Rules for Recovery: Impact of Indexed Disaster Funds on Shock Coping in Mexico

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Government provision of disaster transfers is typically hampered by liquidity constraints and by weak rules and administrative capacity to disburse reconstruction resources. We show that by easing these hurdles, Mexico's indexed disaster fund (Fonden) considerably accelerates economic recovery after a disaster. To estimate Fonden impact on recovery, as measured by night lights, we exploit the heavy rainfall index that determines program eligibility. We find that, for one year after a disaster, eligible municipalities are 6 percent brighter than those ineligible, with gains likely concentrated among less resilient municipalities. We additionally document how Fonden rules shield resources from political abuse.
JEL: Q54, H12, H84, I38, O10.

Extreme weather events is 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 70 percent 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 transfers, the bulk of which spent on reconstruction projects (Ghesquiere and Mahul, 2010). These projects include the restoration of lifeline infrastructures such as roads, electricity, and safe water, and are expected to reduce the duration of costly periods of disruption of 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

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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 explicit rules and administrative capacity to minimize delays and leakages in the disbursement of reconstruction resources.

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 responsibility covers the 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 relative to discretionary local government reconstruction efforts. 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 events 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 index insurance rules. Specifically, a municipality is eligible for Fonden resources when rainfall exceeds 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 four 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 the change in night lights is 6 percent higher in eligible municipalities than in ineligible municipalities. Among municipalities near the cut-off that received Fonden because they experienced rainfall over the threshold compared to those that did not, we estimate a Local Average Treatment Effect (LATE) of roughly 29 percent. 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 month zero to three, during which we observe no impact of Fonden on night lights. (ii) A phase of active recovery, extending from months four to 15, during which we find an increasing effect of Fonden on night lights. (iii) A phase of catching up, extending from month 16 to 23, during which the gap in night lights between eligible and ineligible municipalities disappears as discretionary reconstruction efforts by local governments take effect. As can be expected with large reconstruction programs, we observe Fonden spillover effects on neighboring municipalities. These effects go in the same direction as the direct effect and 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 nearly as large as the costs of the program. Specifically, we show that our estimate of Fonden LATE is locally constant (Dong and Lewbel, 2015; Cerulli et al., 2017), 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 simple back-of-the-envelope calculation that compares the value of the economic activity generated by Fonden, over a year after a disaster, with its cost. We find that Fonden LATE on night lights is roughly equivalent to a 2.5 percent increase in municipal GDP and that the value of this additional economic activity is about as large as Fonden reconstruction and administrative costs.

The third set of results documents heterogeneity in the effect of Fonden. Specifically, we provide supporting evidence to argue that Fonden investments in road reconstruction may yield the largest benefits. We also document that municipalities that are less resilient because they lack the public infrastructure to mitigate damage from extreme weather, such as storm drains, benefit disproportionately more from Fonden.

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 their importance for the identification of causality, these results also suggest that Fonden institutional rule based on indexation makes it harder for local governments to manipulate the running variable, protecting resource transfers from political abuse.

Our findings contribute to the literature on the provision and effectiveness of disaster transfers. One strand of this literature has documented how governments in developing economies routinely fail to provide transfers in the aftermath of disasters (Noy and Nualsri, 2011) and how even in industrialized economies, where government transfers are generally available (Melecky and Raddatz, 2011), these transfers tend to be delivered 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 transfers but the expansion of social safety nets. Another strand of this literature has additionally documented that the effectiveness of disaster transfers, which are largely discretionary and susceptible to political influence, depends on the existence of strong democratic institutions and media coverage (e.g., Sen, 1981; Isham, Kaufmann and Pritchett, 1997; Besley and Burgess, 2002; Eisensee and Strömberg, 2007).

By relying on the institutional innovations regularly used by insurance companies to manage risk, national indexed disaster funds offer a promising alternative for governments to overcome the current limitations in the provision and delivery of disaster transfers outlined in the literature. Specifically, these innovations include ex-ante risk financial planning to guarantee the availability of transfers; rules to determine risk ownership and pay claims in a timely fashion; and use of parametric indexes to shield resources against political influence and minimize the cost of assessing losses.

Take up by governments of national indexed disaster funds remains limited. Despite ongoing policy discussions for their creation in Cape Verde, Colombia, Indonesia, Mozambique, and the Philippines, Fonden remains the only operational national indexed disaster fund in the world. Barriers to take up may include 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 estimates of the effect of a national indexed disaster fund on economic recovery. Our findings demonstrate that a pre-financed rules-based government response has the potential to accelerate economic recovery but also highlight that the benefits are not permanent. We additionally inform policy makers by deriving an implied fiscal multiplier which indicates that the economic activity generated by the program is about as large as its cost.

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 through the discretionary reconstruction efforts of local governments. 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 avoidance of poverty traps (Azariadis and Drazen, 1990; Kahn, 2005; Carter et al., 2007; Noy, 2009) or build-back-better effects (Crespo Cuaresma, Hlouskova and Obersteiner, 2008; Hallegatte and Dumas, 2009).

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

I. Disaster response in Mexico

A. *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 transfers efficiently because its financial plan guarantees the availability of funds and because its rules-based operation 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 with a budget allocation to pay for frequently occurring claims, and on risk-sharing instruments to pay for costly but less frequent claims. Specifically, Fonden budget (amounting to no less than 0.4 percent of the federal budget and $\approx$ USD $800 million) is used to pay for frequently occurring losses, for the purchase of excess loss reinsurance, and for the issuance of catastrophe bonds. This financial plan allows Fonden to draw on the payouts of reinsurance and bonds ($\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 two 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 (70 percent), hydraulic infrastructure (supply of safe water 15 percent), low-income housing (11 percent), and education (1 percent) and health (1 percent) 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 have historically made up roughly 93 percent of program expenditures (World Bank, 2012)[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 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 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 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 Federal Register (Official Journal of the Federal Government). 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

[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.

municipalities for the losses experienced.[4] This feature is important because it implies that unlike a standard index insurance contract there is no upward basis risk (experiencing no loss and still receiving an insurance payout). 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 75 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]

B. Non-Fonden disaster response

In contrast, the reconstruction process in municipalities that are ineligible for Fonden falls, by and large, on the discretionary reconstruction efforts of state and municipal governments.[6] While the lack of reporting requirements makes it difficult to provide a comprehensive assessment of these efforts we are able to document several important features. First, during our period of analysis, ineligible municipalities are unlikely to have received other federal reconstruction funds. Specifically, as shown in section IV.B, we fail to find evidence of federal transfers to local governments changing discontinuously. This finding is consistent with both the provisions of the Fiscal Coordination Law, which does not factor in disasters as a basis for adjusting federal transfers, and with the accounts of several senior federal and state officials that had direct knowledge of these efforts. Second, the interviews further revealed that the bulk of reconstruction funding, in the absence of Fonden, came from the reallocation of state and municipal expenditure budgets. Anecdotally, resources initially allocated for building and maintenance of infrastructure were those most frequently diverted for use in reconstruction. Third, also revealed by the interviews, while direct procurement is used to speed

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

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

[6]An important exception is federal non-concession roads which use earmarked ministry of communications emergency funds for reconstruction in the absence of Fonden. While is possible that privately funded rebuilding has also taken place we are unable to document any examples.

up disbursement when allowed under the Public Works and Related Services Law, a large fraction of reconstruction projects have to be executed through the lengthier public tendering process. All in all, the lack of plans to finance and mobilize resources on the part of state and municipal governments implies that the non-Fonden reconstruction process may experience delays at each stage and that it likely entails costly reallocations, such as allowing the deterioration of public infrastructure by forgoing maintenance work.

II. 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 in Mexico between 7:12 pm and 9:18 pm 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.[7] The resulting stable cloud-free night light composites measure, by and large, human-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, Storeygard and Weil, 2011, 2012), regions (e.g., Besley and Reynal-Querol, 2014; Hodler and Raschky, 2014), and cities (e.g., Storeygard, 2016).[8] 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 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 (NOAA, 2015). 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

[7]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.

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

roughly 2.5 million pixels.[9] 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.[10] Next, we aggregate to the municipal level by calculating average municipal night light intensity.[11] For our initial analysis, where we focus on the recovery process in the year following the disaster, we use the resulting municipal-month panel, obtained in the previous step, to calculate for every observation the average DN 12 months before and 12 months after. We then take the natural logarithm of the resulting averages and compute the difference between them. The key outcome variable in the paper is the log difference in average municipal night lights between 12 months before the disaster (months -12 to -1) and 12 months after (months 0 to 11). When we explore the dynamic impact of Fonden in section III.B, we will take advantage of our more granular dataset and construct, as described in that section, month-by-month log difference in night lights.

Data on municipal eligibility to Fonden was assembled by Boudreau (2015) using the archives of Mexico's Federal Register. The archives contain the universe of disaster declarations. As previously mentioned, each declaration lists all municipalities requested and the subset which is eligible for Fonden resources. In addition, the declarations provide a broad classification of the hazard that caused the request. While information on the declarations, for example, allows us to distinguish between geological and hydro-meteorological events, it does not allow for a more detailed classifications, such as distinguishing between heavy rainfall and flooding.[12]

To replicate the verification process for the heavy rainfall rule, the Mexican government granted us access to three Conagua datasets. First, data on historic rainfall at the weather-station-day level (Conagua, 2015*a*). 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 (Conagua, 2015*b*).[13] Third, the mapping between municipalities and the subset of weather stations used for Fonden verification (Conagua, 2015*c*). Using weather

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

[10]We also follow Henderson, Storeygard and Weil (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.

[11]These averages are a measure of light intensity per area and are equivalent to the measures used by Henderson, Storeygard and Weil (2012) and Hodler and Raschky (2014).

[12]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".

[13]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.

station identifiers, we merge the three datasets and calculate the normalized running variable, by subtracting the threshold from the observed rainfall.

Using day and municipal identifiers, we merge the dataset obtained previously with the declarations dataset. In the case of municipalities with multiple weather stations, or natural hazards spanning more than one day, the observation with the maximum of the running variable was chosen. We use the maximum because eligibility to Fonden is triggered when the threshold is crossed at any weather station and during any day. Next using municipality, month, and year identifiers we merge the dataset derived in the previous step with the night lights dataset.[14]

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.[15] During this period we observe 2708 municipal-year requests for Fonden funding generated by a hydro-meteorological event, of which 1923 qualified for Fonden resources.[16]

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 A7.

Table 1—Summary statistics

	Mean	Std. Dev.	Min	Max
Log difference night lights	-0.04	0.19	-1.57	1.91
Rainfall (mm)	81.64	80.40	0	391
Fonden threshold (mm)	89.53	44.10	2	237
Rainfall minus threshold (mm)	-7.89	76.23	-219	297
Above threshold=1	0.36	0.48	0	1
Fonden=1	0.71	0.45	0	1

Note: The sample is composed of municipalities that requested Fonden between 2004 and 2012. There are 2708 municipal-year observations in the sample. The log difference night lights is calculated by taking the difference in the logarithm of the average of the municipal night lights over the 12 months before and after the disaster. Above threshold is an indicator variable equal to one when the rainfall is equal or above the threshold. The Fonden variable is equal to one when the Federal Register reports that a municipality is eligible for Fonden resources.
Source: Boudreau (2015); Conagua (2015*a*,*b*,*c*); NOAA (2015)

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

[15]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.

[16]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. We also exclude 50 observations for which we are unable to calculate the outcome variable. Figure A3 in the appendix maps the municipalities that make up our sample.

Table 1 provides summary statistics for the main variables used in the paper. Our outcome variable, log difference night lights between 12 months before and after the disaster, ranges from -1.6 to 1.9 with a mean of -0.04. Observed rainfall averages 82 millimeters (mm) or approximately 3.2 inches (in), which is roughly 60 percent larger than the 50 mm heavy rainfall definition used by the United Nations World Meteorological Organization. As previously mentioned, we construct the normalized running variable by subtracting the Fonden heavy rainfall thresholds (average 89 mm $\approx$ 3.5 in) from observed rainfall. The running variable has a cut-off at zero, and its support extends from -220 to 300 mm. In the sample, roughly 71 percent of the municipalities that requested Fonden funding were eligible, but only 36 percent qualify under the heavy rainfall rule (observed rainfall in excess of the threshold). This difference occurs because municipalities can also become eligible for Fonden through supplementary hurricane and flooding criteria.

III. Results

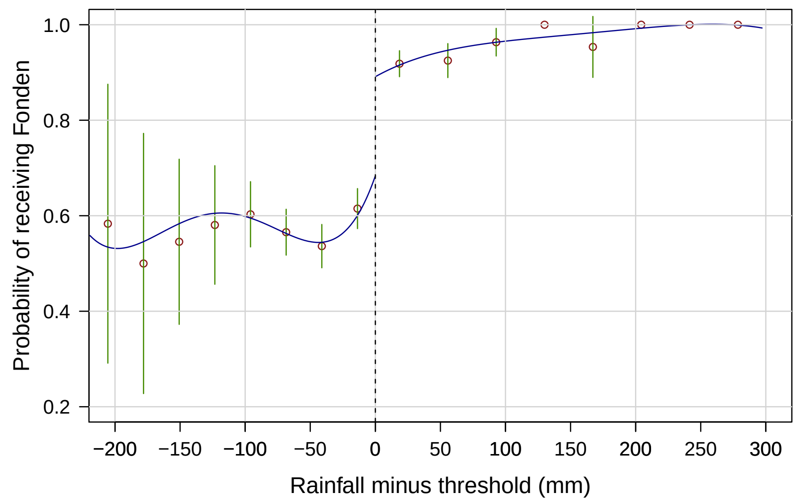
A. *The impact of Fonden on local economic activity*

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, as previously mentioned, the verification of a hydro-meteorological event can occur by meeting the heavy rainfall rule, or by meeting Fonden flooding or hurricane criteria. The validity of the method relies on the assumption that the characteristics of municipalities that could affect changes in night lights vary smoothly with the running variable (rainfall minus threshold). We provide supporting evidence for this assumption in section IV.

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. The circles represent the local mean of the outcome over disjoint bins of the running variable. The error bars are the 95 percent confidence intervals for the local means,[17] and 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 threshold level. Moving from just below to just above the threshold increases the likelihood of receiving Fonden from about 0.65 to 0.88. The figure hints at a strong first stage relationship and implies that Fonden Local Average Treatment Effect (LATE) will be roughly four times larger than that of the Intention-to-Treat (ITT) effect.

[17]Following Calonico, Cattaneo and Titiunik (2015), the number of evenly spaced bins are optimally chosen to minimize the integrated mean square error of the underlying regression function.

(a) First Stage



(b) Intention-to-Treat

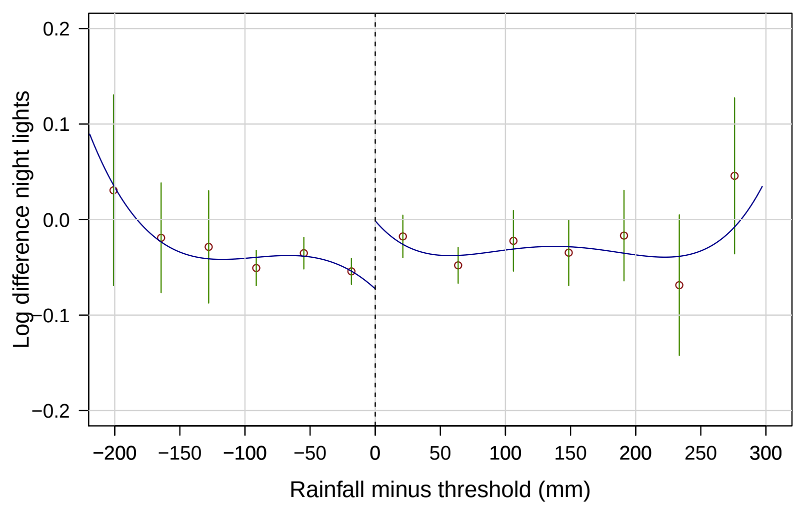


Figure 1. : First stage and Intention-to-Treat

Note: Each graph plots the outcome (probability of receiving Fonden or log difference in night lights between the 12 months before and the 12 months after a disaster) as a function of the running variable (rainfall minus threshold). In each graph, the support of the running variable has been partitioned into disjoint bins. The number of bins is selected to minimize the integrated mean square error of the underlying regression function, as described in Calonico, Cattaneo and Titiunik (2015). The circles plot the local mean of the outcome at the mid-point of each bin. The error bars are the 95% confidence intervals for the local means. The solid lines are fourth-order global polynomials fits (estimated separately on each side of the threshold). Observations to the right of the vertical dashed line are eligible for Fonden

Analogously, figure 1b plots the ITT relationship, that is, log difference night lights, between 12 months before and after the disaster as a function of the running variable. The figure shows a clear jump at the threshold. The change in night lights in municipalities eligible for Fonden under the heavy rainfall rule (immediately to the right of the cutoff), is roughly 0.06 log points (6 percent) 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 threshold.[18]

Next, we use local polynomial methods to estimate the first stage, the ITT, and the LATE. The specific estimating equations are as follows:

$$F_{mt} = \alpha_0 + \alpha_1 ABOVE_{mt} + g(R_{mt}) + v_{mt}, \tag{1}$$

$$Y_{mt} = \beta_0 + \beta_1 ABOVE_{mt} + g(R_{mt}) + \varepsilon_{mt}, \tag{2}$$

where F_{mt} is a binary variable that takes the value of one when a municipality is eligible for Fonden. The variable Y_{mt} represents our measure of the change in local economic activity (log difference night lights) for municipality m affected by a hydro-meteorological event in year t. The variable $g(R_{mt})$ captures the relationship between the outcome and the running variable R_{mt}. The variable ABOVE is an indicator variable for observed rainfall exceeding the heavy rainfall threshold. Finally, ε_{mt} and v_{mt} are error terms. The parameters of interest are the first stage estimate $\hat{\alpha_1}$ in equation 1, the ITT estimate $\hat{\beta_1}$ in equation 2, and the ratio τ_{FRD}=$\hat{\beta_1}/\hat{\alpha_1}$ which can be interpreted as the LATE under some additional assumptions.[19]

To derive point estimates, robust p-values, and confidence intervals for these parameters, we use non-parametric local polynomial methods as described in Calonico et al. (2019). These estimators require a choice of bandwidth selection

[18]While our bin-width choice is entirely data-driven, figures A4a to A4d halve and double the number of bins in order to illustrate that our results are not sensitive to this choice.

[19]As shown by Hahn, Todd and Van der Klaauw (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 III.D and for local smoothness in section IV.A.

algorithm, kernel, and local polynomial order. In the paper, we use primarily two bandwidth selection algorithms. The first, h_{MSE} minimizes the asymptotic mean squared error and is optimal for point estimation. The second, h_{CER} minimizes the asymptotic coverage error rate and is optimal for inference of confidence intervals (Calonico et al., 2019). Our choice of kernel is triangular because as discussed in Cattaneo, Titiunik and Vazquez-Bare (2017), it provides the optimal weights for the h_{MSE}. Our choice of local polynomial is linear and quadratic as recommended by Gelman and Imbens (2019).[20] In all cases, the bandwidth selection algorithm, and the inference of standard errors and confidence intervals have been adjusted for clustering at the municipal level.

Table 2—Impact of Fonden on night lights

	(1)	(2)
Panel A. *First Stage* (α_1)	0.227	0.230
p-value	< 0.001	< 0.001
CI 95 percent	[0.12,0.28]	[0.13,0.31]
Panel B. *Intention-to-Treat* (β_1)	0.059	0.072
p-value	0.010	0.006
CI 95 percent	[0.02,0.12]	[0.02,0.13]
Panel C. *LATE* (τ_{FRD})	0.260	0.313
p-value	0.009	0.011
CI 95 percent	[0.08,0.56]	[0.08,0.61]
Bandwidth (mm)	57.9	40.0
Obs (left|right)	1038|525	741|410

Note: Panel A presents estimates of equation 1, where the dependent variable is eligibility for Fonden resources. Panel B presents estimates of equation 2, where the dependent variable is the log difference in night lights between the 12 months before and after a disaster. Panel C reports the LATE estimate of eligibility for Fonden resources on night lights computed as the ratio of the ITT estimate to the first stage coefficient. Estimates in panel A and B are derived using a triangular kernel and local linear polynomial. The bandwidth selection algorithm used in column 1 is optimal for point estimation; the selection algorithm in column 2 is optimal for inference of confidence intervals. The p-values and 95 percent confidence intervals reported are constructed using robust bias correction and clustering at the municipal level.

Table 2 presents the results from estimating equations 1 and 2 using the h_{MSE} bandwidth (column 1) and the h_{CER} bandwidth (column 2). The first stage estimates in panel A, columns 1 and 2, reveal that being above the threshold increases the probability of receiving Fonden by roughly 23 percentage points relative to the municipalities below the threshold. 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 above the threshold are

[20]In section IV we further show that our results are robust to these choices.

roughly 0.06 to 0.07 log point (6-7 percent) higher than in municipalities below the threshold. Among complier municipalities at the cut-off, our preferred point estimate of Fonden LATE, in panel C column 1, indicates that the program led to a 0.26 log point (29 percent) increase in change in night lights. In all cases, the estimated coefficients are statistically different from zero at the five percent level, and our preferred 95 percent confidence interval, in panel C column 2, is in the 0.08 to 0.61 log point range. Overall, these results provide robust evidence of the capability of Fonden to lessen the decline in economic activity created by extreme weather in the 12 months following the event.

B. The dynamic impact of Fonden

To study the dynamic impact of Fonden, we estimate the impact of the program month-by-month for up to two years after a disaster. Specifically, the outcome variable is the log difference in night lights between the average 12 months before the disaster (same baseline as in section III.A, months -12 to -1) and each month in the post-disaster period, 0,1, etc., up to month 23.

Figures 2a to 2d report the ITT effect of Fonden by plotting the log difference in night lights, at four post-disaster periods, as a function of the running variable. To illustrate key points in the post-disaster dynamics, we have selected two months after (just before fund disbursement), four months after (impact of Fonden first observed), and 12, and 18 months after the disaster. Figure 2a shows that at two months after the disaster, while funds and reconstruction efforts are still being set up, there is no difference between those municipalities just above and below the threshold. At this point, all municipalities face a reduction in night lights of roughly 0.04 log points. At four months after, figure 2b, we observe a jump at the threshold. This jump is still clearly observed at 12 months after, figure 2c. During this period of Fonden-led recovery, 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. By 18 months, figure 2d, municipalities to the left of the threshold have caught up with municipalities to the right of the threshold. Visually, the global polynomials suggest that there are no differences in night lights between municipalities on either side of the threshold.

(a) 2 months after (just before fund disbursement)

(b) 4 months after (first observed Fonden impact)

(c) 12 months after

(d) 18 months after

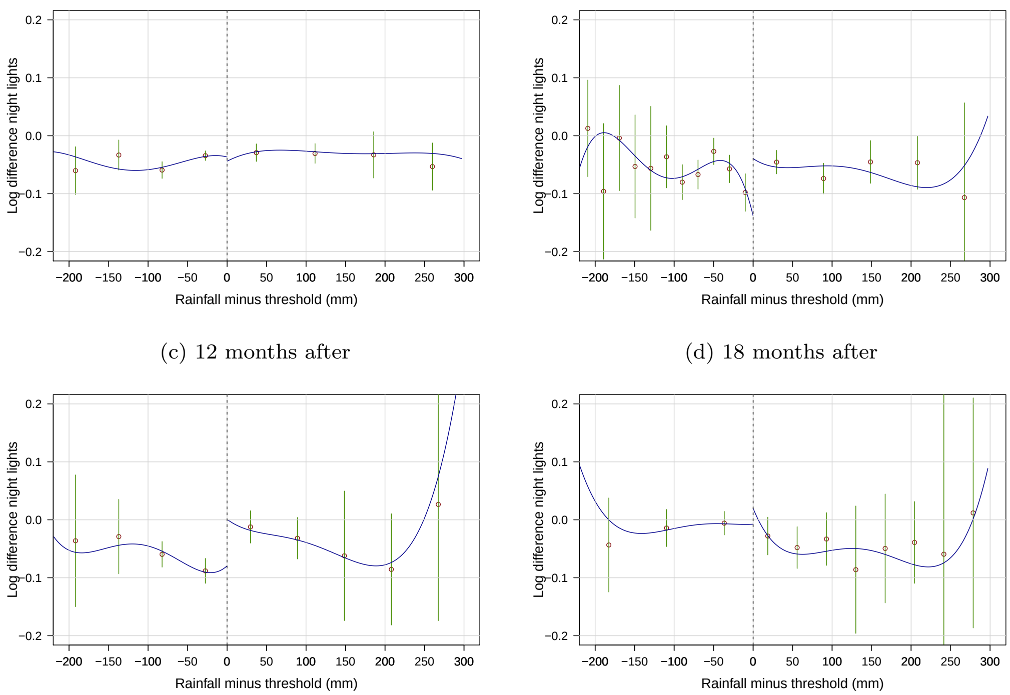


Figure 2. : Dynamics: Intention-to-Treat in various post-disaster months.

Note: The figures plot the log difference in night lights, at four post-disaster periods, as a function of the running variable (rainfall minus threshold). The outcomes are constructed by taking the log difference in night lights between 12 months before the disaster (same baseline as in figure 1b, months -12 to -1), and in months 2, 4, 12, and 18 after the disaster. In each graph, the support of the running variable has been partitioned into disjoint bins. The number of bins is selected to minimize the integrated mean square error of the underlying regression function, as described in Calonico, Cattaneo and Titiunik (2015). The circles plot the local mean of the outcome at the mid-point of each bin. The error bars are the 95% confidence intervals for the local means. The solid lines are fourth-order global polynomials fits (estimated separately on each side of the threshold). Observations to the right of the vertical dashed line are eligible for Fonden under the heavy rainfall criteria.

Next, to provide a more detailed account of the month-by-month impact of Fonden, we report estimates of Fonden LATE for each of the 24 post-disaster months in Figure 3.[21] Consistent with graphical evidence of the ITT, the LATE figure shows that the impact of Fonden can be broadly characterized in three phases. In the very short run, between zero and three months, while Fonden prepares for reconstruction, we fail to find evidence of the program affecting the change in night lights. In the second phase, between months four and 15, we find that Fonden led to a considerable and sustained increase in the change in night lights. In the third phase, between 16 and 23 months, municipalities ineligible to Fonden catch up and, with the exception of months 16 and 21, we can no longer detect at conventional levels a statistically significant impact of Fonden on night lights.

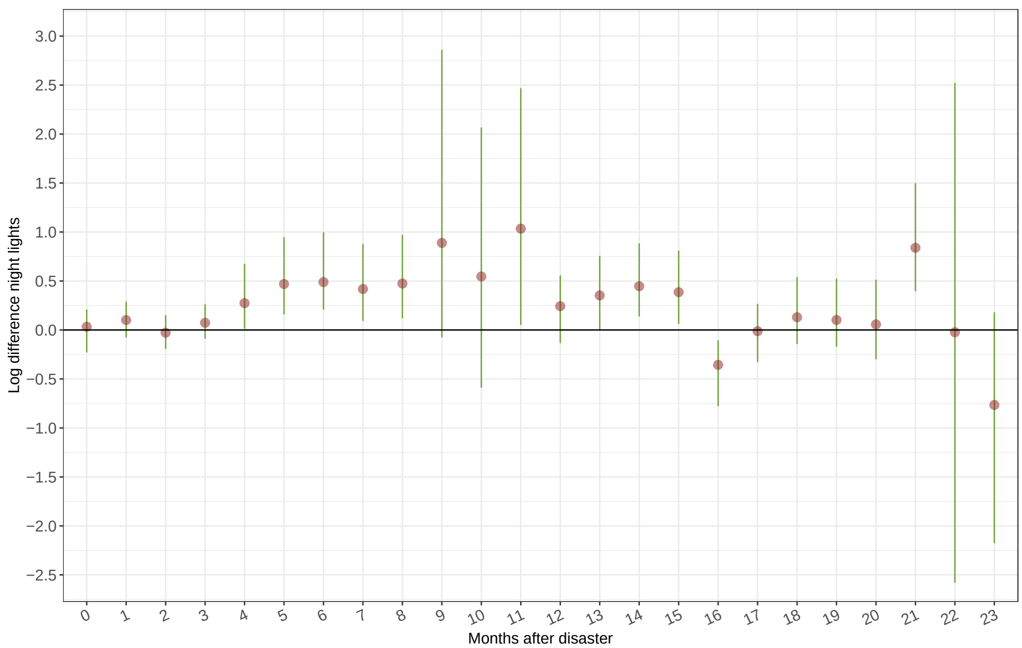


Figure 3. : Month by month impact of Fonden after a disaster

Note: This figure plots coefficients and robust 95% confidence intervals of Fonden LATE. The 24 outcome variables are the log difference in night lights between the 12 months before a disaster (same baseline as in figure 1b, months -12 to -1) and each month in the two years after a disaster. Each plotted coefficient is estimated independently using a triangular kernel, a local linear polynomial, and the average h_{MSE} bandwidth.

The increased variability observed in some months is the result of a reduction

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

in the number of observations. This reduction occurs because night light data is missing for some summer months, in some years.[22] This implies, that the bulk of the events in our sample, which occur during the rainy season in Mexico (May to November), may have one to three months of missing night light data in the summer after the disaster (affecting months 8 to 16 after disaster), and in the following summer (affecting months 20 to 23 after disaster).

To verify that this problem in data collection has no bearing on our results we conduct two robustness exercises. In the first exercise, we construct a balanced night light pixel-month panel by linearly interpolating missing values and we use this dataset to replicate the analysis presented in figure 3. In the second exercise, we use the original night light dataset, but construct the outcome variables using a three month moving average for the post-disaster period. Specifically, we calculate 22 outcome variables where the log difference in night lights is calculated using the difference between the average 12 months before the disaster and each of the post-disaster periods running from months 0 to 2, then months 1 to 3, etc., until months 21 to 23.

Figures A5 and A6 present the results from these two exercises. The figures reveal that, consistent with previous results, the impact of Fonden is first observed at four months, and that this effect, usually of a magnitude of 0.5 log points for compliers at the cut-off, is sustained until month 15. Importantly, the figures also highlight that once ineligible municipalities have caught up by month 17, the estimates of Fonden LATE are small and statistically indistinguishable from zero.

As illustrated in figure A2 in the appendix, the dynamic described in this section 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 to four months of the disaster and fade out by 14 months when the bulk of reconstruction work is expected to be completed.

In conclusion, the findings of this section robustly 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 builds up and is sustained for roughly 12 months in the post-disaster period (months 4 to 15) before declining.

C. 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

[22]NOAA flags the DN recorded in pixels where solar elevation is greater than 14 degrees as contaminated by sunlight. In our sample, missing observations occur primarily in June and July during the last years of operation of each satellite. This pattern is the result of earth northern pole achieving its maximum tilt toward the Sun around June 21, and of satellite orbit degradation leading to earlier observation times (the earliest equatorial crossing in our sample is 7:12 pm local time).

spillover effects, we calculate for each municipality the log difference night lights between the average 12 months before and after a disaster using only information on 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—Spillover effects

		Spillover Effects	
	Baseline (1)	0 to 20 km (2)	20 to 40 km (3)
LATE (τ_{FRD})	0.260	0.234	0.064
p-value	0.009	0.009	0.694
CI 95 percent	[0.08,0.56]	[0.05,0.38]	[-0.09,0.13]
Bandwidth (mm)	57.9	57.9	57.9
Obs (left|right)	1038|525	1038|525	1038|525

Note: The dependent variable is the log difference in night lights between the 12 months before and after a disaster. Column 1 presents estimates of Fonden's LATE from our baseline specification (table 2 column 1, panel C). In columns 2 and 3, the outcome is calculated using only information on pixels that are within the distance to the municipal boundary indicated in the column title. All estimates are derived using a triangular kernel, a local linear polynomial, and a h_{MSE} optimal bandwidth. The p-values and 95 percent confidence intervals reported are constructed using robust bias correction and clustering at the municipal level.

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 baseline specification (table 2 column 1). In column 2, we estimate Fonden LATE among pixels that are within 0 to 20 km of the municipal boundary. We find a statistically significant Fonden LATE that is slightly smaller than our baseline estimate. Next, in column 3, we estimate Fonden LATE among pixels that are within 20 to 40 km of the municipal boundary. In this case, the estimate of Fonden impact is statistically indistinguishable from zero and roughly one fourth the magnitude of our baseline estimate.[23]

On the whole, we find evidence of spillover effects that go in the same direction as our estimates of the impact of Fonden but quickly decay with distance. Thus, to the extent that these limited spillover effects matter, their key implication is that our baseline estimate of Fonden LATE provides a lower bound of the impact of Fonden.[24]

[23] 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 nonoptimal bandwidth, using the optimal h_{MSE} for each estimation.

[24] Another type of spillover effect is that by financing reconstruction efforts among eligible municipalities, Fonden frees up state-level resources that may be used to fund reconstruction among ineligible

D. External validity

As previously discussed, the strong internal validity of Fonden 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 further away from the threshold that qualify for Fonden.

To explore the external validity of ITT estimates, Dong and Lewbel (2015) proposed a methodology to estimate, under weak conditions,[25] 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. More recently, Cerulli et al. (2017) has extended this framework to test the stability of the LATE, 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. (2017)'s algorithm and follow the author's guidance in choosing a local quadratic polynomial and a triangular kernel. We compute TED and CPD using both the h_{MSE} and h_{CER} bandwidth selection algorithms. Table A2 in the appendix, presents estimates of Fonden TED and CPD. The result of the table indicates that in all cases, our estimates of CPD and TED are small and statistically indistinguishable from zero. These findings highlight the stability of the first stage and the ITT, and therefore of the LATE. 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.

Another important implication of estimating a TED close to zero is that, as shown by Dong (2018), it provides supporting evidence in favor of the local independence assumption that underpins our interpretation of τ_{FRD} as Fonden LATE.

E. Fonden implied fiscal multiplier

In this section, we compare the value of the economic activity generated by Fonden in the year after the disaster to the cost of funds disbursed (including administrative and reconstruction costs). This exercise is useful because it allows us to present our baseline result in a monetary metric and because it provides an implied fiscal multiplier of disaster expenditures.[26]

municipalities. As in the previous case, the key implication is that we estimate a lower bound of the impact of Fonden.

[25] They assume continuous differentiability of conditional means.

[26] The benefits of Fonden also include the provision of insurance for public infrastructure and low-income housing, which, even in the absence of a disaster, can alter the risk-management behavior of households, firms, and local governments, potentially allowing them to allocate more resources to more productive (riskier) investments. A comprehensive cost-benefit analysis would encompass this effect too.

Table 4—Implied fiscal multiplier

(1)	Events	1383	-	-
(2)	Effect of Fonden on night lights	0.260	(0.105)	-
(3)	Inverse elasticity of lights with respect to GDP	0.095	(0.038)	-
(4)	Implied effect on GDP growth	0.025	(0.015)	-
(5)	Mean municipal GDP in 2003 (millions \$)	180.160	(7.480)	-
(6)	Gain per municipality (millions \$)	4.430	(2.650)	-
(7)	Total gain (millions)	6127.290	(3660.710)	-
(8)	Gain cost ratio	0.959	(0.573)	[0.017,1.901]

Note: Row 2 reports estimates from table 2 column 1, panel C. Row 3 reports estimates from table A1 column 2. Row 4 is calculated as $(\delta_2 \times \delta_3)$, where δ_j represents the parameter reported in row j of column 1. Because municipal GDP has a heavy-tailed distribution, in row 5, we report the geometric mean. All monetary values are in millions of constant 2010 international dollars. Fonden expenditures in these events totaled \$6391.69. The point estimate in row 8 is calculated as: $\delta_1(\delta_2 \times \delta_3 \times \delta_5)/Cost$. Assuming that covariance and co-skewness are equal to zero its standard error is given by: $\delta_1\sqrt{(\delta_2^2 + se_2^2) \times (\delta_3^2 + se_3^2) \times (\delta_5^2 + se_5^2) - \delta_2^2 \times \delta_3^2 \times \delta_5^2})/Cost$. Standard errors are in parentheses, 90 percent confidence intervals are in brackets.

Table 4 reports the results from this exercise. There are 1383 municipal-year events that received Fonden, and for whom we have complete municipal-level expenditure data.[27] To convert Fonden LATE (measured in night lights growth) to GDP growth, we multiply our baseline estimate of Fonden LATE with the inverse of the elasticity of night lights with respect to state GDP (row 2 × row 3). The implicit assumption we make is that the calculated state-level elasticity is also informative of the unobserved municipal-level elasticity.[28] The resulting estimate, reported in row 4, implies that, in the year following the disaster, GDP grew 2.5 percent 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.[29] All monetary values are in constant 2010 international dollars. As reported in rows 5 and 6, we find that mean 2003 municipal GDP has a value of roughly \$180 million,[30] and that the average gain per municipality (row 4 × row 5) is \$4.4 million. Accordingly, the total gain, reported in row 7, for the 1383 events analyzed here is \$6.1 billion (row 1 × row 6). Last, we derive the implied fiscal multiplier by dividing the total gain by the Fonden expenditures in these municipalities, which totaled \$6.4 billion (Fonden, 2015). As reported in row 8, we find an implied multiplier of 0.96 and are unable to reject the null hypothesis that the

[27] In this exercise, we use all observations, with expenditure information, 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 multipliers and are available upon request.

[28] The inverse elasticity is reported in table A1 column 2. It is calculated at the state level by regressing log GDP on log night lights, state fixed effects, year fixed effects, and state trends. Further details on this calculation can be found in Appendix A.

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

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

ratio is equal to one. This multiplier is, however, conservative both because of the existence of spillover effects, and because the economic recovery generated by Fonden extended for up to 15 months after a disaster.

While our back-of-the-envelope Fonden implied fiscal multiplier has a wide confidence interval (90 percent confidence interval is 0.02 to 1.90), it falls, by and large, within the range of other empirical estimates of returns to infrastructure spending. For example, Gonzalez-Navarro and Quintana-Domeque (2016) randomize the paving of local roads in Mexico and find a cost-benefit ratio in the 0.66 to 1.51 range. More broadly, reviews of recent empirical literature suggest that public spending multipliers are in the 0.5 to 2 range (see Ramey, 2011; Chodorow-Reich, 2019, and references therein).

F. *Heterogeneous effects of Fonden*

To further understand the economic relevance of Fonden, we investigate in table 5 whether the impact of Fonden on economic activity varies with the type of asset that Fonden reconstructs. We also test whether municipalities that may be initially less resilient benefit disproportionately more from the program.

Table 5—Heterogeneous effects of Fonden

Sample split:	Baseline	Primary Fonden expenditure		Road intersection density		Storm drain coverage	
		Roads	Non-roads	Below Median	Above Median	Below Median	Above Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LATE (τ_{FRD})	0.260	0.479	0.173	0.366	0.179	0.553	0.041
p-value	0.009	0.016	0.250	0.053	0.064	0.042	0.622
CI 95 percent	[0.08,0.56]	[0.11,1.10]	[-0.12,0.48]	[-0.01,0.97]	[-0.01,0.46]	[0.02,1.11]	[-0.19,0.31]
Bandwidth (mm)	57.9	46.8	45.2	61.3	70.4	40.7	48.2
Obs (left|right)	1038|525	569|217	425|131	548|289	623|293	381|193	430|242

Note: The dependent variable is the log difference night lights between the 12 months before and the 12 months after a disaster. Column 1 presents estimates of Fonden's LATE from our baseline specification (table 2 column 1). Road intersection density is defined as the number of road intersections per 100 square km in 2003; its median value is 6.34. To proxy storm drain coverage, we use the percentage of dwellings connected to sewage, as measured in the most recent census that predates the natural disaster; its median value is 0.71. Only the estimates for the subsample above and below median storm drain coverage are statistically different from each other (p-value 0.1). All estimates are derived using a triangular kernel, a local linear polynomial, and a h_{MSE} optimal bandwidth. The p-values and 95 percent confidence intervals reported are constructed using robust bias correction and clustering at the municipal level.

Given that prolonged disruptions to the road network may be damaging to all sectors of the economy, we conjecture that Fonden 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 perform a descriptive exercise in which we compare the estimated impact of Fonden using observations where the primary type of municipal expenditure is either roads (68 percent of the sample) or non-roads (hydraulic, education, health, and housing). To facilitate comparisons, column 1 reports the results from our baseline specification (table 2 column 1), and columns 2 and 3 present the results from splitting the sample. While these estimates cannot be given a causal interpretation, given the endogenous sample split, they are consistent with the idea that road reconstruction is a key component of the Fonden led recovery. Specifically, the impact of Fonden estimated in the sub-sample where roads are the primary type of expenditure, in column 2, is statistically significant at the five percent level and more than two and half times as large as that for non-road expenditures, in column 3. Nonetheless, given the wide confidence intervals, we cannot establish that the effect of Fonden by type of reconstructed asset is differential.

Next we investigate whether Fonden is more effective, among municipalities that initially lack infrastructure that can help limit the damages generated by hydro-meteorological events. Specifically, we look at the redundancy of the road network, and the presence of storm drains that can carry rainwater runoff away from streets. To measure initial road redundancy we use the USGS (2003) map of Mexico's roads (which includes paved, gravel, and dirt roads) and calculate for each municipality the density of intersections, that is, the number of road intersections per 100 square km. To measure the storm drains coverage, we use census data on the percentage of dwellings connected to sewage. This measure is a good proxy because storm drains are usually constructed contemporaneously with sewage drains and because in the case of combined sewage, they serve both purposes.

To test whether Fonden has a differential impact, we split the sample at the median of each of our measures (6.34 for intersection density and 71.74 for percentage of dwellings connected to sewage) and estimate the impact of Fonden in each sub-sample. Importantly for the causal interpretation of the results, the measurement of the variables used to split the sample predates the natural disaster, and as shown in table 5 they do not change discontinuously at the threshold. Columns 4 and 5, present results for road intersection density. Columns 6 and 7, report results for our proxy of storm drain coverage. While the coefficients are noisily estimated, taking the point estimates at face value, we find that Fonden benefits disproportionately more municipalities with below median measures of infrastructure that helps mitigate damage. The difference in the impact of Fonden is particularly apparent in the case of our proxy for storm drain coverage where the estimate of the impact of Fonden for the below median sample is an order of magnitude larger than that for the above median sample. Despite the wide confidence intervals, in the case of storm drain coverage, we can reject the null hypothesis of no differential Fonden effects (p-value 0.1). We are, however, in the case of road intersection density unable to reject the null at conventional levels.[31]

IV. 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.

A. 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.

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 4a plots the histogram of the running variable in the range of the h_{mse} estimation bandwidth, 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.[32]

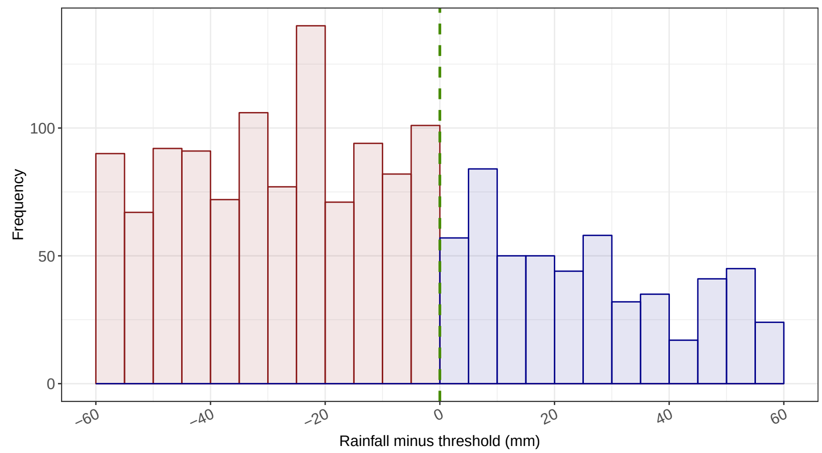
To formally test whether the density of the running variable is continuous at the threshold, we use the local polynomial density estimator and test statistic as described in Cattaneo, Jansson and Ma (2018). Figure 4b plots the estimated empirical density. This graphical representation of the test clearly shows that the running variable is continuous at the threshold.[33] The test statistic can be derived in two ways. In unrestricted testing, the estimates of the empirical density are separately obtained on each side of the threshold. In restricted testing, the statistical power of the test is increased by additionally assuming that the cumulative density function and higher-order derivatives are the same for both groups around the threshold. The null hypothesis of the test is that the density

[31] We also tested splitting the sample at the median of four other variables that broadly capture the economic characteristics of municipalities (road density, percentage of dwellings with piped water, initial log night lights, and infant mortality). We find no differential Fonden effect in any of those cases.

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

[33] Figures A7a and A7b provide analogous graphs using the entire support of the running variable.

(a) Histogram



(b) Estimated Density

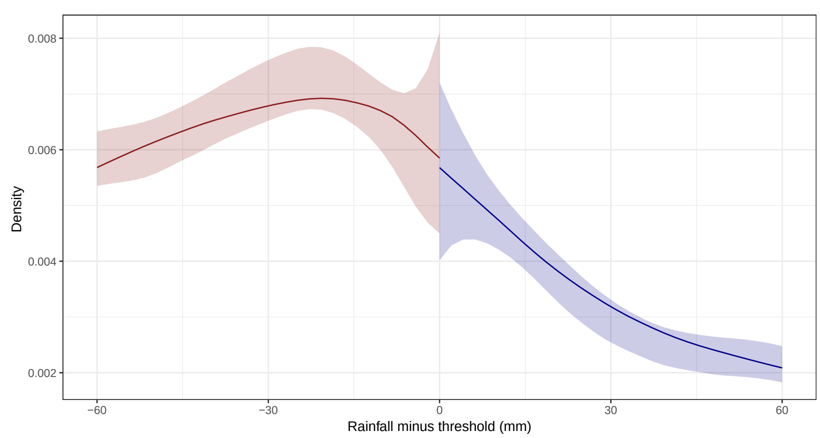


Figure 4. : Histogram and estimated density of rainfall minus threshold

Note: Panels A and B plot the histogram and empirical density of the running variable (rainfall minus threshold) within the bandwidth used for estimation. Analogous graphs for the entire support of the running variable can be found in figures A7a and A7b in the appendix. The p-value for the null hypothesis that the density of the running variable is continuous at the threshold is 0.594 under unrestricted testing and 0.529 under restricted testing. See section IV and Cattaneo, Jansson and Ma (2018) for further details on these tests.

of the running variable is continuous at the threshold. For both restricted (p-value 0.594) and unrestricted (p-value 0.529) testing, we fail to reject the null hypothesis at conventional levels.

To further test whether manipulation could have taken place, we perform in table A3 in the appendix 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 more likely to have experienced manipulation. The test, therefore, consists in checking the sensitivity of our baseline specification (table 2 column 1) when we progressively exclude observations that are within 0.5 mm, 1 mm, etc., up to 2.5 mm on either side 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 (0.26 log points).

Another test for manipulation is whether the predetermined characteristics of municipalities change discontinuously at the threshold. This test follows from the idea that if municipalities cannot precisely manipulate the running variable, there should be no systematic differences between municipalities with similar values 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 a natural disaster used to request Fonden verification. The selected variables can be categorized into three groups. The first group aims at capturing basic features of state capacity, in particular, those related to the provision of public 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 of section III.A, figures A8 to A11 in the appendix plot each of the covariates as a function of the running variable. This graphical analysis does not reveal any clear discontinuities at the cut-off. To formally test whether the predetermined covariates are continuous at the threshold, we estimate equation 2 using as outcome each of the predetermined covariates. Figure 5 plots the resulting point estimates and 95 percent confidence intervals for all variables. To facilitate comparison across variables, we standardize the variables and report 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 who are illiterate, is significant at the 10 percent level before correcting for multiple inference.[34] 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

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

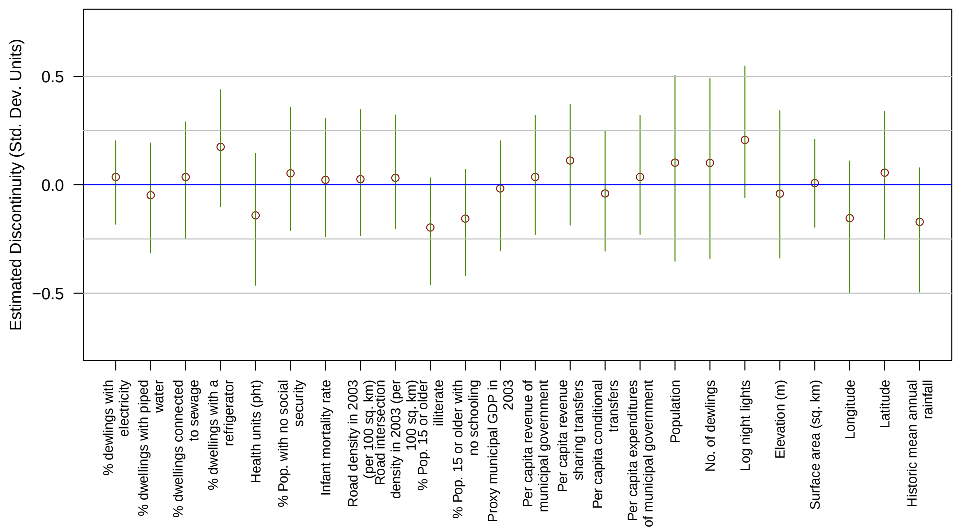


Figure 5. : Balance of municipal characteristics before a hydro-meteorological event

Note: This figure plots estimates of equation 2 using as outcome each of the variables listed. Unless otherwise stated in the label, all variables are measured in the most recent year available that predates a natural disaster used to request Fonden verification. Variables are standardized to facilitate comparison. The circles represent point estimates constructed using a triangular kernel, a local linear polynomial, and a h_{MSE} optimal bandwidth. The error bars represent robust 95% confidence intervals.
Sources: INEGI (2000, 2005, 2010, 2013*a*,*b*, 2014); DGIS (2001); USGS (2003); Conapo (2005); Conagua (2015*a*); NOAA (2015)

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 LATE. Moreover, it suggests that Fonden rules based on indexation have been likely successful at protecting reconstruction resources from political abuse.

B. *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, it is also unlikely that the running variable was used informally by other government agencies for the allocation of resources.

Table 6—Other resource allocation

Dep. Variable:	Total transfers (1)	Revenue sharing (2)	Conditional (3)
Intention to Treat (β_1)	0.011	-0.023	0.008
Robust p-value	0.980	0.448	0.888
Robust 95 percent CI	[-0.08,0.08]	[-0.12,0.05]	[-0.17,0.14]
Bandwidth (mm)	43.5	46.6	45.0
Obs (left|right)	590|320	636|337	604|326
Mean dep. variable	0.125	0.110	0.141

Note: The table presents estimates of equation 2. The dependent variable is the growth in per-capita transfers between the calendar years before and after a disaster. The type of transfer is listed in the column title. Revenue sharing transfers (primarily branch 28 of the federal budget) are awarded using a rule and can be used for any purpose. Conditional transfers (primarily branch 33 of the federal budget) are awarded using both rules and discretion and can only be used for their earmarked purpose. Estimates are derived using a triangular kernel, local linear polynomial, and a h_{MSE} optimal bandwidth. The p-values and 95 percent confidence intervals reported are constructed using robust bias correction and clustering at the municipal level.

Nonetheless, in table 6, we investigate whether government transfers to local governments from the federal government changed discontinuously at the heavy rainfall threshold. Specifically, we estimate equation 2 using as dependent variable the growth in per-capita transfers between the calendar years before and after a disaster for three types of transfers. Column 1 documents that there is no discontinuity for total transfers. In columns 2 and 3, we break up overall transfers into revenue sharing transfers (these funds, primarily branch 28 of the federal budget, are awarded using a rule and can be used for any purpose) and conditional transfers (these funds, primarily branch 33 of the federal budget, are awarded using both rules and discretion and can be used only for their earmarked purpose). The estimated coefficients in column 2 and 3 are small and statistically indistinguishable from zero. The result in column 3 is particularly 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 resource assignment.

C. *Falsification exercises*

We validate the FRD design by observing in the period before a hydro-meteorological event takes place whether the change in night lights is continuous around the threshold. Specifically, figure A12 in the appendix plots the log difference in night lights between two years before an event (months -24 to -13) and the year before (months -12 to -1) 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 2 using the placebo log difference night lights we find a small coefficient (0.007) that is statistically indistinguishable from zero (p-value=0.642).

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 restriction is placed 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 A4 in the appendix presents estimates from these two sets of placebo thresholds along with the 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.

D. Robustness Checks

In table A5 in the appendix, we show that our results are not sensitive to our choice of local polynomial degree, kernel, or bandwidth. In columns 1 and 2, we reproduce the results of table 2 but use a quadratic instead of a local linear polynomial. In both the case of the h_{MSE} bandwidth (column 1) and the h_{CER} bandwidth (column 2) we find point estimates of Fonden LATE that are larger than those estimated with the linear specification. Importantly, all estimated coefficients remain statistically significant at conventional levels. Next, in columns 3 and 4, we use a uniform and an epanechnikov kernel. These kernels are not optimal for the selection of the h_{MSE} bandwidth, but they are commonly used. In column 5, 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. Last, in columns 6 and 7, we recalculate h_{MSE} and h_{CER} allowing for different bandwidths to be chosen on each side of the threshold. As reported in the table, the resulting estimates of Fonden LATE are very similar, and in all cases, they remain statistically significant at the five-percent level.

To further show that the choice of bandwidth has no bearing on our results, figure A13 in the appendix plots estimates of Fonden's LATE and robust 95 percent 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 the five percent level.

In table A6 in the appendix, 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 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 Bluhm and Krause (2018) 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 affected 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, Storeygard and Weil (2012) an address comparability by including year fixed effects to our specification. In all cases, the estimated Fonden LATE are of similar magnitudes and remain statistically significant at conventional levels.

In columns 4 to 5, we investigate whether our results are affected by 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 distribution of the thresholds. Despite the smaller sample size leading to slightly wider confidence intervals in some estimates, we estimate LATE of a very similar magnitude. Moreover, these estimates remain statistically significant at the five percent 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.[35] The top part of figure A14 in the appendix plots the histogram of Fonden heavy rainfall thresholds. We will focus on the 30 to 130 (mm) threshold range, which makes up roughly 80 percent of the density. To explore heterogeneity, we choose within this range six values that are within 20 mm of each other, that is, 30, 50, 80, 90, 110, and 130. We then identify the sub-sample of the 400 treatment and control observations that are closest to each of the six values and estimate LATE for each sub-sample.

The bottom panel of figure A14 plots point estimates and robust 95 percent confidence intervals for Fonden 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 LATE are homogeneous with

[35]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.

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.

V. Conclusion

The primary response of governments to extreme weather events is the provision of disaster transfers. 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 these transfers. In this paper, we showed that, by alleviating these constraints, a national indexed disaster fund can considerably accelerate economic recovery relative to the discretionary reconstruction efforts of local governments. 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 before ineligible municipalities finally catch up. Building on these findings, we derive Fonden's implied fiscal multiplier and conclude that while short-lived the value of the economic activity generated by the program is as large as its cost.

Our results provide some of the first evidence on how rules-based recovery efforts can improve the shock-coping capability of national governments. Our estimates likely underestimate the full value of disaster funds not only because of the existence of spillover effects but also because Fonden may entail additional direct benefits not captured by night lights - such as effects on health and human capital accumulation. Moreover, Fonden may also yield indirect benefits such as reducing fiscal pressure on local governments. Understanding this reduction is important because while we find that municipalities ineligible to Fonden catch up in economic activity through reconstruction efforts of their own, it presumably comes at the expense of current and future infrastructure.

Additional results on the heterogeneous impact of Fonden provide suggestive evidence indicating that reconstruction of lifeline transportation infrastructure such as roads is particularly important and that disadvantaged municipalities that lack public goods to limit damage, such as storm drains, benefit disproportionately more from Fonden.

We also show that an index-based resource transfer program can be resilient to political abuse, a major concern in post-disaster recovery efforts.

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 pre-financed and rules-based Fonden initiative can be a useful role model that can be further refined. In particular, while conditioning payouts to both the triggering of an index and verification and quantification of losses serve to eliminate upside basis risk (experiencing no loss and receiving a payout), downside basis risk remains a concern (experiencing a loss and receiving no payout). Institutional improvements to reduce downside basis risk could include improving the correlation of the index to observed losses or introducing a system for recourse that is resilient to political abuse. Notwithstanding the need for these further improvements, we have shown that a national indexed disaster fund along with tight and enforceable implementation rules can provide an effective option for countries to cope with what can otherwise be dramatic national experiences.

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