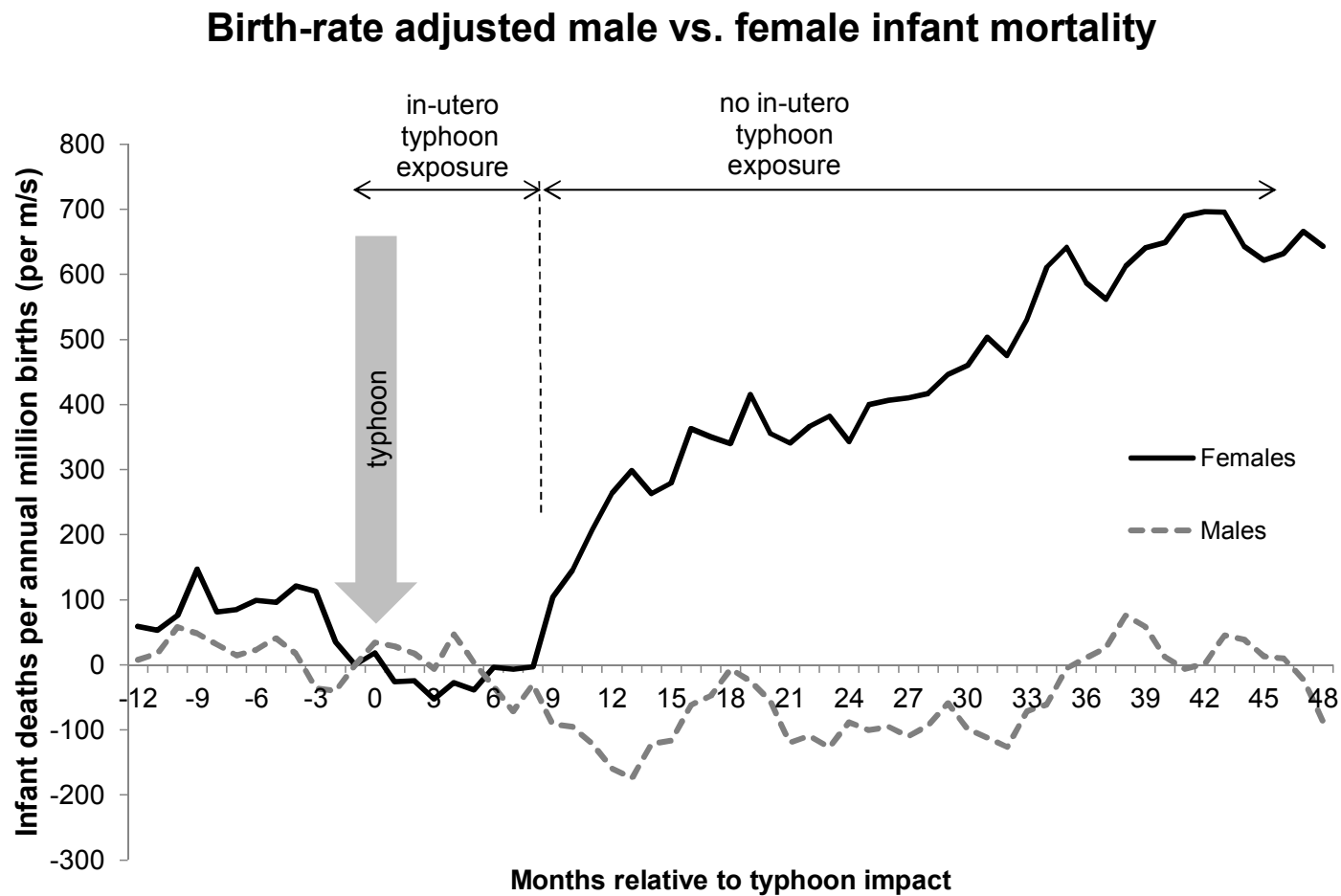
Appendix Figure C.6: Cumulative impact of typhoons on birth-rate-adjusted infant female mortality (black line) and birth-rate-adjusted male infant deaths (dotted grey line). Units are infant deaths per annualized million births based on previous month's birth rate. Cumulative effect normalized such that month prior to typhoon impact is zero. Includes region, year, and month fixed effects, lagged temperature and precipitation controls, and lagged dependent variable.

Appendix Table C.1: Checking for balance on typhoon exposure in FIES data

VARIABLES	(1) Total family size	(2) Single family dwelling (%)	(3) Married (%)	(4) Male (%)	(5) Uneducated	(6) Only primary school	(7) Only secondary school
				Household head characteristics			
Max wind speed, T=0 (m/s)	0.0023	0.03	0.04	0.07*	-0.02	-0.12	-0.23***
	[0.0029]	[0.04]	[0.02]	[0.04]	[0.02]	[0.07]	[0.06]
T + 1	-0.0002	0.03	0.01	0.05**	0.01	0.02	0.08**
	[0.0021]	[0.04]	[0.02]	[0.02]	[0.01]	[0.04]	[0.04]
T + 2	0.0010	0.03	-0.01	0.03	-0.03	-0.26**	0.11*
	[0.0025]	[0.05]	[0.03]	[0.03]	[0.02]	[0.09]	[0.06]
T + 3	-0.0025	-0.01	0.02	0.07*	0.02	-0.08	-0.02
	[0.0022]	[0.08]	[0.04]	[0.03]	[0.02]	[0.08]	[0.09]
T + 4	0.0011	0.01	0.01	-0.01	-0.01	0.10*	0.03
	[0.0021]	[0.06]	[0.02]	[0.02]	[0.02]	[0.05]	[0.04]
Observations	142,789	142,789	142,789	142,789	142,789	142,789	142,789
R-squared	0.0143	0.02	0.01	0.01	0.08	0.14	0.24

Notes: Standard errors clustered at the treatment (province) level in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Lags 0-5 estimated but only shown for 0-4. Includes province and year fixed effects and lagged temperature and precipitation controls.

Appendix Table C.2: Household asset loss to lagged typhoon exposure

VARIABLES	(1) Has improved water (%)	(2) Has faucet (%)	(3) Any toilet (%)	(4) Sealed toilet (%)	(5) Strong roof (%)	(6) Has radio (%)	(7) Has stereo (%)	(8) Has refrigerator (%)	(9) Has AC (%)
Max wind speed, T=0 (m/s)	-0.01	0.04	0.07	0.02	-0.09	-0.02	-0.01	0.03	-0.01
	[0.08]	[0.10]	[0.06]	[0.08]	[0.09]	[0.10]	[0.08]	[0.06]	[0.01]
T + 1	0.04	-0.03	-0.04	-0.18***	-0.06	0.03	-0.13***	-0.08**	-0.00
	[0.06]	[0.07]	[0.04]	[0.06]	[0.06]	[0.05]	[0.04]	[0.03]	[0.01]
T + 2	0.11*	0.30**	-0.02	-0.02	0.04	0.01	0.06	0.11***	0.01
	[0.05]	[0.11]	[0.05]	[0.09]	[0.11]	[0.07]	[0.05]	[0.04]	[0.01]
T + 3	0.03	0.04	0.04	-0.14	0.08	0.00	0.01	-0.03	0.01
	[0.08]	[0.10]	[0.06]	[0.10]	[0.10]	[0.09]	[0.03]	[0.04]	[0.02]
T + 4	-0.03	-0.12***	-0.01	-0.14**	-0.03	-0.01	-0.09**	-0.08**	-0.00
	[0.03]	[0.04]	[0.02]	[0.06]	[0.03]	[0.03]	[0.04]	[0.03]	[0.01]
Observations	107,620	107,620	107,620	107,620	107,620	107,620	107,620	107,620	107,620
R-squared	0.13	0.16	0.16	0.24	0.24	0.06	0.11	0.23	0.02

Notes: Robust standard errors (clustered at province level) in brackets. *** p<0.01, ** p<0.05, * p<0.1. Lags 0-5 estimated but only 0-4 shown. Includes year and province FE, temperature and precipitation controls, and household covariates consisting of: log number of total members in household; log number of working age (¿15) household members; indicator variable for household head being male; and indicator variables for household head's education.

Appendix Table C.3: Wage rate stability to typhoon incidence

VARIABLES	(1) All farm wages (%)	(2) All farm wages (male) (%)	(3) All farm wages (female) (%)	(4) Palay farm wages (%)	(5) Corn farm wages (%)	(6) Coconut farm wages (%)	(7) Sugarcane farm wages (%)
Max wind speed, T=0 (m/s)	0.07	-0.02	-0.09	0.17	0.08	0.03	0.17
	[0.11]	[0.11]	[0.10]	[0.13]	[0.09]	[0.14]	[0.13]
T + 1	0.02	-0.05	-0.13	0.14	0.03	-0.09	0.02
	[0.10]	[0.13]	[0.11]	[0.14]	[0.09]	[0.13]	[0.16]
T + 2	0.02	0.04	0.15	0.14	0.04	0.05	-0.03
	[0.07]	[0.14]	[0.13]	[0.10]	[0.09]	[0.16]	[0.15]
T + 3	0.11	0.05	0.06	0.17	0.03	0.09	-0.03
	[0.09]	[0.12]	[0.14]	[0.12]	[0.11]	[0.12]	[0.13]
T + 4	0.04	0.01	-0.02	0.07	-0.05	0.10	-0.00
	[0.07]	[0.16]	[0.19]	[0.08]	[0.10]	[0.09]	[0.13]
Observations	294	195	195	294	294	271	217
R-squared	0.92	0.92	0.87	0.89	0.90	0.84	0.88
Year range	1985:2008	1994:2008	1994:2008	1985:2008	1985:2008	1985:2008	1985:2008

Notes: Observations at province level. Percent change calculated as log points *100 per m/s of max wind speed. Standard errors (clustered at region level) in brackets. *** p<0.01, ** p<0.05, * p<0.1. Lags 0-5 estimated but only 0-4 shown. Includes year and province FE and temperature and precipitation controls

Appendix Table C.4: Meat prices as a function of typhoon incidence

VARIABLES	(1) Beef lean meat (%)	(2) Beef bone in meat (%)	(3) Pork lean meat (%)	(4) Pork bone in meat (%)	(5) Pork pata (%)
Max wind speed, T=0 (m/s)	0.32	-0.01	-0.06	-0.06	-0.10
	[0.38]	[0.08]	[0.07]	[0.07]	[0.14]
T + 1	0.25	-0.25**	-0.05	-0.09	-0.11
	[0.53]	[0.11]	[0.09]	[0.10]	[0.17]
T + 2	-0.25	-0.17**	0.03	0.06	-0.11
	[0.18]	[0.06]	[0.07]	[0.08]	[0.09]
T + 3	0.29	-0.17	0.09	0.02	-0.04
	[0.45]	[0.10]	[0.10]	[0.09]	[0.09]
T + 4	0.02	-0.11	0.05	0.10	0.02
	[0.20]	[0.08]	[0.10]	[0.09]	[0.09]
Observations	266	252	266	266	266
R-squared	0.68	0.97	0.98	0.98	0.97

Notes: Observations at province level. Percent change calculated as log points *100 per m/s of max wind speed. Standard errors (clustered at region level) in brackets. *** p<0.01, ** p<0.05, * p<0.1. Lags 0-5 estimated but only 0-4 shown. Includes year and province FE and temperature and precipitation controls

Appendix Table C.5: Fruit prices as a function of typhoon incidence

VARIABLES	(1) Bananas (lakatan) (%)	(2) Bananas (latundan) (%)	(3) Bananas (aba) (%)	(4) Mandarins (%)	(5) Mango (carabao) (%)	(6) Mango (piko) (%)	(7) Papaya (%)	(8) Pineapple (%)
Max wind speed, T=0 (m/s)	-0.20	-0.19	0.11	-0.50	-0.07	0.48	-0.10	0.33
	[0.29]	[0.16]	[0.23]	[0.46]	[0.23]	[0.38]	[0.27]	[0.24]
T + 1	-0.26	0.11	1.02***	-0.62	-0.14	0.68*	0.02	0.31
	[0.21]	[0.18]	[0.27]	[0.52]	[0.11]	[0.35]	[0.27]	[0.30]
T + 2	-0.29	-0.15	0.43**	-0.09	0.07	-0.17	-0.33	0.07
	[0.24]	[0.13]	[0.16]	[0.42]	[0.12]	[0.38]	[0.28]	[0.37]
T + 3	-0.33	-0.16	0.50*	0.03	0.38**	0.44	-0.02	-0.14
	[0.26]	[0.21]	[0.24]	[0.42]	[0.17]	[0.28]	[0.24]	[0.34]
T + 4	-0.45**	-0.39*	0.19	-0.03	-0.34***	-0.67**	-0.45	-0.05
	[0.16]	[0.20]	[0.26]	[0.38]	[0.11]	[0.29]	[0.29]	[0.34]
Observations	266	266	266	186	266	227	266	266
R-squared	0.94	0.95	0.90	0.80	0.87	0.79	0.89	0.89

Notes: Observations at province level. Percent change calculated as log points *100 per m/s of max wind speed. Standard errors (clustered at region level) in brackets. *** p<0.01, ** p<0.05, * p<0.1. Lags 0-5 estimated but only 0-4 shown. Includes year and province FE and temperature and precipitation controls

Appendix Table C.6: Grain prices as a function of typhoon incidence

VARIABLES	(1) Rice (fancy) (%)	(2) Rice (premium) (%)	(3) Well-milled rice (%)	(4) Reg. milled rice (%)	(5) Corn (yellow) (%)	(6) Corn (white) (%)	(7) Corn grits (yellow) (%)	(8) Corn grits (white) (%)
Max wind speed, T=0 (m/s)	0.07	0.08	-0.04	-0.05	0.18	0.22	-0.31***	0.27
	[0.16]	[0.12]	[0.05]	[0.06]	[0.32]	[0.30]	[0.06]	[0.26]
T + 1	-0.10	0.12	-0.10	-0.06	-0.10	0.41	-0.33***	0.00
	[0.20]	[0.16]	[0.07]	[0.06]	[0.28]	[0.34]	[0.10]	[0.20]
T + 2	-0.05	0.14	-0.07	-0.08	0.07	0.01	-0.34***	-0.05
	[0.19]	[0.16]	[0.06]	[0.07]	[0.29]	[0.31]	[0.11]	[0.22]
T + 3	-0.15	0.05	-0.10*	-0.03	-0.18	0.21	-0.28***	0.42
	[0.22]	[0.17]	[0.06]	[0.07]	[0.20]	[0.22]	[0.08]	[0.43]
T + 4	-0.22	0.03	-0.06	-0.09*	-0.19	0.02	-0.19*	-0.29
	[0.19]	[0.13]	[0.04]	[0.04]	[0.15]	[0.12]	[0.10]	[0.22]
Observations	195	179	266	263	224	210	260	226
R-squared	0.90	0.92	0.99	0.99	0.89	0.88	0.97	0.92

Notes: Observations at province level. Percent change calculated as log points *100 per m/s of max wind speed. Standard errors (clustered at province level) in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Lags 0-5 estimated but only 0-4 shown. Includes year and province FE and temperature and precipitation controls

Appendix Table C.7: Infant female mortality specification robustness

VARIABLES	(1) Infant female mortality	(2) Infant female mortality	(3) Infant female mortality	(4) Infant female mortality	(5) Infant female mortality
Max wind speed, T=0 (m/s)	-26.15	-18.11	20.31	17.13	23.01
	(16.68)	(18.25)	(17.30)	(18.22)	(23.34)
T + 1	30.44*	27.68*	63.48***	68.15***	74.68***
	(14.98)	(14.92)	(19.43)	(20.85)	(21.12)
T + 2	-7.044	-17.00	17.85	22.80	30.34
	(8.896)	(9.758)	(15.67)	(16.31)	(17.99)
T + 3	15.15	2.132	36.05**	31.74**	39.53**
	(13.02)	(14.65)	(14.29)	(13.92)	(16.20)
T + 4	5.903	1.003	39.29	35.65	42.83
	(15.87)	(18.45)	(22.65)	(25.66)	(25.25)
Observations	265,446	265,446	265,446	265,446	265,446
R-squared	0.000	0.000	0.001	0.001	0.082
Year FE		Y	Y	Y	Y
Region FE			Y	Y	
Lagged temp., precip.				Y	Y
Mother FE					Y

Notes: Mortality shown per million households per year. Standard errors clustered at the treatment (region) level in brackets. *** p<0.01, ** p<0.05, * p<0.1. Lags 0-5 estimated but only shown for 0-4.

Appendix Table C.8: Birth rates by gender

	(1)	(2)	(3)
VARIABLES	Any birth	Male birth	Female birth
Max wind speed, T=0 (m/s)	-150.2	-252.0	94.50
	(181.7)	(142.8)	(71.69)
T + 1	-97.47	-122.8	18.50
	(156.1)	(115.5)	(93.58)
T + 2	27.39	91.89	-75.95
	(180.1)	(113.8)	(87.46)
T + 3	91.89	0.739	90.67
	(157.0)	(147.3)	(59.45)
T + 4	389.8**	174.6	215.6**
	(170.4)	(133.0)	(77.40)
Observations	265,430	265,430	265,430
R-squared	0.168	0.117	0.117

Notes: Births shown per million households per year. Standard errors clustered at the treatment (region) level in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Lags 0-5 estimated but only shown for 0-4. Includes region and year fixed effects, lagged temperature and precipitation controls, and mother fixed effects.