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Cultural Resilience and Economic Recovery: Evidence from Hurricane Katrina?*

Abstract

This paper investigates the critical role of culture for economic recovery after natural disasters. Using Hurricane Katrina as our laboratory, we find a significant adverse treatment effect for plant-level productivity. However, local religious adherence and larger shares of ancestors with disaster experiences mutually mitigate this detrimental effect from the disaster. Religious adherence further dampens anxiety after Hurricane Katrina, which potentially spur economic recovery. We also detect this effect on the aggregate county level. More religious counties recover faster in terms of population, new establishments, and GDP.

Keywords: natural disasters, plant-level productivity, religion, recovery

JEL classification: E23, E32, Z12

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1 Introduction

Natural disasters are a severe threat to economic development (Strobl, 2011). The costs of these events pointing to around three trillion U.S. Dollars and the loss of around one million lives during the 20 years preceding 2005 (Strömberg, 2007). In times in which natural disasters like hurricanes will be more frequent because of climate change (Walsh et al., 2016; Hsiang and Kopp, 2018), a thorough understanding of the economic recovery process on a very granular level is essential. Previous literature shows that the recovery processes of regions affected by a natural disaster are heterogeneous depending on migration, politics, and institutions (Cavallo et al., 2013; Felbermayr and Gröschl, 2014).

In this paper, we focus on the role of religion as a moderating cultural factor in high-impact natural disasters. Religion is supposed to mitigate effects from difficult situations (Schuster et al., 2001; Smith et al., 2000) and thereby can play a central role for regional economies in a recovery process. Furthermore, there is an extensive amount of papers that documents the important role culture (Guiso et al., 2006) and religion beliefs (McCleary and Barro, 2006; Bryan et al., 2020) for economic development. Recent research further documents that people turn to religion in times of severe crises like earthquakes (Bentzen, 2019) or the Covid-19 pandemic (Bentzen, 2020). Moreover, Bentzen and Dalgaard (2020) shows that religion can mitigate economic downturns in crises like the Spanish flu and World War I. Understanding how cultural traits like religion affect economic performance after natural disasters is vital since it can help to allocate government aid more efficiently and develop insurances better to stimulate economies in post-disaster recovery.

The laboratory that we adopt from Schüwer et al. (2019) concerns the South-East of the United States when Hurricane Katrina hit this area in 2005. For our research, we think that Hurricane Katrina and the United States offer a unique opportunity to advance this field of the literature. First, the power with which the hurricane hit the Gulf Coast unexpectedly in 2005 allows us to study the effect of natural disasters on economic activity. Secondly, the United States is the country with the highest rate of religious adherence, and faith-based organizations have a considerable influence. For example, almost 90% of religious organizations actively provide social services (such as employment services, hospital visitation, and educational services) to over 70 million Americans (Gruber and Hungerman, 2007). They also spend almost 24 billion dollars on philanthropic activities yearly (Biddle, 1992).

Our analysis proceeds in three steps: We firstly evaluate the effect of Hurricane Katrina on corporate performance. Evaluating the impact of the hurricane on corporate performance requires a rigorous identification strategy. To accurately evaluate the effect of the hurricane on corporate activity, we face different empirical concerns. While most of the previous research identifies company location with the headquarter, we use fine-grained plant-level data. We evaluate the effect of the hurricane on plant performance. Next, we carefully identify which counties have been hit by the hurricane, and we choose an adequate comparison group following Schüwer et al. (2019). Our robust results show that the hurricane has a long-lasting effect on plant productivity with considerable economic effects. In particular, we find that the hurricane significantly decreases plant productivity on average by 1.1 percentage points in comparison to a control group of unaffected plants.

Second, we investigate which factors can mitigate the negative effect the hurricane has on local economic activities, focusing on religion. We robustly find that plants in more religious counties are less affected by the hurricane's negative impact. We find that our results do not depend on other cultural traits like social capital or human capital, which correlate with religiosity. While we do not find any evidence of the mitigating role of social capital and human capital, the coefficient related to the effect of religiosity in post-disaster performance is still positive and statistically significant.

Third, we test different channels through which religion can affect post-disaster recovery. For that, we use data about the natural disaster experiences of ancestors of residents in treated counties. We find that a higher share of natural disaster experience complements the beneficial effects of religion. We further consider the extensive literature, starting from (Freud, 1961), that analyses the relationship between religion and the human psyche. The literature shows that religiosity has a positive effect on the human psyche when dealing with adverse and unpredictable situations and with emotional distress after a disaster. For example, Schuster et al.

(2001) find that ninety percent of Americans coped with their distress by turning into religion after the 11th September terrorism attack. Smith et al. (2000) show that many of the people affected by the 1993 Mississippi River floods could survive because of the fellowship of church members and strength from God. Similarly, Dehejia et al. (2007) show that involvement with religious organizations in the United States can ensure consumption and happiness against income shocks. Beliefs and sentiments could have a long-lasting effect on aggregate growth (Blanchard, 1993; Gillitzer and Prasad, 2018). Thereby, understanding whether religion can mitigate the negative effect of an unexpected adverse event on the human psyche could have significant consequences for economic recovery. To investigate this hypothesis, we test whether religion can mitigate the negative effect the Hurricane has on psychological disorders, proxied by the popularity of specific search terms in Google Trend. Our findings support this hypothesis; while psychological disorders increases in areas severely hit by the Hurricane, physiological disorders increase less in more religious areas. We thereby add to the recent literature on the Covid-19 pandemic (Andersen et al., 2020; Fetzer et al., 2020) that shows that a considerable share of the economic downturn in the United States, Denmark, and Sweden is due to economic anxiety. We advance here by showing that anxiety effects in crises stemming from natural disasters decrease with religious adherence.

We further consider other possible explanations for our findings. Previous literature highlights the role of religious organizations as a form of social networks and as insurance to economic shocks (Chen, 2010; Dehejia et al., 2007; Auriol et al., 2020). According to this part of the literature and the literature related to the role of social networks in labor markets (Kramarz and Skans, 2014), we find that the probability of being unemployed increases after the Hurricane in treated areas, but less in more religious counties. Similarly, we find that religious networks affect the decision to migrate after the hurricane. Indeed, we find that in more religious counties, people are less likely to migrate. The rationale of this finding is that collectivist individuals are less likely to migrate, and migration cost is higher for people with more reliable local social networks, as in Knudsen (2019) and Kitayama et al. (2006). Moreover, Hungerman (2005) show that churches in the United States provide community services similar to those provided by the government and can substitute government activities. We find that the probability of receiving government social welfare support increases in treated counties after the Hurricane and decreases in more religious but treated counties. This finding is important because it suggests less stress for public finance in disaster-ridden but more religious regions.

We finally document that the positive effects of religion are visible in the aggregate, too. We find that economic outcomes like employment and GDP are significantly less stressed in affected counties with greater religious adherence.

Our paper contributes to the literature on the effect of natural disasters on economic activity. Previous research focused their attention on the effect these have on economic growth, on the labor market, or the role institutions play in mitigating the negative effect of the hurricane.[1] There is less focus on the effect that natural disasters have on corporate performance and what cultural factors allow corporations to recover after a disaster. In this sense, the closer contribution to our paper comes from Hsu et al. (2018). They show that natural disasters harm corporate operating performance, and technology diversity allows corporations to recover faster.

More broadly, our paper as well contributes to the literature on culture and economic outcomes. Only recently have economists started to document the important role culture plays to the economy by shaping people's beliefs and behavior. In particular, religious beliefs, social capital, and human capital proved to play a crucial role in economic growth.[2] We contribute to this literature by showing a novel and

[1]The literature finds mixed evidence on the effect natural disasters have on economic growth. Cavallo et al. (2013) find that only large natural disasters harm growth, driven by political changes. Strobl (2011) document a fall in the growth rate at the county level equal to 0.45 percentage points caused by the hurricanes and driven by wealthier individuals moving away from affected counties. However, the results cancel out in annual terms at the state level. On the other side, Felbermayr and Gröschl (2014) shows that natural disasters hurt growth. However, international openness and democratic institutions reduce their adverse effect. For what concerns the literature on the effect of natural disasters on the labor market, Deryugina et al. (2018) show that Katrina victims' incomes fully recover and even surpass that of controls from similar cities that were unaffected by the storm.

[2]Guiso et al. (2004) show that social capital is associated with greater financial development, while Zak and Knack (2001) shows that social capital is associated with growth. Tabellini (2008) argues that generalized trust and individualism explain institutional development and economic development. (Guiso et al., 2003) show that religious beliefs are associated with several "good" economic attitudes. McCleary and Barro (2006) show that religion boost economic growth. (Barro, 2001) shows that education, especially scientific education, positively affects growth. Spolaore and Wacziarg (2013) provides a review of the literature.

specific channel through which culture could impact economic growth.

Furthermore, our analysis adds to the recent literature that studies how culture affects the performance of corporations. Bloom et al. (2012) shows that companies located in counties with more social capital are more productive because more likely to decentralize. Similarly, Cingano and Pinotti (2016) shows that firms located in high trust regions perform better in those sectors for which deregulation needs are more substantial. Hilary and Hui (2009) show that firms located in counties with higher levels of religiosity display lower degrees of risk exposure, a lower investment rate and less growth, but generate a more favorable market reaction when they announce new investments.

2 The data

For our research, we collect information from different sources, and we use the information at a different level of aggregation. In this section, we are going to discuss the data collection process.

Plant-level data To answer our main research question, we need detailed information on local business activity. We collect information from Infogroup U.S. Historical Business data.[3] Infogroup gathers information on almost the universe of local business activities and importantly provides information on the exact location of the plants, on the number of employees, and plant sales. Infogroup uses yellow and white pages, company filings, county-level public filings, real estate tax assessor data, utility information, and web research to collect the data. They verify the collected information through more than 40 million phone calls each year. An independent audit shows it is similar and, in many cases, more precise for other private business-level datasets such as the National Establishment Time-Series dataset that we use in a robustness check.

Our baseline sample comprises every plant in the South-East of the United States between 1999 and 2010. We choose this period to have a similar spell in the

[3] The Infogroup database on business activity has already been used in recent papers (e.g., Barrot and Sauvagnat, 2016; Partridge et al., 2019; Meltzer et al., 2019; Burge and Rohlin, 2019). For more information, see https://www.infogroup.com/our-data/.

period before and after 2005. The raw data comprises 44,355,170 observations for 8,946,017 plants. We exclude financial companies and the government sector from our sample (7,908,015 plants remain). We further keep only plants with non-missing NAICS information (7,896,392 plant remain) and information about both sales and the number of employees (6,605,845 plants remain). We drop duplicates (6,605,845 plants remain) and plant for which we do not know the exact location (6,505,525 plants remain). In the last step, we drop all singleton observations that still enter our baseline regression with Stata's reghdfe command (Correia, 2017). Thereby, the final data-set comprises 17,125,223 plant-year observations for 2,896,377 plants.

Hurricane Katrina To accurately evaluate which counties have been hit by the hurricane and in order to identify an adequate comparison group, we follow Schüwer et al. (2019). [4] In particular, we classify a county as impacted if, after Hurricane Katrina and the subsequent hurricanes Rita and Wilma, it was eligible for individual and public disaster assistance by the Federal Emergency Management Agency (FEMA). We further consider a county as unaffected if it is located in the Gulf Coast region or a neighboring state not eligible for public or individual disaster assistance. We exclude counties that are eligible for public disaster assistance but not eligible for individual disaster assistance because this criterion is ambiguous. The final sample comprises 512 counties (103 treated counties and 409 used as a comparison group). Figure 1 shows the distribution of the treated and untreated counties across regions.

– Figure 1 around here –

Cultural traits We use various proxies for culture in our study. First, we use religiosity. Our source of information for religiosity data is the Association of Religion Data Archives (ARDA). This database provides a complete enumeration of religious congregations and people affiliated to a congregation. In particular, it contains a county-level geographical variation on the number of churches and the number of members of each church, approximating the Census of American Religion (Finke and

[4]For more details about the hurricane season of 2005 and the various impacts, check Dolfman et al. (2007) and Schüwer et al. (2019).

Scheitle, 2005). Data were collected by the Association of Statisticians of American Religious Bodies (ASARB) and compiled by Glenmary Research Center.[5] We measure religiosity as the rate of adherence in the county where the plant resides. Adherents are defined as "all members, including full members, their children, and the estimated number of other regular participants." We measure religious adherence rates as of the year 2000, which is the first year for which census information on religiosity is available before the hurricane season.

Our second proxy for culture is social capital at the county level as of 2005. The source of information for this variable is the Northeast Regional Center for Rural Development at the Pennsylvania State University. According to the economic literature, we consider that social capital assumes different aspects that could affect economic performance. For this reason, we consider four variables that capture the strength of local cooperative norms and the ramification of social norms: voter turnover and the county-level census response rate and the number of associations and the number of no-profit organizations. Following the literature (e.g., Hasan et al., 2017), we use a principal-component analysis to construct our final measure of social capital.

Third, we use a measure of human capital. Following the literature (e.g., Moretti, 2004), we measure human capital as the share of people over 25 with a university degree. Information comes from the 2005 American Community Survey (ACS). [6]

Using the ACS, we as well compute a measure of ancestors' experience of natural disasters. In order to measure the "natural disaster risk" variable, we rely on the EM-DAT database. The EM-DAT database has a universal coverage on all the natural disasters around the world, starting from the year 1900 and an evaluation of their impact. A disaster is included in the dataset if one of the following criteria is fulfilled: (a) at least ten people have been killed, (b) 100 people have been reported affected, (c) a state of emergency is declared, or (d) international assistance is required. Using this dataset, we measured the number of people dying by country. We normalized it with the country's population of origin and merged the "natural

[5] Previous papers in the finance literature used this data for their empirical analysis (e.g., Kumar et al., 2011; Hilary and Hui, 2009).

[6] Note that the smallest geographic unit in the ACS is the PUMA (a group of counties).

disaster risk" measure with ancestors' information in the ACS. We took the average to measure the local cultural experience of dealing with natural disasters. Fulford et al. (2017) use a similar approach to measure ancestors' cultural characteristics and analyze their impact on economic growth.

Google Trend data We collect information on psychological disorders from the Google Trends portal, which provides data on the relative popularity of different search terms across 210 U.S. metropolitan areas ("media markets" according to the Nielsen DMA definition). More precisely, we collect information on the google searches of the words *depression* and *anxiety* since both are the central disorders caused by a traumatic event.

Individual and aggregate data We use micro-data at an individual level from the American Community Survey (ACS), a national survey database that provides us time-series information on people demographic, sources of income, jobs and educational attainment, among others.

We also collect aggregate information about income, employment, and population from the Bureau of Economic Analysis (BEA). Income is deflated using the CPI-U and reported in constant dollars as in 2000. From the BEA we as well collect information on GDP, available at the county level starting from the year 2000.

A detailed description of all the variables available in our database and their sources is available in Table 1. We report the summary statistics before the hurricane in Table OA1.

Summary statistics and pre-event checks Table 2 shows the summary statistics of our main sample. We split the sample between plants located in treated and untreated counties. We report the mean and the standard deviation values of both the level and the first differences of the variables before the hurricane season. The last column shows the normalized differences. It is crucial for the validity of our difference-in-difference approach that the treated and the comparison groups are similar. According to (Imbens and Wooldridge, 2009), two groups could be considered similar enough to proceed with a linear regression analysis if the normalized differences are within the range of ± 0.25. In our sample, the normalized differences of eight out of eleven variables are within this range; if we consider their level. For the first differences in the pre-2005 period, all variables are within range. Thereby, we conclude that the two groups are similar enough to conduct a linear regression analysis. We provide more detailed summary statistics for all variables that we use in Table OA1.

– Table 1 and Table 2 around here –

3 Econometric framework and baseline results

3.1 Baseline results

We start to test the impact of Hurricane Katrina on plant performance by estimating the following regression:

$$Ln(Sales/FTE)_{it} = \alpha_i + \theta_t + \sum_{t=1999, t\neq 2005}^{2010} \beta_t Treated_i * \theta_t + \epsilon_{it} \quad (1)$$

The dependent variable is the natural logarithm of the ratio between the sales and the number of employees (productivity) of plant i at time t. We decide to take the logarithm in order to deal with the skewness of the variable and to avoid our results to be driven by outliers. According to Schüwer et al. (2019), $Treated$ is a dummy variable equal to one if the plant resides in a county affected by the hurricane. θ is a dummy variable that captures each year in our dataset between 1999 and 2010. In this regression, we interact with the treatment status with the full set of year dummies using the year 2004 as the reference year. Thereby, the coefficients β_t report the differential effect in productivity between treated and untreated plants for a certain year compared to 2004. We saturate the regression with plant fixed effects. Moreover, according to (Bertrand et al., 2004), we adjust standard errors for heteroskedasticity and within-plant variation.

– Figure 2 around here –

We present the β coefficients from Equation 1 and the 95% confidence intervals in

Figure 2. Figure 2 provides several critical results. First, the yearly point estimates show significant differential effects for the years 2005-2010 between treated and untreated plants relative to 2004. In economic terms, this means that relative to the pre-disaster year, treated firms' productivity decrease significantly up to more than 0.6 percentage points compared to the group of untreated plants. The effect is economically meaningful and persistent until the end of the analyzed period. Second, we find that the differences in productivity – relative to 2004 – between treated and untreated plants are not significant for the time before 2005. Third, the absence of significant coefficients in the run-up period to the disaster of 2005 further indicates that both groups follow rather parallel trends in terms of productivity. Again, this is a crucial finding for us since the absence of significant differences and parallel trends before the event is important for the identification through our difference-in-difference setup. We can conclude that the hurricane season of 2005 had a significant negative and lasting effect on the productivity of plants residing in affected counties.

Building on the evidence from Figure 2, we turn to a more conventional difference-in-difference setup and estimate the following regression:

$$Log(Sales/FTE)_{it} = \alpha_i + (\gamma_s \times \theta_t) + \beta Treated_i \times Post_t + \epsilon_{it} \tag{2}$$

$Treated$ is a dummy variable equal to one if the plant is located in a county affect by the hurricane. The dummy $Post$ is 0 for all the preceding periods 1999-2004 and 1 for the periods 2005-2010. $\gamma_s \times \theta_t$ are state times year fixed effects to control for state time-varying characteristics. In this way, we exploit with-in state variation in the severity of the Hurricane. Finally, the β coefficient measures the difference in productivity between treated and untreated plants for the period 2005-2010 relative to the run-up period 1999-2004.

– Table 3 around here –

The β coefficient that we report in Column (1) of Table 3 is negative and statistically significant at the 1% level. The estimate indicates that the hurricane decreases productivity for treated plants by 0.6 percentage points after 2005 relative to untreated plants. This estimate is within range (1 percent on RoA) to the effect measured by, for example, Hsu et al. (2018). Re-scaled in terms of first differences, it implies a relative decrease in productivity growth equal to 1.1 percentage points. Considering the long-lasting decline, the effect is economically meaningful and similar in terms of magnitude to the labor productivity slowdown, which occurred after the Great Recession of 2008-09 (Syverson, 2017).

Next, we analyze the components of our productivity measure – sales and the number of employees, both in logs – separately. We find a negative and statistically significant effect only for the sales variable in Column (2). In particular, after the hurricane season, plants in treated counties saw relatively lower sales by 0.5 percentage points. Re-scaled in terms of first differences, it implies a relative decrease in sales equal to almost one percentage point. The effects of the hurricane on the number of employees is positive; however, the β coefficient in Column (3) is not statistically significant.

3.2 Robustness checks

This subsection provides a battery of robustness checks for the baseline results that we get from estimating Equation (2). To conserve space, we provide the tables in the Online Appendix.

Alternative fixed effects specifications Table OA2 shows that our central coefficient remains negative, statistically significant, and stay within one standard deviation of our preferred specification when we propose alternative fixed effect controls. We report our preferred specification in Column (1). Next, we show that our results are still consistent with our main finding when we exclude state times year fixed effects (Column (2)) when we control for heterogeneity across sectors and additionally include industry times year fixed effects (Column (3)). Our effect also remains intact when we consider a fully saturated regression in which we include both state times year and industry times year fixed effects (Column (4)).

Alternative ways in clustering standard errors Table OA3 shows that our results are not sensitive to alternative ways in clustering standard errors. In our analysis, we decide to cluster the errors at the plant level (Column (1)), the most granular unit of observation. Our results remain statistically significant when we cluster standard errors at the plant and year level (Column (2)), at the state level (Column (3)), and the state and year level (Column (4)).

Placebo treatment Figure OA1 in the Online Appendix shows estimates for the treatment effect for our baseline regression when we assign the treatment status randomly in the cross-section of plants. We thereby test the baseline result by randomly assigning the treatment by Hurricane Katrina to each plant. We use the unconditional probability of residing in a treated county to allocate 1,000 times the treatment status to the plants randomly. For each of these 1,0000 random allocations, we re-estimate the baseline regression. Figure OA1 provides the treatment effects together with the 95% confidence bands. In case the distribution of the treatment status leads to spurious results, we should find significant treatment effects at the 95% level in much more than 5% of the regressions. Our results show significant estimates only in 48 out of 1,000 simulations, which mutes concerns about confounding effects.

Long run effects until 2016 We test the effect of the 2005 hurricane season on plant productivity using a more extended post-disaster period until 2016 and report results in Table OA4. In line with our baseline findings, the beta coefficient remains negative and statistically significant. Again, we find adverse effects both for plant productivity and sales. However, for a longer time spell, we find that the hurricane significantly increases the number of employees for plants residing in treated counties.

Alternative database Our plant-level data comes from Infogroup. Infogroup collects this data by using thousand of alternative sources and is verified through phone calls. Although the information is strongly representative of local business dynamics, it could sometimes be inaccurate. In order to show the robustness of our results, we use an alternative dataset. In particular, we obtain a sample of manufacturing plants from the NETS database.[7] Table OA5 shows that our main findings remain intact when we both consider a shorter (1999-2010) and a longer (1990-2014) period with the NETS database. In terms of magnitude, the effect is even greater concerning our baseline result. In particular, after the hurricane, productivity in manufacturing plants decreases by four percentage points. We hypothesize that manufacturing plants that rely more on machinery and employees know-how are more affected by a natural disaster. When we analyze the effect of the natural disaster on sales and employees separately, we find that due to the 2005-hurricane season plant sales of treated plants relatively decrease by 11 percentage points (Column (2)). In line with our baseline results, we do not find evidence for an effect on plant employees (Column (3)).

The effect of the hurricane on local demand Column (3) and (4) of Table OA2 show that the negative effect of natural disasters on plant productivity holds accounting for trends in supply and demand across sectors by including interacted fixed effects. In this paragraph, we will consider specific sectors to investigate whether a fall in local demand is the driver of our results. Recent literature highlights the crucial role demand plays for corporate productivity and survival (Foster et al., 2008; De Loecker, 2007).

To investigate the role of local demand in our setting, we exploit that no-tradable industries like services and retail sectors rely more on local demand and thereby should face a larger fall in productivity (Mian et al., 2019). In order to identify plants that operate in no-tradable sectors, we follow the Mian and Sufi (2014) classification. We report results in Column (1) of Table OA6. We find that the treatment effect remains significant negative, which suggests that the baseline effect remains for all other sectors than the no-tradable sectors. We further find that the triple interaction effect is negative and statistically significant, too. This term suggests that the hurricane's effect is more severe for plants that rely on local demand.

To further investigate the role of local demand, we single out the construction

[7]The sample we consider is similar to the sample of firms used by (Hsu et al., 2018). More information on the sample collection procedure is available in (Hasan et al.).

sector since local demand for this sector is expected to increase after the hurricane drastically. Again, we identified plants operating in the construction business through the Mian and Sufi (2014) classification. We report our results in Column (2) of Table OA6. We find that the treatment effect is still negative and statistically significant. However, we find an insignificant triple interaction effect for plants in the construction sectors which suggest that plant in this sector endure similar shortfalls of their productivity after the hurricane.

4 The role of culture in post-disaster recovery

Our baseline result shows a robust significant detrimental effect of the 2005 hurricane season for plant productivity. In this section, we analyse whether regional differences in terms of culture affect the impact of the shock on plants. To do this, we employ the following equation:

$$\begin{gathered} Ln(Sales/FTE)_{it} = \alpha_i + (\gamma_s \times \theta_t) + \beta Treated_i \times Post_t + \\ + \gamma Culture_j \times Post_t + \delta Treated_i \times Culture_j \times Post_t + \epsilon_{it} \end{gathered} \tag{3}$$

Culture is a variable that measures a local cultural characteristic in county j. In particular, we employ proxies for religion and social and human capital. In this setting, β measures the effect of the hurricane on plant productivity when the particular proxy for culture is equal to 0. Importantly, δ is the differential effect of culture on post-disaster recovery. $\gamma_s \times \theta_t$ allows us to exploit within-state heterogeneity in cultural characteristics to understand the role local cultural characteristics play in post-disaster recovery.

We start our analysis by investigating the differential effect of religion on post-disaster recovery. Column (1) of Table 4 reports the estimates. In particular, the effect of the hurricane on plant productivity when religion is equal to 0 is equal to 1.68 percentage points. The triple interaction coefficient, however, is positive and statistically significant. In terms of magnitude, it implies that one standard deviation increase in the rate of religious adherence (16 percentage points) is mitigating the negative treatment effect by 0.37 percentage points. Our estimation implies that if the religion rate of adherence of a county is equal to 0.72%, the negative effect of the hurricane on local economic performance is netted out. Since religious adherence in treated counties before 2005 is around 66%, the netting effect is very likely.

Next, we augment our analysis by social capital as an additional cultural trait. In a critical situation, social capital could increase cooperation and foster in this way post-disaster recovery. We build our measure of social capital, as described in the data section. We report our findings in Column (2) of Table 4. The results show three things. First, the treatment effect for plants is negative and statistically significant if they reside in counties with no religion adherence for which our social capital variable is zero. Second, positive values of social capital mitigate this detrimental effect significantly. A one standard deviation increase in social capital (0.56) increases plant-level productivity by 0.25 percentage points to plants residing in counties with social capital equal to zero and absent religion adherence. Third, the religion coefficient remains positive and statistically significant.

We further analyze the additional role of human capital in post-disaster recovery. Recent literature argues that human capital work as a potential mechanism through which religion (in particular Protestantism) can affect economic growth (Becker and Woessmann, 2009). Furthermore, human capital could play a role per se in post-disaster recovery. On this point, (Besley and Burgess, 2002) argue that after natural disasters, governments tend to be more responsive to needs in areas where more people read newspapers, and there is a greater level of human capital. We report our results in Column (4) of Table 4. We find first that the treatment effect turns insignificant. That means that there is no differential effect from the disaster on productivity for plants in counties with zero religion, a social capital outcome of zero, and zero human capital. Second, the triple interaction coefficient of the treatment effect and human capital is negative and significant. This effect means that in the absence of religion and zero social capital, an increase in human capital decreases plant productivity even further. We further find that the triple interaction of the treatment effect and social capital turns insignificant. Moreover, the effect of religion remains significant and positive.

To better assess the results in Column (3), we demean religion, social, and human capital in Column (4) by their average value and re-estimate Equation (3). In this new setting, the β coefficient gives us the effect of the hurricane on productivity when religion, social capital, and human capital are at their average values. We find that the negative effect of the hurricane on productivity is equal to 0.24 percentage points for plants in treated counties with average religion and social and human capital. However, a one standard deviation increase in religion from its average value (an increase of 0.16 percentage points from its average value of 0.64%) increases post-disaster recovery by 0.23 percentage points. It thereby almost rules out the negative effect of the hurricane on local economic performance. Again, we find no evidence for significant differential effects from social and human capital, leaving religion the prime cultural moderator.

— Table 4 around here —

Propensity Score Matching A possible concern of our analysis is that religion reflects other county characteristics that correlate with religion itself as in 2004. In order to deal with this problem, in the baseline regression, we include state $\times$ year fixed effects. We further control for two variables the literature suggests are correlated with religion before the hurricane, that are social capital and human capital.

We further investigate whether religion reflects other county characteristics correlated with religion as in 2004, combining our difference in difference approach with a propensity score matching. Precisely, we match high religious counties (with a value of religion larger than the median value) with less religious counties (with a value of religion smaller than the median value) on a series of county characteristics measured as in 2004 (social capital, human capital, income per capita, population, number of employees and number of establishments). We use a propensity score matching estimated using a logit model. We match each county with the three nearest neighbors with replacement. Replacement improves the quality of the matching while matching with more neighbors has the advantage of using more information to construct the simulated counterfactual of each county but increasing the cost of a possible imperfect match. For this reason, in order to prevent bad matches, we impose a caliper of 5%. Table OA8 shows that the treated and the untreated groups selected following this procedure are well balanced, and there are not any statistical differences in terms of observable characteristics.

We report estimation results of Equation 3 using the new balanced sample in Table OA9. The coefficients of interest are still in line with the results of the main sample. For what concerns the religion coefficient, we find that the triple interaction coefficient is greater than the whole sample coefficient. A possible explanation is that, according to our logit model and to other papers in the literature (e.g., Chen, 2010), religious adherence negatively correlates with income per capita and population, that are negatively correlated with recovery after a natural disaster (Kahn, 2005). We conclude that our results of interest are not affected by any omitted variable characteristics. If any, the propensity score matching suggests that we are estimating a lower bound effect of religion on post-disaster recovery.

Robustness We show that our results on the moderating effects of culture hold when we consider the NETS sample. We show our findings in Table OA7. In Column (1), according to our main finding, we show that plants' productivity in treated counties recovers faster in more religious counties. In Column (2) and Column (3), we gradually control for social capital and human capital. While we find religion to be associated with a greater post-disaster recovery, we do not find any evidence on social and human capital.

Cultural attitudes Our findings explain that religiosity is associated with "good" economic attitudes. In particular, as we explained in the introduction, religion is associated with confidence towards institutions and the market, cooperation, and thriftiness. These characteristics are common across all the religions (Guiso et al., 2004). However, some attitudes are heterogeneous across religions. In this paragraph, we will exploit heterogeneity across religions to better understand the attitudes through which religion could affect post-disaster recovery.

First, we exploit heterogeneity in attitudes between Protestants and Catholics.

We start our analysis by estimating the effect of the Catholics' shares on post-disaster performance. We report results in Column (1) of Table OA10. We find a positive and statistically significant effect on the triple interaction effect. Thereby, a one standard deviation increase in the catholic share (0.12 percentage point increases in Catholics religious adherence) is associated with a post-disaster recovery equal to 0.9 percentage points. In Column (2) of Table OA10, we study the effect of the share of Protestants on post-disaster recovery. Again, the coefficient is positive and statistically significant. However, in terms of economic magnitude, the effect is smaller, with one standard deviation increase in the share of Protestants (0.12 percentage points). It fosters post-disaster recovery by 0.2 percentage points. These results rule out that post-disaster recovery is due to "good" economic attitudes, such as work ethics and pro-investment behaviors.

Next, we analyze the effect of other widespread religions in the United States: Hebraism and Islamism. In Column (3) of Table OA10, we show that the triple-interaction Hebraism coefficient is positive and statistically significant. In terms of magnitude, the effect is even higher concerning the Catholic's coefficient. In particular, a one standard deviation increase in Hebraism (0.5 percentage points) increases post-disaster recovery by 0.14 percentage points. Finally, we test the effect of Islamism on post-disaster recovery. Interestingly, the triple interaction coefficient is negative but not statistically significant. This finding is in line with previous literature that finds a negative effect of Islam religious beliefs on growth (McCleary and Barro, 2006; Campante and Yanagizawa-Drott, 2015).

5 Mechanisms and aggregate county-dynamics

In this section, we will investigate the mechanisms through which plants located in more religious counties exhibit higher post-disaster performance.

Ancestors' experience of natural disasters and religion So far, we find that religion is a critical factor in mitigating the detrimental effects of plant productivity from the 2005-hurricane season. To investigate the potential mechanism, we turn to analyze the effects of ancestors' experience of natural disasters for post-disaster recovery (Hsiang and Jina, 2014).

To measure ancestors' experience of natural disasters, we collect ancestors' information from the 2005 ACS. We build a measure of "Natural Disaster Risk" of its country of origin for each person. In this way, we investigate whatever people that come from a country with higher "natural disaster risk" bring with them a cultural ability to deal with natural disasters that become an essential skill after the strike of Hurricane Katrina.

We use and a variant of Equation (3) with ancestors' experience as the new modifier and report our findings in Table 5. First, in Column (1), the treatment effect on plants in counties without any ancestor experience of natural disasters, and no religious adherence is negative and significant. The β coefficient reveals and economic effect of about 2.47 percentage points. Second, in counties with higher religious adherence, this negative effect is mitigated, which corroborates our previous results. In particular, one standard deviation increases in religiosity is associated with an increase in productivity equal to 0.4 percentage points. Crucially, however, we find a positive and statistically significant triple interaction effect for the treatment effect and ancestors' experience. This effect reveals that productivity is relatively higher for plants in counties with higher ancestors' experience. The effect is as well economic meaning-full; one standard deviation increase in the ancestors' experience index (an increase of 0.042 of the index) is associated with an increase in productivity equal to 0.5 percentage points. It implies that when religion is equal to 0, an increase of 5 standard deviations in the ancestors' experience of natural disaster index from 0 (an index equal to 0.21) net out the negative effect of the hurricane on local economic activity. Column (2) and Column (3) split the sample and focus on the effect of religion in post-disaster recovery in areas with more considerable experience of natural disasters and areas with less experience. While the triple interaction coefficient is positive and statistically significant in both the regressions, the effect of religion in post-disaster recovery is more pronounced in areas where there is a more exceptional natural disaster experience, suggesting that religion and ancestors' experience of natural disasters are complimentary.

— Table 5 around here —

Psychological resilience As we explained in the introduction, a plausible explanation of our findings is that people in more religious counties are significantly less affected by the harmful effect the hurricane has on the human psyche (Schuster et al., 2001; Smith et al., 2000). On the other side, human sentiments have been shown to play a crucial role in economic performance (Blanchard, 1993; Gillitzer and Prasad, 2018).

To test this hypothesis, we collect information on the google searches of the words *depression* and *anxiety* since both are the central disorders caused by a traumatic event. To use google searches is a common approach in the literature. For example, Baker and Fradkin (2017) use Google Search data to study the effects of unemployment insurance policy changes, and Ginsberg et al. (2009) show that search data for 45 terms related to influenza predicted flu outbreaks 1 to 2 weeks before Centers for Disease Control and Prevention (CDC) reports. The rationale for using Google Trends information is that online search dynamics reveal the salience of psychological phenomena (Stephens-Davidowitz, 2014). Furthermore, the same approach has been recently used by Bentzen (2020) to show that the COVID-19 leads to an increase in the level of religious intensity.

More specifically, in order to estimate the impact of the Hurricane on the human psyche and to show that religion can mitigate the negative impact on psychological well-being, we estimate the following regression:

$$\Delta PhysiologicalDisorder_j = \alpha Treated_j + \beta Treated_j \times Religion_j + \gamma Religion_j + \epsilon_j \tag{4}$$

Religion is the share of religious adherence in county j and *Physiological Disorder* is the variation of the google search index of the word depression or anxiety between the year 2006 and year 2004 scaled by the google search index in the year 2004.[8]

We report our results in Table 6. The estimates in Column (1) and (3) show that depression and anxiety significantly increase in treated counties between 2004

[8] We could not collect information for depression before the year 2004 since Google Trends provides information starting from 2004.

and 2006. The results show that the level of google searches for the word anxiety relatively increases by 72% (the coefficient is 0.363, and the average delta anxiety is 0.501) and of the word depression by 130% (the coefficient is 0.521, and the average delta depression value is 0.387) in treated counties. However, this negative effect is less severe in counties with higher religious adherence, as we show in Column (2) and (4). One standard deviation increases in religion decrease depression by 0.15. Moreover, a one standard deviation increases in religion decreases depression by 0.11. Thereby, our results indicate that religion helps people to stay in balance after the shock, which potentially lifts their ability to recover faster.

— Table 6 around here —

Religion organizations as providers of services In this paragraph, we are going to test the role of religious organizations in the United States as a form of social networks and as a form of social insurance to economic shocks using micro-data from the American Community Survey for the period 2000-2010.[9] In particular, we estimate the following equation:

$$Y_{ut} = \alpha_j + (\gamma_s \times \theta_t) + \beta Treated_u \times Post_t + \gamma Religion_j \times Post_t + \\ + \delta Treated_u \times Religion_j \times Post_t + \Gamma X_{ut} + + \epsilon_{ut} \tag{5}$$

Y are four alternative outcome variables for the individual u. We control for county and year fixed effects. Finally, we as well include in our model a matrix X of individual characteristics. In particular, we control for the age of the individual and for a series of dummy variables that take value equal to one if the individual is a female, if he/she has a degree, if he/she is married, if he/she is black, if he/she participates to any social activity and if he/she has born outside the United States.

We report our findings in Table 7. First, we find that the hurricane positively affects the probability of being unemployed by around five percentage points. However, we find that a one standard deviation increases in religiosity, decreasing the probability of an individual being reported as unemployed after the hurricane's

[9]For these exercises, we limit the sample on people belonging to the labour force.

strike by 1.15 percentage points. Thereby, our results corroborate existing literature like Kramarz and Skans (2014) who emphasize the role of social networks in the labor market. Moreover, conditional on being employed, we do not find any evidence that religion affects an individual's probability of reporting a higher wage after 2005 (Column (2)). These findings suggest that religious organizations could help match the workers in the labor market after the hurricane, sustaining local economic activities.

Next, we take into account in our analysis government fiscal cost after a natural disaster. On this point, Deryugina (2017) shows that in the United States, hurricanes significantly increase indirect transfers' cost, arising from SSI benefits, which are much higher concerning direct fiscal costs through disaster aid. We consider the fact that previous literature highlights the role of religious organizations in the United States as providers of services, showing a substitution effect of faith activities on government spending (e.g., Gruber and Hungerman, 2007; Hungerman, 2005). According to this strand of the literature, we provide empirical evidence that religious organizations could mitigate the negative effect a natural disaster have on the fiscal cost. In particular, our results in Column (3) and Column (4) show that the use of social income assistance[10] and welfare income[11] increase in treated counties after 2005. Importantly, however, we find accordingly to Andersen et al. (2017) that this increase is counterbalanced in more religious counties, suggesting a mutual relationship between religious services and the government.[12]

— Table 7 around here —

The decision to migrate A potential channel through which religion could affect post-disaster recovery is the decision to migrate since migration is an essential determinant of regional recovery after a natural disaster (Strobl, 2011; Hornbeck and Naidu, 2014; Mahajan and Yang, 2017). Even if the effect of social networks on the

[10]Natural logarithm of the amount in dollar units the individual received from Social Security pensions, survivors benefits, or permanent disability insurance, as well as U.S. government Railroad Retirement.

[11]Natural logarithm of the amount in dollar units of pre-tax income the respondent received from various public assistance programs commonly referred to as "welfare," such as federal/state SSI payments, aid to Families with Dependent Children (AFDC) and General Assistance (G.A.).

[12]In this setup, the coefficients are not significant in the last column due to the introduction of state × year fixed effects.

decision to migrate is ambiguous from a theoretical point of view, recent literature suggests that social networks arising from religious organizations and collectivist cultural traits increase the cost of migration (Kitayama et al., 2006; Knudsen, 2019). For this reason, we hypothesize that migration is likely to affect less more religious counties.

In order to investigate this hypothesis, we estimate the following equation:

$$\begin{aligned} Y_{jt} = {} & \alpha_j + (\gamma_s \times \theta_t) + \beta Treated_j \times Post_t \\ & + \gamma Religion_j \times Post_t + \delta Treated_j \times Religion_j \times Post_t + \epsilon_{jt} \end{aligned} \tag{6}$$

Y is the logarithm of the number of people living in county j at time t and α_j are county fixed effects. We report our findings in Column (1) of Table 8. We find that the population in treated counties significantly shrinks by around ten percentage points. However, a one standard deviation increase in religiosity is associated with a population recovery of roughly a quarter of the total population loss.

Aggregate county dynamics We further investigate the implications of our findings on county aggregate dynamics. In particular, in order to estimate the effect of religion on post-disaster recovery, we consider three alternative measures of county economic activity for Y: the number of people employed, the number of establishments, and the GDP measured at the county level (all variable are in natural logarithms).

We report our findings in Table 8. Employment results are reported in Column (2). In line with our previous results from Table 7), we find that employment falls on average by 14 percentage points. However, a one standard deviation increase in religion adherence mitigates the detrimental effect on employment by 2.7 percentage points.

We further consider local economic activity in terms of the number of establishments. Results are reported in Column (3). We find that the number of establishments decreases by around ten percentage points for counties without any religious adherence. However, a one standard deviation increase in religion allows mitigates the effect by two percentage points.

Finally, we consider a full measure of economic activity. In particular, we consider the level of county GDP and report our results in Column (4). We find that GDP falls by almost 14 percentage points in affect counties without religious adherence. However, a one standard deviation increase in religion allows recovering 3.5 percentage points of the fall in GDP.

— Table 8 around here —

6 Conclusions

A growing literature analyzes the effect of climate change in the form of natural disasters on economic outcomes. We advance in this literature by focusing on the role of culture in post-disaster periods. We investigate the effect of the 2005 hurricane season on plant-level productivity and find that the 2005 hurricane season in the United States has a significant and long-lasting negative effect. More critical, we find those cultural traits in the form of higher religious adherence help to mitigate the adverse effects on productivity from a high-impact disaster like Hurricane Katrina. We find evidence that religion eases the detrimental effect because religious adherence makes individuals less anxious. We further document that a higher share of ancestors with natural disaster experience complements the beneficial effects of religion. Last, we find that the positive effects on the plant-level spill over to the aggregate. We find that the effects of the disaster on migration and economic activity are significantly less severe in counties with greater religious adherence.

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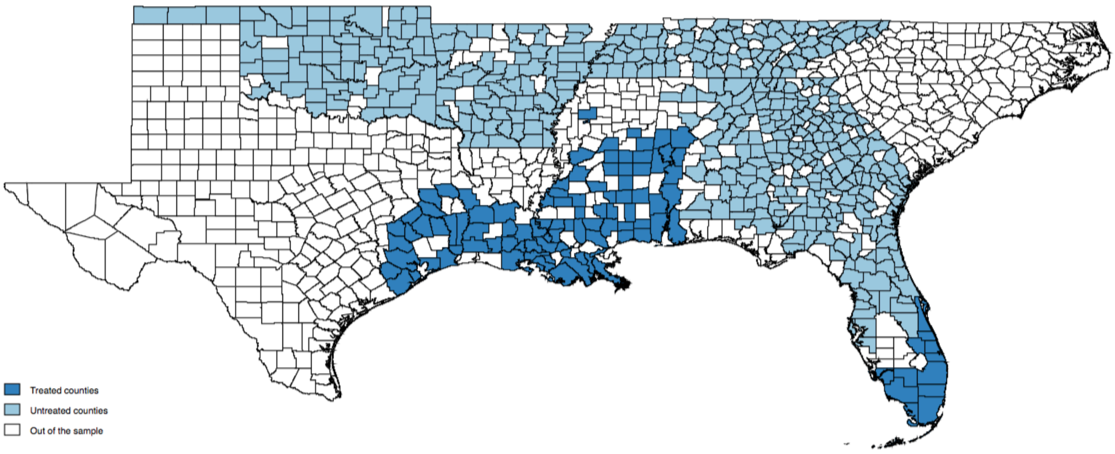
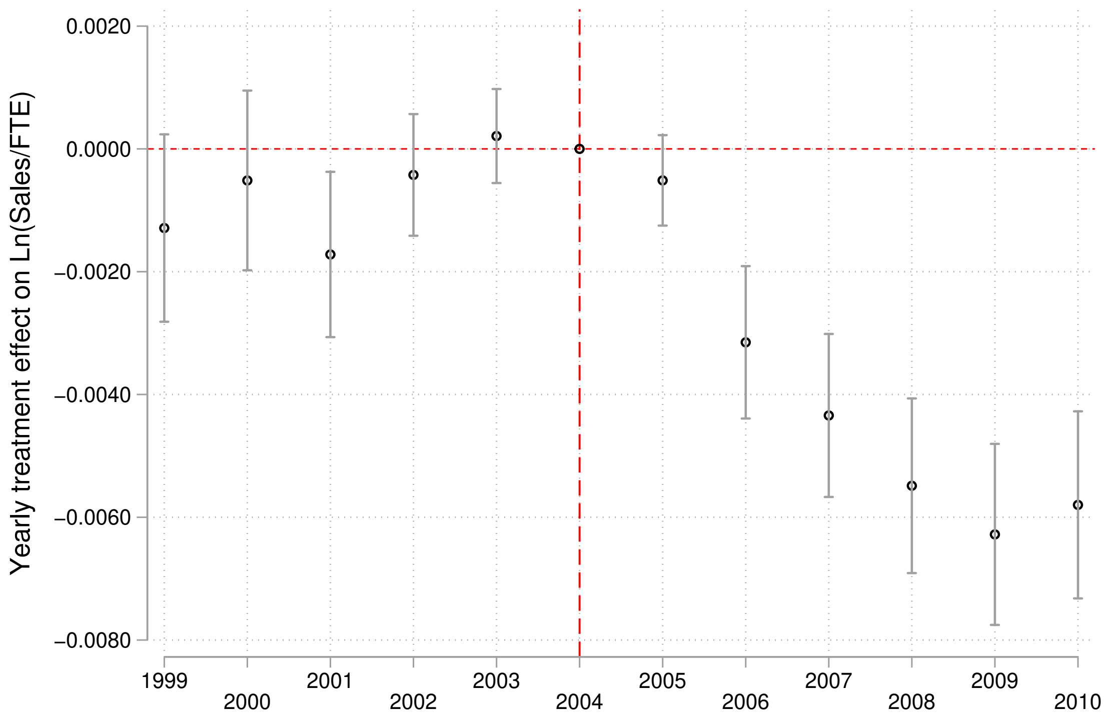
Figures

Figure 1: Distribution of the treated and untreated plants



Notes: The figure shows the treated and untreated counties in our sample similar to Schüwer et al. (2019). A county is defined as treated if, after Hurricane Katrina and the subsequent hurricanes Rita and Wilma have been declared eligible for individual and public disaster assistance by the Federal Emergency Management Agency (FEMA). A county is included in the control group if it is not eligible for public or individual disaster assistance, but it is located in the Gulf Coast region or a neighboring state. We exclude from our sample counties eligible for public disaster assistance but not eligible for individual disaster assistance because this criterion is ambiguous.

Figure 2: Yearly treatment coefficients



Notes: This figure shows the yearly treatment effects from Equation (1) with plant fixed effects but without the state × year fixed effects from our baseline regression. The dependent variable is Ln(Sales/FTE).

Tables

Table 1: Variable description

Variable name	Description	Source
Panel A: Plant Characteristics		
Sales	Estimated sales at plant level	Infogroup
FTE	Number of employees at plant level	Infogroup
Sales/FTE	Labour productivity measured as the ratio between plant sales and employees	Infogroup
Panel B: Cultural Characteristics		
Religion	Rate of religious adherence in the county as in 2000. Adherents are defined as" all members, including full members, their children, and the estimated number of other regular participants"	ARDA
Catholics	Rate of religious adherence to Catholicism in the county as in 2000. Adherents are defined as" all members, including full members, their children, and the estimated number of other regular participants"	ARDA
Protestants	Rate of religious adherence to a protestant religion in the county as in 2000. Adherents are defined as" all members, including full members, their children, and the estimated number of other regular participants"	ARDA
Jewish	Rate of religious adherence to Judaism in the county as in 2000. Adherents are defined as" all members, including full members, their children, and the estimated number of other regular participants"	ARDA
Islam	Rate of religious adherence to Islam in the county as in 2000. Adherents are defined as" all members, including full members, their children, and the estimated number of other regular participants"	ARDA
Social Capital	Principal component analysis of two variables that capture the strength of local cooperative norms (voter turnover and the county-level response rate) and two variables that capture the ramification of social norms (the number of associations and the number of no-profit organizations) measured at the county level as in 2005	NERCRD
Human Capital	Share of the population over 25 years old that holds a degree measured at PUMA level as in 2005	ACS
Ancestors' Experience of Natural Disasters	Average of the ancestors' "natural disaster risk" (computed as ancestors' country of origin people dying for a natural disaster scaled by country population) of the locals measured at PUMA level as in 2005. The index has then be multiplied by 100.	ACS
Delta Depression	Variation of the google search index of the word depression between 2006 and 2004 scaled by the google search index in the year 2004 measured at Nielsen DMA level	Google Trends
Delta Anxiety	Variation of the google search index of the word anxiety between 2006 and year 2004 scaled by the google search index in the year 2004 measured at Nielsen DMA level	Google Trends

This table provides the list of the variables available in our database (Column (1)), detailed information on the construction of each variables (Column (2)) and the source of the data (Column (3)).

Table 1: Variable description cont'd

Variable name	Description	Source
Panel C: County Characteristics		
Establishments	Natural logarithm of the count of the establishments in the county	BEA
Employment	Natural logarithm of the count of full-time and part-time jobs in the county	BEA
Population	Natural logarithm of the estimated population of the county	U.S. Census Bureau
GDP	Natural logarithm of the real gross domestic product (GDP) measured estimating the value of the goods and services produced in the county	BEA
Income per capita	Natural logarithm of the income per capita	BEA
Panel D: Individual Characteristics		
Unemployment	Dummy variable equal to one if the individual reports itself as unemployed	ACS
Wage	Natural logarithm of the total wage and salary income for the previous year	ACS
Income from SSI	Natural logarithm of the income the individual received from Social Security pensions, survivors benefits, permanent disability insurance, and U.S. government Railroad Retirement insurance payments, during the previous year	ACS
Income from Welfare	Natural logarithm of the income the individual received during the previous year from public assistance programs commonly referred to as "welfare." Assistance from private charities is not included	ACS
Gender	Dummy variable equal to one if the individual is a female	ACS
Age	Age of the individual at the time of the survey	ACS
Black	Dummy variable equal to one if the individual is black	ACS
Foreign	Dummy variable equal to one if the individual has born outside of the United States	ACS
Gender	Dummy variable equal to one if the individual is a female	ACS
Degree	Dummy variable equal to one if the individual holds a degree	ACS
Married	Dummy variable equal to one if the individual is married	ACS

Table 2: Summary statistics and normalized differences

	Treated		**Untreated**		
	Mean	SD	Mean	SD	ND
Levels					
Ln(Sales/FTE)	3.57	1.35	3.53	1.35	0.02
Sales/FTE	92.14	1032.42	88.71	848.34	0.00
Ln(Sales)	4.91	1.76	4.89	1.78	0.01
Sales	1032.15	51627.97	1015.00	12680.40	0.00
Ln(FTE)	1.68	0.92	1.70	0.95	-0.02
FTE	10.67	65.06	11.52	77.02	-0.01
Religion	0.66	0.17	0.64	0.16	0.11
Social Capital	-1.17	0.56	-0.69	0.59	-0.59
Human Capital	0.25	0.05	0.24	0.08	0.04
First differences					
ΔLn(Sales/FTE)	0.53	0.93	0.54	0.93	-0.01
ΔSales/FTE	37.48	699.95	38.44	630.89	-0.00
ΔLn(Sales)	0.54	0.99	0.55	0.99	-0.01
ΔSales	446.19	35699.44	492.06	9205.89	-0.00
ΔLn(FTE)	0.00	0.21	0.00	0.21	0.01
ΔFTE	0.16	21.16	0.12	32.82	0.00

This table shows descriptive statistics for all variables we use in our plant-level analyses. We separate the sample between treated and untreated plants and counties and shows the statistics for the pre-2005 period. The sample comprises 2,896,377 plants in 512 counties. The upper part shows the pre-2005 levels while the lower part shows average first differences for this period. The last column provides normalized differences. See Table 1 for a detailed description of every variable.

Table 3: Baseline results

	(1)	(2)	(3)
Dependent variable	Ln(Sales/FTE)	Ln(Sales)	Ln(FTE)
Post × Treated	-0.0056***	-0.0052***	0.0010
	(0.0009)	(0.0015)	(0.0010)
Fixed effects			
Plant FE	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes
Adjusted R2	0.9695	0.9497	0.9218
Plants	2,896,377	2,896,377	2,896,377
Observations	17,125,223	17,125,223	17,125,223

This table shows regression results for Equation (2) for different dependent variables mentioned in the second row. Standard errors are adjusted for heteroskedacity and within plant correlation. ***, **, *: denote significant at 1, 5 and 10 percent level respectively. See Table 1 for a detailed description of every variable.

Table 4: The role of culture

	(1)	(2)	(3)	(4)
Dependent variable		Ln(Sales/FTE)		
Post × Treated	-0.0168***	-0.0102***	-0.0045	-0.0024**
	(0.0026)	(0.0032)	(0.0044)	(0.0010)
Post × Religion	-0.0350***	-0.0274***	-0.0254***	-0.0254***
	(0.0026)	(0.0029)	(0.0029)	(0.0029)
Post × Religion × Treated	0.0232***	0.0165***	0.0148***	0.0147***
	(0.0045)	(0.0047)	(0.0047)	0.0047
Post × Social Capital		-0.0045***	-0.0018**	-0.0018**
		(0.0007)	(0.0008)	(0.0007)
Post × Social Capital × Treated		0.0044***	0.0012	0.0011
		(0.0013)	(0.0013)	(0.0013)
Post × Human Capital			-0.0489***	-0.0489***
			(0.0048)	(0.0048)
Post × Human Capital × Treated			-0.0257**	-0.0257
			(0.0110)	(0.0110)
Fixed effects				
Plant FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Adjusted R2	0.969	0.969	0.969	0.965
Plants	2,896,377	2,896,377	2,896,377	2,896,377
Observations	17,125,223	17,125,223	17,125,223	17,125,223

This table shows regression results for variants for Equation (3) in which we interact our baseline effects with pre-2005 proxies for culture on the county level. Standard errors are adjusted for heteroskedacity and within plant correlation. ***, **, *: denote significant at 1, 5 and 10 percent level respectively. See Table 1 for a detailed description of every variable.

Table 5: Ancestors Experience of Natural Disasters and Religion

	(1)	(2)	(3)
Dependent variable		Ln(Sales/FTE)	
Post $\times$ Treated	-0.0247***	-0.0117**	-0.0155***
	(0.0029)	(0.0049)	(0.0044)
Post $\times$ Religion	-0.0320***	-0.0240***	-0.0530***
	(0.0026)	(0.0033)	(0.0050)
Post $\times$ Treated $\times$ Religion	0.0294***	0.0148**	0.0247***
	(0.0046)	(0.0060)	(0.0082)
Post $\times$ Ancestors' Experience	-0.1842***		
	(0.0175)		
Post $\times$ Treated $\times$ Ancestors' Experience	0.1191***		
	(0.0193)		
Fixed effects			
Plant FE	Yes	Yes	Yes
State$\times$Year FE	Yes	Yes	Yes
Adjusted R2	0.9695	0.9703	0.9792
Plants	2,896,377	1,381,127	1,515,250
Observations	17,125,223	8,471,131	8,654,092

This table shows regression results for Equation (3) in which we interact our baseline effects with pre-2005 proxies for culture on the county level. Standard errors are adjusted for heteroskedacity and within plant correlation. ***, **, *: denote significant at 1, 5 and 10 percent level respectively. See Table 1 for a detailed description of every variable.

Table 6: Psychological Resilience

	(1)	(2)	(3)	(4)
Dependent variable	Anxiety	Anxiety	Depression	Depression
Treated	0.3628***	0.4833***	0.4115***	0.5206**
	(0.0406)	(0.1016)	(0.0264)	(0.1834)
Treated × Religion		-0.9424***		-0.6889**
		(0.2115)		(0.2124)
Religion		0.7868***		0.5475***
		(0.1796)		(0.1047)
Adjusted R2	0.047	0.464	0.124	0.531
County	512	512	512	512
Observations	512	512	512	512

This table shows regression results for Equation 4 using as dependent variable delta depression and delta anxiety computed using Google Trends. Standard errors are adjusted for heteroskedacity and within state correlation. ***, **, *: denote significant at 1, 5 and 10 percent level respectively. See Table 1 for a detailed description of every variable.

Table 7: Religion and social services

	(1)	(2)	(3)	(4)
Dependent variable	Unemployed	Wage	Income from SSI	Income from welfare
Post × Treated	0.0492***	-0.0670*	0.1443***	0.0115
	(0.0035)	(0.0349)	(0.0400)	(0.0227)
Post × Religion	0.0446*	-0.0721	0.1290	0.0333**
	(0.0204)	(0.0456)	(0.0748)	(0.0098)
Post × Treated × Religion	-0.0993***	0.0683	-0.2841**	-0.0109
	(0.0126)	(0.0579)	(0.0836)	(0.0603)
Fixed effects				
Individual Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Adjusted R2	0.029	0.240	0.002	0.010
County	50	50	50	50
Observations	50,687	46,059	50,687	50,687

This table shows regression results for Equation 5 for different dependent variables mentioned in the second row and using the American Community Survey (ACS) database. Standard errors are adjusted for heteroskedacity and within state and year correlation. ***, **, *: denote significant at 1, 5 and 10 percent level respectively. See Table 1 for a detailed description of every variable.

Table 8: Aggregate effects

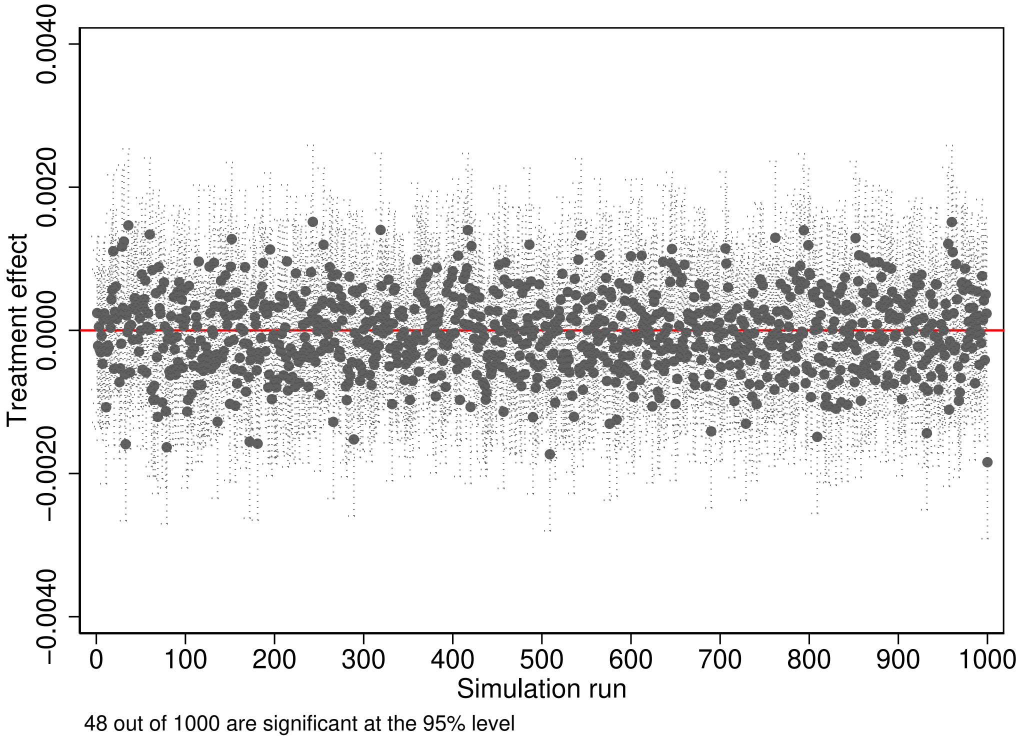
	(1)	(2)	(3)	(4)
Dependent variable	Population	Employment	Establishments	GDP
Post × Treated	-0.1021***	-0.1338**	-0.1043**	-0.1375**
	(0.0254)	(0.0424)	(0.0448)	(0.0493)
Post × Religion	-0.2032***	-0.2114***	-0.2485***	-0.2156**
	(0.0397)	(0.0604)	(0.0613)	(0.0611)
Post × Treated × Religion	0.1094**	0.1651*	0.1247	0.2130**
	(0.0412)	(0.0731)	(0.0693)	(0.0719)
Fixed effects				
County FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Adjusted R2	0.999	0.997	0.998	0.997
Counties	512	512	512	349
Observations	6,144	6,144	6,144	3,490

This table shows regression results for Equation 6 for different dependent variables mentioned in the second row and using aggregate county data. We further interact with pre-2005 proxies for religion on the county level. Standard errors are adjusted for heteroskedacity and state and year correlation. ***, **, *: denote significant at 1, 5 and 10 percent level respectively. See Table 1 for a detailed description of every variable.

Online Appendix

This Appendix is for Online Publication and provides further details on the data and results of the article.

Figure OA1: Placebo treatment



Notes: This figure shows the treatment effect β and 95% confidence bands from 1,000 regressions of Equation (2) in which we randomly assign the treatment status to the plants.

Table OA1: Summary Statistics before the Hurricane

Variables	Mean	SD	p25	p75
	Panel A: Plant Characteristics			
Ln(Sales/FTE)	3.55	1.35	2.48	4.71
Ln(Sales)	4.90	1.77	3.53	6.08
Ln(FTE)	1.69	0.94	1.10	2.08
	Panel B: County Characteristics			
Establishments	6.63	1.27	5.73	7.27
Employment	9.32	1.39	8.33	10.08
Population	10.52	1.16	9.72	11.15
GDP	13.90	1.44	12.88	14.81
Income per capita	10.05	0.19	9.93	10.14
	Panel C: Cultural Characteristics			
Religion	0.68	0.19	0.55	0.81
Catholics	0.06	0.12	0.01	0.04
Jewish	0.00	0.01	0.00	0.00
Islam	0.00	0.00	0.00	0.00
Social Capital	-0.94	0.71	-1.39	-0.53
Human Capital	0.18	0.05	0.14	0.21
Ancestors' experience of natural disaster	0.03	0.02	0.02	0.04
Delta Anxiety	0.50	0.52	0.11	0.71
Delta Depression	0.39	0.35	0.21	0.56
	Panel D: Census micro-data			
Age	39.13	12.96	29.00	48.00
Unemployed	0.05	0.21	0.00	0.00
Income from wage	9.18	2.97	9.31	10.60
Income from INCSSI	0.03	0.48	0.00	0.00
Gender	0.52	0.50	0.00	1.00
Degree	0.27	0.44	0.00	1.00
Income from welfare	0.03	0.49	0.00	0.00
Married	0.55	0.50	0.00	1.00
Foreign	0.21	0.40	0.00	0.00
Black	0.19	0.40	0.00	0.00

This table shows descriptive statistics for the pre-2005 period for all variables we use in analyses. See Table 1 for a detailed description of every variable.

Table OA2: Variations of fixed effects

	(1)	(2)	(3)	(4)
Dependent variable	Ln(Sales/FTE)			
Treated × Post	-0.0056***	-0.0033***	-0.0035***	-0.0051***
	(0.0009)	(0.0005)	(0.0005)	(0.0008)
Fixed effects				
Plant FE	Yes	Yes	Yes	Yes
Year	subsumed	Yes	subsumed	subsumed
Industry×Year FE	No	No	Yes	Yes
State×Year FE	Yes	No	No	Yes
Adjusted R2	0.9695	0.9695	0.9768	0.9768
Plants	2,896,377	2,896,377	2,896,377	2,896,377
Observations	17,125,223	17,125,223	17,125,223	17,125,223

This table shows regression results for Equation (2) for different sets of fixed effects mentioned in the middle part of the table. Standard errors are adjusted for heteroskedacity and within plant correlation. ***, **, *: denote significant at 1, 5 and 10 percent level respectively. See Table 1 for a detailed description of every variable.

Table OA3: Variations of standard errors

	(1)	(2)	(3)	(4)
Dependent variable	Ln(Sales/FTE)			
Treated × Post	-0.0056***	-0.0056**	-0.0056***	-0.0056***
	(0.0009)	(0.0019)	(0.0010)	(0.0011)
Fixed effects				
Plant FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Standard error cluster				
Plant	Yes	Yes	Yes	Yes
Year	No	Yes	No	Yes
State	No	No	Yes	Yes
Adjusted R2	0.9695	0.9695	0.9695	0.9695
Plants	2,896,377	2,896,377	2,896,377	2,896,377
Observations	17,125,223	17,125,223	17,125,223	17,125,223

This table shows regression results for Equation (2) using alternative ways of clustering the standard errors that are mentioned in the middle part of the table. ***, **, *: denote significant at 1, 5 and 10 percent level respectively. See Table 1 for a detailed description of every variable.

Table OA4: Baseline results considering a longer spanning period

	(1)	(2)	(3)
Period		1999-2016	
Dependent variable	Ln(Sales/FTE)	Ln(Sales)	Ln(FTE)
Post × Treated	-0.0065***	-0.0036**	0.0034***
	(0.0010)	(0.0017)	(0.0011)
Fixed effects			
Plant FE	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes
Adjusted R2	0.9453	0.9341	0.9213
Plants	1,551,777	1,551,777	1,551,777
Observations	16,955,107	16,955,107	16,955,107

This table shows regression results for Equation (2) for different dependent variables mentioned in the second row and using a longer spanning period (1999-2016) with respect to our baseline specification. Standard errors are adjusted for heteroskedacity and within plant correlation. ***, **, *: denote significant at 1, 5 and 10 percent level respectively. See Table 1 for a detailed description of every variable.

Table OA5: Baseline results for alternative data

	(1)	(2)	(3)	(4)	(5)	(6)
Period		1990-2014			1999-2010	
Dependent variable	Ln(Sales/FTE)	Ln(Sales)	Ln(FTE)	Ln(Sales/FTE)	Ln(Sales)	Ln(FTE)
Post × Treated	-0.0480**	-0.1190**	-0.0682	-0.0323*	-0.1164***	-0.0786**
	(0.0194)	(0.0553)	(0.0495)	(0.0181)	(0.0417)	(0.0354)
Fixed effects						
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.8486	0.8260	0.8315	0.8982	0.8653	0.8700
Plants	7,103	7,103	7,103	6,113	6,113	6,113
Observations	123,077	123,077	123,077	62,051	62,051	62,051

This table shows regression results for Equation (2) for different dependent variables mentioned in the second row and using an alternative database with respect to our baseline results. Standard errors are adjusted for heteroskedacity and within county correlation. ***, **, *: denote significant at 1, 5 and 10 percent level respectively. See Table 1 for a detailed description of every variable.

Table OA6: The role of local demand

	(1)	(2)
Dependent variable	Ln(Sales/FTE)	
Treated × Post	-0.0042***	-0.0043***
	(0.0009)	(0.0009)
NonTradable	0.0330***	
	(0.0021)	
Treated × NonTradable	-0.0487***	
	(0.0035)	
Post × NonTradable	0.0831***	
	(0.0008)	
Treated × Post × NonTradable	-0.0047***	
	(0.0012)	
Construction		-0.0759***
		(0.0027)
Treated × Construction		-0.0226***
		(0.0043)
Post × Construction		0.0922***
		(0.0008)
Treated × Post × Construction		-0.0013
		(0.0014)
Fixed effects		
Plant FE	Yes	Yes
State×Year FE	Yes	Yes
Adjusted R2	0.9696	0.9696
Plants	2,896,377	2,896,377
Observations	17,125,223	17,125,223

This table shows regression results for variants for Equation (2) in which we interact our baseline effects with dummy variables indicating different industry sectors. We cluster standard errors on the plant level. See Table 1 for a detailed description of every variable.

Table OA7: The role of culture using an alternative database

	(1)	(2)	(3)
Dependent variable	Ln(Sales/FTE)	Ln(Sales/FTE)	Ln(Sales/FTE)
Treated × Post	-0.136***	-0.110**	-0.140**
	(0.042)	(0.054)	(0.071)
Treated × Religion	-0.076**	-0.063	-0.068*
	(0.037)	(0.040)	(0.038)
Treated × Religion × Post	0.149**	0.126*	0.135*
	(0.064)	(0.070)	(0.071)
Treated × Social Capital		-0.008	-0.004
		(0.011)	(0.012)
Treated × Social Capital × Post		0.015	0.011
		(0.021)	(0.021)
Treated × Human Capital			-0.065
			(0.066)
Treated × Human Capital × Post			0.093
			(0.151)
Fixed effects			
Plant FE	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes
Adjusted R2	0.849	0.849	0.849
Plants	7,103	7,103	7,103
Observations	123,077	123,077	123,077

This table shows regression results for Equation (3) in which we interact our baseline effects with pre-2005 proxies for culture on the county level and using an alternative database with respect to our baseline results. Standard errors are adjusted for heteroskedacity and within plant correlation. ***, **, *: denote significant at 1, 5 and 10 percent level respectively. See Table 1 for a detailed description of every variable.

Table OA8: Summary statistics and normalized differences

	Treated Mean	Untreated Mean	p-value
Social Capital	-1.059	-1.102	0.654
Human Capital	0.172	0.169	0.712
Population	10.272	10.146	0.291
GDP	13.660	13.496	0.420
Establishments	6.496	6.332	0.365
Employment	9.149	8.990	0.425
Income Per Capita	10.102	10.079	0.410

This table shows that the treated and untreated counties in our matching procedure are well balanced across a serious of observable characteristics. The first column report the average value of the variable in the treated group. The second column report the average value of the variable in the untreated group. The last column show the p-value of a t-test on the difference. See Table 1 for a detailed description of every variable.

Table OA9: Propensity score matching and the role of culture

	(1)	(2)	(3)	(4)
Dependent variable	Ln(Sales/FTE)			
Post × Treated	-0.0252**	-0.0328***	-0.0210	-0.0028
	(0.0099)	(0.0124)	(0.0142)	(0.0078)
Post × Religion	-0.0451***	-0.0430***	-0.0238***	-0.0238***
	(0.0050)	(0.0056)	(0.0063)	(0.0063)
Post × Treated × Religion	0.0385***	0.0458***	0.0354***	0.0354***
	(0.0096)	(0.0118)	(0.0126)	(0.0126)
Post × Social Capital		-0.0016	0.0042**	0.0042**
		(0.0017)	(0.0020)	(0.0020)
Post × Social Capital × Treated		-0.0028	-0.0062*	-0.0062*
		(0.0033)	(0.0035)	(0.0035)
Post × Human Capital			-0.0645***	-0.0645***
			(0.0098)	(0.0098)
Post × Human Capital × Treated			-0.0470	-0.0470
			(0.0373)	(0.0373)
Fixed effects				
Plant FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Adjusted R2	0.970	0.970	0.970	0.970
Plants	590,485	590,485	590,485	590,485
Observations	3,480,604	3,480,604	3,480,604	3,480,604

This table shows regression results for variants for Equation (3) in which we interact our baseline effects with pre-2005 proxies for culture on the county level. The sample is selected using a propensity score matching approach. Standard errors are adjusted for heteroskedacity and within plant correlation. ***, **, *: denote significant at 1, 5 and 10 percent level respectively. See Table 1 for a detailed description of every variable.

Table OA10: Attitudes

	(1)	(2)	(3)	(4)
Dependent variable		Ln(Sales/FTE)		
Post × Treated	-0.0164***	-0.0062***	-0.0073***	-0.0052***
	(0.0016)	(0.0015)	(0.0012)	(0.0009)
Post × Catholics	-0.0965***			
	(0.0096)			
Post × Catholics × Treated	0.0973***			
	(0.0103)			
Post × Protestants		0.0159***		
		(0.0037)		
Post × Protestants × Treated		0.0133**		
		(0.0055)		
Post × Jewish			-0.3186***	
			(0.0230)	
Post × Jewish × Treated			0.2928***	
			(0.0251)	
Post × Islam				-1.2323***
				(0.0632)
Post × Islam × Treated				-0.1393
				(0.1407)
Fixed effects				
Plant FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Adjusted R2	0.969	0.969	0.969	0.969
Plants	2,896,377	2,896,377	2,896,377	2,896,377
Observations	17,125,223	17,125,223	17,125,223	17,125,223

This table shows regression results for variants of Equation (3) in which we interact our baseline effects with pre-2005 alternative religion organization measures on the county level. Standard errors are adjusted for heteroskedacity and within plant correlation. ***, **, *: denote significant at 1, 5 and 10 percent level respectively. See Table 1 for a detailed description of every variable.

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