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Insuring Growth

The Impact of Disaster Funds on Economic Reconstruction in Mexico

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Abstract

Climate change has considerably increased the likelihood of experiencing extreme weather events. Governments in developing countries have a limited capacity to smooth the losses created by extreme weather, and could potentially benefit from the introduction of disaster funds, that is, ex-ante budgeting allocations for post-disaster reconstruction. So far the implementation of disaster funds has been limited, in part because it is still unclear whether disaster funds provide a cost-effective way of coping with these losses. By taking advantage of the sharp rules that govern the municipal-level eligibility for reconstruction funds in Mexico, this paper provides some of the first estimates of the impact of disaster funds on local economic activity. The main finding is that access to disaster funding boosts local economic activity between 2 and 4 percent in the year following the disaster. Another finding is that the positive impact of disaster funds on local economic recovery can persist for as long as a year and a half after the disaster. Consistent with these findings, we additionally show that access to disaster funding leads to a large and sustained 76 percent increase in the growth of local construction employment. This labor market impact slightly precedes the overall increase in local economic activity.

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Insuring Growth: The Impact of Disaster Funds on Economic Reconstruction in Mexico

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1 Introduction

With continuing greenhouse gas emissions in excess of the absorptive capacity of land and oceans, inexorably contributing to climate change, damages from extreme weather events are likely to increase in the coming decades (Emanuel, 2013; Mendelsohn et al., 2012). Governments in developing countries have a limited ability to smooth the shocks created by extreme weather events. In particular, budget reallocations following a disaster tend to be inefficient, and often result in costly liquidity crunches (Mahul, 2011). For these reasons, ex-ante risk financing instruments like national disaster funds are a primary focus of Sovereign Disaster Risk Financing efforts. Given the large resources required to set up these funds, a key question is whether disaster funds provide a cost effective tool to cope with the losses created by natural disasters. Taking advantage of a unique natural experiment and dataset, this paper provides some of the first evidence on the causal impact of disaster funds on economic recovery.

We circumvent endogeneity in the provision of rapid reconstruction funds by using a fuzzy regression discontinuity design that exploits the rules that govern municipal level eligibility to reconstruction funds from the Mexican disaster fund Fonden.[1] Since only municipalities that have officially experienced a disaster, as determined by event thresholds, are eligible for disaster funds, we recover causal estimates of the impact of disaster funds on local economic activity in three steps. In the first step, we compare the post disaster economic outcomes of municipalities that are just below and above the thresholds that define the occurrence of the disaster. In the second step, we account for data restrictions by estimating how moving from just below to just above the threshold increases the likelihood of being eligible for Fonden. In the third step, we recover the causal impact of Fonden on local economic activity by rescaling the coefficient derived in the first step by the coefficient derived in the second step.

We measure changes in economic activity at the municipal level using high resolution satellite imagery that allows us to measure the intensity of light as observed from outer-space. Because our night light measure is a good proxy of subnational level economic activity we are able to track the differential economic performance created by the rapid provision of reconstruction funds.

Our main finding is that municipalities with access to Fonden grew between 2 to 4% more than those without Fonden in the year following the disaster. Conservative benefit cost ratios, for the same time period, are in the 1.52 to 2.89 range. The paper additionally documents the impact of Fonden over the post disaster period. We find that the economic expansion triggered by the program peaks 15 months after the disaster, and that from this point onward municipalities without access to Fonden begin to catch-up. Consistent with the previous findings, the paper additionally documents a large and sustained increase in the growth of construction employment

[1] A municipality is a second level administrative unit in Mexico. There are currently 2461 municipalities.

that slightly precedes the overall increase in local economic activity. At its peak this labor market effect is in the order of 76%.

The rest of the paper is organized as follows. Section 2 gives a brief background of Mexico's disaster fund Fonden. Section 3 explains the identification strategy. Section 4 discusses the datasets used. Section 5 presents the results. Section 6. shows that nights lights are a good proxy of subnational economic activity in Mexico. Section 7 concludes.

2 Background

Fonden is a fund set up by the Mexican government to manage the risk created by natural disasters. Fonden was first introduced in 1996, but it was not used operationally until 1999. The program is financed by a protected budget appropriation and through the placement of catastrophe bonds. Mexico is the first developing country to use this type of bonds to transfer part of its catastrophe risk to capital markets (Cardenas et al., 2007). While FONDEN was designed to finance some ex-ante risk management interventions through the complementary Fopreden fund, its primary purpose is funding emergency relief operations and reconstruction efforts (Mahul, 2011). Currently, the bulk of Fonden funds is spent on the reconstruction of low-income housing and public infrastructure (World Bank, 2012).

Crucially for our paper, Fonden disbursement of funds has been determined by a clear set of operational rules since its onset. These rules balance accountability and transparency concerns with a timely disbursement of funds. The operational rules have been revised on five occasions, but since 2004, they include the event thresholds used in this paper. The process for accessing and executing reconstruction funds can be divided into four steps: (i) declaration of a natural disaster; (ii) damage assessment and request for reconstruction funding; (iii) disbursement of resources and reconstruction; (iv) public reporting of post-disaster activities.

Step (i) uses the event thresholds defined in the operational rules to determine whether a declaration of disaster can be issued. Since this verification process is central to our identification strategy, we discuss this step in detail in the following section.

Step (ii) begins within 24 hours of the declaration of disaster when a damage assessment committee is formed. This committee, comprised of both federal and state representatives, visits the affected area and determines the extent of damages. The findings and supporting documentation, including itemized reconstruction costs, are verified by an inter-ministerial commission before being sent for final approval to Fonden. In the majority of cases, this process is completed within three months. One important feature of this setup is that Fonden funding will be proportional to the damages experienced in a municipality.

Step (iii) differs depending on the ownership of the damaged asset. Federal assets are fully covered by Fonden and reconstruction is executed by a federal entity. State or municipal government assets only have partial Fonden coverage (50% in most cases), and reconstruction is executed by both federal entities and private service providers. The partial Fonden coverage has been successful at enticing local governments to participate in the Fonden process. Nonetheless, the greater degree of coordination with local governments implies that federal owned assets are likely to be reconstructed in shorter time frames. Average projected reconstruction time is seven months.

Step (iv) involves the publishing of detailed records on post-disaster allocations. This real time publication occurs via the website of the Mexican Secretariat of the Interior. Readers interested in further details are referred to Chapter 3 in World Bank (2012).

Following this disbursement process, in a year of frequent and severe natural disasters like 2010, the program responded to 54 disasters, with some of those disasters affecting areas that spanned over 94 municipalities. During that year alone Fonden provided \$6.4 billion (PPP, constant 2005 international dollars) in rapid reconstruction funds. In an average year Fonden responds to 33 disasters, and on average 14 municipalities are affected per disaster. Average municipal Fonden expenditures amount to roughly \$4.2 million and median expenditures to \$1 million. Overall median yearly program expenditures amount to \$972 million, or \$8.3 per capita.

Mechanisms to mitigate the impact of disasters

As previously mentioned, the bulk of Fonden expenditures is related to reconstruction efforts. These efforts include the reconstruction of federal and state roads, the provision of funds to reconstruct low-income housing, and the rebuilding of hydraulic, health, and educational infrastructure. These expenditures can provide a double gain to economic development. First, by coping with the losses created by natural disasters. Second, by enabling local governments and households to reallocate resources from safer but inefficient low-risk low-return productive activities to more risky higher-yielding activities.

Our current analysis estimates the impact of Fonden on economic activity at different points in the post-disaster period. The focus of our analysis takes place in the 2004-2013 period when road expenditures accounted for the bulk of overall expenditures.[2] Accordingly, we expect Fonden to affect economic activity primarily by enabling municipalities to quickly rebuild their road network following a disaster.

[2] The shares of expenditure by category vary year by year depending on the type of damages that have occurred. During the period of analysis, road expenditures accounted for 57% of overall expenditures, and for more than 65% of expenditures in five of the years analyzed.

3 Empirical Strategy

This paper assesses the impact of Fonden by comparing economic outcomes across essentially identical municipalities who happen to differ in their eligibility to Fonden funding. This occurs because the event thresholds used to determine whether a natural disaster has occurred effectively discretize a continuous measure of the intensity of a disaster into an eligible and a non-eligible group. It is thus possible to observe a set of municipalities that experienced a natural disaster of a similar magnitude, but where only a subset of those municipalities are "officially" considered to have experienced a natural disaster.

The details of this process are as follows. The process begins with a request from the state governor. This request contains a list of municipalities that are believed to have experienced damages as a result of a natural disaster. The request is verified by an independent technical agency that compares measurements of the intensity of the disaster to the thresholds set out in Fonden operational guidelines. For example, in the case of heavy rainfall, the national water commission CONAGUA compares the rainfall at the weather station representative of the requested municipality to the Fonden heavy rain threshold, that is, rainfall greater or equal to the percentile 90 of historic rain recorded at that weather station. CONAGUA will then list the municipalities that pass the threshold, and a declaration of disaster will be issued for this set of municipalities. As previously mentioned, the declaration of disaster is important because it determines eligibility to Fonden funding.

Fonden covers a broad range of events including: earthquakes, forest fires, heavy rainfall, tropical storms, hurricanes, landslides, hail storms, areal flooding, and riverine flooding. In this paper we will focus on heavy rainfall events because of data availability. Heavy rainfall events account for as much as 68% of all events, and for as much as 51% of overall program expenditures. In spite of the sharp rule that determines when a heavy rainfall event has taken place, we use a fuzzy regression discontinuity design because we are unable to perfectly distinguish between heavy rainfall events and other types of events, and because we are unable to fully match municipalities to the set of weather stations used for verification.

In the fuzzy regression discontinuity design we estimate two causal effects: the effect of crossing the percentile 90 threshold on the probability of receiving Fonden, and the effect of crossing the percentile 90 threshold on local economic activity. Specifically, we run the following regressions:

$$f_{mt} = \gamma_0 + \gamma_1 z_{mt} + \gamma_2 g(r_{mt} - c_{mt}) + \gamma_3 g(r_{mt} - c_{mt}) * z_{mt} + \theta_t + v_{mt} \tag{1}$$

$$y_{mt} = \beta_0 + \beta_1 z_{mt} + \beta_2 g(r_{mt} - c_{mt}) + \beta_3 g(r_{mt} - c_{mt}) * z_{mt} + \theta_t + \varepsilon_{mt} \tag{2}$$

$$\hat{\pi_1} = \frac{\hat{\beta}_1}{\hat{\gamma_1}} \tag{3}$$

Equation 1, the first stage, is estimated by regressing a dummy that takes the value of one when municipality m in year t receives Fonden, f_{mt}, on an indicator variable that takes the value of one when an observation falls above the threshold, z_{mt}. That is, $z_{mt} = \mathbb{1}(r_{mt} \geq c_{mt})$ where r_{mt} is the amount of rainfall on the day requested and c_{mt} is the percentile 90 threshold. The function $g(r_{mt} - c_{mt})$ represents the relationship between the outcome and the forcing variable, that is, millimeters of rainfall to the percentile 90 threshold. We will consider various ways of modeling this relationship. First we will model $g(\cdot)$ as a flexible polynomial function on either side of the threshold and use the full sample to estimate it. Second, we will assume that $g(\cdot)$ is linear and use a sample that falls within an optimal bandwidth to estimate it. To determine the bandwidth we will use the methods proposed by Imbens and Kalyanaraman (2012) and Calonico et al. (2014b).

Equation 2, the reduced form, is derived by regressing our measure of local economic activity, y_{mt}, on z_{mt}. The estimation procedure is analogous to that of equation 1. Next, we derive the impact of Fonden on local economic activity, π_1, by rescaling the reduced form coefficient of z_{mt} by its first stage coefficient.[3] Following Henderson et al. (2012) we include year fixed effects in all of our specifications in order to ensure the comparability of satellite imagery over time.

4 Data

For our analysis, we use data from several sources. We proxy changes in municipal level economic activity by 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 are in a 101 min near-polar orbit. This orbit implies that the satellites are capable of observing every location on earth at roughly the same local time each day. In the case of Mexico the satellite overpass occurs between 7 and 8 pm local time. These satellites use Operational Linescan System (OLS) sensors to measure the intensity of earth based lights. The National Oceanic and Atmospheric Administration (NOAA) has developed a methodology to generate image composites that filter transient light observed in the raw images. 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. The resulting stable cloud-free night light composites measure, by and large, man-made lights. These measures of night lights have been shown to be good proxies for economic activity at the country level

[3] In order to derive standard errors for $\hat{\pi_1}$ we will instead estimate the coefficient using 2SLS.

(Henderson et al., 2011, 2012) and at lower levels of aggregation (Harari and La Ferrara, 2013; Michalopoulos et al., 2014; Bundervoet et al., 2015; Alesina et al., 2016). Specifically, related to our paper the work of Bertinelli and Strobl (2013) and Elliott et al. (2015) have shown, respectively for the Caribbean and for China, that not only are night lights a reliable proxy of the economic damages brought about by natural disasters, but that it is night lights measured at lower levels of aggregation which provide the most reliable proxy. In section 6 we present our own tests of the relationship between night lights and economic activity at the subnational level in Mexico.

NOAA publicly provides composites in yearly frequency covering the 1992 to 2012 period. These satellite-year datasets have a spatial resolution of approximately 30 arc seconds, that is, each pixel roughly represents a one kilometer square cells. Each pixel has an associated digital number (DN) which represents the intensity of lights normalized across satellites in a scale ranging from 0 (no light) to 63 (maximum light). Given the operational lifespan of the satellites we will use data from the F16 satellite for the 2004 to 2009 period, and from the F18 satellite for the 2010 to 2012 period. Following Henderson et al. (2011) our subnational measure of night lights will be constructed by summing the DN across all pixels that are within the subnational boundary, dividing the sum by the area of the observed pixels, and then taking the log of the previous number. We will calculate this measure of brightness at both the state and municipal level, and refer to it from this point on as log night lights. The key outcome variable will be the change in log night lights between the year the disaster takes place and the following year.

In addition to the publicly available imagery, NOAA has produced, especially for this paper, monthly frequency composites for the 2004 to 2013 period. These satellite-month datasets are derived using the same process and raw images as the annual composites. In addition to calculating log night lights at the municipal and state level as we did with the annual composites. We will construct two additional sets of night light measures from monthly composites. The first will take advantage of the overlapping coverage of the F15 and F16 satellite during the 2004 the 2007 period, and use as source data pixel level averages from the two satellites. The second will calculate our log night lights measure from composites where we have excluded top coded pixels, that is, pixels with a DN of 63.

Unfortunately, late sunset during summer months leads to missing log night lights data for some parts of Mexico, every year, between June and August. In addition in 2009 due to degradation of the sensor on board the F16 satellite we have up to 7 months of missing night light information. In order to overcome the constrains created by missing data, we will take averages over monthly log night lights. In our preferred specification the key outcome variable is the log difference between the average for the 12 months before the disaster and the average at various points in the post disaster period. One important implication of using these averages in conjunction with stable night light imagery is that our results will not be affected by transient phenomena such as cloud cover of ephemeral light sources.

In addition to night lights, we provide direct evidence of the impact of Fonden on local economic activity by investigating its impact on employment. The employment dataset is constructed from the labor force survey (LFS) ENOE. Specifically, we produce a quarter-year panel of employment at the municipal level for the 2005 to 2013 period. The LFS is produced by the Mexican statistical office INEGI. The survey samples 120,000 dwellings per quarter in both urban and rural municipalities. It has a focus and structure similar to that of the Current Population Survey, and at any given point in time, it provides information on roughly half of Mexico's municipalities. As in the case of night lights, the outcome of interest is the log difference in employment between the quarter the disaster takes place and various quarters in the post-disaster period.

The national water commission (CONAGUA) provided us with three datasets: (i) Data on historical rainfall at the day-weather station level, this dataset spans the 1920 to 2015 period, and contains the universe of weather stations. (ii) The weather station-month level triggers for Fonden eligibility. (iii) The mapping between municipalities and representative weather stations. These datasets where merged with numeric weather station identifiers when available, and with string weather station identifiers when not. In spite of using natural language processing algorithms, we are still unable to fully match municipalities to all the possible weather stations used for verification. The resulting dataset is a municipal-month level panel that allows us to observe the rainfall mm to the Fonden heavy rainfall threshold. For events spanning more than one day the maximum was chosen.

Data on municipal level requests and approvals for disaster declarations were constructed from the archives of Mexico's official diary. Data on municipal level Fonden expenditures, and days between disaster and authorization of funds are provided by the Ministry of Finance (MoF).

Given the introduction of the percentile 90 heavy rainfall rule in 2004 and the availability of log night lights, we are primarily interested in two samples. When working with annual composites, the set of relevant events will be those that occur between 2004 and 2011.[4] In this period we observe 3,083 municipal heavy rainfall requests. Of these, we have complete weather and Fonden threshold information for 1,745. As shown in table 1, using 2000 census data, we find no evidence of systematic differences between municipalities with missing and complete information. When we turn to monthly composites we are able to use the complete sample of heavy rainfall request which covers the period between 2004 and 2013. In this case we observe 5,652 municipal heavy rainfall requests and we have complete information for 2,825. Tables 2 and 3 present summary statistics of the key variables for each sample.

[4] Note that while annual night light data are available until 2012, we are interested in the change in night lights between the year the disaster takes place and the following year.

5 Results

5.1 The impact of Fonden on local economic activity

Figure 1a plots the mean probability of receiving Fonden relative to rainfall millimeters (mm) to the threshold. The optimal bin width is calculated following Calonico et al. (2014a).[5] The figure reveals a potential jump in the probability of receiving Fonden. Moving from just below to just above the threshold increases the likelihood of receiving Fonden from about 60% to 80%. The previous figure additionally plots a 4th order polynomial fit estimated separately on each side of the threshold. The polynomial fit reveals that the underlying relationship between the probability of receiving Fonden and rainfall mm to the threshold could be potentially captured by a second or third order polynomial function of $g(\cdot)$.

In order to investigate the sensitivity of these results to the choice of bin-width, in figures 1c to 1f, we respectively double and triple the number of bins. These figures produce consistent results, thereby bolstering the idea that the probability of receiving Fonden increases by approximately 20 percentage points at the threshold.

Next in figure 1b we plot the mean change in log lights between the year a disaster occurs and the following year relative to rainfall mm to the threshold. The figure reveals a clear jump in brightness at the threshold. Moving from just below to just above the threshold increases brightness by roughly 0.07 log points. As in the previous case, figures 1d and 1f, illustrate that this result is robust to the choice of bin width. The figures further reveal that in the absence of Fonden, night lights become dimmer as the relative intensity of the disaster increases, that is, as the we move towards the threshold from the left. This finding is important because it suggests that night lights are capable of measuring the economic slowdown brought about by natural disasters. Moreover, consistent with the idea that Fonden reconstruction funding is proportional to the damages, the figures also illustrate that the relationship between night lights and the relative intensity of disaster disappears after the threshold has been crossed.

In order to illustrate that the underlying relationship between night lights and intensity of disaster is not being driven by areas with sparse data, in figure 2 we restrict the sample to observations that are within 150 mm of the threshold, and plot once again the mean change in log lights in relation to the forcing variable. Consistent with the previous results, we find, that the negative relationship between night lights and intensity of disaster only occurs in the absence of Fonden.

[5] The number of bins is chosen using is a data-driven method whose objective is to create a plot that allows us to detect discontinuities in the underlying regression function without imposing smoothness in the estimator. Specifically, the algorithm chooses the optimal number of bins such that the Integrated Mean Square Error is minimized, see Calonico et al. (2014a) for details.

Table 4 presents the regression analog of figures 1a and 1b. Panel A presents OLS estimates of equation 1. Panel B presents OLS estimates of equation 2, and 2SLS estimates of the impact of Fonden on local economic activity π_1. Columns 1 to 4 present various specifications of the functions $g(\cdot)$. Specifically, in columns 1 and 2 we estimate using the full sample and assume that function $g(\cdot)$ is a second or a third order polynomial. In columns 3 and 4, we assume that $g(\cdot)$ is linear and restrict the sample to within 50.5 mm and 57.3 mm as determined by two optimal bandwidth calculations. Standard errors are clustered at the municipal level.

Consistent with figure 1a, the estimates of panel A reveal that crossing the threshold increases the probability of receiving Fonden between 13% to 19% and that this jump is statistically significant in all cases. Similarly, the reduced form estimates in panel B reveal that municipalities above the threshold grew by roughly 0.04 log points more than municipalities below the threshold. Once we rescale these reduced form coefficients, we find that Fonden led to an increase in the range of 0.196 to 0.37 log points. While these coefficients are only statistically significant at the margin, the estimated gains in night lights imply considerable increases in local economic activity. Specifically, in the first row of panel C, we calculate the impact of Fonden on local economic activity by multiplying the IV estimates with the elasticity of log night lights to GDP from the annual fluctuations specification, table 6 panel A column 2. Our estimates indicate that municipalities with access to Fonden grew between 2 to 4% more than those without Fonden in the year following the disaster.[6]

In order to get a better sense of the magnitude of the changes in economic activity we additionally derive Fonden's heavy rainfall benefit cost ratios. This calculation is preformed in four steps. First, we restrict the sample to 790 municipalities that received Fonden funds between 2004 and 2011 and for whom we have complete information on the resources allocated by the program. Second, we proxy municipal GDP before the introduction of Fonden, by multiplying UNDP estimates of municipal GDP per capita in 2000 by municipal population. Third, we calculate the dollar value of the economic activity generated by FONDEN by multiplying municipal GDP by the product of the elasticity of light to GDP and our IV estimate of the impact of Fonden, that is, we multiply the level of GDP by the additional growth created by Fonden. Fourth, we sum across municipalities to derive the total benefit and cost of the program.[7]

To account for the uncertainty in estimating the elasticity of light to GDP, and of estimating the impact of Fonden on night lights, the third step of the calculation is preformed using coefficients drawn from two normal distributions. In each case the mean of the distribution is set to the point estimate, and the standard deviation is set to the standard error. Steps three to four are then repeated 5,000 times using random draws of coefficients described on step three. We then

[6] Note that the counter-factual is not no reconstruction response at all, but rather non-Fonden discretionary reconstruction response.

[7] Since UNDP GDP estimates are in 2005 PPP USD we convert Fonden reconstruction expenditures to the same units.

take the simulated total benefits generated by Fonden and compute the mean and the standard deviation.

The second row of panel C reports the average total benefit from the simulations divided by the total cost. Rows three and four report the total benefit one standard deviation below and above the mean divided by the total cost. All in all, while our ratios vary too broadly to clearly pin down the effect of Fonden, they are of a reasonable magnitude. The average benefit cost ratio, across specifications, lies in the 1.52 (with a probability of 0.66 of being greater than one) to 2.89 (with a probability of 0.8 of being greater than one) range, and is therefore consistent with previous estimates of fiscal multipliers. These cost-benefit ratios might, however, be too conservative as they account for the overall expenditures of Fonden while assuming that the benefit of the program is only accrued in the year following the disaster.

5.2 The dynamic impact of Fonden on local economic activity

As previously mentioned, we turn to month frequency night lights data to document the dynamic impact of Fonden on local economic activity. Figures 3a to 3d plot the mean change in log night lights relative to rainfall millimeters (mm) to the threshold, at four key points in the post disaster period. Specifically, the four outcome variables are the night lights log difference between the average 12 months before the disaster and the average at 3, 5, 15, and 20 months after the disaster. The figures suggest that the impact of Fonden can be broadly characterized in three phases. In the very short run, while funds and reconstruction efforts are being put into place, we find no difference between those municipalities just above and below the threshold. Between 5 and 15 months after the disaster, we see a clear jump in brightness at the threshold. At its peak, 15 months, moving from just below to just above the threshold increases brightness by roughly 0.1 log points. From 15 to 19 months, municipalities at the left of the threshold begin to catch up to those at the right of the threshold. At 20 months there seems to be no difference between municipalities with and without access to Fonden.

In order to provide a detailed account of the dynamic impact of Fonden, figures 4a to 4c plot the coefficients and 90% confidence intervals derived from estimating equations 1 to 3. Each plotted coefficient corresponds to a separate OLS regression where the dependent variable is the night lights log difference between the average 12 months before the disaster and the average at various points in the post disaster period. We begin with a post-disaster average at 3 months, and then we incrementally increase this average by a month for up to 30 months.

In order to ensure that our estimates of the impact of Fonden at different points in time are comparable, we use the following procedure. First, following Calonico et al. (2014b), we calculate the optimal bandwidth for each of our dependent variables, that is, the change in local economic activity at different points in the post-disaster period. Second, using the bandwidths derived in the first step, we calculate an average optimal bandwidth. Third, we estimate equations 2 and 3 assuming a linear $g(\cdot)$ and restricting the sample to the average optimal bandwidth.

Figure 4a plots the coefficients derived from estimating the first stage. Consistent with the results derived in the previous section we find that crossing the threshold increases the probability of receiving Fonden by roughly 16%. The first stage coefficient is the same at every point in time because the sample is constructed to remain constant.

Figure 4b plots the reduced form coefficients. Consistent with the findings and description of figure 3, the coefficients illustrate an incremental increase in brightness for municipalities above the threshold that peaks at approximately 15 months. Next in figure 4c we plot the instrumental variables coefficients. These coefficients are our sharpest estimates of the impact of Fonden on night lights. The coefficients illustrate a progressive build up of the impact of Fonden on night lights which peaks 15 months after the disaster has taken place, 0.6 log points (t=1.9). The coefficients also reveal that Fonden has a statistically significant impact on log night lights for up to 17 months.

Given that the timing of the observed gains depends to a large extent on the ability of Fonden to quickly mobilize funds for reconstruction, figure 4d plots the fraction of municipalities with authorized funds at different points in the post disaster period. Figure 4d suggest that in roughly 80% of the cases Fonden funding was authorized and ready to be used for reconstruction within 3 months of a disaster. Taking together the time required for disbursement of funds with the average projected reconstruction time of 7 months suggest that, consistent with our findings, the earliest impact of Fonden on local economic activity should occur between 3 to 10 months after a disaster.

It is possible that reconstruction could be delayed or take longer to complete, thus extending the period in which Fonden has a direct impact on economic activity. Interviews with Fonden managers indicate that the bulk of delays correspond to projects where the assets damaged are owned by state governments. This follows, as mentioned in section 2, from the additional coordination efforts requiered for state owned assets. Accordingly, our estimates of the impact of Fonden in the first few months following a disaster, are likely to correspond to the reconstruction of federal assets. Reconstruction of federal assets accounts for 43% of overall Fonden expenditures.

Next in figure 5 we investigate the sensitivity of these results to our choice of specification. Figure 5a reports for convenience the IV estimates of the previous figure. Figure 5b reports IV estimates from a specification that uses the full sample and assumes a cubic $g(\cdot)$ function. Figures 5c and 5d report IV estimates from specifications that assume a linear $g(\cdot)$ function but that respectively restrict the sample to the minimum or the maximum optimal bandwidth. While specifications 5b to 5d produce similar results to those of figure 5a, they suggest different time periods in which we are able to detect a statistically significant effect of Fonden on night lights. For example, figure 5b indicates that Fonden has a statistically significant effect between 7 and 18 months, while figure 5d indicates that the impact of Fonden could be detected for up to two years after the disaster.

In figures 6a and 6b we verify that our composite processing choices have had no bearing on the results. Specifically, in figure 6a instead of using pixel level averages that use information from overlapping satellites when available, we limit ourselves to information derived solely from the F16 and F18 satellites. In figure 6b we additionally address the concern that our estimates might be biased by the presence of top coded pixels, and exclude these very bright, but upper truncated pixels from the analysis. While, as expected, these estimates are less precisely estimated than those of figure 5c, they are of similar magnitudes and they further confirm the time period over which the impact of Fonden can be confidently established.

All in all, these figures consistently indicate that Fonden has a statistically significant impact on night lights between 7 and 17 months after a disaster has taken place. The coefficients also suggest that the implied economic impact of Fonden is of considerable magnitude. In figure 5a the 12 month point estimate is 0.57 log points (t=1.93). This coefficient implies that municipalities with access to Fonden grew 6.5% more than those without Fonden in the year following the disaster.[8]

This estimate of the impact of Fonden is not directly comparable with the ones derived from the annual light composites, because it is derived from a different sample.[9] Nonetheless, taken at face value it does suggest that the estimates derived from annual composites are likely to be lower bounds of the impact of Fonden.

The key difference between the estimates, is that the estimates derived from annual composites are naturally constrained by the calendar year. Accordingly, these estimates will necessarily average over events that can last as many as 12 or 23 months after the disaster has taken place. Since the effect of Fonden on night lights begin to decrease after 15 months it is reasonable for the annual composites to provide smaller estimates of the impact of Fonden on night lights.

In order to further investigate the dynamics of the impact of Fonden in figures 6c we estimate the impact of Fonden when the dependent variable is the night lights log difference between the average 12 months before the disaster and a 9 month moving average in the post disaster period. Figure 6d reports results from a similar exercise where we use a 12 month moving average. The key finding, is that consistent with our previous results the impact of Fonden on night lights is largest between 7 and 15 months in figure 6c and between 4 and 15 months in figure 6d. In all

[8] We calculate the impact of Fonden on local economic activity by multiplying the IV estimate by the elasticity of light to GDP from the annual fluctuation specification, table 6 panel B column 2.

[9] Monthly composites cover a longer time period, thereby allowing us to use a larger sample of events, see section 4 for details.

cases, our results indicate that the impact of Fonden is not permanent, and that its dynamics can be characterized by a three phase process: setup for reconstruction, reconstruction, and catch up by municipalities not covered by Fonden.

5.3 The dynamic impact of Fonden on construction employment

Next we turn to quarterly employment data. These data allow us to provide direct evidence of the impact of Fonden on local economic activity, as well as to document the time path of reconstruction work. While we find no evidence of an overall effect on employment, see figure 7, we do find that Fonden has a considerable impact on construction employment. Specifically, figures 8a to 8f plot the mean growth in construction employment, at different points in the post disaster period, relative to rainfall millimeters (mm) to the threshold. Specifically, the six outcome variables are the log difference in construction employment between the quarter the disaster takes place and the next six quarters, in one quarter steps.

In spite of the coverage of the LFS only allowing us to use half of the previous sample, we find that the time path of growth in construction employment is consistent with our previous findings. In particular, in the very short run, we find no evidence of differential growth in employment at threshold. However, at 6 months or more, we begin to observe a differential effect at the threshold. This effect appears to peak, in a very clear jump of roughly 25% 12 months after a disaster has taken place.

As in the previous case, we provide a more detailed account of the dynamic impact of Fonden on employment growth by sequentially estimating equations 1 to 3 for each of the six quarters following a disaster (3 to 18 months). Each plotted coefficient corresponds to a separate OLS regression. In all regressions, it is assumed that function $g(\cdot)$ is linear, and the sample is restricted to the set of observations that fall within the average optimal bandwidth.

Figure 9a plots the first stage coefficients. These coefficients provide strong evidence of a first stage among the municipalities that make up this smaller sample. Specifically, we find that crossing the threshold leads to an increase in the probability of receiving Fonden of 35%. Next figure 9b plots the reduced form coefficients, and figure 9c plots the 2SLS coefficients. As expected given the smaller sample size these coefficient are noisly estimated. Nonetheless, the estimated effect sizes are of considerable economic magnitude. Moreover, the path of the coefficients strongly indicate that 6 months after a disaster, Fonden leads to a large and sustained increase in the growth of employment in the construction sector. At its peak the point estimates indicate, that Fonden increased construction employment by as much as 76%. This effect size is reasonable because municipalities are likely to operate as local labor markets,[10] because

[10] Less than 3% of LFS respondents report moving to a different municipality in order to find or keep their current job.

the labor force required for reconstruction tends to be considerable, and because Fonden uses reconstruction schemes that are specifically designed to employ the local community.[11]

5.4 Falsification Exercises

The identifying assumption that underpins our regression discontinuity design is that potential outcomes are smooth functions of the forcing variable as the threshold is crossed. One potential threat to this assumption is that individuals might be able to game the Fonden assignment rule. It is unlikely that third parties could have tampered with weather stations run by CONAGUA not only because these weather stations serve a variety of purposes both civilian and military, but also because few individuals outside of CONAGUA could have known the thresholds or be able to identify the subset of weather stations used to determine Fonden eligibility. Nonetheless, in order to investigate whether manipulation is possible, we examine the density of the forcing variable. If Fonden is being manipulated then we would expect to observe bunching of observations to the right of the threshold. Formally, we use the sorting test proposed by McCrary (2008). In figure 10a we plot the density of the forcing variable as it crosses the threshold. The solid line is the density of the forcing variable as estimated by local linear regression, the dashed lines represent confidence intervals. The overlapping confidence intervals suggest that there is no discontinuous change in the density across the threshold. The p-value of the McCrary sorting test associated with this graph is 0.42. We thus fail to reject the null that the forcing variable is smooth across the threshold.

We can provide further support for the validity of the identifying assumption by establishing that log night lights do not change discontinuously at the threshold in the years preceding a natural disaster. Figure 10b plots the change in log night lights between two years before a disaster has taken place and the following year. The figure reveals no apparent discontinuity at the thresholds. Moreover, when we estimate the impact of Fonden it yields a small coefficient that is statistically indistinguishable from zero, 0.016 (t=0.45).

6 Night lights as proxies of subnational economic activity

While our primary interest lies in determining whether log night lights can predict changes in municipal level GDP, in the absence of this type of data we begin our analysis by investigating the relationship between log night lights and proxies of economic activity at the municipal level. Specifically, we calculate by municipality, from the 2005 population conteo and the 2010 population census, the number of dwellings with the following characteristics: dwelling has non

[11] In particular, Fonden housing reconstruction efforts occur through the temporary work program. This program is designed to hire homeowners to rebuild their own houses.

dirt floors, has television, has fridge, has washing machine. We additionally compile data from various administrative records that allow us to observe at the municipal level: the number of users of electricity, the number of car registrations, and the number of building licenses for both industrial and residential use.

Given the frequency with which these data are available, panel A of table 5 uses a long difference specification in which we test whether the five year log change in the number of dwellings of the various characteristics previously described is related to five year change in log night lights. In all cases columns 1 to 4, we find that the log night coefficient is positive and that it is sharply estimated. The R^2 is in the 6 to 8% range. In panel B of the same table, we turn to administrative records available in yearly frequency. In this case we use a log log specification that includes both municipal and year fixed effects. As in the previous case we find that our measure of log nights is positive albeit less precisely estimated in columns 3 and 4 where the number of observations is limited.

Next, we investigate the relationship between log night lights and state level GDP.[12] 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 26 states that have requested Fonden funding in the 2004-2011 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. Panel A of table 6 uses log night lights derived from annual composites. Panel B of the same table uses log night lights derived from pixel averaged monthly composites. 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 0.24.

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 0.11 (t=2.6). 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

[12]The source of state level GDP data is INEGI. GDP is measured in constant 2008 pesos.

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 the 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, in the range of 7 to 10%, reflects solely the contribution of night lights to explaining within-state and within-year variation in GDP.

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 2012 on the change in log night lights between 2004 and 2012. We find a positive and sharply estimate elasticity, and an R^2 in the 40 to 44% range. 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. Interestingly, our results for subnational data in Mexico are of very similar magnitude to those derived for the World by Henderson et al. (2011) and for Africa by Bundervoet et al. (2015).

7 Conclusion

This paper exploits the sharp rules that govern eligibility to Fonden funding for post-disaster reconstruction to derive some of the first estimates of the causal impact of disaster funds on local economic activity. Our results indicate that, in the year following the disaster, municipalities with access to Fonden grew between 2 to 4% more than those without Fonden. The reconstruction effort led to a 76% increase in construction employment and this effect preceded in time the recovery in local economic activity. Conservative benefit-cost ratios, in the 1.52 to 2.89 range (respectively with probabilities of 0.66 and 0.8 of being larger than one), suggest that Fonden has provided cost-effective protection from the public service disruptions caused by natural disasters. We additionally document the impact of Fonden over time. We find that the economic expansion generated by Fonden peaks roughly between 7 and 17 months after a disaster has taken place, and that from that point onward municipalities without access to Fonden begin to catch up. On the whole, given the scale of gains to local economic activity brought about by availability and rapid disbursement of disaster funds, these results suggest that policy makers in other countries could be encouraged to consider using pre-disaster funding schemes such as Fonden to enhance their own response capabilities.

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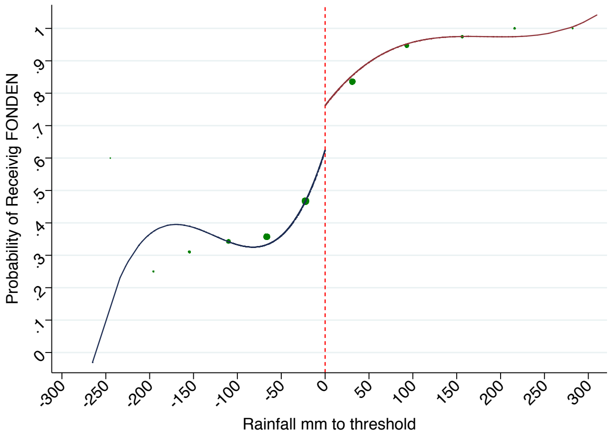
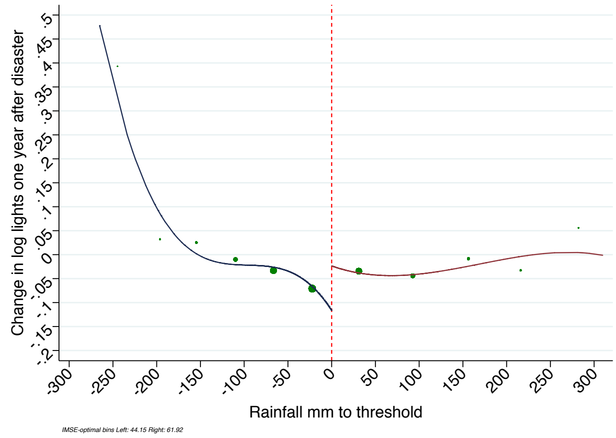
8 Figures

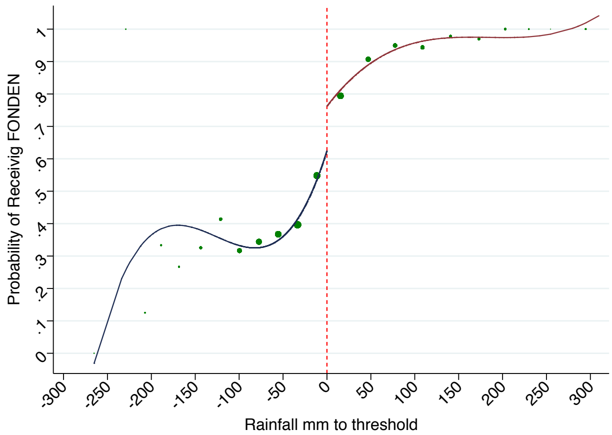
Figure 1: First stage and reduced form at various bin widths



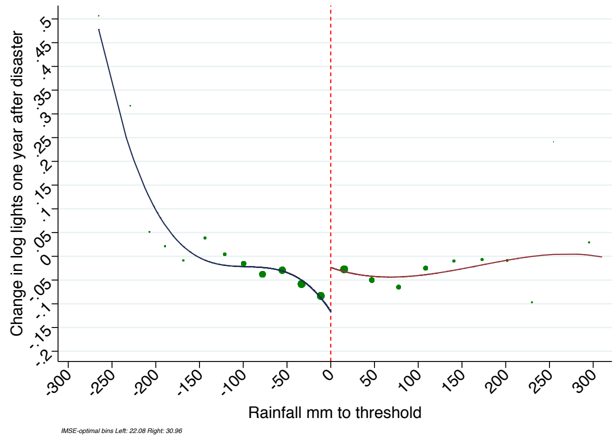
(a) Prob. of receiving Fonden, First Stage



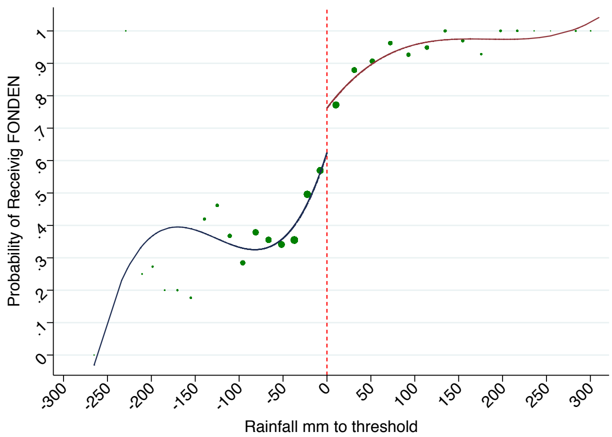
(b) △ log night lights, Reduced Form



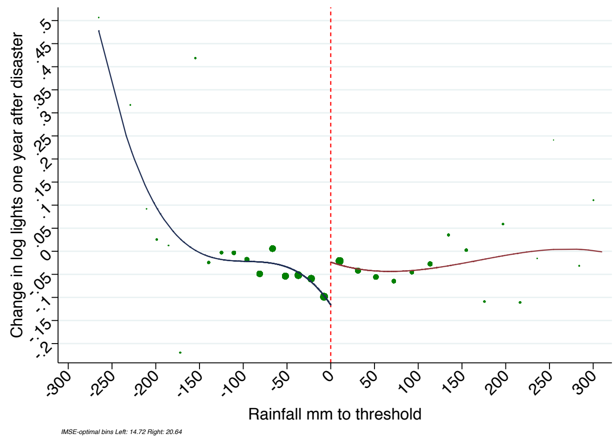
(c) Prob. of receiving Fonden, First Stage (bins x 2)



(d) △ log night lights, Reduced Form (bins x 2)



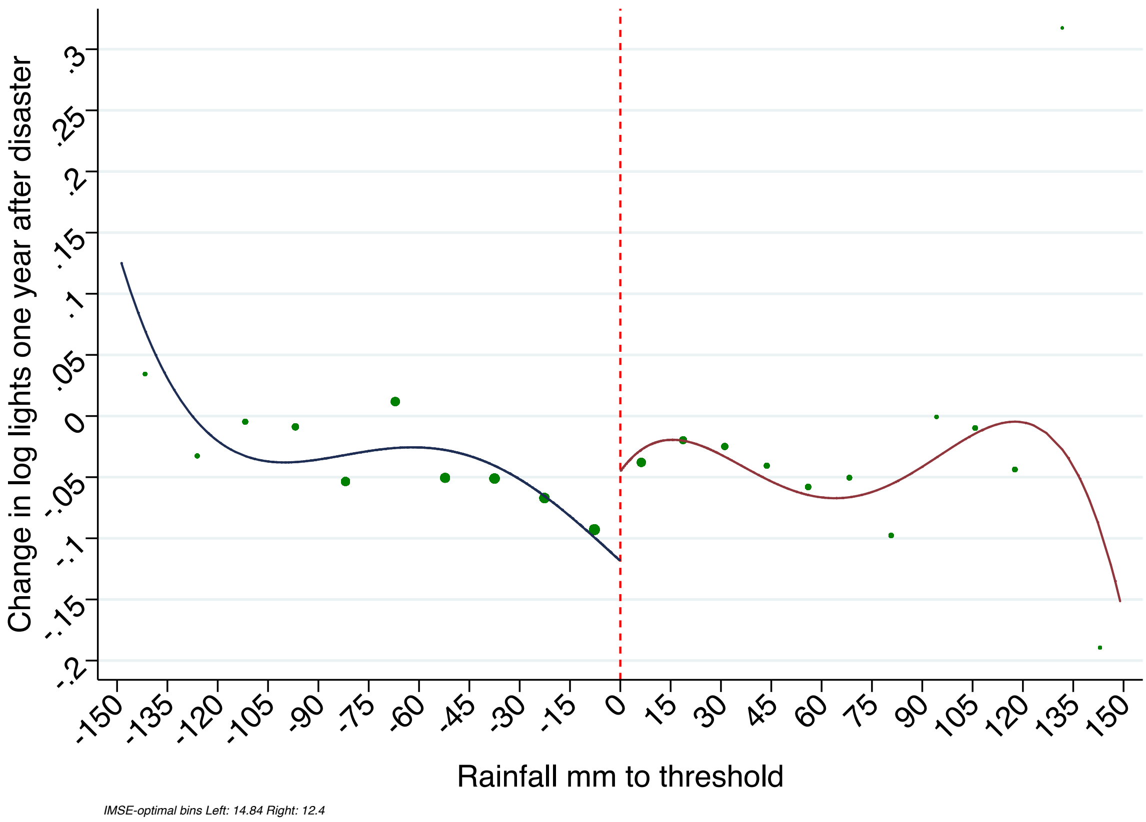
(e) Prob. of receiving Fonden,First Stage (bins x 3)



(f) △ log night lights, Reduced Form (bins x 3)

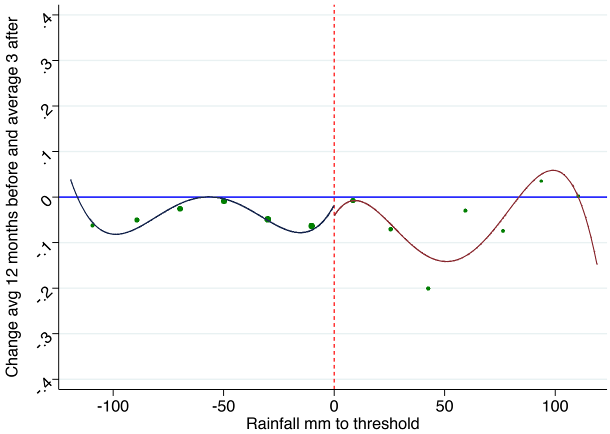
Note: The sample is composed by the municipalities that have requested Fonden funding. The figures plot the local average at the mid-point of each bin, and a 4th order polynomial fit estimated separately on each side of the threshold. The size of the markers is proportional to the number of observations in each bin. The forcing variable is rainfall mm to the percentile 90 threshold. The dependent variable for figures on the left is a dummy take the value of one when a municipality receives Fonden. The dependent variable for figures on the right is the log change in night lights between the year the disaster takes place and the following year. The optimal bin width is calculated following Calonico et al. (2014a). In order to investigate the sensitivity over the choice of bin-width, in figures 1c to 1f, we double and triple the number of bins.

Figure 2: Change in log night lights by rainfall mm to the threshold

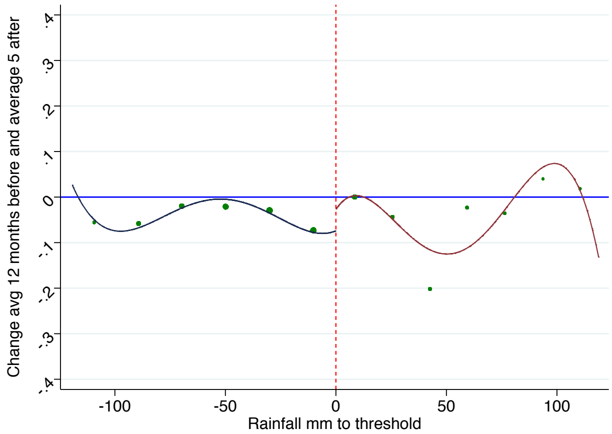


Note: This figure plots the local average at the mid-point of each bin, and a 4th order polynomial fit estimated separately on each side of the threshold. The size of the markers is proportional to the number of observations in each bin. The forcing variable is rainfall mm to the percentile 90 threshold. The sample has been restricted to observations where the forcing variable is between -150 mm to 150 mm, approximately a 2% trim on each side. The dependent variable is the log change in night lights between the year the disaster takes place and the following year. The optimal bin width is calculated following Calonico et al. (2014a).

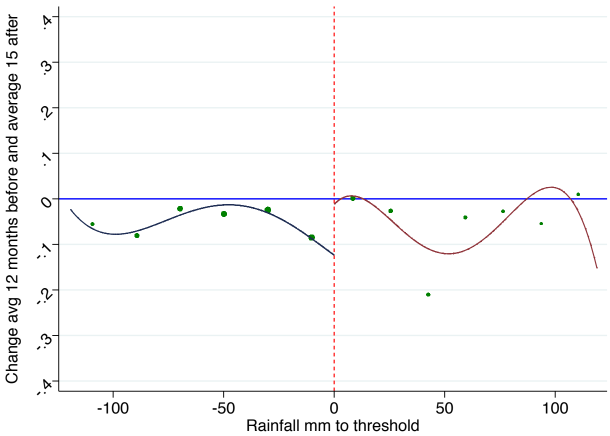
Figure 3: Dynamics of Fonden impact: reduced form at various post disaster periods.



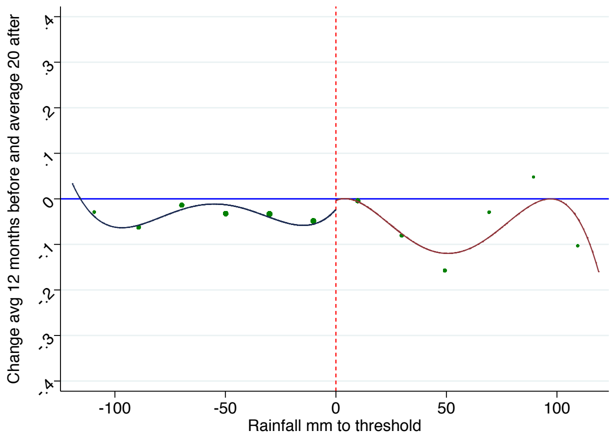
(a) △ log night lights, 0 to 3 months after



(b) △ log night lights, 0 to 5 months after



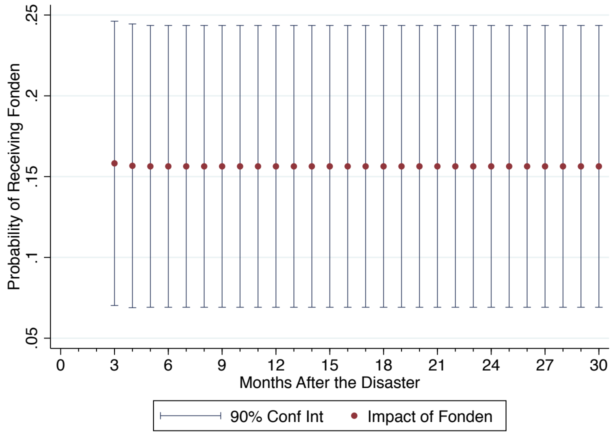
(c) △ log night lights, 0 to 15 months after



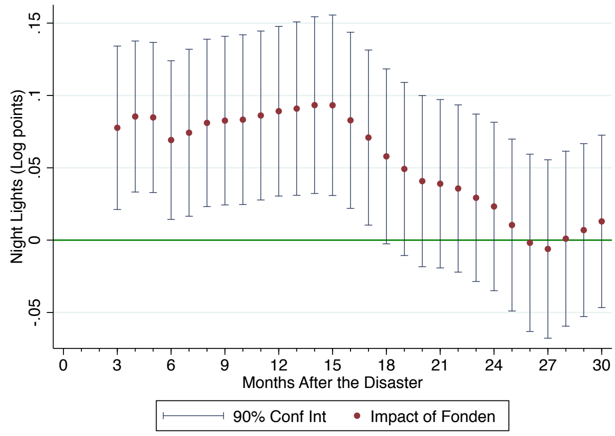
(d) △ log night lights, 0 to 20 months after

Note: The figures plot the local average at the mid-point of each bin, and a 4th order polynomial fit estimated separately on each side of the threshold. The size of the markers is proportional to the number of observations in each bin. The forcing variable is rainfall mm to the percentile 90 threshold. The dependent variable is the log change in night lights between the average in the 12 months before the disaster and the cumulative average at different points in the post disaster period. The optimal bin width is calculated, for each figure, following Calonico et al. (2014a).

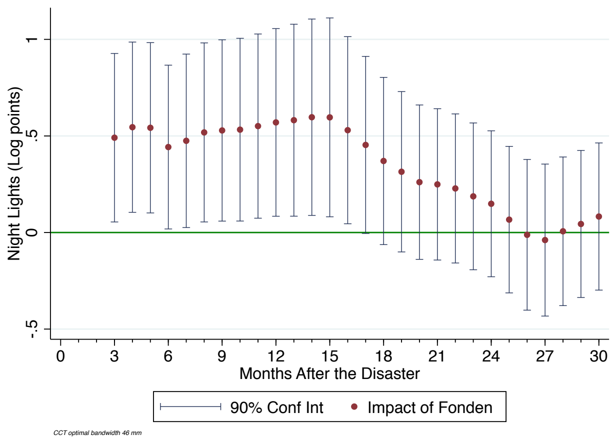
Figure 4: Dynamic impact of Fonden on night lights



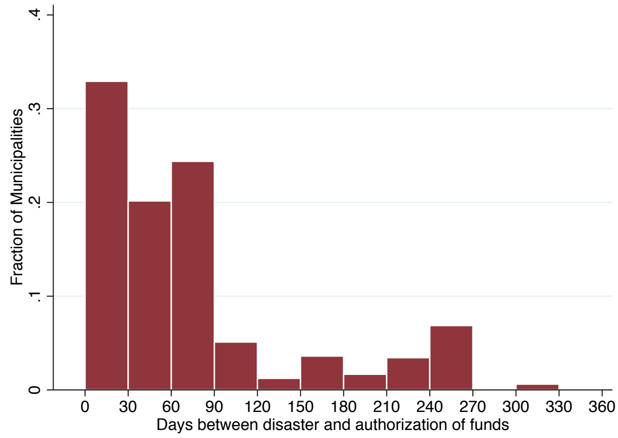
(a) Prob of receiving Fonden, First Stage



(b) △ log night lights, Reduced Form



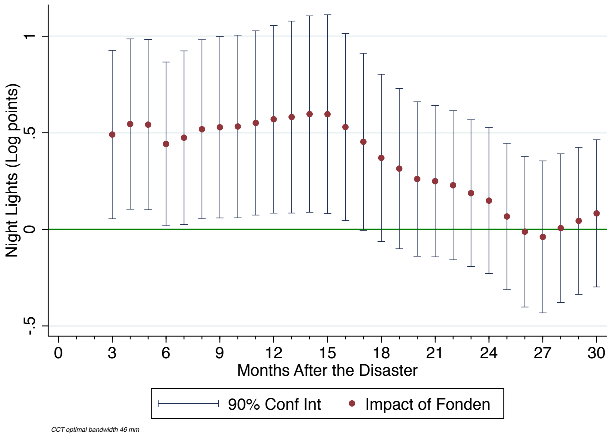
(c) △ log night lights, IV



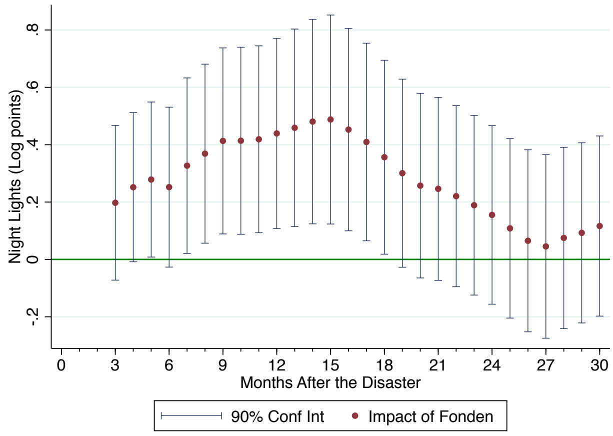
(d) Timing of Fund Authorization

In figures (a) to (c), the dependent variable is the log change in night lights between the average in the 12 months before the disaster and the cumulative average at different points in the post disaster period. Each plotted coefficient corresponds to a separate OLS regression where it is assumed that function $g(\cdot)$ is linear, the sample is restricted to the set of observations that fall within the average optimal bandwidth. Specifically, the following procedure was used: (i) The optimal bandwidth for each coefficient was derived by following Calonico et al. (2014b). (ii) In order to guarantee that all coefficients are estimated on the same sample, the average optimal bandwidth is calculated. (iii) All regressions are estimated within this average optimal bandwidth. The 90% confidence intervals are calculated using standard errors clustered at the municipal level. The night light data is derived from monthly composites where pixels have been averaged for years in which there is coverage of more than one satellite. Figure (d) plots the fraction of municipalities with Fonden funding in relation to the number of days between disaster and the authorization of funds.

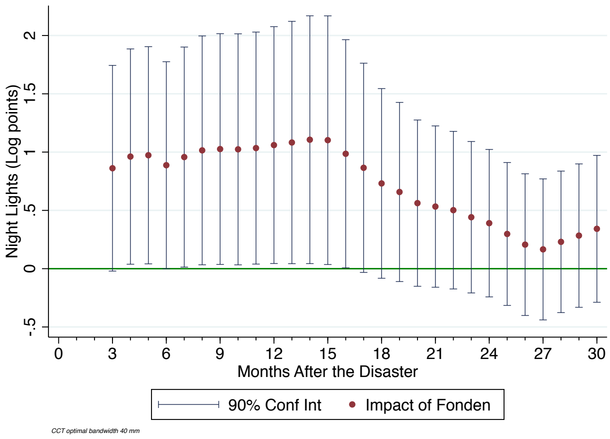
Figure 5: Robustness checks I



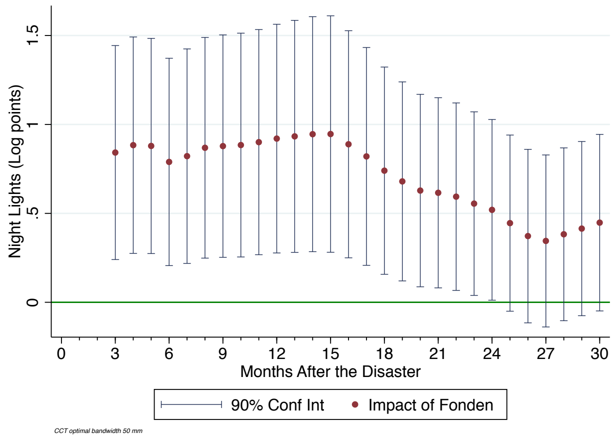
(a) Average optimal BW CCT



(b) Full sample cubic $g(\cdot)$



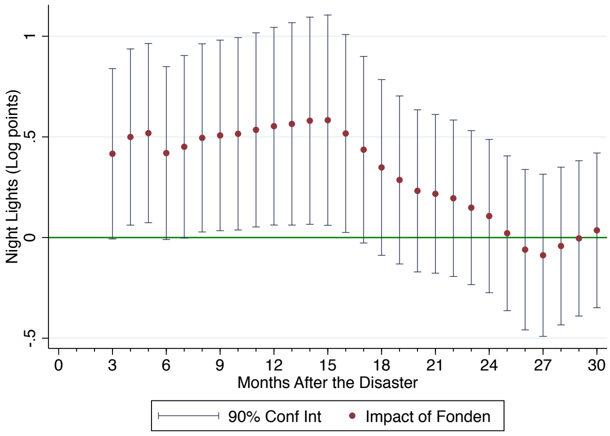
(c) Maximum optimal BW CCT



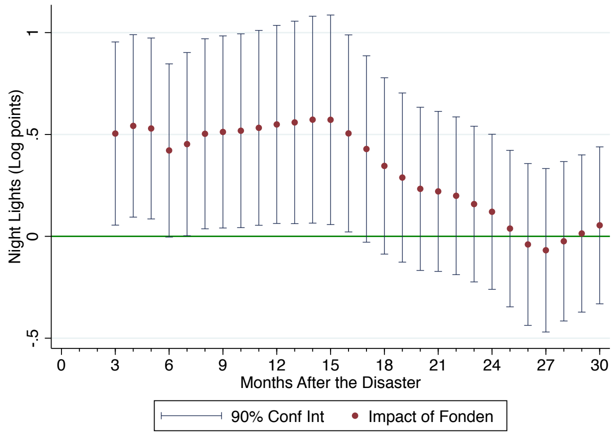
(d) Minimum optimal BW CCT

In all figures the dependent variable is the log change in night lights between the average in the 12 months before the disaster and the cumulative average at different points in the post disaster period. In figures (a) (c) and (d), each plotted coefficient corresponds to a separate OLS regression where it is assumed that function $g(\cdot)$ is linear. In each case the sample is restricted to the set of observations that fall within the average, the maximum or the minimum optimal bandwidth. Specifically, the following procedure was used: (i) The optimal bandwidth for each coefficient is derived by following Calonico et al. (2014b). (ii) In order to guarantee that all coefficients are estimated on the same sample, the average, maximum, and minimum optimal bandwidth is calculated. (iii) Each set of regressions are estimated within each of these bandwidths. In figure (b) each plotted coefficient corresponds to a separate OLS regression where the full sample is used and where it is assumed that function $g(\cdot)$ is cubic. The 90% confidence intervals are calculated using standard errors clustered at the municipal level. The night light data is derived from monthly composites where pixels have been averaged for years in which there is coverage of more than one satellite.

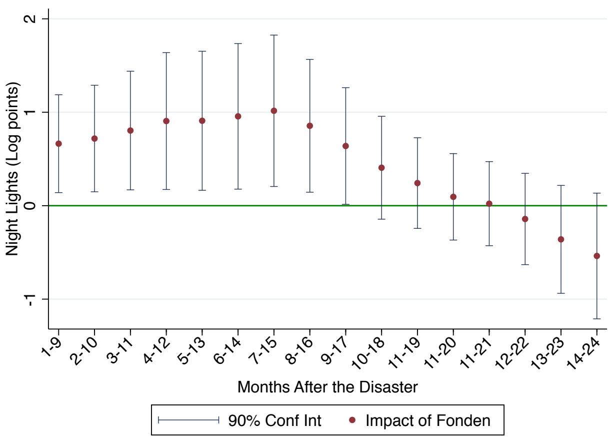
Figure 6: Robustness checks II



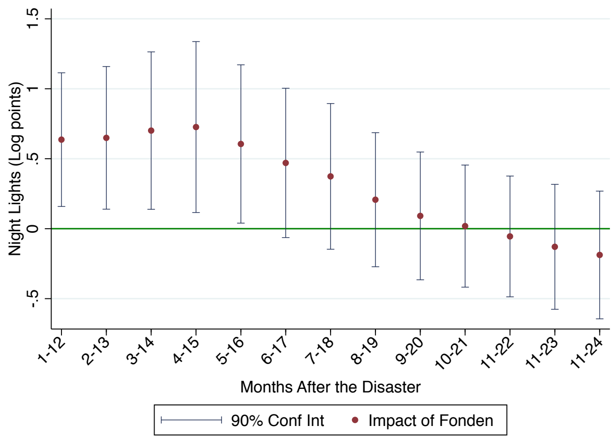
(a) Satellites F16 and F18 Only



(b) Excluding top coded pixels



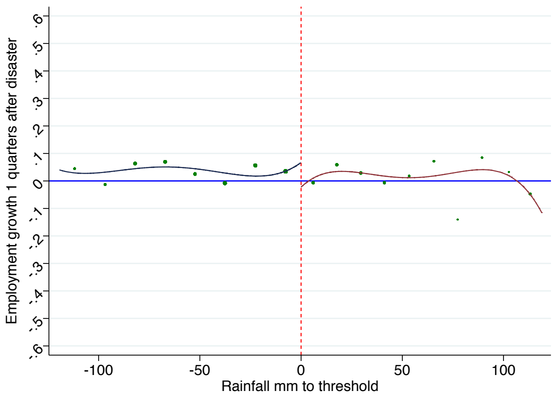
(c) Post disaster 9 month moving average



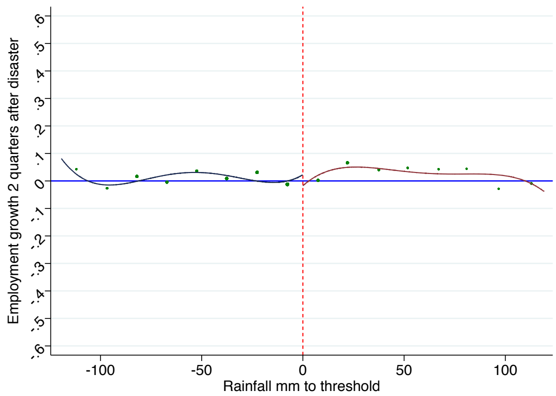
(d) Post disaster 12 month moving average

In figures (a) and (b) the dependent variable is the log change in night lights between the average in the 12 months before the disaster and the cumulative average at different points in the post disaster period. In figure (c) the dependent variable is the log change in night lights between the average in the 12 months before the disaster and a 9 month moving average in the post disaster period. In figure (d) the dependent variable is the log change in night lights between the average in the 12 months before the disaster and a 12 month moving average in the post disaster period. In all figures each plotted coefficient corresponds to a separate OLS regression where it is assumed that function $g(\cdot)$ is linear. In each case the sample is restricted to the set of observations that fall within the average optimal bandwidth. The specific procedure is described in the footnote of figure 4 The 90% confidence intervals are calculated using standard errors clustered at the municipal level. In figure (a) the night light data is not averaged at the pixel level, instead of using data from both the F15 and F16 satellites for the 2004-2007 period, we use only data from the F16 satellite. In figure (b) the night light data is derived from composites where top coded observations have been dropped. In figure (c) and (d) the night light data is derived from monthly composites where pixels have been averaged for years in which there is coverage of more than one satellite.

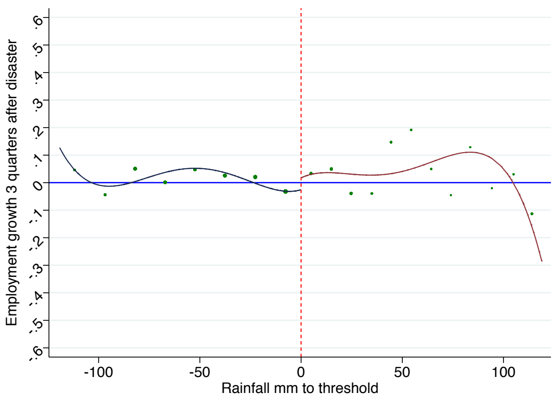
Figure 7: Employment growth by rainfall mm to the threshold



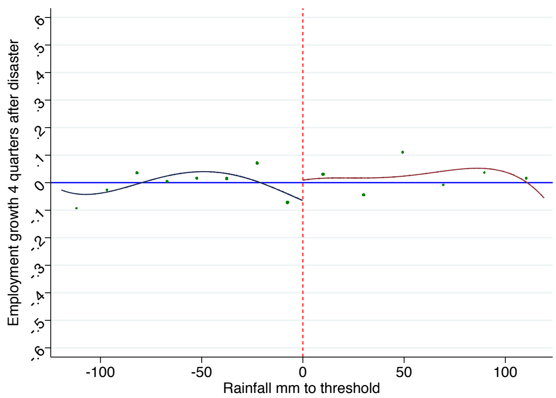
(a) 3 months After Disaster



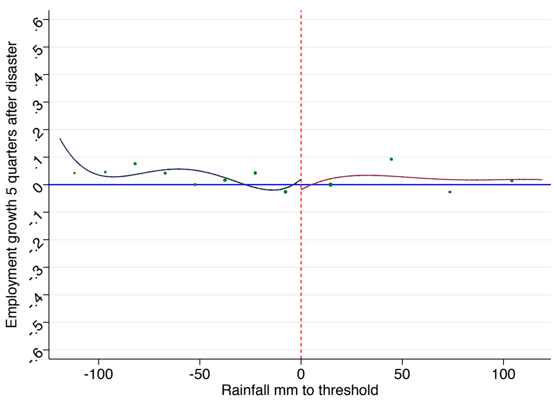
(b) 6 months After Disaster



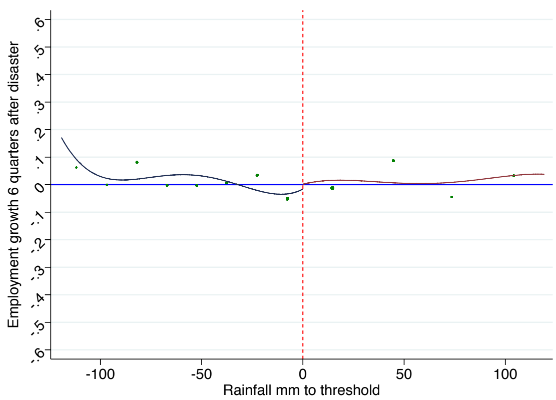
(c) 9 months After Disaster



(d) 12 months After Disaster



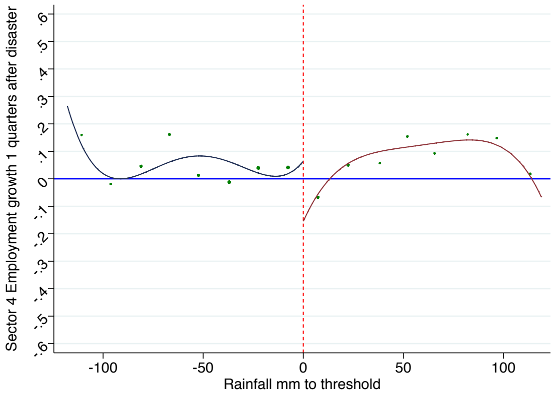
(e) 15 months After Disaster



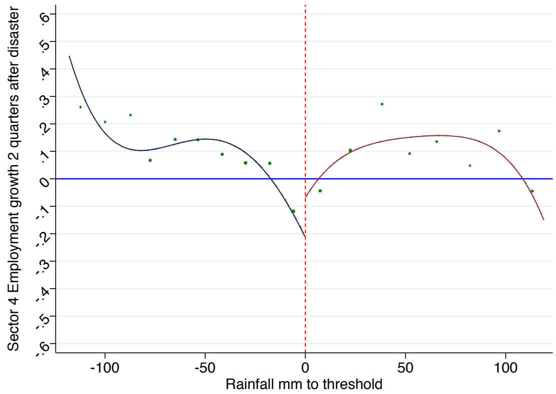
(f) 18 months After Disaster

Note: The figures plot the local average at the mid-point of each bin, and a 4th order polynomial fit estimated separately on each side of the threshold. The size of the markers is proportional to the number of observations in each bin. The forcing variable is rainfall mm to the percentile 90 threshold. The dependent variable is the log change in employment between the quarter the disaster takes place and various quarters in the post disaster period. The optimal bin width is calculated, for each figure, following Calonico et al. (2014a).

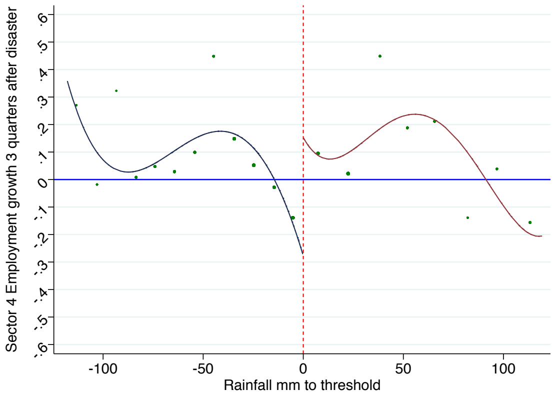
Figure 8: Construction employment growth by rainfall mm to the threshold



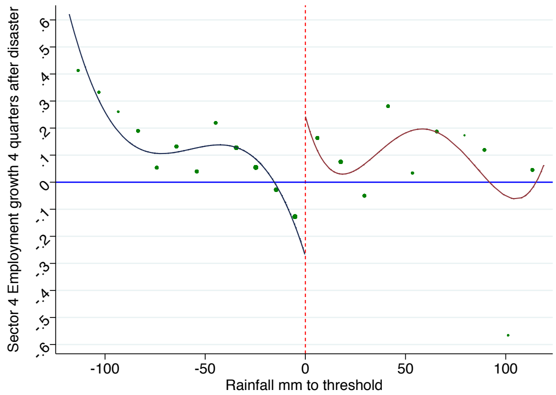
(a) 3 months After Disaster



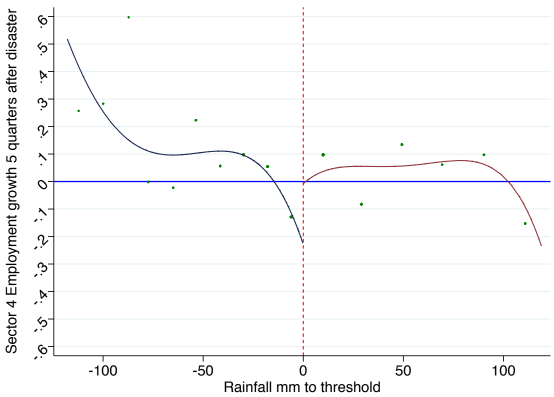
(b) 6 months After Disaster



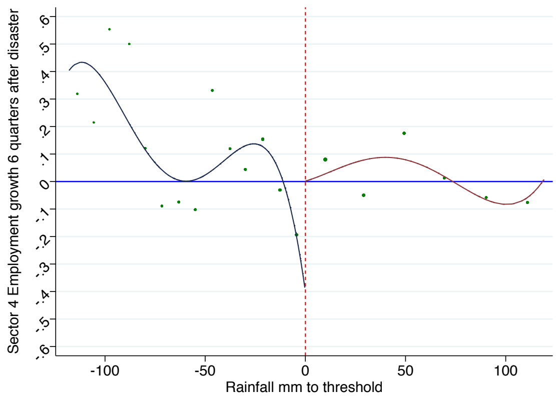
(c) 9 months After Disaster



(d) 12 months After Disaster



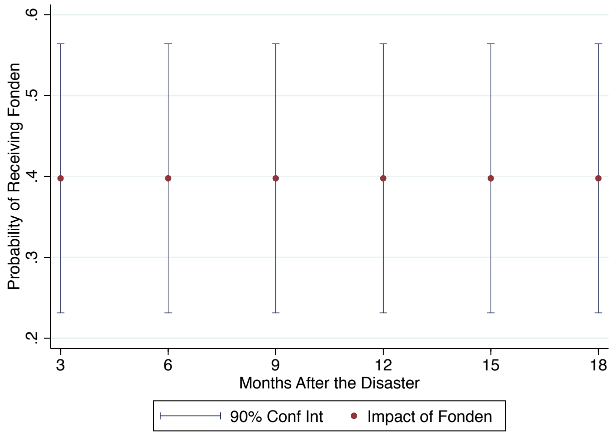
(e) 15 months After Disaster



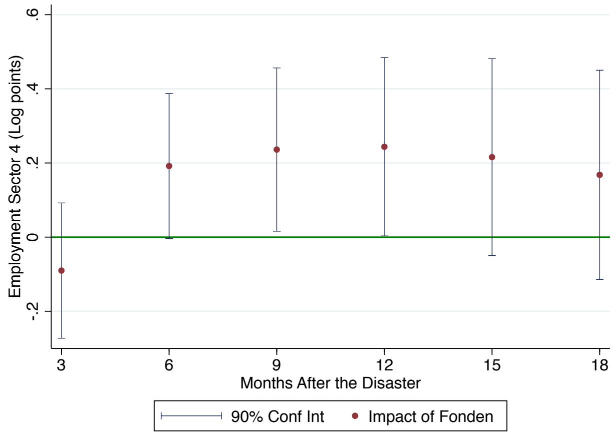
(f) 18 months After Disaster

Note: The figures plot the local average at the mid-point of each bin, and a 4th order polynomial fit estimated separately on each side of the threshold. The size of the markers is proportional to the number of observations in each bin. The forcing variable is rainfall mm to the percentile 90 threshold. The optimal bin width is calculated, for each figure, following Calonico et al. (2014a).

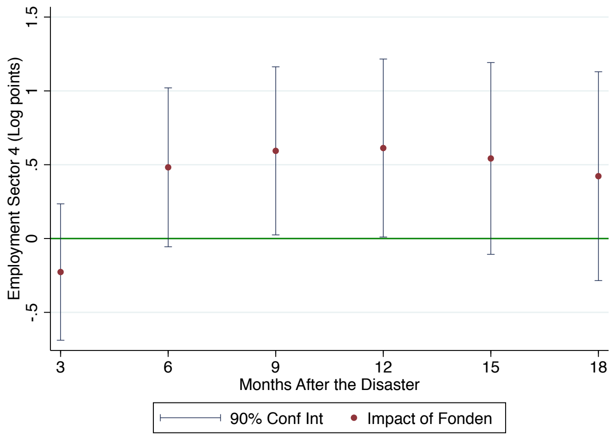
Figure 9: Impact of Fonden on Employment growth in the Construction Sector



(a) Prob of receiving Fonden, First Stage



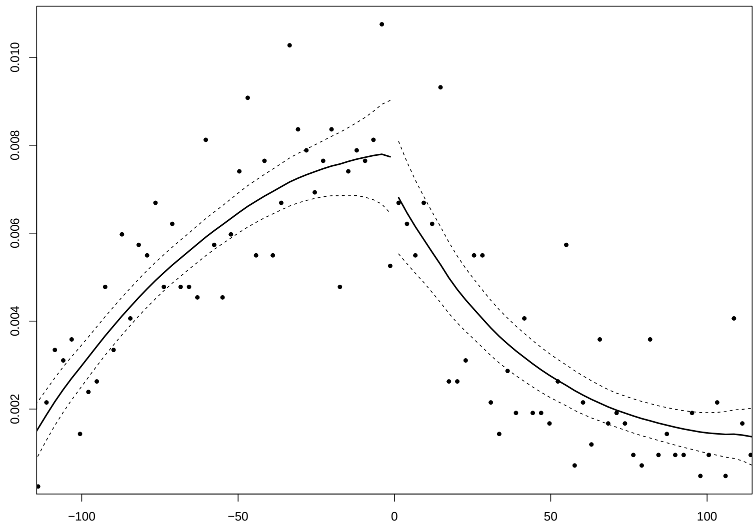
(b) △ log construction employment, Reduced Form



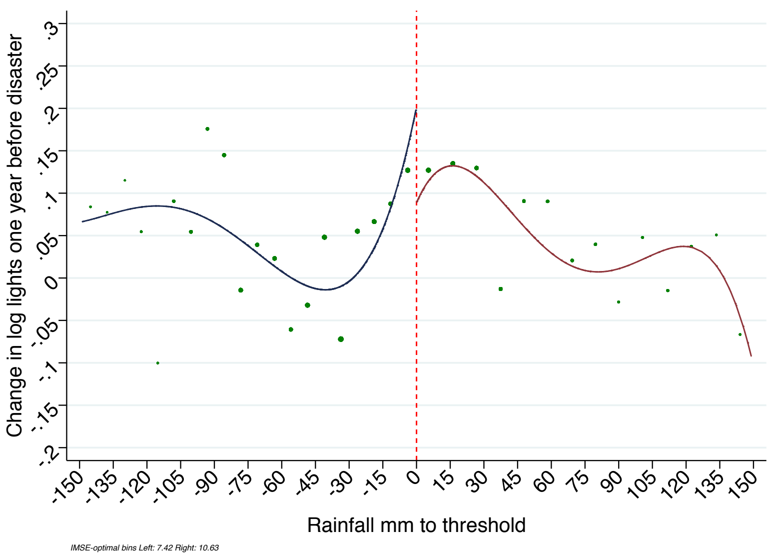
(c) △ log construction employment, IV

Note: Each plotted coefficient corresponds to a separate OLS regression where it is assumed that function $g(\cdot)$ is linear, the sample is restricted to the set of observations that fall within the average optimal bandwidth. Specifically, the following procedure was used: (i) The optimal bandwidth for each coefficient was derived by following Calonico et al. (2014b). (ii) In order to guarantee that all coefficients are estimated on the same sample, the average optimal bandwidth is calculated. (iii) All regressions are estimated within this average optimal bandwidth. The 90% confidence intervals are calculated using standard errors clustered at the municipal level.

Figure 10: Falsification exercises



(a) Density of forcing variable across the threshold



(b) Placebo: Change in night lights one year before disaster

Note: Figure (a) plots the density of the forcing variable in relation to rainfall mm to the threshold. The solid line is the density of the forcing variable as estimated by local linear regression, the dashed lines are the corresponding confidence intervals. The p-value of McCrary sorting test associated with this graph is 0.42. Figure (b) plots the local average at the mid-point of each bin, and a 4th order polynomial fit estimated separately on each side of the threshold. The size of the markers is proportional to the number of observations in each bin. The forcing variable is rainfall mm to the percentile 90 threshold. The dependent variable is the change in log night lights between two years before a disaster has taken place and the following year. The optimal bin width is calculated following Calonico et al. (2014a).

9 Tables

Table 1: Balance between municipalities with complete and missing information

	Mean mun. with missing information	Mean mun. with complete information	Difference of means (se)
No of Dwellings	9168.7	9036.6	132.0
			(1480.9)
with non dirt floor	7901.9	7306.8	595.0
			(1389.4)
with electricity	8591.0	8308.3	282.6
			(1427.6)
with tap water	7803.4	7079.2	724.3
			(1359.5)
with connection to sewage	7280.9	6628.0	653.0
			(1363.6)
with toillets	8302.1	7917.8	384.3
			(1406.6)
with tv	7842.3	7315.9	526.4
			(1383.4)
with fridge	6674.5	5715.3	959.3
			(1233.9)
with washing machine	5234.0	4088.3	1145.7
			(1011.4)
with pc	948.4	647.1	301.3
			(217.1)

Note: Standard errors in parentheses. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.Characteristics of dwellings are derived from 2000 census data. The sample is composed of municipalities that have requested Fonden between 2004 and 2011. The missing information group corresponds to municipalities missing either night lights, percentile 90 thresholds, or rainfall data in the same sample period.

Table 2: Summary statistics annual frequency night light data

Variable	Obs	Mean	Std. Dev.	P5	P95
Change in log light	1745	-.04	.28	-.43	.48
FONDEN=1	1745	.58	.49	0	1
Above threshold	1745	.36	.48	0	1
mm to threshold	1745	-13.09	74.94	-116.1	120.8
Inches to threshold	1745	-.52	2.95	-4.57	4.76
Rainfall mm	1745	93.21	79.5	4.5	265
Rainfall Inches	1745	3.67	3.13	.18	10.43

Note: Change in log lights refers to the change in log night light between the year the disaster takes place and the following year. Average rainfall refers to the average of maximum daily rainfall recorded for each municipality and disaster declaration pair.

Table 3: Summary statistics monthly frequency night light data

Variable	Obs	Mean	Std. Dev.	P5	P95
Change in log light	2833	-.05	.39	-.35	.24
FONDEN=1	2833	.58	.49	0	1
Above threshold	2833	.36	.48	0	1
mm to threshold	2833	-11.2	76.41	-111.7	133.55
Inches to threshold	2833	-.44	3.01	-4.4	5.26
Rainfall mm	2833	90.2	80.81	2	259.5
Rainfall Inches	2833	3.55	3.18	.08	10.22

Note: Change in log lights refers to the change in log night light between the year the disaster takes place and the following year. Average rainfall refers to the average of maximum daily rainfall recorded for each municipality and disaster declaration pair.

Table 4: The impact of Fonden

	(1)	(2)	(3)	(4)
Panel A: First Stage				
Variables	Fonden=1	Fonden=1	Fonden=1	Fonden=1
Above threshold (γ_1)	0.194***	0.140***	0.129**	0.157***
	(0.042)	(0.0510)	(0.0530)	(0.0506)
Panel B: Reduced Form & 2SLS				
Variables	$\triangle$ log light	$\triangle$ log light	$\triangle$ log light	$\triangle$ log light
Above threshold (β_1)	0.038**	0.0382	0.0481**	0.0439**
	(0.018)	(0.0235)	(0.0235)	(0.0222)
$\widehat{Fonden}$ (π_1)	0.196*	0.272	0.372	0.280*
	(0.104)	(0.199)	(0.238)	(0.167)
Observations	1,745	1,745	922	1,016
Specification	quadratic	cubic	linear	linear
Sample	Full	Full	Optimal bw	Optimal bw
			IK: 50.5 mm	CCT: 57.3 mm
Panel C: Impact of Fonden on economic activity				
Impact on local GDP %	2.21	3.07	4.20	3.16
Simulated benefit cost ratios				
Average	1.52	2.11	2.89	2.17
1 std dev. below Avg.	0.47	0.26	0.61	0.54
1 std dev. above Avg.	2.57	3.96	5.16	3.79
P(b/c>1)	0.66	0.71	0.80	0.76

Note: Standard errors clustered at the municipal level in parentheses. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels. All regressions include year fixed effects. Panel A presents OLS estimates of equation 1. Panel B presents OLS estimates of equation 2, and 2SLS estimates of the coefficient π_1. The label specification referrers to the polynomial order of the function $g(r_{mt} - c)$. In column 3, the optimal bandwidth was derived following Imbens and Kalyanaraman (2012). In column 4 the optimal bandwidth was derived following Calonico et al. (2014b). The impact on local GDP is derived by multiplying the 2SLS estimate by the elasticity of light to GDP. The details of this calculation and of the simulated fiscal multiplier can be found in sections 6 and 5.1.

Table 5: Night lights and municipal proxies of economic activity

	(1)	(2)	(3)	(4)
Panel A: Change in dwelling characteristics between census 2005 and 2010				
Variables	△ ln dwellings non dirt floors	△ ln dwellings with tv	△ ln dwellings with fridge	△ ln dwellings with wash machine
△ ln (lights/area)	0.262***	0.177***	0.200***	0.411***
	(0.034)	(0.026)	(0.025)	(0.048)
Observations	2,204	2,204	2,203	2,191
R^2	0.056	0.079	0.057	0.083
Panel B: Other economic proxies derived from administrative records				
Variables	ln users of electricity	ln car registrations	ln industrial building licenses	ln residential building licenses
ln(lights/area)	0.035***	0.063***	2.548*	0.491
	(0.011)	(0.017)	(1.438)	(0.378)
Observations	15,498	17,024	667	1,542
Municipalities	2,118	2,118	246	459
(Within municipality) R^2	0.120	0.570	0.081	0.055

Note: Standard errors clustered at the municipal level in parentheses. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels. Panel A uses a five year difference specification and has no other controls. Panel B includes both municipal and year fixed effects.

Table 6: Elasticity of night lights to State GDP

	Base Specification	Annual Fluctuations	Asymetric Fluctuations	Long Difference
	(1)	(2)	(3)	(4)
Variables	ln(GDP)	ln(GDP)	Res ln(GDP)	ln(GDP)
Panel A: log night lights derived from annual composites				
ln(lights/area)	0.246**	0.113**		0.978***
	(0.093)	(0.043)		(0.205)
|+ Res ln(lights/area)|			0.254*	
			(0.132)	
|- Res ln(lights/area)|			-0.239*	
			(0.131)	
(Within state) R^2	0.847	0.947	0.069	0.412
Panel B: log night lights derived from pixel averaged month composites				
ln(lights/area)	0.236***	0.115***		0.936***
	(0.060)	(0.035)		(0.247)
|+ Res ln(lights/area)|			0.263*	
			(0.141)	
|- Res ln(lights/area)|			-0.210**	
			(0.088)	
(Within state) R^2	0.852	0.948	0.096	0.444
Observations	234	234	234	26
State FE	✓	✓	In demean	.
Year FE	✓	✓	In demean	.
State Trend	.	✓	.	.

Note: Standard errors clustered at the state level in parentheses. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels. Mexico has 32 states. The sample has been restricted to the 26 states that have applied for Fonden funding between 2004 and 2011.