Insuring Growth: Indexed Disaster Funds and Risk Response in Mexico

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Government provision of disaster aid is typically hampered by liquidity constraints and lack of rules and administrative capacity to disburse reconstruction resources. We show that by easing these hurdles, Mexico's indexed disaster fund (Fonden) substantially lessens losses from extreme weather. To estimate Fonden's impact on economic recovery, as measured by night lights, we exploit the rainfall index that determines program eligibility. We find that, for 15 months after a disaster, eligible municipalities are 10% brighter than those ineligible, with gains concentrated among less resilient municipalities. We additionally document how Fonden rules curb moral hazard and shield resources from political abuse. *(JEL Q54, H12, H84, I38, O10.)*

Extreme weather events are one of the main channels through which the climate interacts with the economy. During the last decade, average annual losses due to extreme weather events amounted to $144 billion and were roughly 1.7 times larger than corresponding losses during the 1990's (Swiss Re, 2018). These costs are likely to increase as the frequency and severity of extreme weather events caused by climate change are predicted to worsen (IPCC, 2012; Emanuel, 2017). Following an extreme weather event, governments' most common shock-coping response is the provision of disaster aid, the bulk of which is spent on reconstruction projects (Ghesquiere and Mahul, 2010). These projects include the restoration of lifeline infrastructure such as roads, electricity, and safe water, and are expected to reduce the duration of costly periods of disruption to economic activity (Gurenko and Lester, 2004). In developing economies, reconstruction efforts are commonly stifled by two key constraints (Clarke and Dercon, 2016). First, funding for reconstruction is typically only arranged after a disaster occurs. This practice leads to costly liquidity gaps that delay the start of reconstruction efforts and to resource mobilization with high opportunity costs on growth and social welfare. Second, even when funding is available, countries usually lack specialized rules and administrative capacity to minimize delays and leakages in the disbursement of reconstruction resources.

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In this paper, we study Mexico's Fund for Natural Disasters (Fonden), a national indexed disaster fund designed to overcome these constraints. Fonden reduces liquidity gaps by arranging for the financing of reconstruction efforts before a disaster occurs. Specifically, instead of raising funds using budget reallocations, post-disaster borrowing, tax increases, or foreign disaster aid, Fonden relies on an annual budget allocation and risk transfer instruments that include the purchase of excess loss reinsurance and the issuance of catastrophe bonds. Fonden also uses a rules-based system to disburse reconstruction resources with minimum delays and leakages. The rules define which hazards and assets are covered, and describe in detail the procedures that should be followed to verify the occurrence of a qualifying disaster (primarily using indexes), transfer resources to affected municipalities, and contract, execute, and audit reconstruction projects. Fonden's responsibility covers reconstruction of public infrastructure and low-income housing.

We analyze whether Fonden helps reduce the disruption to economic activity that follows an extreme weather event, its cost-effectiveness, heterogeneity in the impact of the program, and its effect on risk management behavior. Our unit of analysis is the municipality, the administrative unit below a state. In absence of information on municipal level economic activity, we follow the recent literature and proxy changes in economic activity using night lights (see Donaldson and Storeygard, 2016, for a literature review). Among extreme weather events, we focus on the set of hydro-meteorological shocks that make up the bulk of Fonden expenditures, that is heavy rainfall, flooding, and hurricanes. To estimate the causal impact of Fonden on economic activity, we take advantage of Fonden's index insurance rules. Specifically, a municipality is eligible for Fonden resources when rainfall occurs in excess of a predetermined threshold. If the heavy rainfall rule is not triggered, a municipality may still be eligible for Fonden transfers by meeting the heavy wind or flooding criteria. The heavy rainfall rule is important for identification because it allows us to compare those municipalities that were barely eligible and those that were barely ineligible for a payout. Because compliance with the rainfall index is imperfect, due primarily to the supplementary wind and flooding criteria that we do not observe, we exploit this rule using a fuzzy regression discontinuity design.

Our results fall into five categories. The first set of results relates to the shock-coping impact of Fonden on night lights. We find that the program can considerably reduce the disruption to economic activity generated by hydro-meteorological events. In the year following an event, we observe that ineligible municipalities become dimmer while those eligible remain relatively brighter. Our preferred Intention-to-treat (ITT) estimate indicates that night lights are 10% brighter in eligible municipalities than in ineligible municipalities. Among municipalities near the cut-off that received Fonden because they experienced rainfall in excess of the threshold compared to those that did not, our estimate of the Local Average Treatment Effect (LATE) shows that Fonden increased night lights by roughly 50%.

This considerable lessening of the decline in economic activity in the year following the disaster is not permanent. We find that, consistent with administrative records, the impact of Fonden over time can be characterized in three phases: (i) A phase of setup for reconstruction, extending from months zero to four, during which we observe no impact of Fonden on night lights. (ii) A phase of active recovery, extending from months five to 15, during which we find an increasing effect of Fonden on night lights that peaks at the end of the period. (iii) A phase of catching up, extending from months 16 to 24, during which the impact of Fonden on night lights progressively decreases. As can be expected with large reconstruction programs, we observe spillover effects on neighboring municipalities. These effects go in the same direction as the direct effect and quickly decay with distance.

The second set of results suggests that our previous findings may be externally valid and that the shock-coping benefits of Fonden are likely larger than the costs of the program. Specifically, we show that our estimate of Fonden's LATE is locally constant (Cerulli et al., 2016; Dong and Lewbel, 2015), that is, that the estimated effect does not change with the running variable. This finding is important because it implies that our estimate is likely informative beyond the subset of complier municipalities near the cut-off. Next, we perform a series of back-of-the-envelope calculations on benefits and costs. We find that Fonden's LATE on night lights is roughly equivalent to a 4% increase in municipal GDP and that the value of the economic activity generated by Fonden is 1.4 times larger than the cost of the program.

The third set of results documents heterogeneity in the effect of Fonden. Specifically, we provide supporting evidence to argue that it is Fonden investments in road reconstruction that yield the largest benefits, and that municipalities that may be initially less resilient, because they lack water management infrastructure, benefit disproportionately more from Fonden.

The fourth set of results illustrates that, even in the absence of extreme weather events, Fonden may alter households' risk management behavior because it reduces their risk of experiencing a loss. Specifically, we use a difference-in-differences design that compares municipalities where rainfall shocks are less salient (historically low rainfall) with municipalities where these shocks are more salient (historically high rainfall) before and after the introduction of Fonden. Our focus is on testing whether the provision of subsidized disaster insurance encourages households to settle in disaster-prone areas. We find that Fonden led to a 4% increase in the share of flood-prone land that is inhabited, but that this effect disappeared after Fonden tightened-up rules on relocation of households away from high risk areas.

Finally, we show that our estimates of the impact of Fonden are robust and have a causal interpretation. Specifically, we provide supporting evidence to show that the heavy rainfall rule was not manipulated, and that it is unlikely to have affected night lights through alternative channels. We offer results from two placebo exercises, conduct a broad set of robustness checks, and show that predetermined covariates capturing the capacity of local governments and other characteristics of municipalities are continuous at the cut-off. Besides its importance for identification of causality, these results also suggest that Fonden's institutional rule based on indexation makes it hard for local governments to manipulate the running variable, protecting resource transfers from political abuse.

Our findings contribute to the literature on effectiveness of disaster aid. This literature has documented both the lack of incentives to provide discretionary disaster aid in the absence of strong democratic institutions and media coverage (e.g., Sen, 1981; Besley and Burgess, 2002; Eisensee and Strömberg, 2007) and the largely dysfunctional nature of government responses to extreme weather events. For example, Noy and Nualsri (2011) argue that in developing economies the fiscal response to natural disasters leads to increased losses because governments tend to decrease expenditures and increase taxes in the aftermath of disasters. By comparison, in industrialized economies governments generally respond to disasters by increasing expenditures, but these additional expenditures are mainly provided through programs that are neither designed nor funded to deal with extreme weather shocks. As recently shown by Deryugina (2017), the largest component of the fiscal response following hurricanes in the US is not disaster aid but the expansion of social safety nets.

National indexed disaster funds offer a promising alternative to improve the provision of disaster aid because they allow governments to rely upon some of the institutional innovations that insurance companies regularly use to manage risk. These innovations include ex-ante risk financial planning to guarantee the availability of funds; rules to determine risk ownership, pay claims, and curb moral hazard; and use of parametric indexes to minimize the cost of assessing losses and shield resources against political influence.

Take up by governments of national indexed disaster funds remains limited, presumably due to their large setup costs and lack of quantitative information on their overall benefits, or on the benefits of specific innovations. This is in general the case for index insurance which has been widely studied in the context of smallholder agriculture (Carter et al., 2017) but about which little is known in the context of catastrophe insurance deployed at a national scale.

In this paper we fill this gap by providing the first causal estimate of the effect of a national indexed disaster fund on economic recovery and on the risk management response of households. We thereby demonstrate the potential that a rules-based government response has to mitigate the disruption to economic activity generated by extreme weather. These findings are important because the institutional innovations embodied in Fonden can be easily replicated in other countries.

Our results also add empirical evidence to the literature on the economic impact of natural disasters (see Cavallo and Noy, 2009; Kellenberg and Mobarak, 2011; Klomp and Valckx, 2014, for literature reviews), where a consensus is yet to be reached on the extent to which disasters can harm or spur economic growth, and on how these effects may vary depending on disaster type and intensity. We find that in Mexico large rainfall events have a short-run negative effect on local economic growth. While our results highlight that Fonden has accelerated economic recovery by one year or two, they also indicate that its effect on growth is not permanent because municipalities that are not eligible for Fonden catch-up. We thus do not, at least over a two years period after the disaster, find evidence of mechanisms that could create permanent differences such as poverty traps (Azariadis and Drazen, 1990; Kahn, 2005; Noy, 2009; Carter et al., 2007) or build-back-better effects (Crespo Cuaresma et al., 2008; Hallegatte and Dumas, 2009).

The paper is organized as follows. Section 1 provides information on Fonden. Section 2 describes the data. Section 3 presents the identification strategy and the results. Section 4 gives supporting evidence on our identification assumptions and robustness checks. Section 5 concludes.

1 Mexico's Fonden Disaster Fund

Fonden is a federal program that became operational in 1999 and is designed to insure public infrastructure and low-income housing against natural disasters. It is expected to provide disaster-aid efficiently because its financial plan guarantees the availability of funds and because its rules-based system ensures the timely execution of reconstruction funds.

As argued by Clarke and Dercon (2016), there are strong parallels between the institutional innovations embodied in Fonden and the way an insurance company operates. To guarantee the availability of funds after a disaster of any size, like an insurer, Fonden uses a financial plan that relies on its budget allocation to pay for frequently occurring claims, and on risk-sharing instruments to pay for costly but less frequent claims. Specifically, Fonden's budget (no less than 0.4 percent of the federal budget and $\approx$ USD \$800 million) is used to pay for frequently occurring losses, for the purchase of excess loss reinsurance, and for the placement of catastrophe bonds. This financial plan allows Fonden to draw on the payouts of reinsurance and bonds ($\approx$ USD \$700 million) to cover the costs of large disasters. In the case of a rare disaster, that is large enough to exhaust all of Fonden sources of funding, Fonden is designed to continue operating through an exceptional budget allocation. This exceptional allocation draws primarily from Mexico's Oil Surplus Fund (World Bank, 2012).

Also like an insurance company, Fonden relies on three sets of rules. The first defines risk-ownership, by specifying ex-ante the assets and perils that the program covers. While Fonden coverage extends to several types of private and public assets, as revealed by program expenditure data, the main types are: roads (61%), hydraulic infrastructure (supply of safe water 19%), low-income housing (6%), and education (1%) and health (1%) infrastructure.[1] Regarding perils, the program protects against several geological and hydro-meteorological hazards. In this paper, we focus on rainfall, flooding, and hurricanes because these hazards make up 93% of the claims and 96% of program expenditures.[2]

The second set of rules defines the procedure for the verification and payment of claims. This procedure can be broadly divided into three steps: (i) verification of the occurrence of a disaster; (ii) damage assessment; and (iii) disbursement of resources, reconstruction, and auditing.

Like with index insurance, Fonden verification is, for most hazards, based on comparing a measure of the intensity of the hazard to a predefined threshold. The verification process begins with a request made by the governor of an affected state or by a federal ministry with affected assets. The request contains a list of municipalities that are believed to have experienced damages from a natural disaster. In the case of hydro-meteorological events, the technical agency designated to perform the verification is Conagua (the national water authority). To corroborate the occurrence of heavy rainfall, flooding, or hurricanes, Conagua relies primarily on a heavy rainfall rule. Since 2004, this rule establishes that heavy rainfall occurs if daily rainfall at any of the municipality's representative weather stations is greater than, or equal to, the percentile 90 of maximum historic daily rainfall for the month in which the event took place. In addition to the heavy rainfall rule, Conagua also uses Fonden's supplementary criteria for the verification of hurricanes and flooding. Specifically, the occurrence of a hurricane can also be verified when sustained winds exceed 80 km/h. Similarly, flooding is also verified when Conagua confirms that water has pooled in areas not normally submerged, or that a body of water has overflown past its normal limits.[3]

Conagua concludes the verification process by submitting to Segob (the Secretariat of the Interior) a list of the municipalities that were requested and a list of the municipalities

[1] Figure A1 in the appendix provides further details by plotting Fonden expenditures by year and type of reconstruction.

[2] We exclude from the analysis hazards covered by Fonden for whom we have no measure of their intensity. These hazards include: Avalanche, earthquake, forest fire, heavy snow, landslide, subsidence, seaquake, severe drought, severe hailstorm, tornado, tsunami, and volcanic eruption.

[3] Our weather dataset does not allow us to replicate the verification exercise performed by Conagua using thresholds other than heavy rainfall.

with a verified disaster. Among verified municipalities, Segob further confirms, using a preliminary damage report, that the disaster has exceeded the local operational and financial response capabilities and issues a disaster declaration in the Official Newspaper. The disaster declaration lists the requested and verified municipalities. Only municipalities listed as verified in the disaster declaration are considered eligible for Fonden.

In the next step, among municipalities with a verified disaster, Fonden acts like an indemnity insurance contract because it quantifies and fully compensates municipalities for the losses experienced.[4] To quantify the losses, a damage assessment committee, comprised of both federal and state representatives, visits the affected area, documents in detail the extent of damages, and issues a damage report. This report provides geocoded photographic evidence of damages and itemized reconstruction costs. The committee's work is audited by an inter-ministerial commission and by Fonden before disbursement. On average this step is completed within 76 days of the disaster. Most municipalities have funds ready for disbursement within three months. Since 2009, reconstruction of lifeline infrastructure has been further expedited by allowing partial disbursements to take place immediately after disaster verification.

In the last step, design and contracting of reconstruction work is undertaken by several federal agencies, such as the Ministry of communication. These agencies can follow their operating procedures and hire third-party service providers when necessary. In exchange for using Fonden resources, they are required to submit progress reports to Fonden regularly. On average, reconstruction is expected to last for 150 days. The bulk of construction work is completed within a year of fund disbursement.[5]

The third set of Fonden rules aims at curbing moral hazard behavior. In the case of low income households which we will examine in section 3.7, Fonden rules ban the reconstruction of dwellings in high-risk areas, but permit the use of program resources for the re-location of households to safe areas. Initially, Fonden rules allowed re-located households to maintain ownership of high-risk land in exchange for pledging that the land would not be use for residential purposes. Over time program rules have become more stringent on re-located beneficiaries. The revised 2009 Fonden rules banned beneficiaries from undertaking any type of construction on high risk land, while the revised 2011 rules made eligibility to re-location resources contingent on the transfer of high-risk land to the municipal government.

In contrast, the reconstruction process in municipalities that do not receive Fonden resources is predominantly discretionary. As revealed by interviews with senior federal and

[4]State and municipal government assets are subject to a cost-sharing provision by which Fonden provides only partial coverage (50% in most cases).

[5]Figure A2 plots the histogram of time to disbursement and of planned reconstruction times.

state civil protection officials, non-Fonden reconstruction is undertaken primarily by state and municipal governments who, by and large, lack plans to finance or disburse reconstruction expenditures.[6] Specifically, our interviews indicate that local governments rely on budget reallocations and on non-standardized procurement processes. These budget reallocations may be costly because they entail delays in the mobilization of resources, and because they frequently divert maintenance resources that prevent the deterioration of infrastructure. Similarly, the reliance on direct procurement and on non-standardized tendering processes may increase delays and the leakage of public resources. Thus, while local governments may be able to mobilize resources for reconstruction, our prior is that these resources are likely to arrive later than those of Fonden and presumably at higher cost.[7]

2 Data

We proxy changes in municipal level economic activity using imagery from the United States Air Force Defense Meteorological Satellite Program (DMSP). Specifically, we use imagery gathered by three satellites: F15, F16, and F18. These satellites observe every location on earth between 8:30 pm and 10 pm solar local time. These weather satellites use the Operational Linescan System (OLS) sensor to record cloud formation by measuring the amount of moonlight reflected by clouds at night. On nights with low or no cloud cover the sensor instead detects the light emissions coming from earth's surface. The National Oceanic and Atmospheric Administration (NOAA) has developed a methodology to compile daily DMSP imagery into monthly and annual composite images that filter the transient light observed in the raw images.[8] The resulting stable cloud-free night light composites measure, by and large, man-made lights.

As discussed by Donaldson and Storeygard (2016), under the assumption that lightning is a normal good, night lights provide a plausible proxy for economic activity. In a quickly expanding literature night lights have been shown to be a good proxy for economic activity at several levels of aggregation: countries (e.g., Henderson et al., 2011, 2012), regions (e.g., Besley and Reynal-Querol, 2014; Hodler and Raschky, 2014), and cities (e.g., Storeygard, 2016).[9] Importantly for our paper, since the 1970s night lights have been regularly used in the remote sensing literature, and more recently in the economic literature, to both measure

[6]An important exception is federal non-concession roads which use earmarked ministry of communications emergency funds for reconstruction in the absence of Fonden.

[7]We were unable to document examples of large-scale privately funded reconstruction projects.

[8]Natural sources of transient lights include, for example, the bright half of the lunar cycle, auroral activity, and forest fires, see Elvidge et al. (1997) for details on the filtering process.

[9]In appendix A we provide additional evidence on the strong relationship between night lights and economic activity in Mexico using state level data.

the immediate losses in the aftermath of a disaster and to track the post-disaster recovery process (see Klomp, 2016; Nguyen and Noy, 2018, and references therein).

NOAA produced for this paper a series of night light composites. These composites cover the entire geographic area of Mexico at roughly one square km resolution and provide information at monthly frequency. In addition to filtering transient light, NOAA also performed an inter-calibration process for our composites. This process was developed to allow over time comparisons between composites. Details of the algorithm used by NOAA can be found in Weng (2014).

The night light dataset is composed of 168 satellite-month composites each with roughly 2.5 million pixels.[10] Each pixel in a composite contains information on the intensity of lights, usually called the digital number (DN), in a scale ranging from 0 (no light) to 63 (maximum light), and on the number of cloud free nights used to create the composites. To derive unique monthly DN values for years with overlapping satellite coverage we take pixel level weighted averages across satellites, where the weights are given by the number of cloud-free observations.[11]

For our initial analysis, and in order to match night lights with other calendar year datasets, we aggregate the pixel-month panel, obtained in the previous step, in a pixel-year panel.[12] This is accomplished by taking pixel level averages of the DN across months. When we explore the dynamic impact of Fonden in section 3.2, we will take advantage of our more granular dataset and construct average night lights over different time periods as described in that section. Next, we aggregate to the municipal level by calculating average municipal night light intensity.[13] We then take the natural logarithm of the resulting calculation and compute its change over time. The key outcome variable in the paper is the log difference in average municipal night lights between the year the disaster takes place and the following year.

Data on municipal eligibility to Fonden was assembled by Boudreau (2016) using the archives of Mexico's Official Newspaper. The archives contain the universe of disaster declarations. As previously mentioned, each declaration lists all municipalities requested and the subset which is eligible to Fonden. In addition the declarations provide a broad classification of the hazard that caused the request. While information on the declaration, for example, allows us to distinguish between geological and hydro-meteorological hazards, they don't

[10]Our dataset excludes lights generated by gas flares as determined by Elvidge et al. (2009).

[11]We also follow Henderson et al. (2012) and take simple averages across satellites. The results from the unweighted averages produce estimates that are nearly identical albeit with slightly larger standard errors.

[12]The resulting dataset is similar to the yearly frequency night light composites that are publicly available.

[13]This average is a measure of light intensity per area, and is equivalent to the measures used by Henderson et al. (2012) and Hodler and Raschky (2014).

allow for a more detailed classifications, such as distinguishing between heavy rainfall and flooding.[14]

To replicate the verification process for the heavy rainfall rule, the Mexican government granted us access to three Conagua datasets. First, data on historical rainfall at the weather-station-day level. This dataset contains the universe of weather stations and rainfall records. Second, a weather-station-month level dataset containing the thresholds used to verify Fonden eligibility.[15] Third, the mapping between municipalities and the subset of weather stations used for Fonden verification. Using weather station identifiers, we merge the three datasets and calculate a normalized running variable, rainfall mm to the threshold, by subtracting the threshold from the observed rainfall.

Using day and municipal identifiers, we merge the dataset obtained in the previous step with the declarations dataset. In the case of municipalities with multiple weather stations, or natural hazards spanning more than one day, the maximum of the running variable was chosen. This is done because eligibility to Fonden is triggered when the threshold is crossed at any weather station and during any day. Next we aggregate the previous dataset to the municipal-year level and we merge it with the night lights dataset.[16]

Our period of analysis takes place between 2004 and 2012. It is determined by the introduction of the heavy rainfall rule in 2004 and the last available year of night lights data in 2013.[17] During this period we observe 2701 municipal-year requests for Fonden funding generated by a hydro-meteorological hazard, of which 1930 qualified for Fonden resources.[18]

We have additionally collected various complementary municipal-year level datasets. These include from the Ministry of Finance (MoF), administrative records from Fonden detailing expenditures, time to disbursement, and planned reconstruction times; and from INEGI, census data, expenditures and revenues of municipal governments, and State level GDP. A complete list of additional datasets and sources used can be found in table A6.

Table 1 provides summary statistics for the main variables used in the paper. Our

[14]As can be expected in the case of related hazards, the words rainfall, hurricane, and flooding often appear in the same request. The sentence where they appear usually includes the conjunction "and" in Spanish: "e" and "y".

[15]Conagua calculated these thresholds in 2004, 2007, and 2011. We received the thresholds for 2007 and 2011, but not for 2004, as they were not preserved when Conagua upgraded its computer system. For 2004, we received the rainfall dataset used by Conagua and detailed instructions on how to compute the percentile 90 from the engineer charged with the calculation.

[16]In the case of multiple requests during a year we code an observation as eligible for Fonden if it received Fonden in at least one request during the year.

[17]OLS imagery is not available after 2013 because the program was discontinued in favor of higher resolution VIIRS imagery. The two types of images are not comparable.

[18]We exclude from the analysis 229 observations for which we are unable to calculate the running variable. While these observations are covered by the weather station network, at the time of the disaster, the weather station used for verification was out of service.

outcome variable log difference night lights (NL) ranges roughly from -2.5 to 2.5 with a mean of -0.028. We find that roughly 70% of the municipalities that requested Fonden funding were eligible, but only 36% would qualify under the heavy rainfall rule. This occurs because, as previously mentioned, municipalities are also eligible to Fonden through supplementary hurricane and flooding criteria.

The normalized running variable is measured in millimeters (mm) and has a cut-off at zero. The running variable support extends from -220 to 300 mm. This variable is constructed from the heavy rainfall Fonden thresholds (average 89 mm $\approx$ 3.5 inches (in)) and observed rainfall (average 82 mm $\approx$ 3.2 in). To get a better sense of the magnitude of rainfall events in our sample, consider that the United Nations World Meteorological Organization defines a heavy rainfall event as occurring when daily rainfall exceeds 50 mm $\approx$ 2 inches. Alternatively, consider that in terms of 24 hour rainfall observed at the peak of hurricane Harvey, the largest event in our sample ($\approx$ 20 in) is of a similar magnitude as the rainfall observed in Harris county Houston. By comparison, an average event in our sample is of a similar magnitude as the rainfall experienced in Montgomery county, which is 50 miles north of Harris county.

3 Results

3.1 The impact of Fonden on local economic activity

We use the heavy rainfall rule to identify the causal impact of Fonden on economic reconstruction, exploiting the discontinuous change in Fonden assignment that occurs at the threshold rainfall level. We use a fuzzy regression discontinuity (FRD) design because eligibility to Fonden requires the disaster to exceed local response capabilities (which is almost always the case) and because the verification of a hydro-meteorological event can occur by meeting the heavy rainfall rule, or by meeting Fonden's flooding or hurricane criteria. The validity of the method relies on the assumption that characteristics of municipalities that could affect changes in night lights vary smoothly with the running variable, which we will verify in section 4.

We begin with a graphical illustration of the FRD design. Figure 1a plots the probability of receiving Fonden as a function of the running variable, with 95% confidence intervals.[19] The solid lines are fourth-order global polynomials fits, estimated separately on each side of the threshold. The figure reveals a jump in the probability of receiving Fonden at the

[19]Following Calonico et al. (2015), the evenly spaced bins are optimally chosen to minimize the integrated mean square error.

threshold level. Moving from just below to just above the threshold increases the likelihood of receiving Fonden from about 0.65 to 0.90. The figure hints at a strong first stage relationship, and implies that Fonden's Local Average Treatment Effect (LATE) will be roughly four times larger than that of the Intention-to-Treat (ITT) effect.

Analogously, figure 1b plots the ITT relationship. That is, log difference night lights, between the year the disaster occurs and the following year, as a function of the running variable. The figure shows a clear jump at the threshold. Change in night lights in municipalities eligible for Fonden under the heavy rainfall rule (immediately to the right of the cutoff), is roughly 10% (0.1 log points) higher than in ineligible municipalities (immediately to the left of the cutoff). The global polynomial additionally reveals two interesting features of the relationship between night lights and the relative intensity of rainfall. First, among ineligible municipalities, night lights become progressively dimmer as the running variable approaches the cut-off from the left, i.e., as rainfall increases up to the threshold level. Second, consistent with the idea that Fonden reconstruction funding is proportional to damages, we find that the relationship between night lights and the running variable is, by and large, flat after the cut-off.[20]

The regression analogs of figures 1a and 1b are recovered by estimating the following equations:

$$Y_{mt} = \beta_0 + \beta_1 ABOVE_{mt} + g(R_{mt}) + \varepsilon_{mt}, \tag{1}$$

$$F_{mt} = \alpha_0 + \alpha_1 ABOVE_{mt} + g(R_{mt}) + v_{mt}, \tag{2}$$

where Y_{mt} represents our measure of the change in local economic activity (night lights) over the year after the disaster for municipality m hit by a shock in year t, F_{mt} is a binary variable that denotes a municipality receiving Fonden, $g(R_{mt})$ captures the relationship between the outcome and the running variable R_{mt}, ABOVE is an indicator variable for observed rainfall exceeding the heavy rainfall threshold, and ε_{mt} and v_{mt} are error terms. The parameters of interest are the ITT estimate $\hat{\beta}_1$ in equation 1, the first stage estimate $\hat{\alpha}_1$ in equation 2, and τ_{FRD}=$\hat{\beta}_1/\hat{\alpha}_1$ which can be interpreted as the LATE under some additional assumptions.[21] To derive point estimates, robust p-values, and confidence intervals for these parameters we

[20] While our bin-width choice is fully data driven, figures A3a to A3d halve and double the number of bins in order to illustrate that our results are not sensitive to this choice.

[21] As shown by Hahn et al. (2001) τ_{FRD} can be interpreted as the LATE under three additional assumptions. The first is monotonicity, that is that experiencing rainfall in excess of the threshold does not decrease the probability of receiving Fonden for any municipality (which seems plausible). The second is the existence of a first stage. The third, local independence, implies that in a neighborhood around the threshold assignment to Fonden under the heavy rainfall threshold is as good as random, and that assignment affects night lights only via Fonden treatment. Dong (2018) has recently shown that a local smoothness assumption can be used instead of local independence. We provide supporting evidence for local independence in section 3.4 and for local smoothness in section 4.1.

use local polynomial methods as described in Calonico et al. (2018).[22]

Table 2 presents the results from estimating equations 1 and 2. The nonparametric local polynomial estimates are derived under several choices of bandwidth, kernel, and local polynomial order. Specifically, we use two optimal bandwidth selection algorithms. The first h_{MSE} (odd columns) minimizes the asymptotic mean squared error and is optimal for point estimation. The second h_{CER} (even columns) minimizes the asymptotic coverage error rate and is optimal for inference of confidence intervals (Calonico et al., 2018). Throughout the paper we use a triangular kernel because as discussed in Cattaneo et al. (2017b) it provides the optimal choice of weights for the h_{MSE}.[23] We limit our choice of local polynomials to linear (columns 1 and 2) and quadratic (columns 3 and 4) as recommended by Gelman and Imbens (2018).

Panel A presents estimates of the first stage and panel B of the ITT effect and of Fonden's LATE. The estimates in panel A, columns 1 and 2, reveal that being above the threshold increases the probability of receiving Fonden by roughly 24 percentage points. These coefficients are statistically significant at the one percent level. The intention-to-treat estimates in panel B, columns 1 and 2, reveal that change in night lights in municipalities intended for treatment under the heavy rainfall rule are roughly 10% (0.1 log points) higher than in municipalities below the threshold. Among complier municipalities at the cut-off, our preferred point estimate of Fonden's LATE τ_{FRD}, in column 1, indicates that the program led to a 0.4 log point (50%) increase in change in night lights. In all cases the estimated coefficients are statistically different from zero at the one percent level, and our preferred 95% confidence interval, in column 2, is in the 0.15 to 0.84 log point range.

Next, in columns 3 and 4, we repeat the previous exercise using instead a local quadratic polynomial. The estimates of Fonden's LATE for both bandwidths are slightly larger than those of columns 1 and 2. Importantly, all estimated coefficients remain statistically significant at the five percent level, and the 95% confidence intervals for the LATE do not include zero. Overall, these results provide robust evidence of the capability of Fonden to lessen the decline in economic activity created by extreme weather events.

3.2 The dynamic impact of Fonden

To study the dynamic impact of Fonden, we take advantage of the monthly frequency of the night lights data, and construct windows of post-disaster observations that are at different distances of the disaster date. We do this in two ways, first by extending the length of the

[22] In all cases the bandwidth selection methods and the inference of standard errors and confidence intervals have been adjusted for clustering at the municipal level.

[23] In section 4 we further show that our results are robust to the choice of kernel.

post-disaster period and second by considering post-disaster periods away from the disaster date. We discuss these two approaches in turn.

In the first analysis, we measure change in night lights between the 12 months before the disaster occurred and post-disaster periods of 0-3 months, 0-4 months, etc., up to 0-24 months. We repeat the analysis of section 3.1 with each of these post-disaster periods. Figures 2a to 2d report the ITT effect of Fonden for 4 cases, with a plot of the log difference in night lights as a function of the running variable. We have selected 3, 5, 15, and 24 months after the disaster because they illustrate key points in the post-disaster dynamics. We also report estimates of Fonden's LATE for each of the 21 post-disaster periods in Figure 3a.[24]

The series of ITT figures indicate that the impact of Fonden can be broadly characterized in three phases. In the very short run (illustrated by the 0-3 months post-disaster period), while funds and reconstruction efforts are being set up, we find no difference between those municipalities just above and below the threshold. During this phase all groups face a reduction in night lights of roughly 0.05 log points. In the second phase, starting at five months we see a clear jump at the threshold, this jump progressively increases until roughly 15 months. During this period the global polynomials indicate that while night lights are dimmer for municipalities to the left of the threshold, this loss is less important for those to the right of the threshold. In the third phase, illustrated by the 0 to 24 months post-disaster period, municipalities to the left of the threshold catch up with municipalities to the right of the threshold. Visually, the global polynomials suggest that by 20 months there are no differences in night lights between municipalities on either side of the threshold.

Consistent with graphical evidence of the ITT, the LATE figure provides further evidence supporting characterization of the dynamics of Fonden as a three stage process. Regardless of specification, starting at five months and continuing up to 15, we see an incremental build up of the impact of Fonden on night lights. This increase is followed by a progressive decline. After 18 months we can no longer detect, at conventional levels, a statistically significant Fonden LATE.

In terms of magnitude, the 0 to 12 month coefficient is roughly two-fifths smaller than that of our benchmark point estimate of section 3.1. One reason why this could occur is because this precise definition of the post-disaster period always includes the first three months after the disaster, while in using calendar years in 3.1, for all disasters that happen between January and September of a year, the 3 months immediately after the disaster are included in the reference disaster year. These are months when municipalities on either side

[24] As before, we use a triangular kernel, a local linear polynomial and an h_{MSE} bandwidth. To ensure that our coefficients are comparable to each other, we present estimates derived using one of three common bandwidths, specifically the average, the minimum, and the maximum of the 21 optimal h_{MSE} bandwidths.

of the threshold are equally affected by the hazard.

As illustrated in figure A2 this dynamic closely coincides with the period of maximum activity implied by Fonden administrative records. The records indicate that Fonden interventions, by and large, start within three-four months of the disaster and fade out by 14 months when the bulk of reconstruction work is expected to be completed.

In the second analysis, we focus on estimating Fonden LATE during the active recovery phase, by using this time a 9-month moving average for the post-disaster period. We thus define the first post-disaster period as the span of time running from months one to nine after the disaster, then months two to ten, etc., until months 16 to 24. Figure 3b plots the point estimates and robust 95% confidence intervals for this exercise. The figure reveals that, consistent with previous results, the impact of Fonden increases progressively, peaks between four and 12 months, and then starts to decline. Focusing on the period in which reconstruction has begun produces estimates that are remarkably similar in magnitude to our benchmark of section 3.1. Specifically, the point estimate of Fonden's LATE between 4 and 12 months ranges from 0.36 to 0.4 log points depending on bandwidth choice.[25]

In conclusion, the findings of this section show that the impact of Fonden is only observed after the disbursement process has, by and large, taken place. They also highlight that the impact of Fonden is not permanent, but rather that it progressively build ups, peaks at roughly 15 months in the post disaster period, and then declines.

3.3 Spillover effects

Given the scale and nature of Fonden interventions, it is possible that the impact of the program may spill over to neighboring municipalities. For example, the reconstruction of an arterial road is likely to benefit all neighboring municipalities and not only the municipality where reconstruction work took place. To study spillover effects, we calculate for each municipality the log difference night lights between the year the disaster takes place and the following year using neighboring pixels at various distances. These are pixels that are outside the boundaries of the municipality but that are within a given distance of their border.

Table 3 provides evidence of localized spillover effects that go in the same direction as our estimates of the impact of Fonden. To facilitate comparisons, in column 1, we reproduce the results from our benchmark specification (table 2 column 1). In column 2, we estimate Fonden's LATE among pixels that are within 0 to 20 km of the municipal boundary. We

[25] These results, are not driven by the choice of length of the moving average: smaller and longer durations yield results that are consistent with the dynamics that have been described. For example, estimates using a 12 month moving average reveal that the impact of Fonden is concentrated between four and 15 months following a disaster. The impact of Fonden is statistically significant at the one-percent level, and its magnitude is in the 0.35 to 0.37 log point range.

find a statistically significant Fonden LATE that is roughly three fifths the magnitude of our benchmark estimate. Next, in column 3, we estimate Fonden's LATE among pixels that are within 20 to 40 km of the municipal boundary. In this case, the estimate of Fonden's impact is small and statistically indistinguishable from zero.[26]

On the whole, we find evidence of spillover effects that quickly decay and that go in the same direction as our estimates of the impact of Fonden. Thus, to the extent that these limited spillover effects matter, their key implication is that our benchmark estimate of Fonden's LATE provides a lower bound of the impact of Fonden.

3.4 External validity

As previously discussed, the strong internal validity of Fonden's LATE comes at the cost of deriving an estimate that only applies to a small sub-population, namely the subset of complier municipalities near the threshold. From a policy perspective, we are particularly interested in understanding whether Fonden leads to similar effects, both in terms of sign and magnitude, among a broader group of municipalities such as those with nearby values of the running variable.

To explore the external validity of the LATE, Dong and Lewbel (2015) proposed a methodology to estimate, under weak conditions,[27] the derivative of the treatment effect with respect to the running variable. Intuitively, a treatment effect derivative (from here on TED) that is small and statistically indistinguishable from zero indicates that the ITT is locally constant, and hence is more likely to have external validity. Another reason why we are interested in estimating TED is that, as shown by Dong (2018), a TED close to zero provides evidence in favor of the local independence assumption that underpins our interpretation of τ_{FRD} as Fonden's LATE.

More recently, Cerulli et al. (2016) have extended this framework to fuzzy regression discontinuity designs by introducing the complier probability derivative (from here on CPD), which analogously measures the stability of the complier population.

To estimate TED and CPD, we use Cerulli et al. (2016)'s algorithm and follow the authors guidance in choosing a local quadratic polynomial and a triangular kernel. We compute TED and CPD using both optimal h_{MSE} and h_{CER} bandwidths.

Table 4 presents our estimates of Fonden's TED and CPD. Results show that both our first stage and Fonden's LATE are stable. For both CPD and TED, regardless of specification

[26]To guarantee comparability of the coefficients in columns 1 to 3, we estimate all coefficients using the same sample as column 1 (same bandwidth). We verified that these findings are not driven by imposition of this non optimal bandwidth, using the optimal h_{MSE} for each estimation.

[27]They assume continuous differentiability of conditional means.

in columns 1 and 2, the estimates are very small and statistically indistinguishable from zero. These findings are important because they suggest that municipalities that are further away from the threshold are likely to experience Fonden treatment effects that are of similar magnitude as those right at the threshold. Moreover, a TED close to zero additionally implies that the local independence assumption is likely to hold in our setting.

3.5 Cost-Benefit analysis

The impact of Fonden on the economy stems primarily from two mechanisms. First, Fonden can directly enhance economic recovery by improving the government's shock coping response following a natural disaster. Second, Fonden can indirectly alter risk-management behavior by insuring public infrastructure and low income housing against natural disasters. For example, Fonden may indirectly induce households, firms, and local governments to allocate more resources to more risky investments. These investments may include higher yielding production activities (a potential benefit of insurance), but also induce reconstruction of housing in high risk areas (a well known moral hazard effect of subsidized insurance). We do not have information on the indirect effects of beneficial risky investments and only find limited suggestive evidence of moral hazard in housing reconstruction in section 3.7. In this section, we limit our analysis to the direct shock coping benefits that are measured by night lights and compare them with the cost of the program.

Table 5 reports the results. There are 1378 municipal-year requests that were awarded Fonden and for which we have complete municipal-level Fonden expenditures.[28] To convert Fonden's LATE (measured in night lights growth) to GDP growth, we multiply our estimate of Fonden's LATE with the inverse of the elasticity of night lights with respect to state GDP.[29] The implicit assumption we make is that the calculated state-level elasticity is also informative of the unobserved municipal-level elasticity. The resulting estimate implies that, in the year following the disaster, GDP grew 3.9% more in municipalities with Fonden than those without.

Next, we calculate the average gain per municipality by multiplying the increase in growth generated by Fonden with a proxy of municipal GDP in 2003.[30] We find that mean 2003 municipal GDP has a value of roughly (USD 2010 PPP) 184 million.[31] Multiplying this

[28]In this exercise we use all of the sample and assume homogeneous treatment effects. We also performed exercises where we use a smaller number of observations in the neighborhood of the cut-off. These exercises yield very similar results and are available upon request.

[29]Specifically, we use the annual fluctuations specification. In appendix A we show that night lights can be used to predict short- and long-term growth of state level GDP.

[30]To proxy municipal GDP, we divide state GDP across municipalities proportionally to their population.

[31]Because proxy municipal GDP has a heavy-tailed distribution, we use the geometric mean. Using the

value by our estimate of the impact of Fonden on GDP growth gives an average gain per municipality of (USD 2010 PPP) 7.2 million, and a total gain of (USD 2010 PPP) 9.9 billion. In the last column we divide the total gain by Fonden expenditures in these municipalities. We find that the benefit of Fonden is 1.4 times greater than its cost, but we cannot reject the null hypothesis that the ratio is equal to one.

While our estimate of Fonden cost-benefit is imprecisely estimated (90% confidence interval is 0.08 to 2.72) it is remarkably consistent with both empirical evidence on the returns to infrastructure spending, and with the predictions of macroeconomic models. For example, Gonzalez-Navarro and Quintana-Domeque (2016) randomize the paving of local roads in Mexico and find a cost-benefit ratio of 1.09. Other empirical studies, that use subnational level data and instrumental variable strategies, conclude that public spending multipliers are in the 1.4 to 2 range, (Acconcia et al., 2014; Fishback and Kachanovskaya, 2010). More recently, Leeper et al. (2017) quantify government spending multipliers in the US using a DSGE model. They find short-run multipliers that are approximately 1.3.

3.6 Heterogeneous effects of Fonden

To further understand the economic relevance of Fonden, we investigate in table 6 whether the impact of Fonden on economic activity varies with the type of asset that Fonden reconstructs and whether municipalities that are initially less resilient benefit disproportionately more from the program.

Given that prolonged disruptions to the road network are damaging to all sectors of the economy, we conjecture that Fonden's road reconstruction expenditures are particularly effective at mitigating the losses from extreme weather. Because expenditure type can only be observed among municipalities that receive Fonden, we begin with a descriptive exercise in which we compare the estimated impact of Fonden using observations where the primary type of municipal expenditure is either roads (61% of the sample) or non-roads (hydraulic, education, health, and housing). Panel A columns 1 and 2 present the results. While these estimates cannot be given a causal interpretation given the endogenous sample split, they are consistent with the idea that roads reconstruction is particularly important for lessening the decline in economic activity after a disaster. Specifically, the impact of Fonden estimated in the sub-sample where roads is the primary type of expenditure, in column 1, is sharply estimated and roughly twice as large as that for non-road expenditures, in column 2, which is only statistically significant at the ten-percent level.

In columns 3 to 6, we provide further evidence of the importance of road reconstruction

median instead of the geometric mean produces nearly identical results.

by studying heterogeneity with respect to resilience of the road network. Specifically, since disruptions in municipalities with less road redundancy are likely to be more damaging, we investigate whether the impact of Fonden varies with the initial density of the road network. Using the U.S. Geological Survey 2003 map of Mexico's roads (which includes paved, gravel, and dirt roads) we calculate for each municipality road density (road kilometers per 100 square km) and intersection density (number of nodes per 100 square km). Importantly, as shown in figure 6 both of our measures of road network density do not change discontinuously at the threshold. To test whether Fonden has a differential impact, we split the sample at the median of each of our density measures (7.93 for road density and 6.38 for intersection density) and estimate the impact of Fonden in each sub-sample.

While we find that Fonden leads to increased economic activity in all municipalities, consistent with our prior, we also find that Fonden benefits disproportionately more municipalities with below median road network density. This is the case for both road density (columns 3 and 4) and intersection density (columns 5 and 6). The difference in the impact of Fonden is particularly clear in the case of intersection density where the estimate for below median is 3.3 times larger than that for above median intersection density. These results are consistent with the idea that market integration may mitigate some of the losses from extreme weather (Burgess and Donaldson, 2010), but they also highlight that, in places with limited redundancy, the effectiveness of trade may hinge on the ability of governments to keep transportation networks operating.

Next, in columns 7 and 8, we study whether Fonden benefits more municipalities that are less resilient because they lack water management infrastructure. In the absence of a direct measure of the municipal prevalence of storm drains, we use the percentage of dwellings connected to sewage.[32] As before, we show in figure 6 that the pre-Fonden percentage of dwellings connected to sewage is continuous at the normalized threshold. We then proceed by splitting the sample at the median 72% and estimate the impact of Fonden in each sub-sample. While the coefficients are noisily estimated, taking the point estimates at face value clearly indicates that municipalities with below median connections to sewage benefit disproportionately more from Fonden. These results highlight the importance of Fonden among disadvantaged municipalities that lack specialized public goods to manage disaster risk.[33]

[32]The presence of sewage drains is a good proxy for storms drains because they are usually constructed contemporaneously, or as in the case of combined sewage serve both purposes.

[33]We also tested splitting the sample at the median of three other variables related to resilience. We find no differential Fonden effect using the percentage of dwellings with piped water, and larger Fonden effects for below median night lights, and above median infant mortality. These differential effects are consistent with those of dwellings connected to the sewage, but they are less sharply estimated.

All in all, the results in table 6 suggest that Fonden's impact on economic recovery is likely driven by interventions that minimize disruptions to the road network, and that impact of the program may be larger in municipalities that are initially less resilient.

3.7 Risk-management responses to Fonden

In this section, we investigate whether the provision of insurance through Fonden altered risk-management behavior in housing construction. There is mixed evidence in the literature on the impact of subsidized natural disaster insurance on risk management behavior. Whether insurance coverage induces moral hazard or not depends on whether those who purchase insurance are highly risk averse and take other precautionary measures that reduce risk. For example, in the U.S., a well documented problem of the subsidized insurance from the National Flood Insurance Program (NFIP) is that a small number of repetitive loss properties (1.2 percent of the policies) account for up to 24 percent of total claims (Michel-Kerjan, 2010). Accordingly, it has been widely argued that the NFIP reduces the incentives to re-locate to safe areas (King, 2013), and even that it may explain why the U.S. has failed to adapt to hurricane damage (Bakkensen and Mendelsohn, 2016). Nonetheless, recent studies on the impact of the NFIP on housing development, purchase of insurance, and risk reduction activities tend not to find evidence of moral hazard (Browne et al., 2018; Hudson et al., 2017).

In the case of Fonden, as discussed in section 1, the program provides free disaster insurance for low income housing. Repetitive loss properties are in principle not a primary concern for Fonden because program rules ban reconstruction in high risk areas. Resources for affected households in high risk areas are instead used to re-locate housing to safe areas. Nonetheless, Fonden's pre-2011 rules may have encouraged development in high risk areas because they allowed beneficiary households to receive housing in a safe area while maintaining ownership of their high risk land.

To study this potential effect of the availability of Fonden on housing construction in high-risk areas, we contrast municipalities where rainfall shocks are less salient with those where rainfall shocks are more salient, before and after the year 1999 when Fonden was put into place.[34] To construct a proxy measure of the share of high-risk area that is plausibly inhabited, we collect flood maps from Conagua and calculate for each municipality and year the share of high-risk area (defined as 1-in-2 year floodplain) where night lights are visible.

Our sample is composed of all municipalities in Mexico between 1993 and 2013. The

[34] Our definition of how salient rainfall shocks are in a municipality relies on the average annual rainfall in the 25 years that preceded Fonden. Municipalities with above median rainfall are considered more salient, those below less salient.

econometric specification is a regression of the share of high-risk area that is plausibly inhabited on year and municipality fixed effects, and the interactions between the rainfall salience dummy and the year dummies. The comparison group is municipalities with low salience in 1998 (the year before Fonden became operational). Coefficients are reported in figure 4. The figure reveals that there are no pre-trends (all the coefficients up to 1998 included are small and not significantly different from zero) and that Fonden leads to an increase in the share of high-risk land that is inhabited. Using a standard pre-post definition of time (as opposed to year fixed effects), we estimate that Fonden led on average to a 1.1 percentage points increase in the share of the high-risk area that is inhabited (p-val=0.002). Since the average pre-Fonden share is 0.27, the effect of Fonden roughly corresponds to a 4% increase.[35]

Importantly, figure 4 also shows that after 2011 Fonden has no impact on the share of high-risk land that is inhabited. As previously mentioned, this post 2011 period coincides with revised Fonden rules that aimed at curbing moral hazard behavior by conditioning re-location resources to the transfer of high risk land to local governments.

4 Validation and falsification of the FRD design

In this section we provide supporting evidence for our identification assumptions. First, we show using several tests that the running variable is unlikely to have been manipulated. Second, we show that Fonden assignment is unlikely to have affected night lights through channels other than Fonden funding. Third, we further illustrate the validity of the FRD design by conducting two falsification exercises and a wide range of robustness checks.

4.1 Manipulation of the running variable

The Fonden verification process is unlikely to be susceptible to manipulation for several institutional reasons. First, there is no formal appeals process to challenge Conagua's decision. Second, tampering with weather stations is unlikely because they serve a variety of purposes both civilian and military. Third, the subset of weather stations used for Fonden verification and the percentile 90 thresholds are not known outside of Conagua. Fourth, there is little time for collusion because Conagua's decision must be issued within four days of the request for verification.

[35] We also tested other outcomes. For households, we tested whether Fonden affected construction in areas at high-risk of landslides. For local governments, we tested whether Fonden altered their expenditures in public investments or their ability to borrow. We don't present these results because there is clear evidence of a differential pre-trend with each of these outcomes.

Nonetheless, to test whether municipalities could have manipulated the running variable, we take advantage of McCrary (2008) observation that in the absence of manipulation the density of the running variable should be continuous around the threshold. Figure 5a plots the histogram of the running variable in the range of the estimation bandwidth h_{mse}, with the dashed line representing the normalized heavy rainfall threshold. Visually, there is no apparent excess density to the right of the threshold as would be expected if municipalities were trying to game the Fonden eligibility rules.[36]

To formally test whether the density of the running variable is continuous at the threshold, we use the local polynomial density estimator and test statistic developed by Cattaneo et al. (2017a). Figure 5b plots the estimated empirical density. This graphical representation of the test clearly shows that the running variable is continuous at the threshold.[37]

Table 7 formally confirms the previous results.The null hypothesis is that the density of the running variable is continuous at the threshold. The optimal bandwidth for the test is calculated by minimizing the asymptotic MSE. The bandwidth selection can be performed allowing for different bandwidths on each side of the threshold, or using a common bandwidth for both sides. Rows 1 and 2 present the resulting test static for each case. In row 3, we use a common bandwidth and additionally assume that the cumulative density function and higher order derivatives are the same for both groups around the threshold (restricted inference). As explained by Cattaneo et al. (2018), this restriction is reasonable in the context of manipulation testing and generates improvements in terms of statistical power. Importantly, in all cases we fail to reject the null hypothesis at conventional levels.

To further test whether manipulation could have taken place, we preform in table A2 a "donut-hole" robustness check. This test takes advantage of the observation that, if rainfall measures were tampered with, municipalities closest to the threshold would presumably be the ones most likely to have experienced manipulation. The test therefore consists in checking the sensitivity of our preferred specification table 2 column 1 when we progressively exclude observations that are within 5 mm of the threshold. We find that in all cases the impact of Fonden remains statistically significant at the five-percent level, and that the point estimate of the LATE is at least as large as the effect we initially estimated (0.4 log points).

Another test for manipulation is whether the predetermined characteristics of municipalities change discontinuously at the threshold. This follows from the idea that if municipalities lack the ability to precisely manipulate the running variable there should be no systematic differences between municipalities with similar values of the running variable.

[36]The mode of the running variable is located to the left of the threshold because, even among a sample of municipalities requested for verification, rainfall events that are smaller than the heavy rainfall threshold are relatively more common.

[37]Figures A4a and A4b provide analogous graphs using the entire support of the running variable.

We focus on 24 variables drawn from the census and administrative records. Unless otherwise stated, all variables are measured in the most recent year available that predates the request for Fonden funding. The selected variables can be categorized in three groups. The first group aims at capturing basic features of state capacity, in particular those related to the provision of publics goods (e.g., electricity, water, health, education, roads). This set of variables is important because presumably municipalities with greater state capacity might be more effective at lobbying for Fonden resources. The second set of variables measures the financial capacity of local governments. The third captures basic features of the municipality's geography and population.

Using the same methodology as used in section 3.1, figures A5 to A8 plot each of the covariates as a function of the running variable. This graphical analysis does not reveal any clear discontinuities at the normalized threshold. To formally test whether the predetermined covariates are continuous at the threshold, we estimate equation 1 using as outcome each of the predetermined covariates. Figure 6 plots the resulting point estimates and 95% confidence intervals for all variables. To facilitate comparison across variables, we standardize the variables and present estimates in standard deviation units. We find that in 23 out of 24 cases the predetermined covariates are statistically indistinguishable from zero. The only exception, percent of population 15 or older with no schooling, is significant at the 10% level before correcting for multiple inference.[38] These results strongly indicate that the predetermined covariates appear to be continuous at the threshold.

On the whole, these empirical results are consistent with the idea that the Fonden institutional setup makes it hard for local governments to sort around the heavy rainfall threshold. Accordingly, we conclude that manipulation of the running variable is unlikely in this setting. This result is important because it provides supporting evidence for our identification assumptions and for the local smoothness assumption that underpins our interpretation of τ_{FRD} as Fonden's LATE. Moreover, it suggests that Fonden's rules based on indexation have been successful at protecting reconstruction resources from political abuse.

4.2 Assignment of other post-disaster resources

Both our extensive review of government procedures for the allocation of post-disaster resources in Mexico and our interviews with Fonden administrators failed to uncover any instance in which the running variable could directly affect non-Fonden resource allocations. Given that the heavy rainfall thresholds are known only to Conagua, its also unlikely that the running variable was used informally by other government agencies for the allocation of

[38]We correct for multiple inference using sharp FDR q-values as described in Anderson (2008).

resources.

Nonetheless, in table 8 we investigate whether government transfers to local governments from both the federal and state government changed discontinuously at the heavy rainfall threshold. Specifically, we estimate equation 1 using as dependent variable the growth in per-capita transfers between the year the disaster takes place and the following year for three type of transfers. Column 1 documents that there is no discontinuity for overall transfers. In columns 2 and 3, we break up overall transfers into revenue sharing transfers (these funds are awarded using a rule and can be used for any purpose) and conditional transfers (these funds are awarded using both rules and discretion and can be used only for their earmarked purpose). The estimated coefficient in column 2, revenue sharing transfers, is statistically indistinguishable from zero. The estimated effect size is large relative to its average, but the implied increase in the transfer represents less than 5% of the average Fonden expenditure. The coefficient in column 3, conditional transfers, is small and statistically indistinguishable from zero. This result is important because as previously mentioned some conditional transfers can be discretionarily awarded and these type of transfers include resources earmarked for the construction of infrastructure. All in all, we conclude that that the heavy rainfall rule is unlikely to affect night lights through channels other than Fonden assignment.

4.3 Falsification exercises

We also illustrate the validity of the FRD design by investigating in the period before the hazard takes place whether night lights are continuous around the threshold. Specifically, figure A9 plots the log difference in night lights between two years before a hazard and the year before the hazard as a function of the running variable. The figure reveals no apparent discontinuity at the threshold. Consistent with the graphical analysis, when we estimate equation 1 using the predetermined log difference night lights we find a small coefficient that is statistically indistinguishable from zero, -0.038 (robust p-val=0.379).

Another exercise that can be used to validate the FRD design is to estimate the impact of Fonden at placebo thresholds. To carry out this test we begin by restricting the sample to observations with nonnegative values of the running variable. This is done in order to exclude the true threshold. Next we estimate the impact of Fonden at placebo thresholds. The thresholds are given by the first five deciles of the running variable. We then restrict the sample to observations with negative values of the running variable and repeat the previous exercise. Table A3 presents estimates from these two sets of placebo thresholds along with estimate at the true threshold for comparison. We find no evidence of Fonden treatment effects at any of the placebo thresholds. In all cases the placebo estimates are statistically indistinguishable from zero at conventional levels. We conclude that night lights only change discontinuously at the normalized zero threshold.

4.4 Robustness Checks

In table A4 we show that our results are not sensitive to the choice of kernel and bandwidth. In column 1, instead of simultaneously choosing the h_{MSE} for both the first stage and the ITT, we follow common practice and use the h_{MSE} bandwidth of the ITT. In columns 2 and 3, we use a uniform and a epanechnikov kernel. These kernels are not optimal for the selection of the h_{MSE} bandwidth but they are commonly used. In columns 4 and 5, we recalculate h_{MSE} and h_{CER} allowing for different bandwidths to be chosen on each side of the threshold. The resulting estimates of Fonden's LATE are similar, and in all cases the coefficients remain statistically significant at the one-percent level.

To further show that the choice of bandwidth has no bearing on our results, figure A10 plots estimates of Fonden's LATE and robust 95% confidence intervals for various bandwidths. The largest bandwidth is one and a half times the optimal h_{MSE} while the smallest is half the h_{MSE}. We further divide this range into 10 equal intervals and present estimates for each. As expected, the figure shows that larger bandwidth choices lead to reduced variance and increased bias. Importantly, even over this wide range of bandwidths, our estimates of Fonden's LATE are of similar magnitudes and remain statistically significant at conventional levels.

In table A5, we further show that our estimates are robust to various issues. We begin with issues related to night lights. It is common practice to use all available night lights imagery and take pixel level averages in years with overlapping satellite coverage. To show that our results are robust to this choice, column 1 uses imagery only from the newest satellite that is available in each time period. Next, we address the issue of top-coding, that is that certain areas of the globe are too bright for the OLS sensor to accurately track. Recent work by Krause and Bluhm (2016) suggests that the problem of top-coding could affect not only pixels with a digital number of 63 (the maximum), but all pixels with a digital number greater than 55. To show that our results are not affect by top coding, in column 2 we exclude all pixels with DN greater than 55 (0.6 percent of our sample). Last, while our composites have been specifically created by NOAA to be comparable over time, in column 3 we follow Henderson et al. (2012) an address comparability by including year fixed effects to our specification. In all cases the estimated Fonden LATE's are of similar magnitudes and remain statistically significant at the five-percent level.

In columns 4 to 5, we investigate whether our results are affected by the exclusion of municipalities that received Fonden on consecutive years. Specifically, in column 4, we exclude all municipalities that received Fonden in the year before or after each request. In column 5, we expand the window to two years before and after. Next, in columns 6 and 7, we exclude municipalities whose eligibility to Fonden depends on extreme heavy rainfall thresholds, that is, the bottom and top deciles of the thresholds distribution. In spite of the smaller sample size leading to wider confidence intervals, we estimate similar Fonden LATE. These estimates remain statistically significant at conventional levels in all cases.

Last, we use the methods proposed by Cattaneo et al. (2016) to study how the impact of Fonden varies in relation to the value of heavy rainfall thresholds that are not extreme.[39] The top part of figure A11 plots the histogram of Fonden heavy rainfall thresholds. We will focus on the 30 to 130 (mm) threshold range which makes up roughly 80% of the density. To explore heterogeneity we choose within this range six threshold values that are within 20 mm of each other, that is: 30, 50, 80, 90, 110, and 130. For each of these values we separately estimate Foden's LATE using only the 400 treatment and control observations that are closest to each value.

The bottom part of figure A11 plots point estimates and robust 95% confidence intervals for Fonden's treatment effect at each of the six threshold values, a quadratic polynomial fit for these six treatment effects, and the value of the pooled Fonden LATE. The figure shows that all point estimates are positive and that most have values similar to the pooled Fonden LATE. The quadratic polynomial fit further indicates that, by and large, Fonden's LATE is homogeneous with respect to the value of the thresholds. The smaller sample size for each of the six estimates generates wide confidence intervals that include zero in most cases. By comparison, our pooled estimate of Fonden LATE is statistically significant at the one-percent level because we gain statistical power by aggregating the sample across thresholds.

5 Conclusion

The primary response of governments to extreme weather events is the provision of disaster aid. Their capacity to respond is however commonly constrained by liquidity gaps and by lack of specialized rules and administrative capacity that facilitate the effective disbursement of disaster aid. In this paper we showed that, by alleviating these constraints, a national indexed disaster fund can considerably mitigate the disruption to economic activity generated

[39] Specifically, we use a continuous non-cumulative threshold approach. This approach best fits our setting because: (i) the values of the percentile 90 thresholds are continuous, (ii) the value of the thresholds is unrelated to the Fonden funding amounts, (iii) knowledge of observed rainfall is not sufficient to know the threshold the municipality faces.

by extreme weather events. We measure changes in local economic activity using night lights and identify the causal effect of Fonden, Mexico's disaster fund, by exploiting discontinuities in the rules that determine eligibility to the program. We find that Fonden considerably reduces the decline in night lights in the aftermath of a disaster and that this effect is sustained for about a year. Building on these findings, we perform a cost-benefit analysis and conclude that the value of the economic activity generated by Fonden is likely larger than the cost of the program. These results provide the first evidence on how disaster funds can considerably improve the shock coping responses of national governments. They likely under-estimate the full value of disaster funds as effective shock-coping can have additional positive benefits not well captured by night lights such as effects on health and human capital accumulation.

Additional results on the heterogeneous impact of Fonden suggest that reconstruction of lifeline transportation infrastructure such as roads is particularly important and that municipalities that lack redundancy in their transportation network may benefit disproportionately more from Fonden. These results suggest that the effectiveness of trade and other adaptive responses to extreme weather may depend on the ability of governments to keep transportation networks operating. We also find that municipalities that are initially less resilient, because they lack water management infrastructure, benefit more from Fonden. Moral hazard effects under the form of inducing construction in flood-prone areas may have been initially present, but were subsequently removed by stricter rules on reconstruction.

These results are important for policy-makers as most developing countries are currently notably under-prepared in coping with the losses created by extreme weather events. In that sense, the Fonden initiative can be a useful role model. We have shown that a national indexed disaster fund along with tight and enforceable implementation rules can be an effective option for countries to cope with what can otherwise be dramatic national experiences.

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Tables and Figures

Table 1: Summary statistics

	Mean	Std. Dev.	Min	Max	Obs.
Log difference NL	-0.028	0.241	-2.556	2.585	2701
Fonden=1	0.715	0.452	0	1	2701
Above threshold=1	0.366	0.482	0	1	2701
R_i (mm)	-7.527	76.343	-219.2	297.15	2701
Fonden Threshold (mm)	89.489	44.132	1.5	236.8	2701
Rainfall (mm)	82.879	81.034	0	457.8	2701

Table 2: Impact of Fonden robust bias-corrected local polynomial estimates

	(1)	(2)	(3)	(4)
Panel A: First Stage				
	Dependent variable: Fonden=1			
Above Threshold (α_1)	0.241	0.237	0.219	0.249
Robust p-value	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
Panel B: Intention to treat and LATE				
	Dependent variable: Log difference NL			
Above Threshold (β_1)	0.099	0.107	0.103	0.126
Robust p-value	0.001	0.002	0.017	0.005
RD LATE (τ_{FRD})	0.411	0.453	0.471	0.505
Robust p-value	0.001	0.004	0.038	0.015
Robust 95% CI	[0.194, 0.798]	[0.154, 0.837]	[0.026, 0.868]	[0.099, 0.898]
h	62.817	43.369	79.244	51.890
$N_W^-\|N_W^+$	1120|552	797|419	1343|631	937|490
Bandwidth Selection	$\hat{h}_{MSE}$	$\hat{h}_{CER}$	$\hat{h}_{MSE}$	$\hat{h}_{CER}$
Polynomial degree	$p = 1$	$p = 1$	$p = 2$	$p = 2$

Note: Panel A presents estimates of equation 2, Panel B present estimates of equation 1 and of the LATE. Point estimators are constructed using a triangular kernel, the order of the polynomial and the optimal bandwidth is indicated in each column. Robust p-values and 95% confidence intervals are constructed using bias-correction with robust standard errors clustered at the municipal level. The size of the bandwidth h is expressed in mm. $N_W^-|N_W^+$ denote the effective number of observations used for estimation in each side of the bandwidth.

Table 3: Spillover effects

	(1)	(2)	(3)
	Dependent variable: Log difference NL		
	Within Mun.	0-20 km around Mun.	20-40 km around Mun.
RD LATE	0.411	0.246	0.036
Robust p-value	0.009	0.002	0.951
Robust 95% CI	[0.119,0.836]	[0.095,0.408]	[-0.129,0.054]
h	62.817	62.817	62.817
$N_W^-\|N_W^+$	1120|552	1120|552	1120|552

Note: This table presents estimates of the LATE, in columns 2 to 3 the Log difference NL is calculated using pixels that are within the distance to the municipal boundary indicated in the column title. Point estimators are constructed using a triangular kernel, a local linear polynomial, and an h_{MSE} optimal bandwidth. Robust p-values and 95% confidence intervals are constructed using bias-correction with robust standard errors clustered at the municipal level. $N_W^-|N_W^+$ denote the effective number of observations used for estimation in each side of the bandwidth.

Table 4: Complier probability derivative and treatment effect derivative

	(1)	(2)
CPD	0.0015742	0.0014824
p-value	0.495	0.752
TED	0.0041573	0.0028432
p-value	0.765	0.905
h	77.93	49.615
$N_W^-\|N_W^+$	1329|627	913|465
Bandwidth Selection	$\hat{h}_{MSE}$	$\hat{h}_{CER}$
Polynomial degree	$p=2$	$p=2$

Note: This table provides estimates of the complier probability derivate as described in Cerulli et al. (2016), and of the treatment effect derivative as shown in Dong and Lewbel (2015). All specifications use a triangular kernel and a local quadratic polynomial. $N_W^-|N_W^+$ denote the effective number of observation used for estimation in each side of the bandwidth.

Table 5: Cost Benefit Analysis

	(1) Obs. N	(2) Fonden effect on NL growth	(3) Inverse elasticity NL to GDP	(4) Implied effect on GDP growth	(5) Mean Mun. GDP in 2003 (Millions)	(6) Gain per Mun.	(7) Total Gains (Millions)	(8) Benefit/Cost ratio
	1378	0.411	0.095	0.039	184.3	7,163,489	9,871.29	1.399
Std. Err.		(0.154)	(0.038)	(0.022)	(7.68)	(4,120,169)	(5,677.59)	(0.805)
90% CI								[0.076, 2.724]

Note: Fonden's LATE is taken from table 2 column 1. The inverse elasticity of night lights to GDP is taken from table A1 column 2. Because municipal GDP has a heavy-tailed distribution the estimate in column 5 corresponds to the geometric mean. All values are in (USD 2010 PPP). Standard errors in parentheses. The point estimate in column 8 is calculated using: $N(\beta_2 \times \beta_3 \times \beta_5)/Cost$. Where the subscript represents the column in which the coefficient is reported. Assuming that covariance and co-skewness are equal to zero the standard error is given by: $N\sqrt{(\beta_2^2+se_2^2)\times(\beta_3^2+se_3^2)\times(\beta_5^2+se_5^2)-\beta_2^2\times\beta_3^2\times\beta_5^2})/Cost$.

Table 6: Heterogeneous effects of Fonden

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: Log difference NL							
Sample split	Primary expenditure		Road density km		Road intersection density		Connection to sewage	
	Roads	Non-roads	Below Median	Above Median	Below Med.	Above Med.	Below Med.	Above Med.
RD LATE	0.487	0.255	0.559	0.243	0.676	0.208	0.814	0.045
Robust p-value	0.001	0.081	0.011	0.047	0.007	0.098	0.053	0.588
Robust 95% CI	[0.255, 0.964]	[-0.033, 0.573]	[0.153, 1.208]	[0.004, 0.613]	[0.24, 1.523]	[-0.045, 0.531]	[-0.01, 1.482]	[-0.189, 0.333]
h	65.665	56.953	65.821	72.403	65.496	73.545	38.317	51.004
$N_W^-\|N_W^+$	816|310	575|189	578|284	630|303	579|292	641|299	362|181	446|258

Note: This table presents estimates of Fonden's LATE. Point estimators are constructed using a triangular kernel, a local linear polynomial, and an h_{MSE} optimal bandwidth. Robust p-values and 95% confidence intervals are constructed using bias-correction with robust standard errors clustered at the municipal level. $N_W^-|N_W^+$ denote the effective number of observation used for estimation in each side of the bandwidth.

Table 7: Continuity of the running variable

	h_-	h_+	N_w^-	N_w^+	p-value
Method					
Unrestricted, 2-h	41.589	37.675	772	393	.802
Unrestricted, 1-h	34.505	34.505	657	371	.245
Restricted (1-h)	44.231	44.231	816	422	.435

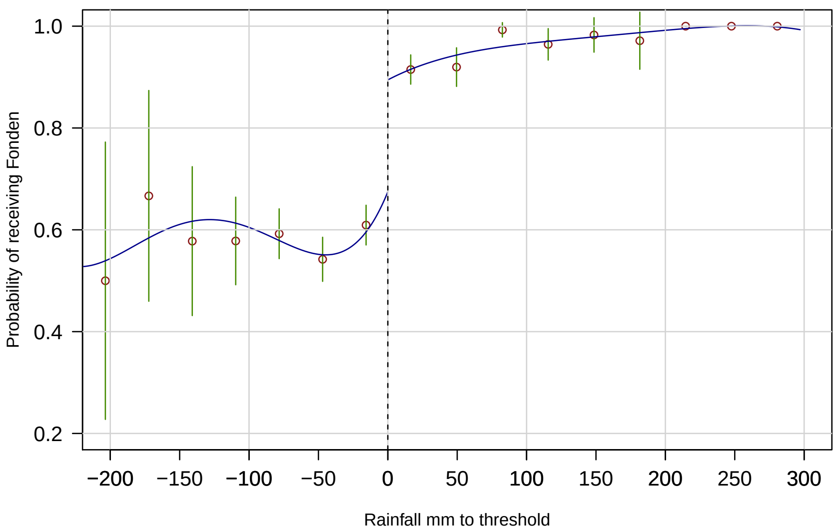
Note: This table presents results for Cattaneo et al. (2017a) test for continuity of the density of the running variable. The null hypothesis is that the density of the running variable is continuous at the threshold. The threshold of the normalized running variable is zero. h_- and h_+ denote the length of the bandwidth on each side of the threshold. N_W^+ denote the effective number of observation used by the test on each side of the bandwidth. The method column reports: unrestricted inference with two distinct estimated bandwidths (2-h), unrestricted inference with one common estimated bandwidth (1-h), and restricted inference with one common estimated bandwidth (1-h).

Table 8: Other resource allocation

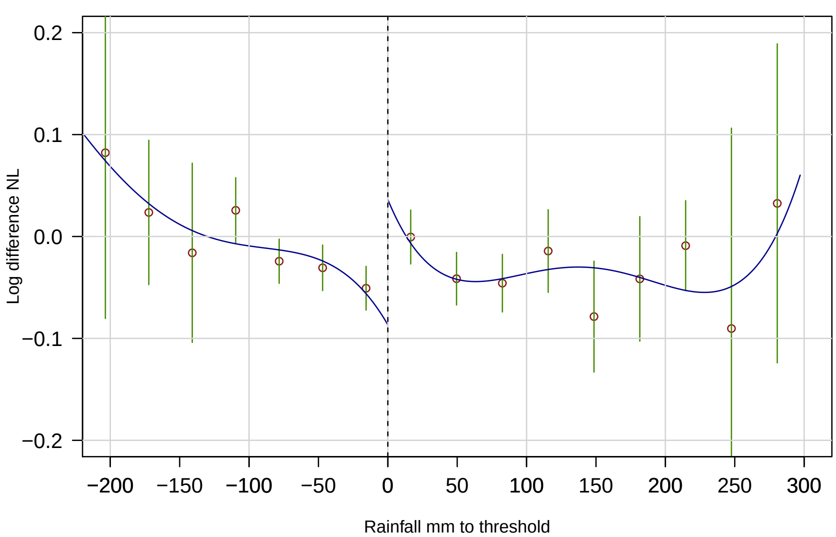
	(1) Growth of per capita transfers to municipalities	(2)	(3)
	Total	Revenue sharing	Conditional
Above Threshold	0.013	0.033	-0.009
Robust p-value	0.94	0.401	0.791
Robust 95% CI	[-0.085, 0.091]	[-0.039, 0.097]	[-0.199, 0.152]
$\hat{h}_{MSE}$	33.551	45.768	50.223
$N_W^- \| N_W^+$	478|281	641|337	698|374
Mean dep. variable	0.093	0.093	0.118

Note: The table presents estimates of equation 1 where the outcome is as indicated in the column title. Point estimators are constructed using a triangular kernel, a local linear polynomial, and an h_{MSE} optimal bandwidth. Robust p-values and 95% confidence intervals are constructed using bias-correction with robust standard errors clustered at the municipal level. $N_W^-|N_W^+$ denote the effective number of observations used for estimation in each side of the bandwidth.

Figure 1: First stage and ITT



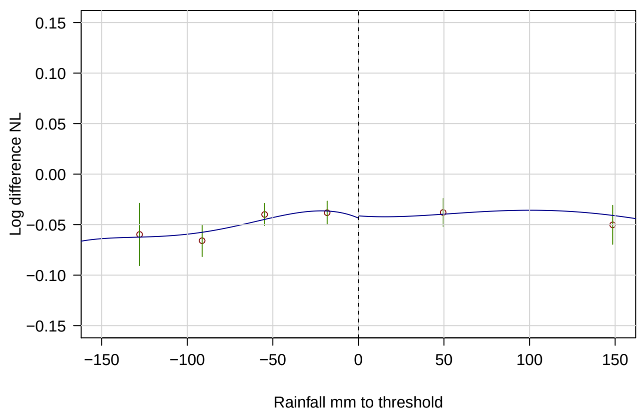
(a) First stage



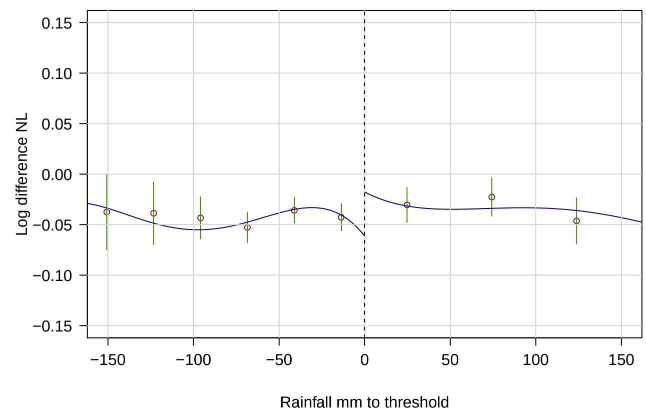
(b) ITT

Note: The figures plot each outcome (probability of receiving Fonden and night lights) as a function of the normalized running variable, that is, rainfall mm to the heavy rainfall threshold. Specifically, the figures plot at the mid-point of each bin the average and the 95% confidence interval of the outcome. The number of bins is selected to minimize the integrated mean square error. The solid lines are fourth-order global polynomials fits. These lines are constructed from raw data and fitted separately on each side of the threshold. The vertical dashed line indicates the cut-off of the normalized running variable that determines eligibility to Fonden.

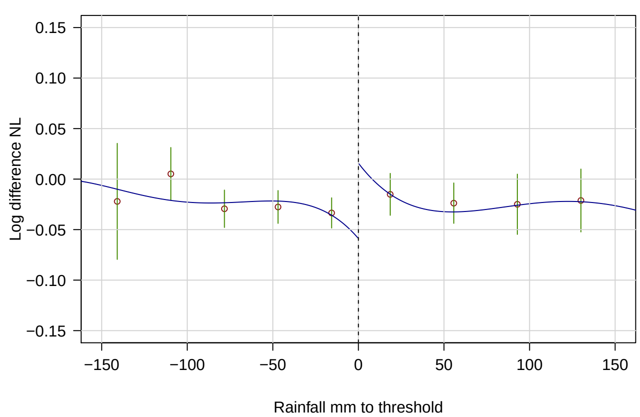
Figure 2: Dynamics of Fonden impact: ITT at various post disaster periods.



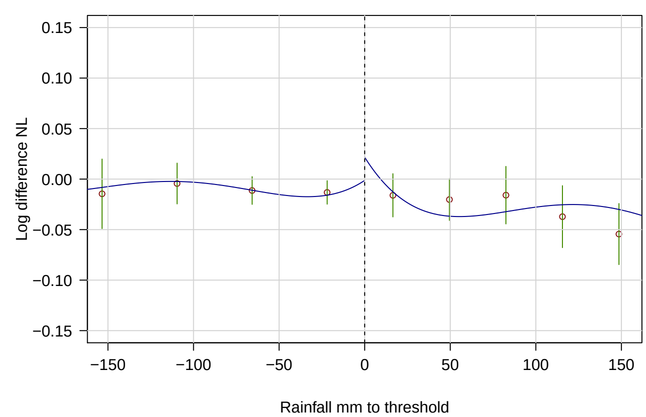
(a) Post-disaster: log night lights, 0 to 3 months after



(b) Post-disaster:log night lights, 0 to 5 months after



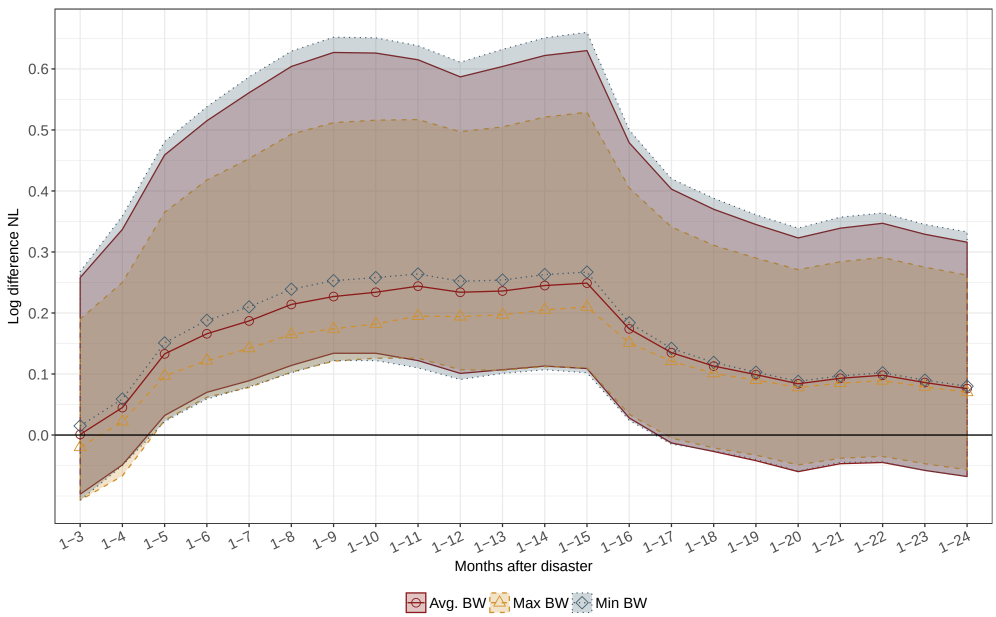
(c) Post-disaster: 0 to 15 months after



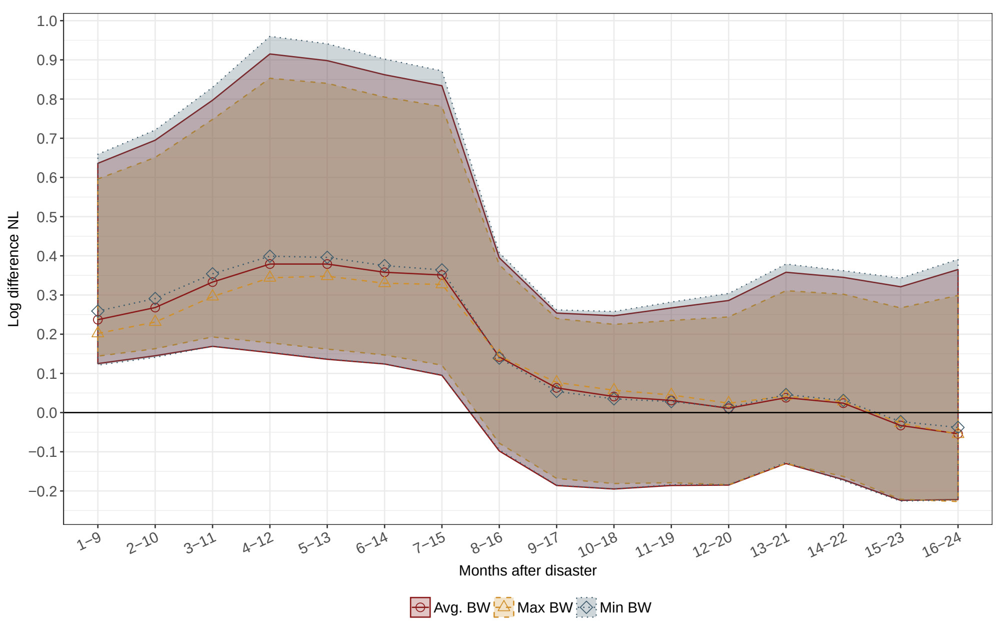
(d) Post-disaster:0 to 24 months after

The figures plot log difference night lights at different point of the post disaster period as a function of the normalized running variable, that is, rainfall mm to the heavy rainfall threshold. Specifically, the figures plot at the mid-point of each bin the average and the 95% confidence interval of the outcome. The number of bins is selected to minimize the integrated mean square error. The solid lines are fourth-order global polynomials fits. These lines are constructed from raw data and fitted separately on each side of the threshold. The vertical dashed line indicates the cut-off of the normalized running variable that determines eligibility to Fonden

Figure 3: Dynamics of Fonden impact: LATE at various post-disaster periods



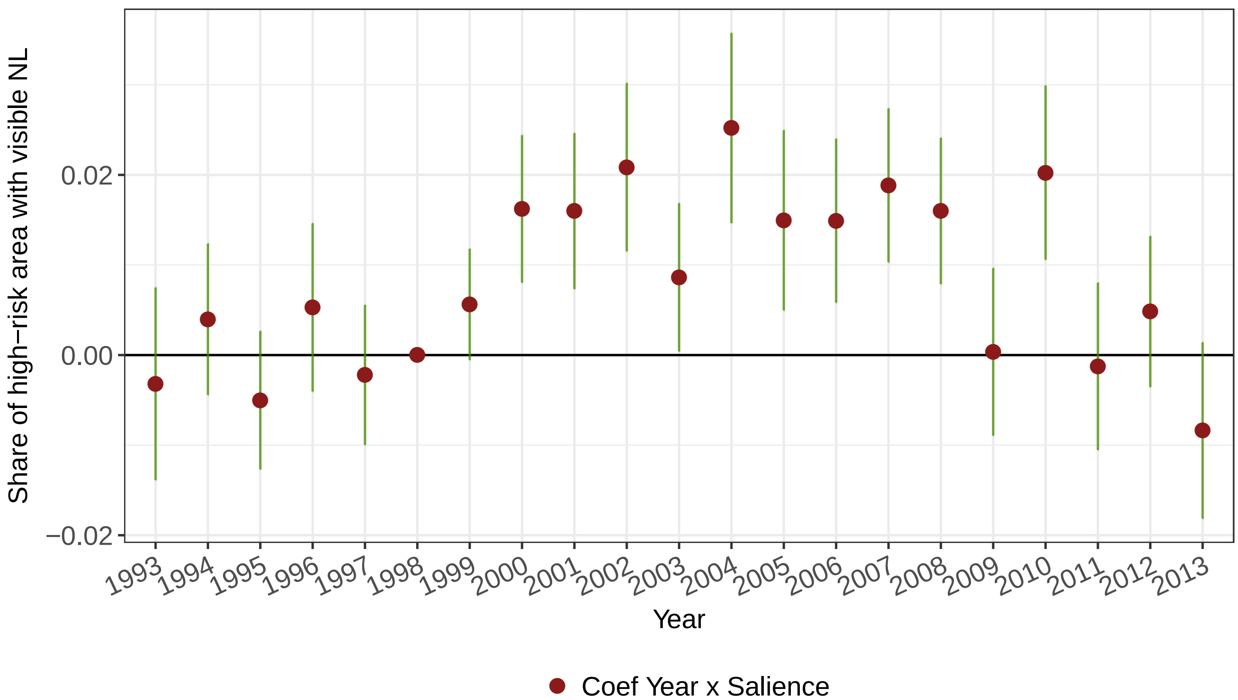
(a) Cumulative Average



(b) 9 month moving average

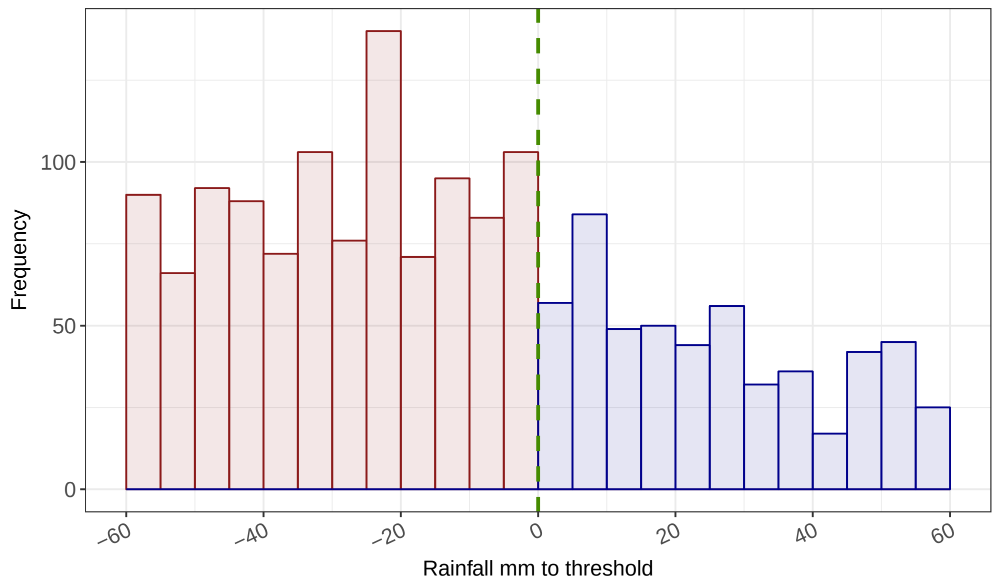
Note: Sub-figure a plots coefficients and robust 95% confidence intervals of Fonden LATE. The outcome variable is the log difference in night lights between the average 12 months before the disaster occurs and the average in the months following the disaster as indicated in the graph. Each plotted coefficient is estimated independently using a triangular kernel, a local linear polynomial and one of three common bandwidths. Estimates derived using the same bandwidth are comparable to each other. The common bandwidths are derived by calculating the optimal h_{MSE} bandwidth for each coefficient and then calculating the average, the minimum and the maximum of the optimal bandwidths. LATE estimates using the average bandwidth are represented by circles, minimum by triangles, and maximum by diamonds. Sub-figure b repeats the previous exercise using as outcome the log difference in night lights between the average 12 months before the disaster occurs and a 9 month moving average in the post disaster period.

Figure 4: Risk-management response to Fonden

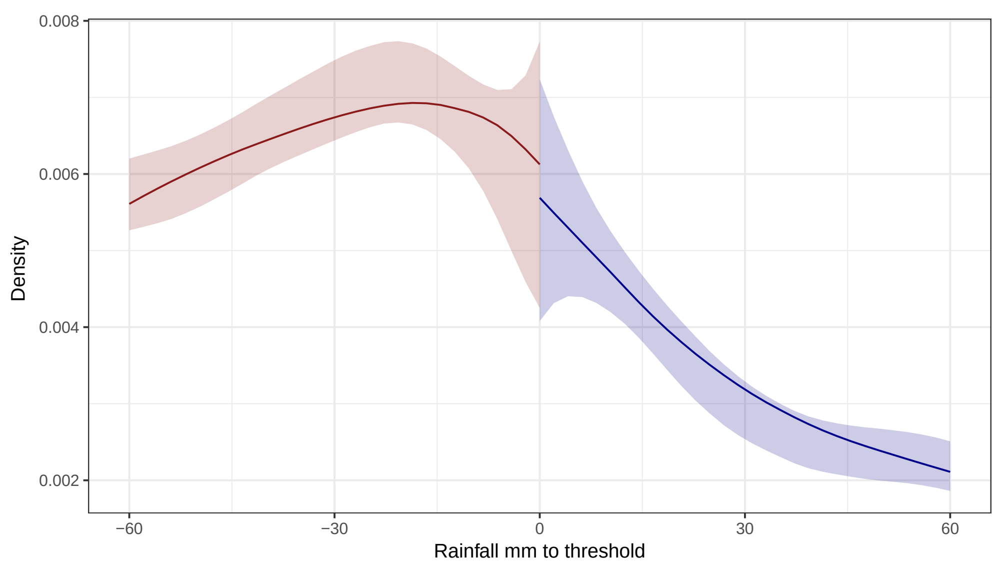


Note: Fonden became operational in 1999. The figure plots the coefficients of the interaction between the salience dummy and the year dummies. The comparison group is low salience municipalities in 1998. The regression include municipal and year fixed effects.The error bars correspond to 95 percent confidence intervals constructed using robust standard errors clustered at the municipal level.

Figure 5: Histogram and estimated density of running variable



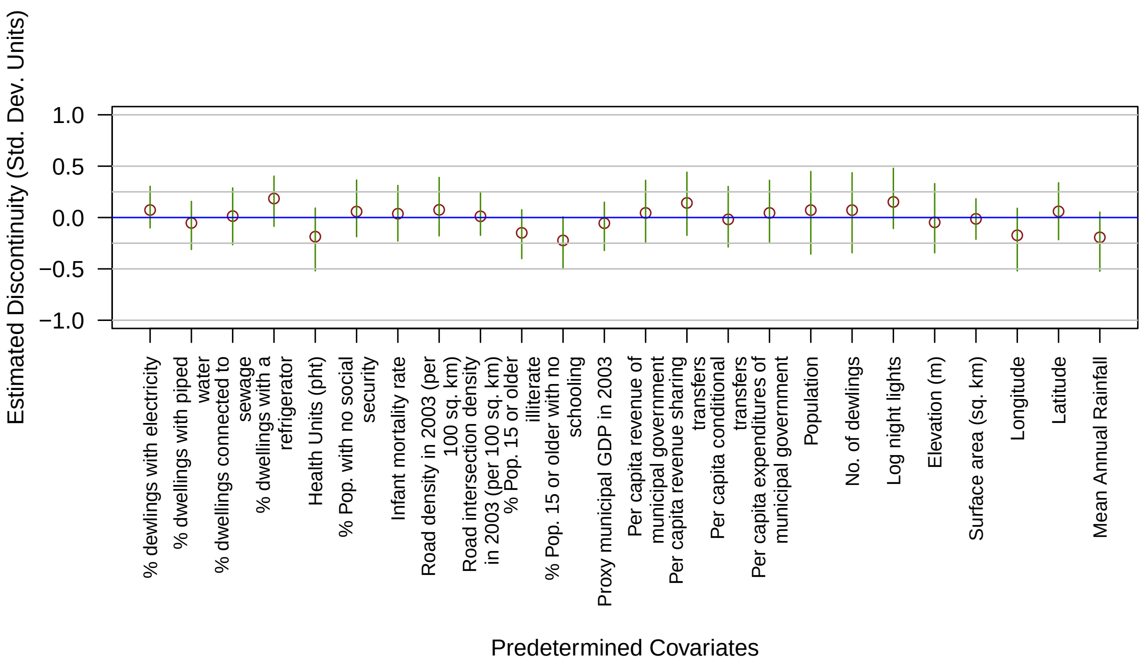
(a) Histogram



(b) Estimated Density

Note: Sub-figure A plots the histogram of the running variable within the h_{mse} estimating bandwidth. Sub-figure B plots the estimated empirical density. This estimate is derived using the methods proposed by Cattaneo et al. (2018). Analogous graphs for the entire support of the running variable can be found in figures A4a and A4b in the appendix.

Figure 6: Continuity tests of predetermined covariates



Note: All variables are standardized to facilitate comparison across variables. The circles represent point estimates constructed using a triangular kernel, a local linear polynomial, and an h_{MSE} optimal bandwidth. The solid lines represent robust 95% confidence intervals.

APPENDIX - FOR ONLINE PUBLICATION

A Predicting State level GDP growth with night lights

While our primary interest lies in determining whether night lights growth can predict municipal GDP growth, in the absence of this data we instead investigate the relationship between growth of night lights and state GDP growth. Given that our primary purpose is to estimate an elasticity of light to GDP that would allow us to back out the impact of Fonden on local economic activity, we restrict the sample to the 28 states that have requested Fonden funding in the 2004-2012 period. We follow the approach taken by Henderson et al. (2011) and focus primarily on determining whether night lights are able to predict year to year growth, annual fluctuations, recession and expansions, and long term growth.

Table A1 presents the main results. The benchmark specification regresses log GDP on log night lights, state fixed effects, and year fixed effects. Standard errors are clustered at the state level in all cases. Column 1 presents the result of the benchmark specification. We sharply estimate an elasticity of roughly 0.21.

Next, in column 2 we test whether night lights are capable of predicting annual fluctuations by extending the previous specification to include state trends. Since we are primarily interested in short term deviations from the state growth path, this is the key specification for our analysis. As in the previous case we sharply estimate an elasticity in the order of 0.1 (p-val=0.02).[40] This result is important because it suggests that night lights do a reasonably good job of predicting annual fluctuations in GDP.

In column 3 we test for ratchet effects, that is whether, relative to the state mean over time, increases and decreases in night lights are symmetrically related to increases and decreases in GDP. This calculation is preformed in two steps: (i) We demean the data by regressing GDP and lights on year and state fixed effects. (ii) We regress the GDP residuals on absolute value positive lights residuals, and absolute value negative lights residuals. We find that the coefficients are very similar in magnitude and that they have the opposite signs. We thus conclude that night lights are capable of picking up both economic expansions and economic downturns.

In terms of R^2, note that the R^2 reported in columns 1 and 2 is a within state R^2, it still accounts for the role of year dummies. The R^2 reported in column 3, 8%, reflects solely the contribution of night lights to explaining within-state and within-year variation in GDP.

[40]The wild cluster bootstrap (5000 iterations) produces a p-value of 0.027

Last in column 4, we look at the ability of night lights to predict long-term growth. This is done using a long difference specification where we regress the change in log GDP between 2004 and 2013 on the change in log night lights between 2004 and 2013. We find a positive and sharply estimated elasticity, and an R^2 of 0.38. All in all, while our sample size is small compared to those of other papers in the literature, our results validate the idea of using night lights as a proxy for economic activity at the subnational level in Mexico.

Table A1: Elasticity of night lights to GDP

	(1) Base Specification	(2) Annual Fluctuations	(3) Asymmetric Fluctuations	(4) Long Difference
	ln(GDP)	ln(GDP)	Res ln(GDP)	ln(GDP)
ln(lights/area)	0.215	0.095		0.618
	(0.065)	(0.038)		(0.163)
	[0.003]	[0.02]		[0.001]
|+ Res ln(lights/area)|			0.169	
			(0.118)	
			[0.162]	
|- Res ln(lights/area)|			-0.256	
			(0.111)	
			[0.029]	
Observations	280	280	280	28
R-squared	0.885	0.957	0.078	0.377
State FE	✓	✓	In demean	.
Year FE	✓	✓	In demean	.
State Trend	.	✓	.	.

Note: Standard errors clustered at the state level in parentheses, p-values in squared brackets. Mexico has 32 states. The sample has been restricted to the 28 states that received Fonden between 2004 and 2012.

B Tables and Figures

Table A2: Donut-hole Analysis

Donut-hole Radius	RD Estimate	Robust p-value	Robust 95% CI	$\hat{h}_{MSE}$	Obs.	Excluded obs left	Excluded obs right
0	.411	.001	[0.194, 0.798]	62.82	1672	0	0
.5	.426	.002	[0.196, 0.840]	61.79	1643	3	7
1	.552	.002	[0.27, 1.232]	62.08	1617	30	10
1.5	.665	.016	[0.158, 1.522]	47.38	1269	33	13
2	.703	.004	[0.313, 1.705]	56.2	1456	39	21
2.5	.421	.017	[0.098, 1.015]	56.53	1436	61	26

Note: Sensitivity of the LATE estimate to the exclusion of observations that are within 5 mm of the threshold. Point estimators are constructed using a triangular kernel, a local linear polynomial, and an h_{MSE} optimal bandwidth. Robust p-values and 95% confidence intervals are constructed using bias-correction with robust standard errors clustered at the municipal level.

Table A3: Placebo cutoffs

Row	Alternative cutoff	RD Estimate	Robust p-value	Robust 95% CI	$\hat{h}_{MSE}$	$N_W^-\|N_W^+$
1	-46.2	.116	.853	[-1.022, 0.845]	14.42	232|250
2	-36.1	-1.403	.979	[-8.537, 8.311]	11.91	196|222
3	-26.8	-.236	.895	[-1.415, 1.236]	15.12	261|286
4	-19.5	.912	.349	[-1.197, 3.385]	13.05	279|223
5	-9.1	-.622	.126	[-2.276, 0.28]	6.12	113|102
6	0	.411	.001	[0.194, 0.798]	62.82	1120|552
7	8	-1.611	.27	[-4.733, 1.325]	21.13	98|236
8	15.4	.007	.451	[-0.781, 0.347]	16.32	197|155
9	26.2	-1.486	.948	[-19.31, 20.641]	14.45	145|110
10	38.2	-.986	.696	[-4.623, 3.087]	12.88	109|87
11	53.1	.264	.846	[-1.568, 1913]	16.5	108|92

Note: Estimates of the LATE at the true zero cut-off and at various placebo cut-offs. The sample in rows 7 to 11 is restricted to nonnegative values of the running variable, the placebo cut-off are given by the first five deciles. The sample in rows 1 to 5 is restricted to negative values of the running variable, the placebo cut-offs are determined in an analogous manner. In all cases point estimators are constructed using a triangular kernel, a local linear polynomial, and an h_{MSE} optimal bandwidth. Robust p-values and 95% confidence intervals are constructed using bias-correction with robust standard errors clustered at the municipal level

Table A4: Robustness Checks I

	(1)	(2)	(3)	(4)	(5)
Panel A: First Stage					
	Dependent variable: Fonden=1				
Above Threshold	0.234	0.285	0.234	0.246	0.237
Robust p-value	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
Panel B: RD treatment effects					
	Dependent variable: Log difference NL				
	RF h_{MSE}	Kernel		Asymmetric h	
RD Late	0.419	0.356	0.408	0.419	0.475
Robust p-value	0.007	$p < 0.001$	0.002	0.005	0.009
Robust 95% CI	[0.126, 0.804]	[0.192, 0.620]	[0.188, 0.809]	[0.138, 0.787]	[0.125, 0.875]
h	54.646|54.646	62.987|62.987	58.582|58.582	46.026|63.333	31.776|43.725
$N_W^-\|N_W^+$	986|508	1125|552	1048|526	855|552	609|419
Bandwidth Selection	$\hat{h}_{MSE}$	$\hat{h}_{MSE}$	$\hat{h}_{MSE}$	$\hat{h}_{MSE2}$	$\hat{h}_{CER2}$
Kernel	Triangular	Uniform	Epanechnikov	Triangular	Triangular

Note: Panel A presents estimates of equation 2, Panel B present estimates of the LATE. Point estimators are constructed using the kernel and optimal bandwidth algorithm indicated in each column. Robust p-values and 95% confidence intervals are constructed using bias-correction with robust standard errors clustered at the municipal level. The size of the bandwidth h is expressed in mm. $N_W^-|N_W^+$ denote the effective number of observations used for estimation in each side of the bandwidth.

Table A5: Robustness Checks II

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: First Stage							
	Dependent variable: Fonden=1						
Above Threshold	0.235	0.24	0.228	0.271	0.28	0.255	0.2
Robust p-value	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
Panel B: RD treatment effects							
	Dependent variable: Log difference NL						
	NL alternative definitions			Multiple exposure to Fonden		Extreme Thresholds	
	New Sat. only	Exclude top coded pixels	Year Fixed Effects	Exclude obs. with Fonden in year before or after	Exclude obs. with Fonden two years before or after	Exclude bottom decile thresholds	Exclude top decile thresholds
RD LATE	0.406	0.412	0.352	0.444	0.569	0.423	0.376
Robust p-value	0.007	0.001	0.023	0.001	0.003	0.004	0.032
Robust 95% CI	[0.122, 0.77]	[0.2,0.805]	[0.051, 0.7]	[0.218,1.099]	[0.138 , 0.919]	[0.151,0.819]	[0.038, 0.855]
h	60.012	64.565	52.492	66.214	47.108	61.596	48.786
$N_W^-\|N_W^+$	1079|536	1153|546	942|493	915|423	527|264	1016|465	797|424

Note: Panel A presents estimates of equation 2, Panel B present estimates of the LATE. Point estimators are constructed using a triangular kernel, a local linear polynomial, and an h_{MSE} optimal bandwidth. Robust p-values and 95% confidence intervals are constructed using bias-correction with robust standard errors clustered at the municipal level. $N_W^-|N_W^+$ denote the effective number of observations used for estimation in each side of the bandwidth. The dependent variable in column 1 is constructed using only information form the newest satellite available. Column 2 excludes pixels whose value DN exceed 55. The specification in column 3 includes year fixed effects. Columns 4 to 7 exclude observations as indicated in the column title.

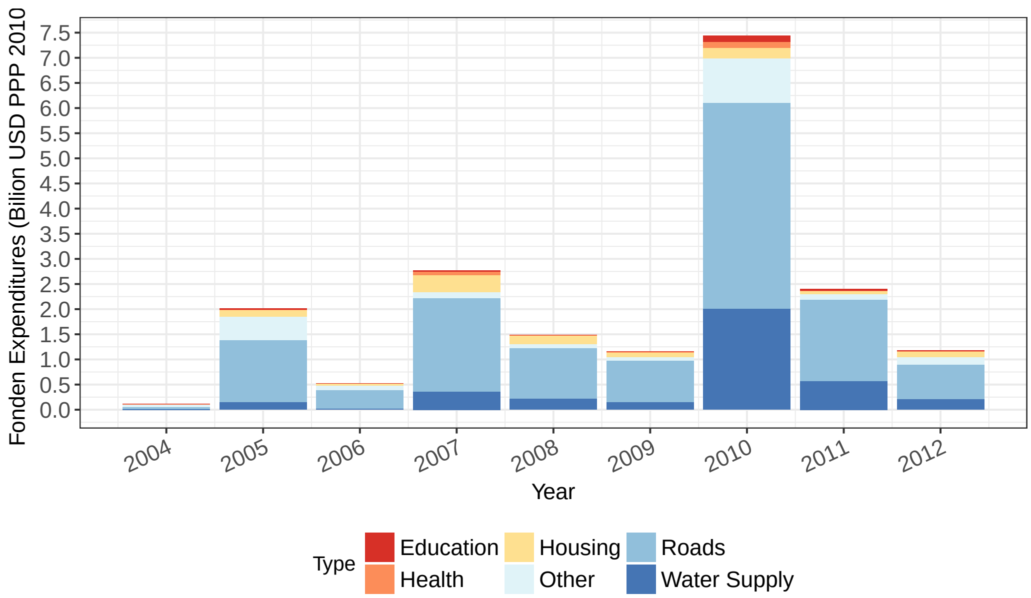
Table A6: Additional datasets and Sources

Variable	Source
INEGI (The National Institute of Statistics and Geography)	

Population
No. of dwellings
Pop. with no social security
Pop. with no social security
Pop. 15 or older illiterate
Pop. 15 or older with no schooling
Dwellings with electricity
Dwellings with piped water
Dwellings connected to sewage
Dwellings with a refrigerator
Elevation
	Census
	`http://www.beta.inegi.org.mx/proyectos/ccpv/2000/default.html`
	`http://www.beta.inegi.org.mx/proyectos/ccpv/2005/default.html`
	`http://www.beta.inegi.org.mx/proyectos/ccpv/2010/default.html`

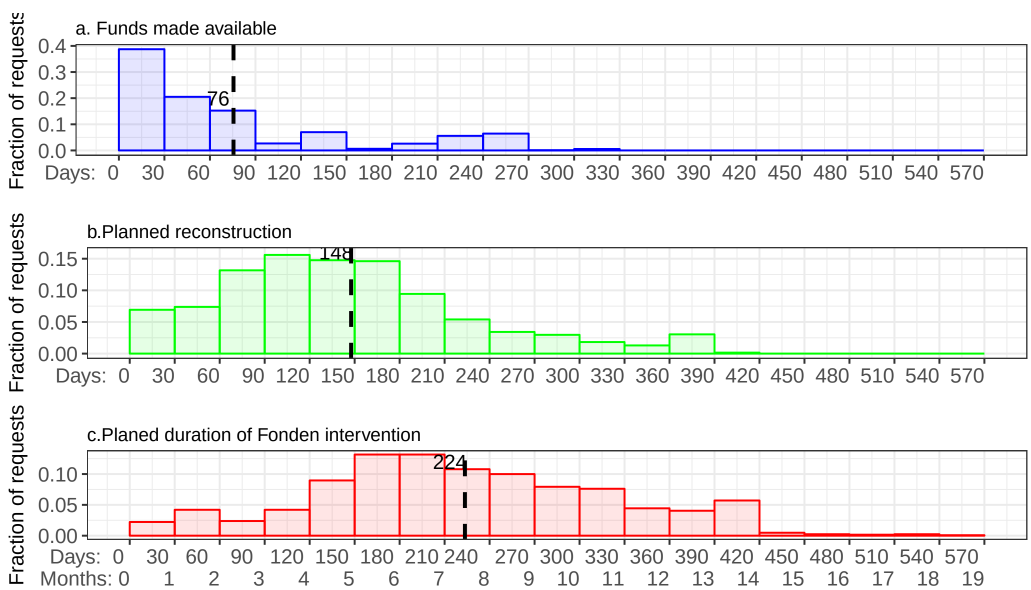
Revenue of municipal government Expenditures of municipal government Total transfers Discretionary federal transfers targeted federal and state transfers	Public finances of municipalities `http://www.beta.inegi.org.mx/proyectos/registros/economicas/finanzas/`
Municipal surface area Centroid longitude Centroid latitude	Municipal boundaries `http://www.inegi.org.mx/geo/contenidos/geoestadistica/m_geoestadistico.aspx`
State level GDP	`http://www.inegi.org.mx/est/contenidos/proyectos/cn/pibe/default.aspx`
Fund for Natural Disasters Fonden	
Fonden expenditures Fonden disbursement times Fonden planned reconstruction times	Fonden online database
Other Datasets	
Health Units per 100.000	SINAIS
Infant mortality rate	CONAPO
Road Network 2003	US Geological Survey Global GIS Databases
Areas at high risk of flooding	CONAGUA
PPP Exchange Rates	World Bank

Figure A1: Fonden Expenditures by year and type of reconstruction



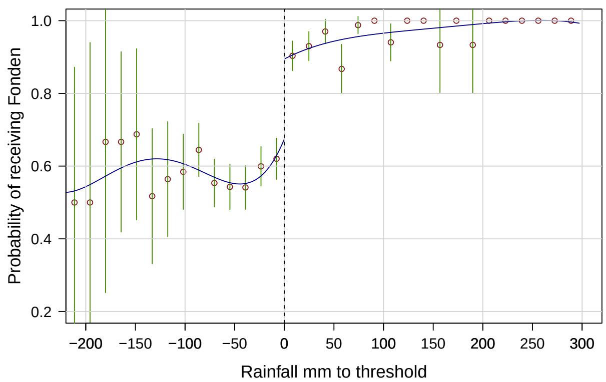
Note: Author's calculations from Fonden administrative records. Expenditures are measured in Billion USD PPP 2010

Figure A2: Fonden fund disbursement and planned reconstruction times

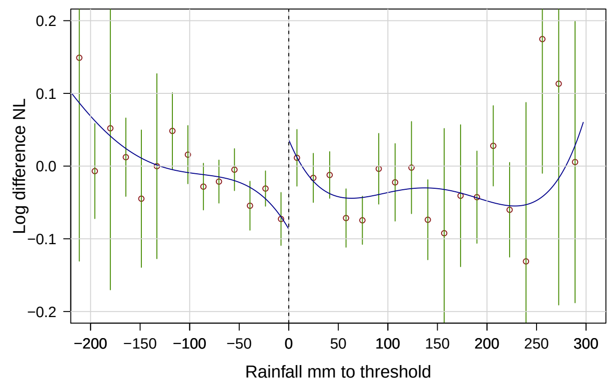


Note: Author's calculations from Fonden administrative records. Planned duration of Fonden intervention include both disbursement and planned reconstruction.

Figure A3: First stage and ITT



(a) First stage (bins x 2)



(b) ITT (bins x 2)

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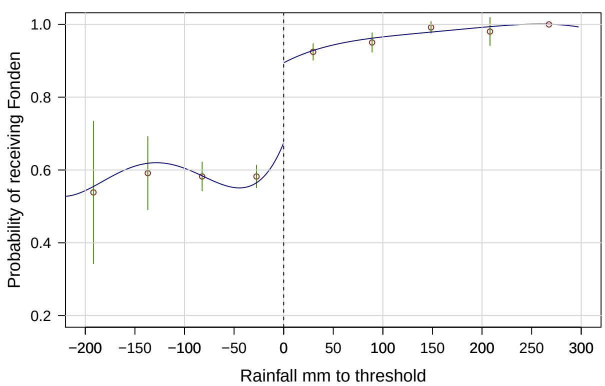
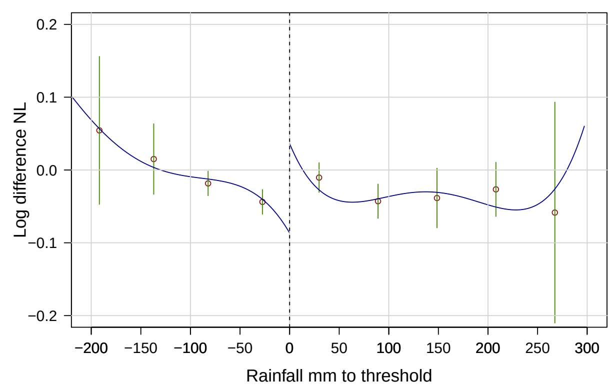


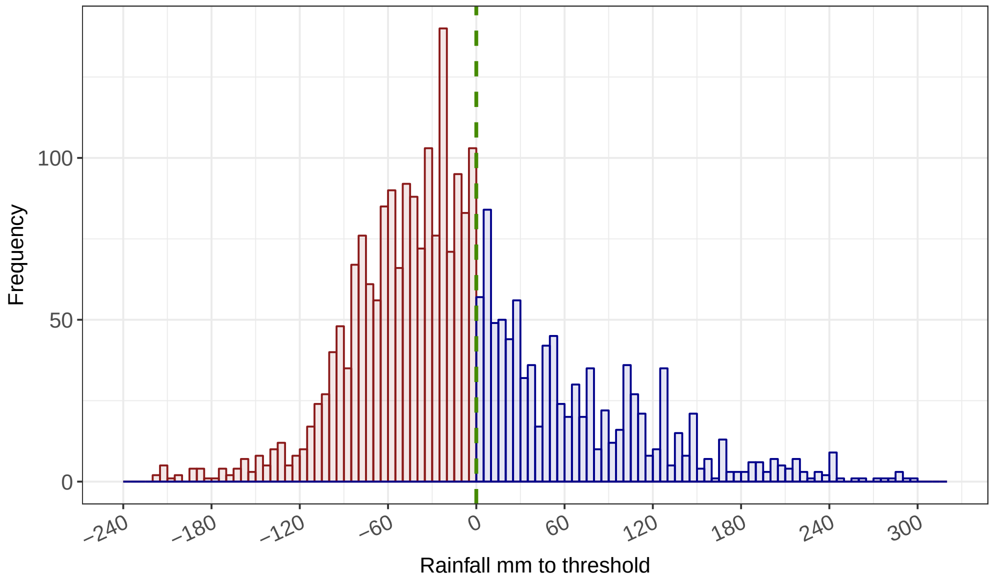
(c) First stage (bins / 2)



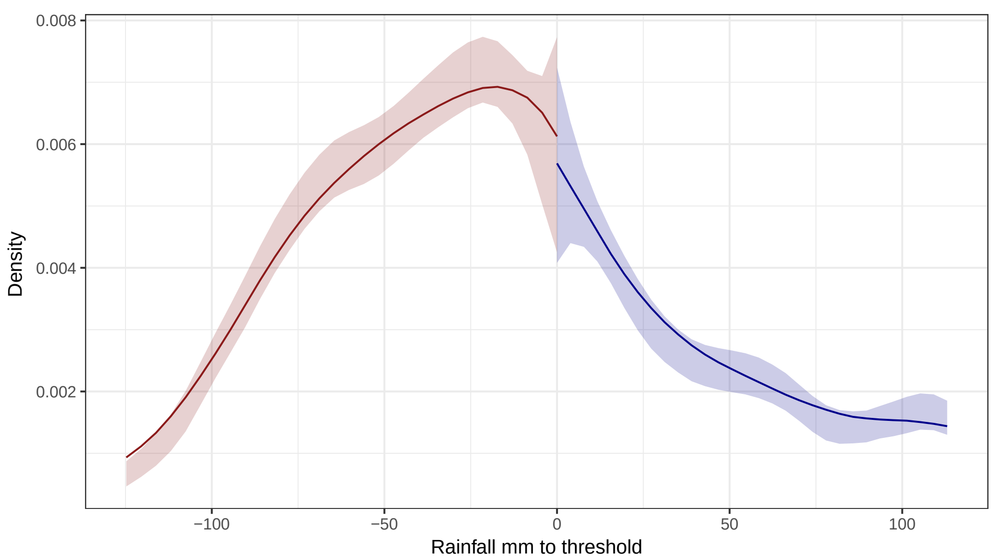
(d) ITT (bins / 2)

Note: The figures plot each outcome (probability of receiving Fonden and night lights) as a function of the normalized running variable, that is, rainfall mm to the heavy rainfall threshold. Specifically, the figures plot at the mid-point of each bin the average and the 95% confidence interval of the outcome. The number of bins is selected to minimize the integrated mean square error. The solid lines are fourth-order global polynomials fits. These lines are constructed from raw data and fitted separately on each side of the threshold. The vertical dashed line indicates the cut-off of the normalized running variable that determines eligibility to Fonden.

Figure A4: Histogram and estimated density of running variable



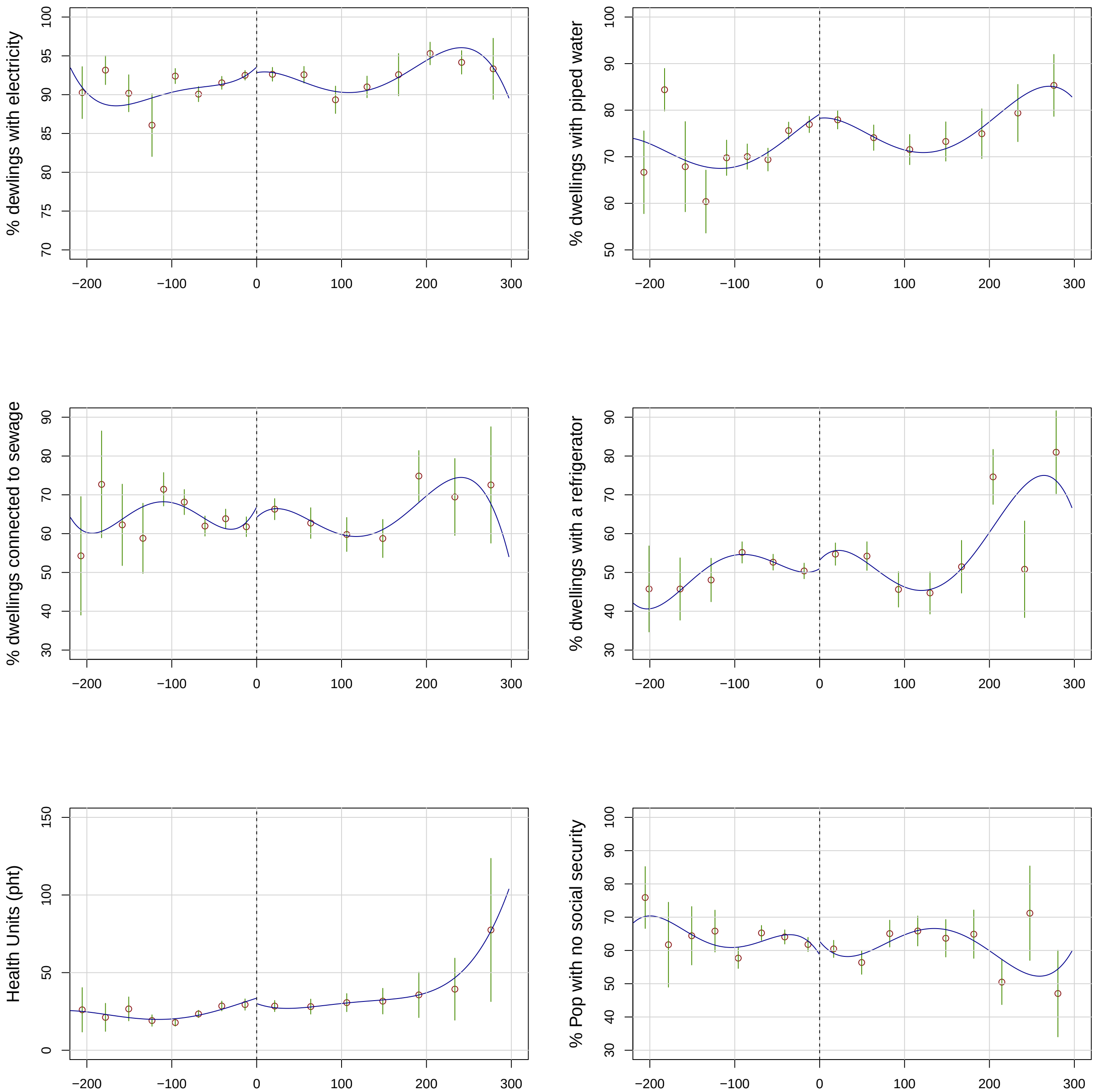
(a) Histogram in BW



(b) Estimated Density in BW

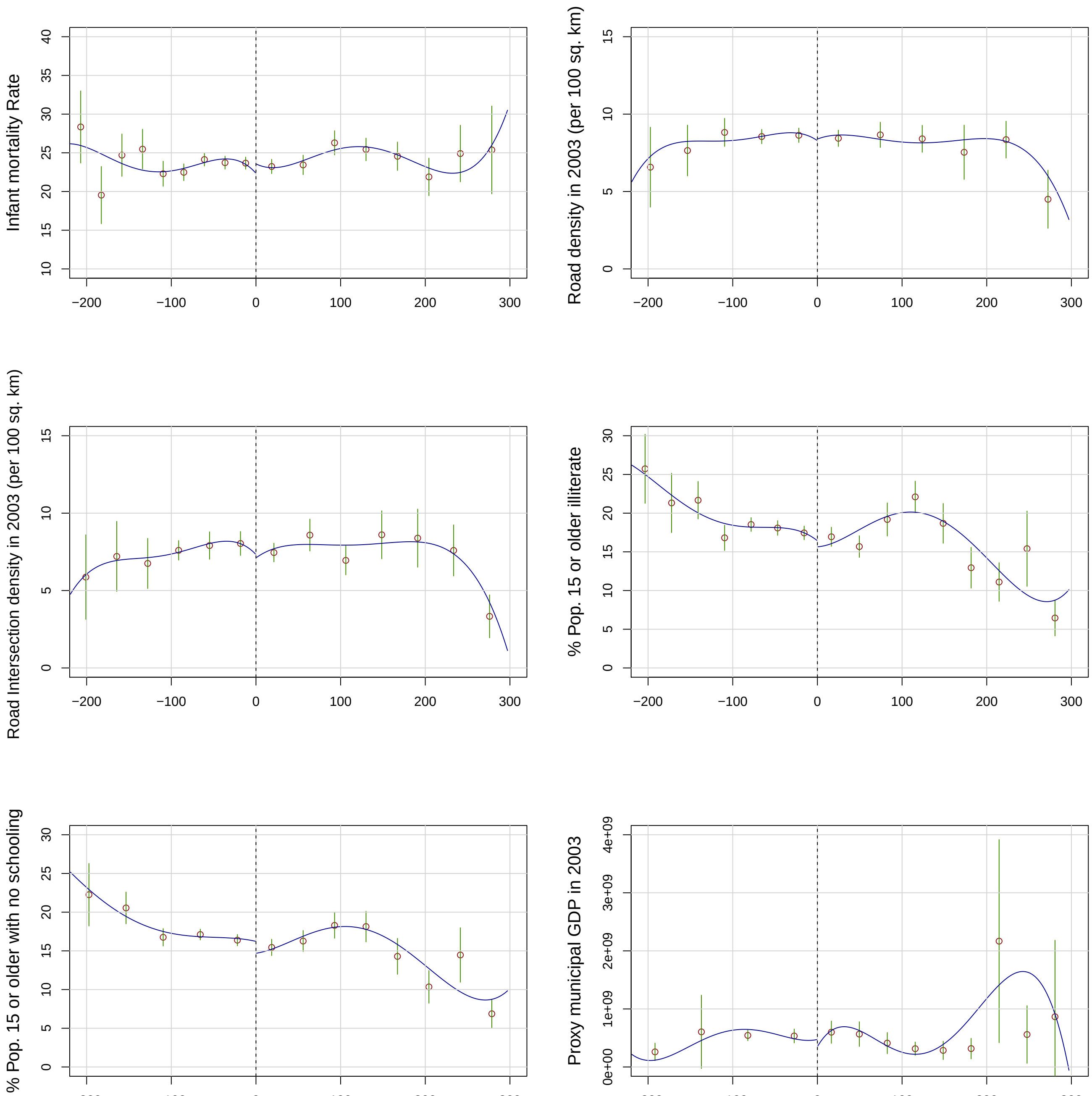
Note: Sub-figure A plots the histogram of the running variable. Sub-figure B plots the estimated empirical density. This estimate is derived using the methods proposed by Cattaneo et al. (2018).

Figure A5: Predetermined Covariates I



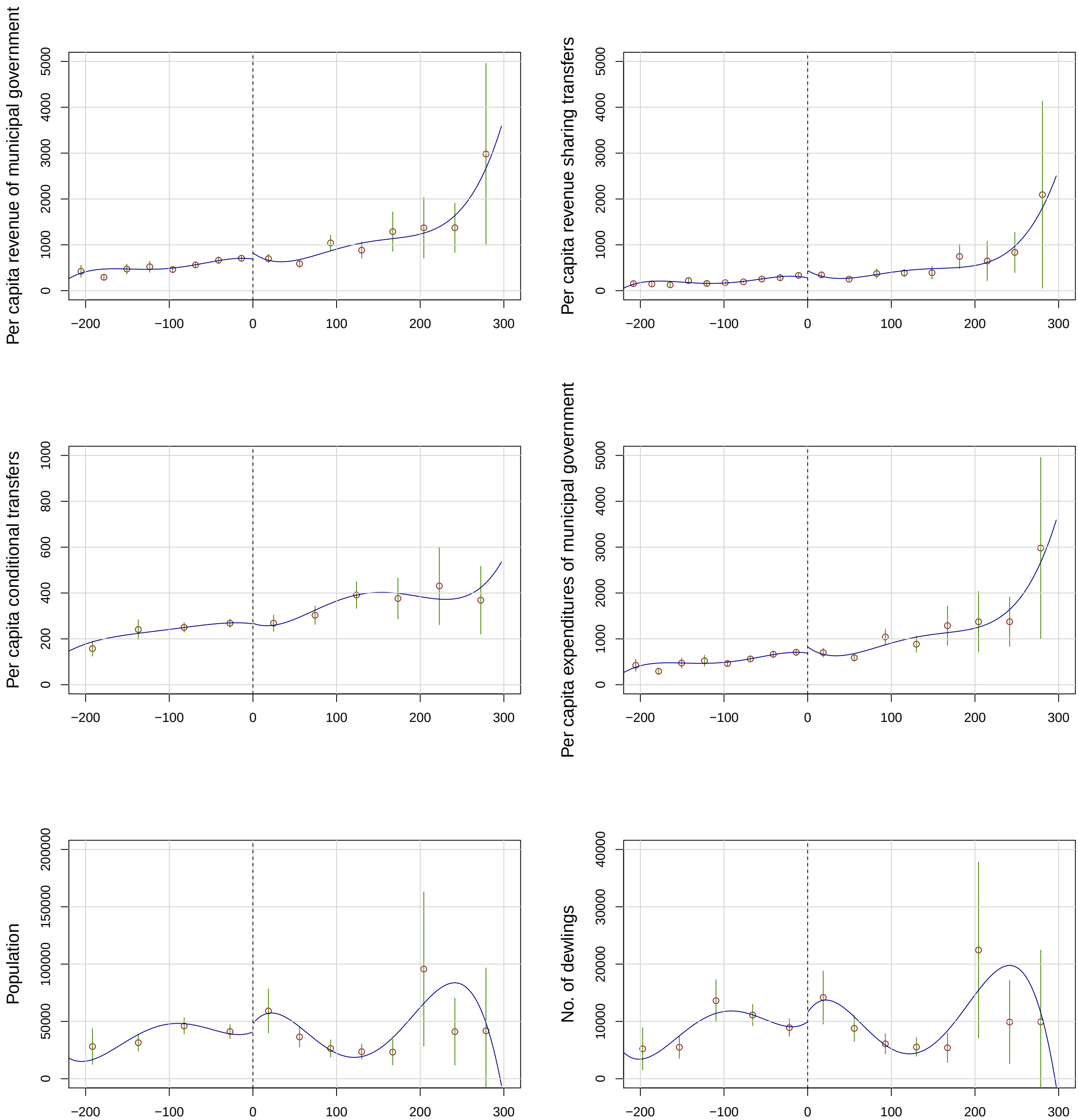
Note: The figures plot each outcome as a function of the normalized running variable, that is, rainfall mm to the heavy rainfall threshold. Specifically, the figures plot at the mid-point of each bin the average and the 95% confidence interval of the outcome. The number of bins is selected to minimize the integrated mean square error. The solid lines are fourth-order global polynomials fits. These lines are constructed from raw data and fitted separately on each side of the threshold. The vertical dashed line indicates the cut-off of the normalized running variable that determines eligibility to Fonden.

Figure A6: Predetermined Covariates II



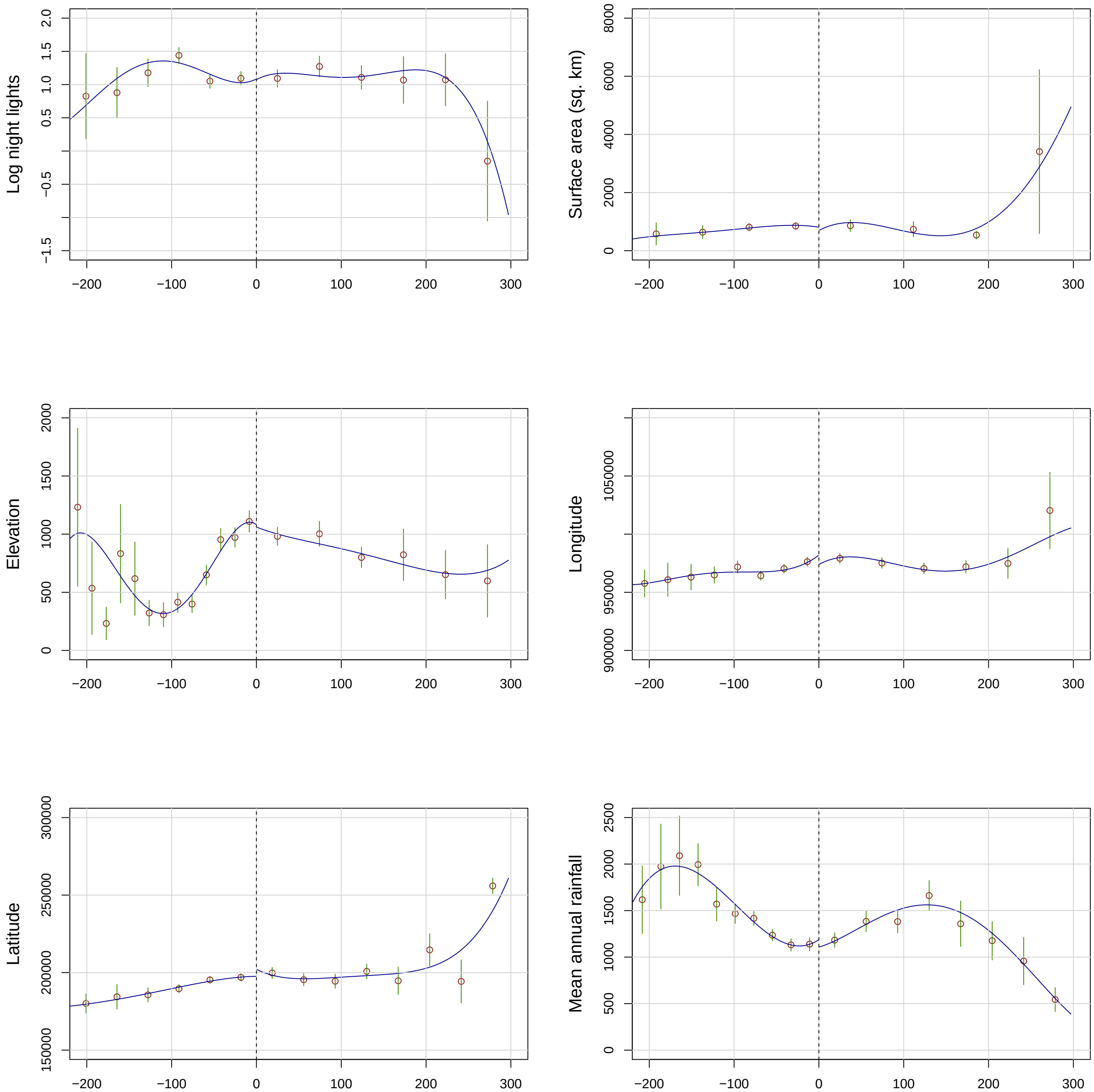
Note: The figures plot each outcome as a function of the normalized running variable, that is, rainfall mm to the heavy rainfall threshold. Specifically, the figures plot at the mid-point of each bin the average and the 95% confidence interval of the outcome. The number of bins is selected to minimize the integrated mean square error. The solid lines are fourth-order global polynomials fits. These lines are constructed from raw data and fitted separately on each side of the threshold. The vertical dashed line indicates the cut-off of the normalized running variable that determines eligibility to Fonden.

Figure A7: Predetermined Covariates III



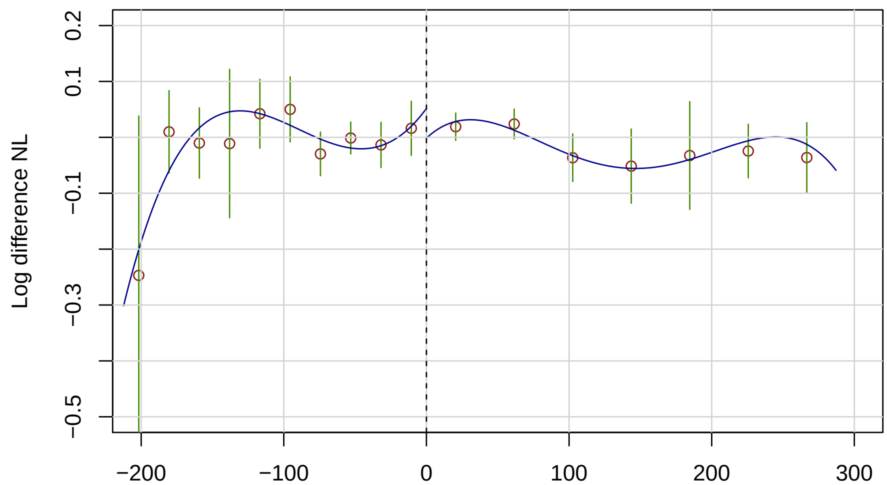
Note: The figures plot each outcome as a function of the normalized running variable, that is, rainfall mm to the heavy rainfall threshold. Specifically, the figures plot at the mid-point of each bin the average and the 95% confidence interval of the outcome. The number of bins is selected to minimize the integrated mean square error. The solid lines are fourth-order global polynomials fits. These lines are constructed from raw data and fitted separately on each side of the threshold. The vertical dashed line indicates the cut-off of the normalized running variable that determines eligibility to Fonden.

Figure A8: Predetermined Covariates IV



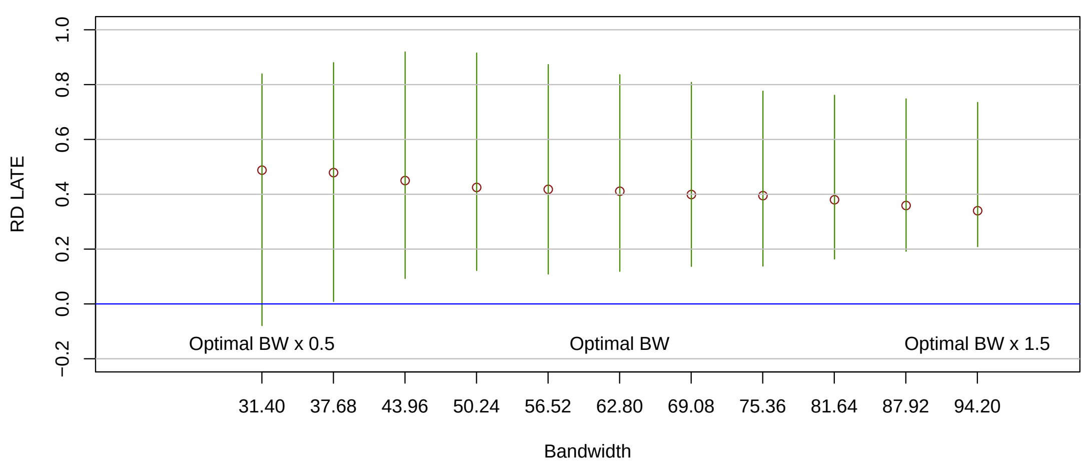
Note: The figures plot each outcome as a function of the normalized running variable, that is, rainfall mm to the heavy rainfall threshold. Specifically, the figures plot at the mid-point of each bin the average and the 95% confidence interval of the outcome. The number of bins is selected to minimize the integrated mean square error. The solid lines are fourth-order global polynomials fits. These lines are constructed from raw data and fitted separately on each side of the threshold. The vertical dashed line indicates the cut-off of the normalized running variable that determines eligibility to Fonden.

Figure A9: Placebo



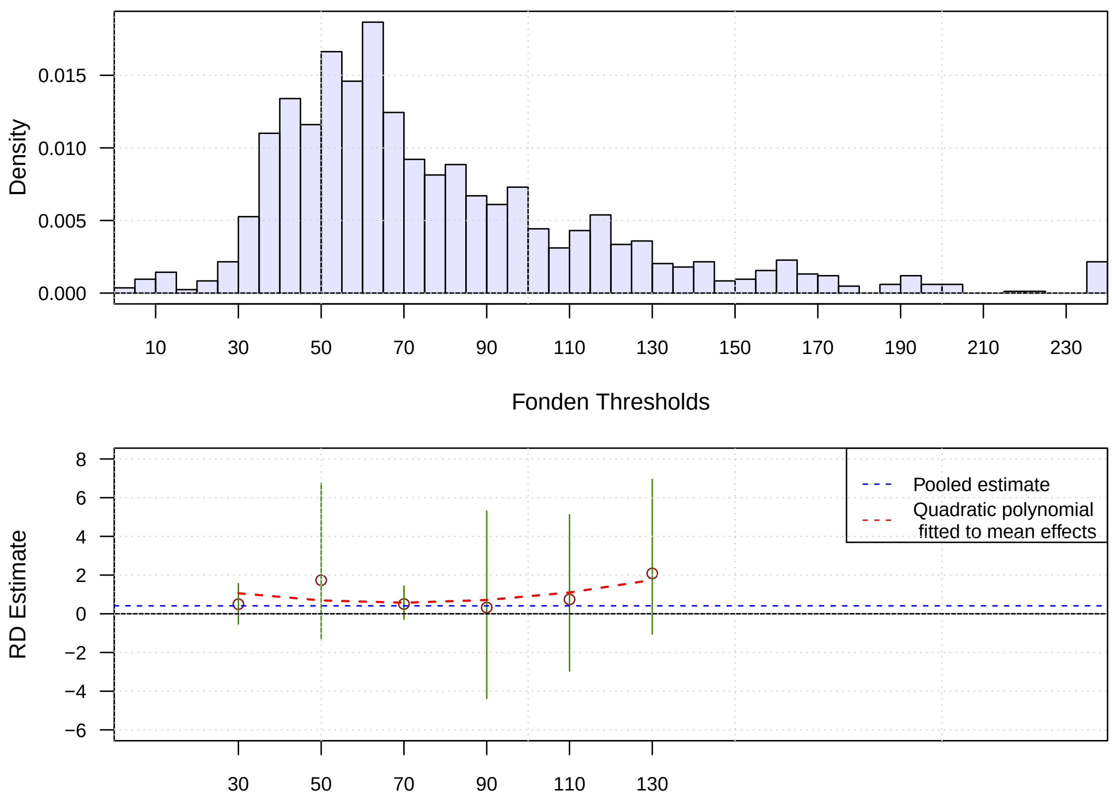
Note: The figure plots (Placebo) log difference night lights as a function of the normalized running variable, that is, rainfall mm to the heavy rainfall threshold. Specifically, the figures plot at the mid-point of each bin the average and the 95% confidence interval of the outcome. The number of bins is selected to minimize the integrated mean square error. The solid lines are fourth-order global polynomials fits. These lines are constructed from raw data and fitted separately on each side of the threshold. The vertical dashed line indicates the cut-off of the normalized running variable that determines eligibility to Fonden

Figure A10: Fonden impact sensitivity to Bandwidth



Note: Estimates of Fonden LATE at 10 evenly spaced bandwidths. The smallest bandwidth 31.4 mm is 50% smaller than the optimal h_{MSE} bandwidth, the largest 94.3 mm is 50% larger than the optimal h_{MSE}. The circles represent point estimates constructed using a triangular kernel, a local linear polynomial, and the bandwidth indicated by the graph. The solid lines represent robust 95% confidence intervals.

Figure A11: Fonden treatment effect curve



Note: Sub-figure A plots the histogram of Fonden's Heavy rainfall thresholds. Sub-figure B plots point estimates (circles) and 95% confidence intervals (solid green lines) of Fonden's LATE at six threshold values. Each estimate of Fonden's LATE uses only the 400 treatment and control observations that are closest to each threshold. Sub-figure B also plots Fonden's pooled LATE taken from table 2 column 1 (dashed blue lines), and a quadratic polynomial fit of Fonden's LATE at the six threshold values (red dashed lines).