Relief Assistance Programs and Natural Disasters: Empirical Evidence on the Resilience of U.S. Counties using Dynamic Propensity Score Matching*

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Daniele Bondonio+
Robert T. Greenbaum++

Abstract

This paper utilizes a novel dynamic propensity score matching approach for multiple cohorts of U.S. counties between 1989 and 1999 to examine the ability of local economies to absorb and bounce back from rare natural disasters under the existing relief assistance provisions. Affected counties are sorted based on the disaster intensity, measured in terms of per-capita federal disaster relief, and carefully matched to similar counties that did not experience a disaster in the same reference year or the preceding and following years. Trends in county-level post-disaster business establishments, employment, and payroll of the affected counties are compared to counterfactual trends of non-disaster comparison counties using a difference-in-difference estimator. In the short run, all affected counties experienced a drop in economic activity that was particularly noticeable in the higher-intensity disasters. In the longer run, counties with lower unemployment and higher income prior to disasters were able to return to their estimated counterfactual trends by three years after a disaster. Counties with lower pre-disaster socioeconomic conditions still lagged in growth relative to comparison counties that did not suffer disasters, particularly in the cases of lower-intensity disasters relief compensation. Policymakers can use this information to better prepare responses for future natural disasters.

Keywords: Disaster Recovery; Natural Disasters; Resilience, Propensity Score Matching; Economic Development

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+ Università del Piemonte Orientale. Via Cavour 84, 15100 Alessandria (Italy) (+39) 131-283-712. daniele.bondonio@uniupo.it

++ John Glenn College of Public Affairs, The Ohio State University. 1810 College Road, Columbus, OH 43210-1336 (+1) 614-292-9578. greenbaum.3@osu.edu

1. INTRODUCTION

The enormous short-term social, structural, and economic toll of disasters on local communities is unambiguous. Numerous studies have quantified the costs of these disasters, speculated on changes in their frequency and impacts, and compared the costs and benefits of public versus private insurance. Future costs associated with natural disasters are likely to grow, as both the frequency and severity of natural disasters are projected to increase with global climate change (Ferris and Petz, 2013). Even absent climate change, costs are likely to rise due to changes in population distribution. The U.S. population and economic activity continue to move into areas more susceptible to natural disasters, such as costal locations, increasing both future exposure and vulnerability to disasters (Van der Vink, et al., 1998; Changnon and Changnon, 1999; Preston, 2013; Fraser, et al., 2016).

While the costs of coping with disasters are likely to increase, the effectiveness of relief incentives to businesses is unclear despite fact that the U.S. federal government spends billions of dollars in federal disaster relief payments, subsidized loans, and tax incentives to help rebuild disaster areas (Gravelle, 2005). Most existing evidence relies on case studies of individual events, making it difficult to draw broad implications, or on studies in which the entire country is the unit of analysis, making it difficult tease out the more localized effects of disasters. Additionally, because almost all disasters are accompanied by relief assistance and because the intensity of that assistance is typically proportional to disaster severity, the specific impact of the relief programs alone compared to a counterfactual of disasters occurring without assistance can never be rigorously estimated. Many studies fail to acknowledge such impact identification constraints (Cochrane, 2004). Finally, additional factors besides relief assistance programs may contribute to the longer-term ability of communities to recover from destructive events. For

example, the resilience of a community in terms of its ability to absorb, bounce back from, or adapt to a disruption (Martin and Sunley, 2015), may be also a function of its pre-disaster social and economic characteristics and pre-disaster planning. Overall, the few studies examining the longer-run effects of natural disaster recovery have mixed findings (Cavallo and Noy, 2011).

This paper fills these gaps in the literature in three ways. First, it examines both the ability to absorb a shock, often called static or ecological resilience (Martin and Sunley, 2017), and the ability to bounce back from a shock, often referred to as dynamic or engineering resilience (Rose, 2004). The paper focuses on the combined effects of a natural disaster and the related disaster relief efforts to estimate whether communities stricken by disasters display static resilience, as measured by their ability to sustain their economic growth in the short-run of one after the disaster, and dynamic resilience, as captured by their ability to bounce back three years after the disaster. Second, in response to Cavello and Noy's (2011) call for more research that establishes the appropriate counterfactual, the paper captures dynamic resilience by comparing the economic growth of affected counties to trends of carefully matched counties with similar characteristics that neither suffered a disaster nor received subsequent assistance. Third, the paper investigates how county resilience is affected by the interaction of socioeconomic pre-disaster characteristics of median household income and unemployment rates and the severity of the disaster as captured by the intensity of the federal disaster relief compensation. This is of particular policy relevance, as it can shed important light on the adequacy of federal and state disaster relief on the necessity to differentiate the relief interventions based on the pre-disaster socioeconomic characteristics and the importance of pre-disaster planning.

The empirical analysis utilizes a dynamic propensity score matching (DPSM) approach that sorts each annual cohort of counties struck by disasters into two disaster-intensity categories

(measured with reference to the median of the per-capita relief compensation) and two categories of pre-disaster economic conditions (in terms of median household income and unemployment rates). Separately for the two groups of disaster intensities, each affected county is carefully matched to a comparison group of unaffected counties belonging to the same category of pre-disaster conditions and sharing a similar propensity score that is estimated on the base of relevant county-specific covariates. After matching, a difference estimator (DD) compares the changes between the pre- and post-disaster trends of the affected and comparison counties in terms of number of establishments, employment, and total payroll.

To avoid relying on parametric functional form assumptions and to avoid reliance on heavy model dependence of the impact estimates, the DPSM-DD analysis focuses on the subsample of affected and unaffected counties that did not experience any other disaster in a period before and after the disaster. This conservative approach enables the observation of unaffected pre-disaster trends and the avoidance of treatment contamination concerns in the post-disaster period. Finally, to further reduce model dependence of the results, a straightforward non-parametric approach is adopted to address potential spatial-spillovers of the disasters.

This DPSM-DD approach is a novelty for longitudinal econometric analyses on spatially distributed data. Compared to the traditional longitudinal multiple regression framework, the DPSM-DD estimator avoids reliance on arbitrary functional forms that include the many interaction terms needed to accommodate the temporal dependence of the outcomes and the possible spatial spillovers. Compared to the conventional propensity score matching (PSM) approach, our dynamic specification avoids reliance on control variables that are fixed at an initial point in time for all subsequent annual cohorts of disasters. Rather, the matching process separately pinpoints with high accuracy the specific pre-disaster periods for each cohort of

affected counties. This feature enables the reconstruction of a specific and more reliable estimate of the counterfactual trend for all of the affected counties.

The DPSM-DD analysis is implemented using county level data drawn between 1989 and 1999 from multiple sources. Information on disaster declarations and relief assistance provisions come from the Department of Homeland Security's (DHS) Federal Emergency Management Agency (FEMA); information on disaster lending comes from the United States Small Business Administration (SBA); and information on business establishment employment, payroll, and industrial sector come from the Census Bureau's County Business Patterns (CBP).

The results of the DPSM-DD analysis indicate that in terms of static resilience, within one year after a disaster, all affected counties faced lower growth of employment, total payroll and number of establishments compared to counterfactual growth estimated from the sample of unaffected counties with the same pre-disaster characteristics and trends. For both the groups of counties with pre-disaster socioeconomic conditions below and above the median, the size of this short-run negative growth gap is higher for the disasters with high-intensity relief compensation, with point estimates from -2.75 to -3.10 percentage points (p.p.), than for the low-intensity disasters with point estimates from -1.43 to -2.06 p.p. In terms of dynamic resilience, the DPSM-DD analysis shows that the affected counties with stronger pre-disaster socioeconomic conditions were able to fully bounce back within three years to their no-disaster counterfactual growth trends of employment, payroll and number of establishments. This was the case for both lower and higher intensity disasters. The dynamic resilience of counties with lower pre-disaster socioeconomic conditions was generally weaker but with a higher sensitivity to disaster intensity. When faced with lower intensity disasters, these counties still significantly lagged their counterfactual trends (ranging from 2.1 to 2.4 p.p.) three years after the disaster. However, for

disasters that entailed relief compensations that were above the median, the negative growth gaps shrank to approximately half that from the short-run results, ranging from 1.0 to 1.3 p.p., and were not statistically significantly different from zero for the employment and payroll outcomes. This may be an indication that less well-off counties are particularly vulnerable to natural disasters that may require more of their own resources for recovery.

The remainder of the paper is organized as follows. The next section presents a brief review of the literature on government recovery incentives, including a discussion of the FEMA and SBA programs. That is followed by the empirical estimation strategy, a description of the data and descriptive statistics, the sensitivity analysis and the discussion of the results and their implications.

2. REBUILDING COMMUNITIES

Economic resilience pertains to the ability of an economy to either bounce back to its pre-shock state, adapt to the new state, or to remain at the earlier state by minimizing losses (Rose, 2004; Hill, et al., 2012). Thus, the degree of resilience is a function not only the severity and frequency of shocks to the economy but also of the pre-shock characteristics of the local economy and the effectiveness of the disaster relief efforts. The primary federal programs designed to bolster resilience and the existing literature examining local resilience to disasters are discussed below.

Disaster relief efforts

Subsequent to a major disaster, financial assistance is provided by a number of local, state, and federal agencies, as well as by charitable organizations such as the Red Cross. The relative role of the federal government has grown tremendously, increasing from around one percent of post-

disaster relief in 1953 to 70 percent by the mid-1970s (Clary, 1985; Barnett, 1999). The primary sources of non-agricultural federal disaster assistance are FEMA and the SBA (Barnett, 1999).

After a presidential declaration of a disaster or emergency, FEMA provides housing and non-housing assistance to both affected individuals and businesses. FEMA direct assistance aims to address uninsured losses by helping to cover critical expenses and is not intended to restore property to pre-disaster conditions. The housing assistance consists of money or direct assistance for temporary housing and the repair and replacement of homes not covered by insurance. Non-housing assistance directs money to necessary expenses and serious needs caused by the disaster, including medical and funeral costs, household items, and clean up items. FEMA also provides services such as crisis counseling and unemployment assistance, and FEMA provides additional public disaster recovery assistance in the form of grants to nonprofit organizations and state and local governments.

Within a declared disaster area,[1] SBA assistance takes the primary form of direct below-market loans (not grants) to individual homeowners, renters, and businesses to assist with uninsured real and personal property losses through the Physical Disaster Loan Program. The loans can be used to restore property to pre-disaster conditions or to protect the property against similar future disasters. SBA's Economic Injury Disaster Loan Program also provides below market loans to businesses that have suffered economic injury due to the disaster to assist with necessary financial obligations they would have otherwise not been able to meet. Economic Injury Disaster Loans represent only about 20% of SBA disaster assistance. The SBA lending provides afflicted areas with capital infusions intended to aid economic resiliency though the provision of economic stimulus via the creation and retention of jobs, support of businesses, and

[1] Beyond a presidential disaster declaration, SBA's disaster assistance programs may also be triggered by a disaster declaration from a state governor or the Secretary of the U.S. Departments of Agriculture or Commerce or by the SBA itself.

stabilization of the local tax base. The federal government has also experimented with tax incentives to encourage businesses to invest in improvements to help with post-disaster recovery, such as in the form of the post-Katrina Gulf Opportunity Zones (Stoker and Rich, 2006).

Local resilience to disasters

Analysis of the economic consequences of disasters is often performed at the national level. Local effects, however, can be missed at these more aggregated levels. For example, Strobl (2011) found that over a quarter of the negative economic impacts on county growth rates due to hurricanes was a result of outmigration of higher income individuals, which partially explained why the same storms had little effect on state-wide or national growth rates.

Even when examined from the perspective of the local economy, previous literature examining how disasters have affected longer-term economic performance is somewhat mixed (Waugh and Smith, 2006; Cavallo and Noy, 2011). In many cases, the negative effects are found to be short-lived. For instance, while Elliott, Strobl, and Sun (2015) found large economic disruptions to local economies in coastal China, the effects were primarily short-term. Similarly, Xiao found that while the 1993 Midwest floods in the United States led to initial declines in per capita income, counties rebounded in subsequent years (Xiao, 2011).[2] Noy and Nualsri (2007) found longer-run negative effects of disasters at the country level using growth models, particularly when human capital is affected.

Conversely, Skidmore and Toya (2002) found positive effects at the national level. The positive effects can stem from the stimulative effects of rebuilding with newer technology and investments in human and physical capital, as well as upon removing previous barriers to growth. In an examination of recovery efforts subsequent to the 2007 flood that devastated East

[2] While Xiao (2011) found no long-run impacts of the flood on income or employment, there were some longer-run negative impacts on the agricultural industry.

Grand Forks, MN, Reese (2006) observed that the disaster not only helped remove some previous political and physical impediments to redevelopment, but it galvanized "Commitment, cooperation, creativity, inclusivity, and flexibility" (Reese, 2006, 229). This, coupled with the significant local and regional foundation support and public aid, arguably left East Grand Forks in a more competitive position than before the flood. Likewise, Siodla (2015) found that the 1906 earthquake and resulting San Francisco Fire served to remove an important barrier to redevelopment, the existence of older structures. Compared to unburned areas, the areas affected by the fire saw much denser development that is still evident over a century later. Further, Hornbeck and Keniston (2017) found positive externalities on nearby unburned properties due to rebuilding after the Boston Fire of 1872.

One explanation for the mixed findings in the literature regarding disaster recovery may be that, across disasters, recovery is likely affected by not only the severity of the disaster and the resulting governmental relief aid, but, perhaps more importantly, the characteristics of the local economy, population, and institutions. In some cases, disasters may compound other pre-existing disadvantages, while in other cases the costs imposed by the disaster may be less than the opportunities created. In their examination of the 1872 Boston Fire, Hornbeck and Keniston (2017) were careful to note that the same fire in a declining city would likely have instead led to negative externalities and therefore economic losses. In their review of the literature on poverty and disasters, Fothergill and Peek (2004) found that socioeconomic status is related not only to how people perceive and prepare for disasters but that it also affects the ability to response to disasters. Beyond greater financial resources providing a source of self-insurance to aid in recovery, individuals with higher incomes were found to be more successful in navigating the disaster relief process gaining greater access to relief resources. Regarding disaster relief

spending, Chang (1984) concluded that part of the success of such efforts depends on how much of the recovery spending remains in the local economy. Barone and Mocetti (2014) demonstrated quite starkly the role of local characteristics by comparing longer-run growth patterns in two Italian regions that were hit by large earthquakes and received post-disaster financial assistance. In one case, there were positive long-run outcomes compared to a synthetic control, while in the other case, there were negative long-run outcomes. The differences were attributed to pre-disaster economic and social conditions, including the quality of institutions. Further, at the national level, Kellenberg and Mobarak (2008) found that pre-disaster per capita income may have non-linear impacts on post-disaster economic growth.

3. EMPIRICAL STRATEGY

Our empirical analysis focuses on estimating whether counties affected by natural disasters are capable of bouncing back to the counterfactual economic trends that they would have experienced in the absence of the disaster and the subsequent relief assistance. Thus, the analysis translates into estimation of the economic growth impacts of *treatments* that consist of the resulting combined damage of a natural disaster and the subsequent benefits of disaster relief compensation. As discussed elsewhere (e.g., King and Zeng, 2006; Ho et al., 2007; Abadie et al., 2014), in the context of similar causal inference analyses with geographically-aggregated panel data, adopting a traditional fixed-effect panel data regression approach would result in estimates that rely heavily on specifying the correct functional form of the model. This is because the suitable regression specifications would have to accommodate, with specific functional form choices, the many lagged and trailing temporal interaction terms needed to model the temporal dependence of outcomes and the many spatial interaction terms required to accommodate the

possible spatial spillovers of the effects. Because very little guidance is typically available to define which specific functional form is best for the model, the results from such regression framework models tend to be subject to high model sensitivity, resulting in high volatility of the impact estimate to the different functional form options.

To overcome these limitations, a synthetic comparison (SC) approach has been proposed in the recent literature for comparative case studies that exploit regional- or country-level data to estimate the impacts of events occurring in a small subset of the geographic areas that serve as units of observation for the analysis (e.g., Abadie et al., 2014; Abadie and Gardeazabal, 2003; Cavallo et al., 2013). Robbins et al. (2015) recently proposed a solution to expand this framework of the SC approach to also include high-dimensional, micro-level data. Robbins et al. (2015) justified this extension of the SC framework as superior to the standard DD approach that requires a strict parallel trend assumption. However, as is well established in a very large body of program evaluation literature (ranging from the seminal work of Rosenbaum and Rubin, 1983, 1985; and Heckman et al., 1997, 1998a, 1998b; Imbens, 2000; Lechner, 2001 to the applications of multiple consecutive cohorts of treated units by Sianesi, 2004, Biewen et al., 2007), in the case of conspicuous samples of units of observations and multiple treated and non-treated units with an adequate set of observable characteristics, a propensity score approach surpasses the need of the parallel trend assumption and constitutes the best suitable estimation strategy for the analysis. In this paper we extend the dynamic propensity score approach used in Sianesi (2004) and Biewen et al. (2007) to the case of panel data with geographical cross-sectional units and multiple treatments occurring in multiple times and multiple units in our period of observation.

The approach also has similarities to the generalized propensity score (GPS) model (Hirano and Imbens 2004, Imai and Van Dijk 2004) implemented by Becker et al. (2012) in the

context of multiple cohorts of treatments occurring in the European regions in consecutive budgetary periods. In our case, however, embedding the various degrees of compensation intensities into the analysis through a GPS model would entail losing the informative focus on estimating resilience outcomes with respect to a counterfactual status of absence of the disaster. The GPS estimates would primarily yield marginal impacts of continuously-varying levels of the relief assistance, with reference to other levels of relief assistance intensities. These estimates would not produce more informative results than those in a discrete categorical setting also because no exogenous variation in the intensity of the compensations can be observed in the data independently from the severity of the disaster. For these reasons, we opted for a novel empirical strategy that implements the features of a dynamic propensity score matching model within the setting of multiple discrete categories of the *treatment* (e.g. Lechner, 2001, 2002; and Bondonio and Greenbaum, 2014) that are based on the different pre-disaster socioeconomic conditions of the counties interacted with different intensities of the disaster compensations. Within such strategy, all impacts are still estimated with reference to the comparison group of no-disaster observations that are used to reconstruct the counterfactual growth trends. This feature enables investigation of the types of communities are capable to fully bounce back to their counterfactual growth trajectory under different categories of disaster intensities, shedding light on the possible need to differentiate future relief interventions based on pre-disaster economic conditions or the differential need for pre-disaster mitigation efforts.

We implement our dynamic propensity score matching (DPSM) procedure by sorting each annual cohort of counties hit by disasters into two categories of pre-disaster socioeconomic conditions (based on median household income and the unemployment rate) interacted with two disaster intensity categories (measured with reference to the median of the per-capita

compensations). Each affected county is carefully matched separately for the two groups of disaster intensities with a comparison group of unaffected counties belonging to the same category of pre-disaster conditions and sharing a similar propensity score that is estimated based on relevant county-specific characteristics. The combined effect of the disaster and the subsequent relief assistance is then estimated separately for each category of affected counties by adding to the matching procedure a difference in difference (DD) scheme that exhaustedly controls for the pre-disaster growth trends of the employment, payroll and establishment outcomes considered in the analysis.

In detail, the DPSM-DD model is operationalized by first sorting county-level panel data into multiple data sets. Each data set is centered on a single reference year ranging from 1992 to 1996[3] and includes three-year periods before and after the reference year. To begin, for each data set, all counties hit by a disaster in the reference year are included. To avoid confounding effects of other recent disasters, which would affect pre-disaster economic levels and trends, all counties that suffered disasters within three years before the particular disaster year are excluded. Similarly, the affected counties that were hit by an additional disaster during the three years subsequent to the reference year are excluded as well, because post-disaster outcomes that were unaffected by another disaster cannot be measured for those counties. Likewise, the pool of potential control counties in each data set to be matched through the PSM procedure includes all counties that were unaffected by a disaster both in reference year and in the previous and subsequent three years. Five such yearly cohorts of treatment counties hit by a disaster (with reference-year t ranging from 1992 to 1996), and suitable potential control counties are identified.

[3] The estimation period is bounded by the availability of the disaster information and relief assistance data from FEMA and SBA data over the period 1989-1999 and the need to include the three-year periods before and after each reference year.

Each yearly cohort of counties is then divided into two groups based on a combined index (I)[4] of median household income and unemployment rate. Within each reference year, the disaster status of each county is sorted into three categories: no disaster, low-intensity disaster (when the per-capita FEMA disaster relief compensation is below the median of the distribution) and high-intensity disaster (with per-capita FEMA compensation above the median). The results produced by the DPSM-DD estimator are in terms of average treatment effects on the treated parameters $\tau(c, w)$[5] = $E\ (Y^1_c - Y^0 |\ T^c = 1, w)$, with w being a category of pre-disaster socioeconomic conditions; Y^0 indicating the economic growth outcome that would be observed if a county i is not hit by a disaster; Y^1_c, indicating the growth outcome that would be observed if a county is hit by a disaster entailing a compensation intensity of category c, and T^c being the disaster status variable. These $\tau(c, w)$ parameters are estimated separately for each group of disaster-hit counties, defined by the interaction of the two categories of compensation-intensities c={low, high} and the two categories pre-disaster socioeconomic conditions $w=\{I^{lw}, I^{hi}\}$. Estimating these categorical impacts $\tau(c, w)$ enables the analysis to hold constant the degree of compensation intensity when informing on the differential resilience of counties with different pre-disaster economic conditions, and, conversely, to hold constant the pre-disaster economic conditions when informing on the differential resilience of counties hit by disasters entailing different degrees of compensation intensities. The propensity score matching (PSM) procedure,

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[4] For each county i, the combined index I_i is operationalized as the sum of the standardized deviations from the median of the two variables:
$I_i = \left(\frac{HOUSINC_i - med(HOUSINC)}{std(HOUSINC)}\right) + \left(\frac{med(UNEMPRT) \ \ - UNEMPRT_i}{std(UNEMPRT)}\right)$, where $HOUSINC_i$ and $UNEMPRT_i$ are the median household income and the unemployment rate of a county i , based on 1990 Census data.

[5] τ(c, w) are in terms of *average treatment effects on the treated* (ATT) defined against a counterfactual status of not incurring in any type of disaster. Such operationalization of the categorical ATTs parameters allows ease of interpretation of the differential impacts for the different subpopulation of the treated counties, compared to other empirical designs developed in the literature (e.g. Gerfin and Lechner 2000, Lechner 2002), in which the effects of a treatment of category *c* are defined against a counterfactual state were the treated units would be randomly assigned to one of the other treatment categories with probabilities given by weights defined by the relative participation frequencies.

leading to the estimation of the $\tau(c, w)$ impacts, begins with the following set of four probit specifications, defined by the interactions of c= {low, high} and w={I^{lw}, I^{hi}}:

$$P[T_i^c = 1] = \Phi[X_{t-1}; X_{90}, \lambda_t] \;\Big|\; i \in w\{I^{lw}, I^{hi}\}, c = \{\text{low, high}\} \qquad (1)$$

where

T_i^c= [0,1], where 1 represents when county *i* is hit by a disaster with categorical intensity *c*, and 0 represents when county *i* is not hit by any disaster in a reference year;

X_{t-1} = set of county-specific local economic characteristics (measured one year before the reference year *t*):

-percent employment in agriculture;

-percent employment in manufacturing and mining sectors;

-percent employment in services, transportation, retail and construction sectors;

X_{90} = set of county-specific 1990 Census characteristics:

-median household income;

-median housing value;

-unemployment rate;

λ_t = set of dummies for the reference years *t*.

The estimation of the first probit specification (1), defined by *c=low* and *w*=I^{lw}, is based on the subsample of counties with either disasters with high-intensity compensations ($T_{i,t}^{c=low} = 1$) or no-disaster ($T_{i,t}^{c=low} = 0$) and belonging to the group of below-median pre-disaster socioeconomic conditions (*w*=I^{lw}). The resulting predicted probabilities [$T^{\wedge c=low} = \Phi[X_{i,t-1}\varphi^{\wedge}, X_i\gamma^{\wedge}, \lambda^{\wedge}_t] \mid w = I^{lw}$] correspond to the propensity score variable ($PS^{c=low}|w=I^{lw}$) that summarizes the most relevant pre-disaster characteristics (X_{t-1}, X_{90}) of the local economy of the counties. This ($PS^{c=low}|w=I^{lw}$) variable in then used to match each county hit by a low-

intensity disaster and with below-median pre-disaster socioeconomic conditions (w=I^{lw}) with a comparison group of non-disaster counties that share the same pre-intervention characteristics and belong to the same category w=I^{lw}. Likewise, the propensity scores ($PS^{c=high}$| w=I^{lw}), ($PS^{c=low}$|w=I^{hi}) and ($PS^{c=high}$|w=I^{lw}) yielded from the other three probit specifications (2) are used to separately find the suitable comparison group for the disaster-hit counties belonging to the other categories of compensation-intensities c and pre-disaster socioeconomic conditions w. All these matching procedures are performed with a radius matching algorithm (with replacement) and a δ tolerance of 0.05.[6]

For each disaster-hit county i, both "short-run" (SR) static resilience (one year after the disaster) and "long-run" (LR) dynamic resilience (three years after the disaster) local impacts α_i are then estimated using the data of the matched non-treated counties and applying the following triple difference (DDD) schemes in the form of[7]

$$\alpha_i^{SR}=\left[\left(\frac{1}{2}\frac{Y_{t+1}-Y_{t-1}}{Y_{t-1}}\right)-\left(\frac{1}{2}\frac{Y_{t-1}-Y_{t-3}}{Y_{t-3}}\right)\middle|\, PS_{it},\, T_{it}=1\right]-\left[\left(\frac{1}{2}\frac{Y_{t+1}-Y_{t-1}}{Y_{t-1}}\right)-\left(\frac{1}{2}\frac{Y_{t-1}-Y_{t-3}}{Y_{t-3}}\right)\middle|\, PS_{it},\, T_{it}=0\right] \quad (2)$$

$$\alpha_i^{LR}=\left[\left(\frac{1}{4}\frac{Y_{t+3}-Y_{t-1}}{Y_{t-1}}\right)-\left(\frac{1}{2}\frac{Y_{t-1}-Y_{t-3}}{Y_{t-3}}\right)\middle|\, PS_{it},\, T_{it}=1\right]-\left[\left(\frac{1}{4}\frac{Y_{t+3}-Y_{t-1}}{Y_{t-1}}\right)-\left(\frac{1}{2}\frac{Y_{t-1}-Y_{t-3}}{Y_{t-3}}\right)\middle|\, PS_{it},\, T_{it}=0\right] \quad (3)$$

Where Y = {employment, number of establishment, total annual payroll}.

The DDD schemes (2) and (3) are added to the propensity score matching procedure to adequately control for any differences in the pre-intervention trends (along the years t-1 – t-3) in specific counties.

[6] The procedures are performed with the *PSmatch2* Stata program (Leuven and Sianesi, 2003).
[7] In both equations (3) and (4), the percentage changes of Y over the two-year periods (i.e. $Y_{t+1}-Y_{t-1}$ and $Y_{t-1}-Y_{t-3}$) and the percentage changes over the three-year periods (i.e. $Y_{t+3}-Y_{t-1}$) are normalized into yearly changes.

Next, the local impacts α_i^{SR} and α_i^{LR} are aggregated across all disaster-hit counties *i* to generate the estimated average treatment effects $\tau\text{^}(c, w)^{SR}$ and $\tau\text{^}(c, w)^{LR}$ for the four separate categories of counties hit by a disaster defined by the interactions of *c* and *w*.[8]

The DPSM-DD estimation model described above is conceptually similar to the dynamic difference in difference model used in Husby et al. (2014) for estimating the impacts of floods and flood mitigation programs in the Netherlands. Compared to this model and to standard panel-data multiple regression frameworks, however, the DPSM-DD reduces the model's sensitivity to the functional form choices of the control variables. This is due to the balancing property of the PS. As is well established in the literature (e.g., Rosenbaum and Rubin, 1983, 1985; Heckman et al., 1997, 1998a, 1998b; Dehejia and Wahba, 1999; Imbens, 2000; Lechner, 2001), this property ensures that the functional forms used in the probit specifications (2) are such to achieve full balancing between treated and non-treated counties within each stratum of similar PS for all the covariates, X..

To further limit the model dependence of the results, the possible treatment contamination issues due to the presence of temporal and spatial spillover effects of the disasters are dealt with non-parametrically. Excluding counties that experienced a disaster in the three years prior or subsequent to the disaster year *t* minimizes treatment contamination issues due to temporal spillover effects. Spatial spillover effects are dealt with in the following straightforward manner. When the exact location of the disaster is confined within the boundaries of a single county, spatial spillovers are assumed to exist within the entire county to which is assigned the treatment status (T=1). When the location of the disaster spans the boundaries of multiple

[8] To assess the pair-wise statistical significance of the differences between the various categorical impacts $\tau(c, w)$, the DPSM-DD model is re-estimated by defining as the counterfactual state the occurrence of a disaster with compensation intensity of the other category c, holding constant the pre-disaster economic conditions *w* and by holding constant the compensation intensity *c* and defining as counterfactual state the belonging to the other pre-disaster categorical conditions *w*.

counties, all such counties that received FEMA disaster relief compensation are assigned a treatment status T=1.[9] Thus, spatial spillovers are assumed to exist within all the counties that overlap any portion of the disaster location. This choice limits the model dependence and volatility of the impact estimates and is consistent with the case-study evidence of more localized impacts of disasters (e.g. Strobl 2011).

4. DATA AND DESCRIPTIVE STATISTICS

The data used in the analysis are compiled from multiple sources. Information on disaster declarations are drawn from a database provided by the Federal Emergency Management Agency (FEMA) detailing all the agency Major Disaster, Emergency Management, and Fire Management Assistance declarations for the 50 states and District of Columbia between 1989 and 1999. Information on declaration date, disaster type, and total value of FEMA assistance were provided for each incident, and information from the Federal Register was used to assign individual counties to each FEMA incident declaration. These data were combined with Small Business Administration (SBA) data on lending under their Disaster Loan Program for the period 1989-1999. Each entry in this data set, representing information on each of the Disaster Loan Program's individual loans disbursed during this period, includes the date of disbursal, amount of the loan, location of the recipient (state, county, city, and ZIP code), industrial classification of the establishment receiving the loan (using SIC or NAICS classification systems, as appropriate), and whether the loan was directed at a business or an individual. Measures of business activity were drawn from County Business Patterns (CBP) data for 1988-2000, including total number of

[9] FEMA data only allow us to identify which counties received assistance in response to a particular disaster but not the distribution of that assistance within and across the affected counties.

establishments, total annual employment, and total annual wages by county. Decennial U.S. Census data from 1990 and CBP data are used for matching.

There have been critiques regarding the political nature of FEMA disaster declarations (e.g., Garrett and Sobel, 2003; Sylves and Buzas, 2007). To address concerns that some events with large damage did not receive presidential declarations or that events with smaller damage were, we compared the mean number of injuries, fatalities, property damage, and crop damage between counties with FEMA declared disasters and counties in the Spatial Hazard Events and Losses Database for the United States (SHELDUS) database that did not receive disaster declarations for our time period. SHELDUS tracks damage exceeding $50,000 from natural hazards at the county level. Counties with disaster declarations had three times as many injuries, approximately twice as many fatalities, nearly twelve times as much property damage, and almost quadruple the amount of crop damage as the counties with natural hazard events that were not FEMA disaster declarations. This provides some strong evidence that, on average, presidentially declared disasters are more severe events.

We further performed sensitivity analysis regarding the operationalization of events by taking into account counties that received SBA assistance without FEMA declarations (which could be triggered by a governor, by the SBA, or by the Secretary of Commerce or Agriculture). Based on the FEMA disaster declarations and SBA assistance information, multiple options are available to operationalize the disaster status of each county in a particular year. As a first option, we code the occurrence of a disaster if a county received some FEMA assistance as a result of presidential disaster or emergency declarations or if it received SBA lending due to disasters that did not result in a presidential declaration. However, for the counties that received SBA disaster relief lending but no FEMA assistance, we coded the occurrence of a disaster only if the SBA

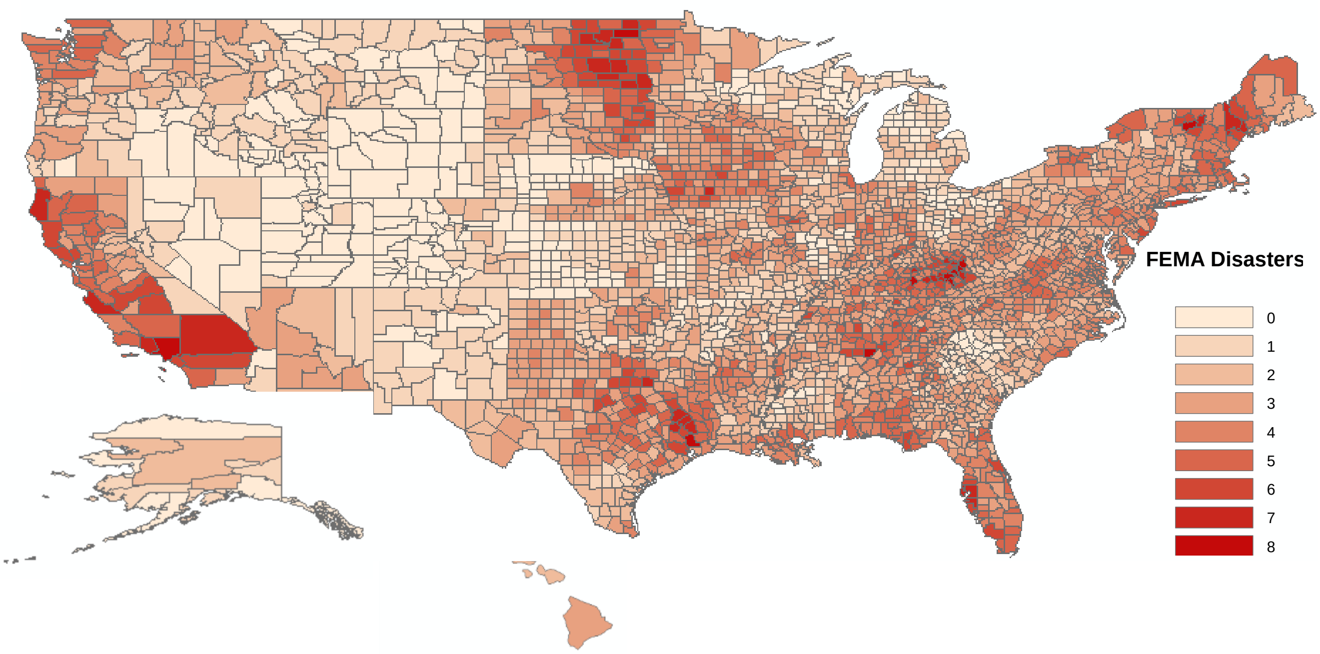
per-capita loan value exceeded the median distribution of the SBA assistance.[10] Counties that had no FEMA assistance and SBA lending below that threshold were considered to have been hit by minor events[11] and were coded as non-disaster counties. As a second option, we coded the occurrence of a disaster only if a county received FEMA assistance with or without the presence of SBA disaster loans. If a county received only SBA disaster loan assistance but not FEMA assistance, no disaster occurrence was coded. As a third option, a disaster occurrence was coded only in the presence of FEMA assistance of non-negligible intensity,[12] and the counties that received only SBA loans, in the absence of FEMA assistance, or FEMA compensations of negligible intensities were completely eliminated from the analysis. This third approach is our preferred option for the analysis, as it ensures a more certain focus on significant events, and it completely eliminates the risk of miscoding as "non-disaster" any counties that received SBA loans or low-intensity FEMA payments that could have indeed been related to some actual disaster events. However, to test the robustness of estimates, we replicated the analysis using the other options for coding the disaster status of counties. While results were similar across all three disaster-coding operationalizations, for clarity of exposition, we proceed by presenting the remaining descriptive statistics and impact estimates for only the third, most restrictive definition.

Figure 1 displays the geographic distribution of the number of FEMA disasters occurring from 1989 to 1999. Coastal areas, as well as the upper-Great Plains, sustained the greatest number of disasters. Over that period, 353 counties did not experience a disaster, 771 counties experienced three disasters (the mode number of disasters) and 11 counties experienced eight

[10] The median is computed on the distribution of disaster with certain non-marginal severity as indicated by the co-existence of both SBA and FEMA assistance.
[11] A second possibility is that they were receiving residual SBA lending from disasters in previous years.
[12] To ensure a strict focus on disasters with non-negligible intensity, we excluded the outliers in the lower tail (below the 5th percentile) of the distribution of the FEMA compensation intensities (in per-capita terms).

disasters (the largest number of disasters). Over this period, slightly over 41% of the disasters can be considered non-winter storms, almost 31% were fires, over 10% were tropical storms or hurricanes, a similar percentage were winter storms, and almost 8% were other disasters, such as a dike failure and volcanic lava flow.

Figure 1. FEMA County Disaster Declarations, 1989-1999



To match counties that had disasters with similar counties that did not experience a disaster, we used 1990 Census data. Because the outcome analysis is limited to the estimation sample of counties that did not experience a disaster in the prior three years or subsequent three years, the cohorts of disasters that we can keep in the estimation sample are those from 1992 to 1996.[13] For this reason, in the remainder of this section, we present the descriptive statistics of both the full sample of counties over the 1989-1999 period and the estimation sample of counties that for the reference years 1992-1996 did not experienced any disaster in three years prior and three-year after each reference year.

[13] This is because the first and last year for which we have complete information on the disasters are 1989 and 1999.

Table 1 presents annual tallies of the number of counties sorted by whether they experienced a FEMA declared disaster in each reference year between 1989 and 1999. In the full sample of counties, the yearly number of counties hit by a FEMA disaster ranged from 290 in 1992, equal to 10.2% of all counties, to 1457 in 1993, equal to 49.1% of the total, with an average yearly proportion of disaster-hit counties of 29.7%.

Table 1. Counties with Disasters

	Full Sample (1989-99)		Estimation Sample (1992-96)	
Year	Number[(a)]	Percent[(b)]	Number[(c)]	Percent[(d)]
1989	299	10.5%		
1990	559	19.9%		
1991	506	17.3%		
1992	290	10.2%	22	4.5%
1993	1457	49.1%	138	33.5%
1994	636	23.2%	36	10.3%
1995	514	17.2%	12	3.4%
1996	1089	36.8%	50	16.5%
1997	673	22.6%		
1998	1104	36.3%		
1999	995	33.2%		
Yearly Avg.	720	29.7%	52	13.1%

Source: FEMA and SBA

(a) Includes all counties with FEMA and/or SBA assistance. When only SBA assistance occurred, the event is deemed a disaster only if the intensity of SBA assistance is above median.

(b) Computed with reference to all no-disaster counties.

(c) Includes only counties with FEMA compensation (with or without SBA assistance) above the 5th percentile of the distribution of the FEMA per-capita intensities and with no other FEMA disaster in the previous and subsequent three years.

(d) Computed with reference to the counties without FEMA disasters in the reference year and in the previous and subsequent three years. Counties that received only SBA assistance or FEMA compensations below the 5th percentile are also dropped from the estimation sample of no-disaster counties.

In the 1992-1996 estimation sample that excludes counties with other disasters in the three-year period before and after the reference year, the yearly percentage of disaster-hit counties is lower,

ranging from 3.4% to 33.5%, with an average of 13.1%. This lower percentage of disaster-hit counties among the estimation sample indicates that a noticeable share of counties is faced by multiple disasters over the course of a six-year period.

Table 2 sorts the number of counties by categories of disaster status and their pre-disaster socioeconomic conditions in terms of the combined index I of median household income and unemployment rate. For the full sample of counties, the distribution of the total number of affected counties (i.e. the annual number of affected counties summed over the entire observation period) shows the highest concentration (36% of the total) in the low-intensity compensation and high-income/low-unemployment category in the pre-disaster period. The lowest concentration (18%) is also in the category of better-off socioeconomic conditions but high-intensity compensation. For the estimation sample, the distribution of disaster-hit counties is more equal across the four categories of compensation intensities and pre-disaster conditions, with the lowest concentrations being 23% (for the two categories of low-income/high-unemployment and low-intensity compensations and high-income/low-unemployment and high-intensity compensations), and the highest being 27% for the other two categories.

In terms of the distribution of the per-capita values of the FEMA compensations, the four categories of disaster-hit counties display a similar patter between the full and the estimation sample, with a much larger dispersion around the mean for the two categories of high-intensity compensations compared to the two categories of low-intensity compensations. For the full sample of counties, the medians of the per-capita FEMA compensations ranges from the $243 to $421 in the two low-intensity counties to the $4,583 to $4,798 range for the two high-intensity counties. For the estimation sample, this same differential ranges from $329 to $391 in the low-intensity categories and $6,534 to $7,904 in the high-intensity categories.

Table 2. Intensity of the FEMA Compensations by Categories of Disaster-Hit Counties, Full Sample and Estimation Sample

	Low-income/High-unempl. in pre-disaster period (w=I^{lw})		High-income/Low-unempl. in pre-disaster period (w=I^{hi})	
	Intensity of FEMA compensation		Intensity of FEMA compensation	
	c= high	*c*= low	*c*= high	*c*= low
Full sample				
Total n. disasters	1538	2094	1438	2845
Avg. yearly n. counties with disasters	140	190	131	259
Percent of total disasters	19%	26%	18%	36%
Per-capita FEMA				
Mean 1=$1	12,545	539	11,147	400
(Std. dev.)	(25,722)	(452)	(23,043)	(422)
Median 1=$1	4,583	421	4,798	243
Estimation sample				
Total n. disasters	71	58	58	71
Avg. yearly n. of counties with disasters	14	12	12	14
Percent of total disasters	27%	23%	23%	27%
Per-capita FEMA				
Mean 1=$1	15,835	506	14,132	506
(Std. dev.)	(27,208)	(413)	(15,643)	(489)
Median 1=$1	7,904	391	6,534	329

Table 3 compares the descriptive statistics of the estimation sample in terms of pre-disaster socioeconomic conditions across the different categories of counties. Within each of the two groups of counties with pre-disaster high-income/low-unemployment or low-income/high-unemployment conditions (based on the combined index I), the differences across the three disaster status categories are quite small for the large majority of variables. This is consistent with the random nature of the disasters and with the fact that, to rigorously estimate the degree to which affected counties bounce back to their counterfactual growth trajectory, the analysis focuses on disasters that were not closely preceded or followed by any other significant disaster.

This, however, limits the sample size of counties included in each category used in the analysis, and some clustering of certain pre-existing conditions can occur in some categories of counties. For the group of counties with below-median values of the index I, this is the case for the median housing values, the pre-disaster payroll growth trend, and the percentage of employment in sectors other than agriculture and manufacturing. In the category of disasters with high-intensity compensations, these variables have statistically significant differences with respect to the mean values of the no-disaster category. There are also statistically significant differences with respect to the no-disaster category among the group of counties with above-median values of the index I. This is the case for median household income, unemployment rate, median housing value and percentage of employment in agriculture in the high-compensation category of disasters and for median household income, unemployment rate and percentage of employment in manufacturing in the low-compensation category of disasters. The statistically significant unbalance between the categories of disaster-hit counties and the no-disaster counties is purged completely by the matching procedure performed within the DPSM-DD estimation model, as shown by the results that are summarized in the next section.

Table 3. Pre-Disaster Characteristic of the Counties by Disaster Status, Estimation Sample

	Lower-income/Higher-unempl. counties ($w=I^{lw}$)			Higher-income/Lower-unempl. counties ($w=I^{hi}$)		
	Higher-compens. disaster (c=high)	Lower-compens. disaster (c=low)	No-disaster	Higher-compens. disaster (c=high)	Lower-compens. disaster (c=low)	No-disaster
Med. household inc. (1=$1)	35,206	36,448	36,354	42,185***	50,185***	46,756
	(6,447)	(6,537)	(6.993)	(8,455)	(8,932)	(10,727)
Unemployment rate	0.083*	0.087	0.090	0.039***	0.054***	0.046
	(0.038)	(0.022)	(0.032)	(0.017)	(0.011)	(0.018)
Med. housing value (1=$1)	63,564***	71,951	70,956	76,525***	111,454	101,003
	(20,359)	(16,843)	(16,748)	(30,265)	(31,181)	(59,824)
% Δ employment (t-1)-(t-3)	0.048	0.038	0.031	0.029	0.018	0.052
	(0.140)	(0,051)	(0.128)	(0.105)	(0.034)	(0.298)
% Δ payroll (t-1)-(t-3)	0.047**	0.012	0.007	0.010	-0.009	0.025
	(0.326)	(0.059)	(0.094)	(0.120)	(0.048)	(0.383)
% Δ n. of establ. (t-1)-(t-3)	0.015	0.022	0.017	0.020	0.024	0.027
	(0.039)	(0.024)	(0.038)	(0.053)	(0.026)	(0.052)
% empl. in agric. (t-1)	0.003	0.003	0.003	0.007*	0.004	0.005
	(0.009)	(0.007)	(0.007)	(0.011)	(0.004)	(0.009)
% empl in manufact. (t-1)	0.256	0.253	0.230	0.220	0.291***	0.198
	(0.184)	(0.165)	(0.164)	(0.154)	(0.133)	(0.166)
% empl in other sect. (t-1)	0.588*	0.647	0.632	0.681	0.640	0.654
	(0.182)	(0.148)	(0.183)	(0.167)	(0.124)	(0.188)

* Statistical significance at the 0.10 level; ** 0.05 level;*** 0.01 level; [T-tests (two-tails) of statistical significance with reference to the no-disaster counties within the same category of pre-disaster conditions].

5. RESULTS

Table 4 illustrates the degree of balancing for all the pre-disaster characteristics of the different categories of counties achieved by the DPMS estimation procedure.[14] The column $\Delta(T^c=1\text{-}T^c=0)$ illustrates the difference between the means of the counties affected by disasters with compensation intensities of category *c* (high or low) and those of the matched comparison group of no-disaster counties. These are reported separately for the two groups of counties below and above the median of the combined index (I) of household income and unemployment-rate. The standardized percentage bias reported in the table is the difference of the sample means of the affected counties of category c and the no-disaster counties as a percentage of the square root of the average of the sample variances in the two groups (Rosenbaum and Rubin, 1985). The t-test and related p-values assesses the equality of means in the two groups based on a regression of the variable on the treatment status indicator.[15]

The DPSM-DD estimator matching procedure purges all statistically significant differences between the categories of disaster-hit counties and the matched comparison groups of no-disaster counties for all pre-disaster control variables. The percentage bias is also always limited below 10% for all the control variables used in the propensity score estimation and below 15% for the pre-disaster growth trends of the outcome variables controlled for by the DD scheme added to the estimation procedure.

[14] For the sake of completeness, the table also includes the pre-disaster growth trends (t-1)-(t-3) of the outcome variables (%Δ employment, payroll and number of establishments) that are excluded from the PS estimation because they are fully controlled for in the analysis by the DD scheme. For the sake of improved readability and space constraints, details on the balancing results for the year dummies are excluded from the table. All year dummies are fully balanced between the categories c of compensation intensities and the no-disaster counties for all groups of pre-disaster conditions.

[15] The regression is based on the support sample and it is weighted using the matching weight variable. The estimation procedure is performed with the Stata procedure *PSmatch2* (Leuven and Sianesi 2003).

Table 4. Balancing of the Pre-Disaster Characteristic Achieved by the DPSM procedure

	Disasters with higher compens. (*c=high*)				Disasters with lower compens. (*c=low*)			
	Δ^* (T^c=1-$T^{\wedge c}$=0)	% bias	t	p>|t|	Δ^* (T^c=1-$T^{\wedge c}$=0)	% bias	t	p>|t|
Lower-income/higher unemployment counties								
Med. household income (1=$1)	-559	-8.3	-0.51	0.610	144	2.1	0.11	0.910
Unemployment rate	-0.003	-9.3	-0.77	0.442	-0.003	-9.1	-0.64	0.523
Med. housing value (1=$1)	-1198	-7.7	-0.72	0.474	837	5.0	0.27	0.788
% Δ employment (t-1)-(t-3)	0.015	8.1	1.16	0.247	0.004	4.4	0.22	0.829
% Δ payroll (t-1)-(t-3)	0.033	11.0	1.24	0.218	0.008	9.8	0.52	0.603
% Δ n. of establ. (t-1)-(t-3)	-0.001	-2.1	-0.11	0.913	0.004	13.3	0.74	0.460
% empl. in agriculture at (t-1)	0.000	-5.0	-0.29	0.769	0.000	-1.7	-0.09	0.925
% empl in manufact. at (t-1)	-0.003	-1.9	-0.11	0.910	0.015	9.3	0.50	0.616
% empl on other sectors at (t-1)	-0.006	-3.5	-0.21	0.834	0.002	1.2	0.07	0.948
Higher-income/lower unemployment counties								
Med. household income (1=$1)	-49	-0.5	-0.03	0.977	450	4.6	0.27	0.790
Unemployment rate	-0.001	-4.1	-0.21	0.831	0.002	9.0	1.36	0.161
Med. housing value (1=$1)	-1006	-2.1	-0.16	0.870	-230	-0.7	-0.03	0.973
% Δ employment (t-1)-(t-3)	0.000	0.2	0.01	0.992	-0.030	-14.2	-0.79	0.434
% Δ payroll (t-1)-(t-3)	0.002	0.7	0.04	0.965	-0.035	-12.7	-0.60	0.550
% Δ n. of establ. (t-1)-(t-3)	0.002	2.9	0.16	0.871	-0.003	-8.3	-0.58	0.563
% empl. in agriculture at (t-1)	-0.001	-9.1	-0.36	0.717	0.000	-2.8	-0.21	0.831
% empl in manufact. at (t-1)	0.006	3.6	0.18	0.858	0.010	9.7	1.22	0.225
% empl on other sectors at (t-1)	0.012	6.6	0.37	0.715	-0.015	-9.2	-0.63	0.531

* $T^{\wedge c}$=1: Counties with disasters.
$T^{\wedge c}$=0: Matched comparison group of counties with no-disasters.

Table 5 summarizes the short-run results of the DPSM-DD analysis in terms of static resilience. For all affected counties, one year after a disaster, the difference-in-difference (DD) growth outcomes of employment, total payroll and number of establishments, display a significant negative gap compared to the counterfactual status of no-disaster. The size of such short-run negative growth gap is -2.87 p.p., -3.10 p.p., and -2.90 p.p. for employment, total payroll and number of establishments, respectively, when the county had lower-income/higher

unemployment pre-disaster conditions and when the disaster entailed a high-intensity of relief assistance. For the same category of disasters with higher compensations, the size of the negative growth gap is also of similar magnitude for the higher-income/lower unemployment counties with estimates ranging from -2.75 p.p. for the establishment outcome to -2.99 p.p. for the payroll outcome. For the disasters with lower compensation intensities, the size of the negative growth gap is lower across all the outcomes and the two categories of counties based on the pre-disaster socio-economic conditions. The impact estimates are in the order of -1.79 to -2.07 p.p. for counties with lower-income/higher unemployment and in the order of -1.43 to -1.75 p.p. for counties with higher-income/lower-unemployment.

The pairwise significance of the impact estimates across the four county categories were tested through re-estimating the DPSM-DD model by defining the counterfactual state as the occurrence of a disaster with the compensation intensity of the other category, holding constant the pre-disaster socioeconomic conditions and by defining the counterfactual state as belonging to the other pre-disaster socioeconomic category, holding constant the compensation intensity. These pairwise tests show that the differences between the impacts for the high-intensity disasters and the low-intensity disasters are all significant at the 0.10 level for both categories of socioeconomic conditions. The larger negative impacts for counties hit by disasters with higher relief assistance are consistent with the fact that the intensity of the compensation tends to be proportional to the destructive force of the disaster and that, in the short-run of one year post disaster, high intensities of the relief assistance cannot have had enough time to produce effects on the real economy, particularly because the assistance often comes with a lag.

Table 5. Short-Run DPSM-DD Impacts by Categories of Disaster-Hit Counties

Outcome Variables DD variations [(t+1)-(t-1)] - [(t-1)-(t-3)]	Lower-income/Higher-unemployment ($w=I^{lw}$)		Higher-income/Lower-unemployment ($w=I^{hi}$)	
	Intensity of FEMA compensation		Intensity of FEMA compensation	
	c= high	*c*= low	*c*= high	*c*= low
Employment (1=1 p.p.)	-2.87**	-1.79*	-2.88**	-1.43*
	(1.44)	(1.06)	(1.39)	(0.75)
Payroll (1=1 p.p.)	-3.10**	-2.07*	-2.99**	-1.75**
	(1.47)	(1.24)	(1.53)	(0.90)
Establishments (1=1 p.p.)	-2.90***	-1.88***	-2.75***	-1.67***
	(0.63)	(0.42)	(0.71)	(0.45)

* Statistical significance at the 0.10 level; ** 0.05 level;*** 0.01 level;

Table 6 illustrates the long-run results in terms of dynamic resilience. Within each category of disaster compensation intensities, the better-off counties with pre-disaster higher-income/lower-unemployment were able to fully bounce back to their counterfactual growth trajectories. For these counties, the DD changes at three-years post disaster of the employment, payroll and establishment outcomes are never statistically different from the estimated counterfactual trends, with point estimates that are in the order of +0.17 to +0.52 when the disasters have higher compensation intensities and in the order of -0.03 to -0.45 when the disasters have lower compensations. The pairwise significance testing confirms that these long-run impacts in the higher-income/lower-employment counties are never significant when the point estimates are compared between the two categories of compensation intensities.

By contrast, for the counties with pre-disaster lower income and higher unemployment rates, dynamic resilience was affected by the intensity of the disaster compensation. When the disaster was accompanied by higher compensation intensity, the lower income/higher unemployment counties were able to recover a very substantial portion of their short-run

negative growth gap, with impact estimates that have a magnitude from -1.03 to 1.30 p.p. and were not statistically significantly different from the counterfactual trends of the employment and payroll outcomes. On the other hand, when the disaster entailed lower compensation intensity, the lower pre-disaster income/higher unemployment counties maintained a longer-run negative growth gap ranging from -2.11 p.p. for the number of establishments to -2.42 p.p. for employment. Pairwise statistical testing confirmed that, holding constant the intensity of the compensation, these differences between the long-run impact estimates of the lower-income/higher unemployment counties and those of the higher-income/lower unemployment counties were always statistically significant (with confidence levels at least below 0.10) for all three economic outcomes and for both categories of compensation intensities.

Table 6. Long-Run DPSM-DD Impacts by Categories of Disaster-Hit Counties

Outcome Variables DD variations [(t+3)-(t-1)] - [(t-1)-(t-3)]	Lower-income/Higher-unemployment ($w=I^{lw}$)		Higher-income/Lower-unemployment ($w=I^{hi}$)	
	Intensity of FEMA compensation		Intensity of FEMA compensation	
	c= high	*c*= low	*c*= high	*c*= low
Employment (1=1 p.p.)	-1.30	-2.42**	0.52	-0.03
	(1.42)	(0.99)	(1.32)	(0.65)
Payroll (1=1 p.p.)	-1.15	-2.37**	0.21	-0.29
	(1.39)	(1.12)	(1.38)	(0.83)
Establishments (1=1 p.p.)	-1.03*	-2.11***	0.17	-0.45
	(0.58)	(0.41)	(0.74)	(0.39)

* Statistical significance at the 0.10 level; ** 0.05 level;*** 0.01 level;

6. SENSITIVITY ANALYSIS AND PLACEBO TEST

To gain statistical efficiency and to address the limited sample size of counties within each category of pre-disaster conditions *w* and intensity of the compensations *c*, the preferred DPSM-

DD estimation procedure followed the pooled approach used in Becker at al. (2012). With this approach, once all the outcomes and control variables are measured separately for each cohort of counties (*treated* and *no-treated*) based on each of the reference years, all the annual databases are pooled for the matching procedure. The possible influence of secular trends is controlled for completely by including the full set of year dummy variables in the probit models. As an alternative to this procedure, the DPSM-DD model can also be implemented with separate matching procedures performed on each annual database. This non-pooled estimation approach entails generating local impacts $\alpha_{it}(c, w)^{SR}$ and $\alpha_{it}(c, w)^{LR}$ for each treated county *i* belonging to a specific reference year *t*. These local impacts are then aggregated across all treated counties *i* to generate the following aggregated average treatment effects for each reference year *t*:

$$\alpha_t(c, w)^{SR} = \frac{\sum_i a_{it}^{SR}}{N_t} \quad (4) \qquad\qquad \alpha_t(c, w)^{LR} = \frac{\sum_i a_{it}^{LR}}{N_t} \quad (5)$$

Where N_t = number of disaster-hit (treated) counties in the reference year *t*. The final impact parameters of interests, $\tau(c, w)^{SR}$ and $\tau(c, w)^{LR}$, are estimated as the weighted average of the year-specific impact estimates $\alpha_t(c, w)^{SR}$ and $\alpha_t(c, w)^{LR}$ across the five reference years. The weights used are N_t.

This non-pooled approach, compared to the preferred (pooled) option, yields a loss of statistical efficiency and a larger distance in the differences between the propensity score of the treated counties and those of the matched comparison groups of no disaster counties. The advantage, however, is the exact controlling for the secular trends of the outcome variables without relying on any functional form assumption in the way the year-dummies are inserted in the probit equations. The adequacy of the functional form choice for the year dummies in the probit specifications of the pooled approach is fully validated by satisfying the balancing

property that entails finding no statistically significant differences between the distribution of the reference years across the treated counties and the non-treated comparison groups.

To test the robustness of the results, however, the first sensitivity analysis test that we performed was to replicate the estimation of the DPSM-DD model using the alternative non-pooled approach described above. In addition, we also re-ran the entire analysis using a set of different matching algorithms that included radius matching with different levels of tolerance δ and nearest available bandwidths. Finally, the analysis was also replicated using different options to operationalize the disaster status of each county in a particular year, as described in section 4.

Results from all replications of the preferred estimation procedure and operationalization of the DPSM-DD model are fully consistent with the impact estimates presented above, with just some lower precision for some of the categorical estimates of the non-pooled approach due to the larger standard errors entailed by the lower statistical efficiency of such an alternative estimation procedure.[16]

As part of the sensitivity analysis, to thoroughly test the absence of any residual bias in the impact estimates, we also performed a placebo test in the form of placing the occurrence of the disasters two years prior to the actual events. In this way, the short-run impact estimates were re-estimated using operationalizations of the outcome variables in terms of DD changes that were all measured in periods prior to the actual disaster. In the case of the absence of any residual bias in the actual DPSM-DD estimates, the results of this placebo test should yield impacts with no statistical significance and magnitude close to zero. As illustrated in Table 7, this was the case for all results.

[16] Detailed results are available upon request to the authors.

Table 7. Results from the Placebo Test

Outcome Variables DD variations	Lower-income/Higher-unemployment ($w=I^{lw}$)		Higher-income/Lower-unemployment ($w=I^{hi}$)	
	Intensity of FEMA compensation		Intensity of FEMA compensation	
	c= high	*c*= low	*c*= high	*c*= low
Employment (1=1 p.p.)	0.06	0,41	0.46	-0.99
	(1.24)	(0.80)	(2.66)	(1.43)
Payroll (1=1 p.p.)	-0.36	0.65	0.33	-0.93
	(1.04)	(0.83)	(3.30)	(1.85)
Establishments (1=1 p.p.)	-0.05	0.34	0.46	-0.17
	(0.52)	(0.34)	(0.82)	(0.39)

* Statistical significance at the 0.10 level; ** 0.05 level;*** 0.01 level;

A final test that we performed as sensitivity analysis was replicating the estimation of the DPSM-DD model by separately considering two different categories of natural disasters along the distinction between fires, floods and hurricanes in coastal areas and versus winter storms and other weather related disasters in non-coastal areas. In principle for the first category of disasters, the endogenous component of their occurrence could be higher than in the second, leading to repetitive patterns of self-selection versus certain areas. However, replicating the analysis separately for each of these two groups of disasters did not yield results substantially different from those presented in Table 5 and 6, albeit for much less precise estimates due to the smaller sample sizes. This lack of heterogeneity in these results can be explained by the fact that the estimation of rigorous counterfactual causal inference calls for focusing on data with both pre-disaster and post-disaster periods without the occurrence of other disasters. Restricting our focus to disasters that do not repeat frequently in the same area removed any strong correlation between the nature of the event and the characteristics of the affected areas or the intensity of the disaster compensation.

7. SUMMARY AND CONCLUSIONS

This paper uses a rigorous counterfactual impact evaluation approach to estimate whether communities stricken by disasters were capable, under the existing relief assistance programs, to resume their counterfactual growth paths that would have occurred in the absence of the disaster and the subsequent assistance. The analysis focuses on both examining static resilience in terms of being able to withstand the disaster, as measured by outcomes one year after the disaster, and dynamic resilience, by measuring the ability to bounce back three years after the disaster. The impact estimates are obtained through a dynamic propensity score matching (DPSM) model, coupled with a difference-in-difference (DD) scheme, in which the pairing of each disaster-hit county with similar unaffected counties is repeated for each consecutive annual cohort of disasters, with outcome and control variables that are specifically measured with respect to each reference year.

The results from our DPSM-DD analysis shows that one year after a disaster, all affected counties display a lower growth of employment, total payroll and number of establishments, compared to the counterfactual status of no-disaster and no-assistance estimated from the sample of unaffected counties with similar pre-disaster characteristics and trends. Holding constant the pre-disaster socio-economic conditions of the counties, the size of such short-run negative growth gap is higher (in the order of -2.75 to -3.10 p.p.) when the disaster entailed a high-intensity of relief assistance than when the disaster entailed a low intensity of assistance (in this case, the negative growth gaps ranged from -1.43 to -2.07 p.p.). This is consistent with the fact that the intensity of the compensation tends to be proportional to the destructive force of the disaster and that, in the short-run of one year post disaster, high intensities of the relief assistance cannot have had enough time to produce effects on the real economy.

Broadening to a three-year post-disaster period and holding constant the severity of the disaster/intensity of the compensation, the counties with a pre-disaster status of household incomes above the median of the distribution and unemployment rates below the median of the distribution displayed a much higher dynamic resilience than the counties with lower incomes and higher unemployment rates. Indeed, at three years post disaster, the higher income/lower unemployment rate counties are able to completely bounce back to their no-disaster counterfactual growth trends with very small and statistically insignificant variations due to the severity of the disaster/intensity of the compensation. This was not the case for the counties with lower incomes and higher unemployment rates. For these counties with lower pre-disaster socioeconomic conditions, the dynamic resilience was noticeably affected by the severity of the disaster and the corresponding intensity of the relief assistance. When the disaster entailed a higher intensity of compensation, the lower income/higher unemployment counties were able to recover a very substantial portion of their short-run negative growth gap. Any remaining differences compared to their no-disaster counterfactual growth trends were not statistically different from zero for employment and payroll outcomes and had a remaining magnitude of only -1.03 to -1.30 p.p. for all three economic outcomes. On the other hand, when the disasters entailed lower compensation intensity, the lower income/higher unemployment counties continued to display a longer-run negative grow gap in the order of -2.11 to -2.42 p.p. that is even slightly higher than that of the short-run estimates.

Thus, by decomposing the impact of disasters across different types of counties based upon both pre-disaster conditions and the intensity of post-disaster relief, the paper helps to reconcile some of the mixed findings from previous research. Consistent with much of that research, we also find that communities are often able to recover from the most severe disasters,

likely at least partially as a function of generous disaster relief that they receive from the federal government. However, the analysis has uncovered the challenges faced by weaker economies that receive lower levels of relief.

The use of a dynamic statistical matching approach across a panel data framework, such as in our DPSM-DD estimation, is the first application of this kind to the examination of resilience to disasters and provides an important model for future such rigorous counterfactual impact evaluations. This contribution to the literature generates more accurate counterfactual growth trends by selecting comparison groups for the affected counties based on pre-disaster characteristics precisely measured with regard to the exact reference year of the disaster. The DPSM-DD approach also avoids the heavy model dependence of the results that is typical of the traditional parametric frameworks in panel data contexts, such as with fixed-effect multiple regression models.

An additional important feature of our estimation model is the exclusion from the analysis of the counties that had disasters in the three previous or subsequent years. This led to estimates that are more reliable by minimizing contamination threats to internal validity at some cost to external validity. This is a necessary tradeoff, as rigorous impact estimates cannot be identified for counties struck by frequent disasters because both the pre- and post-disaster trends would be continuously affected by other disasters. Moreover, by examining the post-assistance resilience of locations where disasters (and the resultant need for assistance) are infrequent and truly unexpected rather than places where disaster risk has already been accounted for in the local economy due to previous disaster occurrences (e.g., Yezer, 2010), policymakers also gain important insight into the question of whether similar assistance programs could be effectively adapted for use in the wake of other low-probability, high-cost emergencies.

The focus of the analysis on rigorous causal inference, however, entails a number of limitations that are well-suited for future research. One limitation is that the estimated impacts are in terms of outcomes that were only related to economic business activities, and this could conceal other important local effects. Future work should incorporate other outcomes that may be affected differentially by pre-disaster characteristics, such as displacement, psychological and financial stress, and residential rebuilding efforts. A second limitation is that the analysis did not lend itself to a full spatial analysis of spillovers. Thoroughly addressing the spatial relationships in the context of rigorous causal inference is a complicated task in that neighboring areas could potentially either be harmed or benefit from the recovery efforts of their neighbors. This is both because of the nature of the externalities (e.g., Hornbeck and Keniston, 2017) and depending on whether the industrial output of the neighboring areas primarily represents complements or substitutes to production in the areas directly affected. In our analysis, we dealt with the spatial spillover effects in a completely non-parametric straightforward manner. Further, future research should also examine the role of the characteristics of neighbors in terms of their influence on regional resilience, because, for example, Deller and Watson (2016) found a relationship between a focal county and the economies of neighboring counties when examining the resilience to a severe economic downturn.

Despite these limitations, our findings have important policy relevance. The aim of the federal, state, and local relief programs is to offset the consequences of disasters, and the adequacy of these programs is revealed by the degree of resilience of the affected communities. Moreover, the estimates of the varying degrees of resilience based on the different types of communities and intensities of the relief assistance are particularly important because they may highlight the need to differentiate future relief interventions, or pre-disaster mitigation efforts,

based on pre-disaster economic conditions. In this regard, the results show that while all types of counties face short-term challenges due to disasters, policymakers should be particularly cognizant of the greater challenges to longer-term recovery faced by economies that have lower pre-disaster incomes and higher unemployment and do not receive the highest intensity of federal relief assistance.

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