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The short-run, dynamic employment effects of natural disasters: New insights from Puerto Rico

Alessandro Barattieri [a], Patrice Borda [b], Alberto Brugnoli [c], Martino Pelli [d,e,f,g], Jeanne Tschopp [h,*]

[a] *ESG UQAM, Case Postale 8888, sucursale Centre-ville Montreal (Quebec), H3C 3P8, Canada*
[b] *Université des Antilles, UFR des Sciences Juridiques et Economiques Campus de Fouillole, BP 270 97157 Pointe–Pitre, Guadeloupe, France*
[c] *University of Bergamo, Department of Economics, Via dei Caniana 2 24127, Bergamo, Italy*
[d] *University of Sherbrooke, Department of Economics, 2500 Blvd de l'Université, Sherbrooke, Q.C., Canada*
[e] *CIREQ, Canada*
[f] *CIRANO, Canada*
[g] *GREDI, Canada*
[h] *University of Bern, Department of Economics, Schanzeneckstrasse 1, 3001 Bern, Switzerland*

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ABSTRACT

We study the short-run, dynamic employment effects of natural disasters. We exploit monthly data for 70 3-digits NAICS industries and 78 Puerto Rican counties over the period 1995–2019. Our exogenous measure of exposure to natural disasters is computed using the maximum wind speed recorded in each county during each hurricane. Using panel local projections, we find that after the "average" hurricane, employment falls by 0.5% on average. Across industries, we find substantial heterogeneity in the employment responses. Employment increases in some industries while in others employment decreases after a hurricane. This heterogeneity can be partly explained by input–output linkages.

1. Introduction

In 2020, for only the second time in history, the World Meteorological Organization ran out of letters to name Atlantic tropical storms, and started using names from the Greek alphabet.[1] Moreover, natural disasters are expected to increase reported direct losses from the current $195 billion a year to $234 billion a year by 2040. This increase of $39 billion could reach up to $100 billion per year if we factor in the indirect costs from supply chain disruptions and other knock-on economic consequences.[2] Given these facts, it is hardly surprising that studying the economic consequences of climate change and natural disasters has become a central research topic in several fields of economics. However, due to data availability, especially in the context of less developed regions, there has been far too little evidence coming from high frequency, detailed industry data. This is relevant, because detailed data can help uncover the economic mechanisms taking place in the aftermath of a disaster. As a step towards filling this gap, this paper studies the short-run, dynamic employment effects within detailed industries of a specific type of natural disasters – i.e. hurricanes – using an ideal laboratory: Puerto Rico.

We exploit a unique feature of Puerto Rico: a frequent and spatially dispersed exposure to hurricanes, combined with the availability of high frequency, detailed employment data. This combination allows us to propose the first estimates of the short-run, dynamic employment effects of hurricanes. Using geo-coded monthly data for 70 3-digits NAICS industries and 78 counties over the period 1995–2019, we examine outcomes up to two years post-hurricane. Another important and novel aspect of our work is to highlight the importance of input–output linkages in industrial adjustments.

With the aid of satellite data, we are able to track the position of the eye of each hurricane and the wind speed within it at six-hour intervals. We then use the output of physical models to interpolate location-specific windspeeds at specific points in time. We are therefore able to measure the intensity of exposure to hurricanes in all of Puerto

* Corresponding author.
E-mail addresses: barattieri.alessandro@uqam.ca (A. Barattieri), patrice.borda@univ-antilles.fr (P. Borda), alberto.brugnoli@unibg.it (A. Brugnoli), Martino.Pelli@USherbrooke.ca (M. Pelli), jeanne.tschopp@vwi.unibe.ch (J. Tschopp).

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[2] "Natural Disasters Could Cost 20 Percent More By 2040 Due to Climate Change", E360 digest 27, 2020, Yale University. https://e360.yale.edu/digest/natural-disasters-could-cost-20-percent-more-by-2040-due-to-climate-change.

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Rico's counties by using the maximum wind speed recorded in each county cell during each hurricane. Exploiting information on wind speed guarantees the absence of any potential endogeneity of our measure with respect to economic outcomes, which can lead to biased results, as shown by Felbermayr and Gröschl (2014). Armed with this exogenous measure, varying over time and at the county level, we explore the dynamic employment effects of hurricanes using local projections. This tool, which has now been used in many contexts, consists of running a sequence of regressions for different prediction horizons. Operationally, we regress the cumulative change of our variables of interest (for instance, employment) on our disaster shock variable at each horizon. The coefficients obtained trace the dynamic responses to a disaster shock. One advantage of local projections is that, unlike panel VARs, they do not impose (potentially incorrect) dynamic restrictions. Moreover, as stressed by Dube et al. (2022), local projections offer a simple tool to solve the problem of dynamic heterogeneous treatment effects that can arise in difference-in-difference approaches with multiple treatments. The richness of our data allows us to explore variation at the county–time, county–industry–time, and industry–time level. In our regressions, we control for pre-trends and seasonal effects.

At the aggregate level, theory predicts that natural disasters can have both detrimental and positive effects on the economy. While the destruction of productive facilities, land, public, and private infrastructures has a direct and negative impact on income and household wealth, the process of reconstruction can trigger positive responses. For instance, capital may be replaced by more productive vintages and flow where its marginal product is the highest. Moreover, reconstruction may take place in better-performing industries, thereby leading to differential responses across sectors (see e.g. Hornbeck and Keniston, 2017; Pelli and Tschopp, 2017). These differential responses may also be influenced by disruptions in daily business activities, the necessity for firms to shut down, changes in demand for certain types of activities (e.g. leisure, entertainment, and hospitality services), shifts in the supply of labor, and the potential reallocation of workers across industries. In the aggregate, the net effect is determined by the dominating force, which depends on the type of natural disaster, its strength, the income group of the affected economy, as well as its industrial structure. Hence, whether natural disasters have a positive or negative impact and how they affect specific sectors are ultimately empirical questions.

As discussed by Hsiang and Jina (2014), there are four possible trajectories an economy can follow in the aftermath of natural disasters: *recovery to trend*, where after a short period of downturn the economy reverts to its pre-disaster level; *no recovery*, where the natural disaster acts as a permanent income shock; *creative destruction*, where the economy temporarily grows faster; and the *build back better* hypothesis, where the shock triggers negative short-lived effects followed by positive economic growth. Each of these hypotheses has found empirical support in the literature (see e.g. Naguib et al., 2022; Cole et al., 2019; Bertinelli and Strobl, 2013; Strobl, 2012; Cuaresma et al., 2008).

Surprisingly, while it is reasonable to expect local shocks to cause heterogeneous responses across industries, most of the literature has focused on the aggregate economic impacts of natural disasters. Perhaps for this reason, from a theory perspective, there is no off-the-shelf theoretical framework yielding clear predictions on how *specific* sectors should respond to natural disasters; hence, we remain agnostic about the direction of the effects across industries. Pelli and Tschopp (2017) discuss a potential theoretical framework that highlights why natural disasters affect industries differentially, but the paper focuses exclusively on tradable goods and the manufacturing sector. A few empirical studies have looked at the impact of natural disasters on *specific* sectors, aggregated at a higher level than in our analysis (see e.g. Roth Tran and Wilson, 2021; Kunze, 2021; Groen et al., 2020; Peri et al., 2020; Loayza et al., 2012; Hsiang, 2010; Belasen and Polachek, 2008). The following patterns emerge: not surprisingly, "Agriculture, hunting, forestry and fishing" and "Wholesale, retail trade, restaurant and hotels" consistently contract, while "Construction" is always found to grow, likely due to the need of reconstruction. On the other hand, the manufacturing sector masks heterogeneities. The nature of our data allows us to explore this heterogeneity in greater detail.

Our main results are threefold. First, after the "average" hurricane, employment falls on average by about 0.5% after about six months. We also find an average increase in the number of unemployed, with no significant changes to the labor force. Average weekly wages increase after six months, but the increase is not statistically significant. Second, we find heterogeneous effects across industries. In some industries, which we call the "strengthened industries", employment increases following a natural disaster. Examples of these industries include NAICS 236 ("Construction of Buildings") and NAICS 238 ("Specialty trade contractors"). In other industries, which we call "weakened" industries, employment decreases. Examples of weakened industries are NAICS 721 ("Accommodation") and NAICS 487 ("Scenic and Sightseeing Transportation"). In a third group of industries, employment does not seem to be directly affected by natural disasters. We call them "neutral" industries. Third, we uncover a potential mechanism that can explain some of the results at the industry level: input–output linkages. For the "strengthened industries", we find a positive and statistically significant relationship between the size of the employment increase 12 months after a disaster shock and the share of output sold to the construction sector.

Finally, while we do not test this formally, the heterogeneous responses of employment to hurricanes across different industries suggest a new concept of resilience: *adaptability-driven employment resilience*, defined as the potential opportunity for workers to reallocate from the contracting industries to the expanding ones in the aftermath of a natural disaster. This could be an important building block of "post-disaster resilience", which was included as one of the three pillars of the "disaster resilience strategy" framework proposed by the IMF (2019). An increase of the adaptability-driven employment resilience could be pursued by introducing new and different vocational training programs, aimed at endowing workers with a set of heterogeneous skills, which are needed for rapid and temporary reallocations across different industries.

The remainder of the paper is structured as follows. The next section discusses the relevant literature. Section 3 presents the data, particularly our measure of exposure to natural disasters. Section 4 discusses our empirical strategy, and Section 5 contains the results. Section 6 reports the robustness checks, and Section 7 concludes.

2. Related literature

This paper is linked to the literature exploring the effects of natural disasters on a variety of different outcomes, such as economic growth (Hsiang and Jina, 2014; Felbermayr and Gröschl, 2014; Bertinelli and Strobl, 2013; Cavallo et al., 2013; Strobl, 2011), firm level outcomes (Pelli et al., 2022; Elliott et al., 2019; Seetharam, 2018; Vu and Noy, 2018), exports (Pelli and Tschopp, 2017), household finance (Deryugina et al., 2018; Gallagher and Hartley, 2017), education (Sacerdote, 2012), housing (Ortega and Taspinar, 2018) and migration (Boustan et al., 2020).

Several papers have looked at the labor market effects of hurricanes, but focusing exclusively on the impacts of the migration caused by the disaster. For instance, McIntosh (2008), Groen and Polivka (2008) and De Silva et al. (2010) present difference-in-difference studies of the local labor market impacts of the migration induced by Hurricane Katrina. McIntosh (2008) finds that in-migration of Hurricane Katrina evacuees into Houston had negative, albeit modest, effects on wages and employment among Houstonians non-evacuees. Similarly, De Silva et al. (2010) find that in-migration led to a fall in quarterly wages in Houston. Groen and Polivka (2008) concentrate on evacuees and find that Katrina caused a decline in both their labor force participation and employment rate and a rise in their unemployment rate. Peri et al. (2020) use Hurricane Maria as an exogenous shock originating in Puerto Rico to study the impact of migration on the labor market outcomes of incumbent workers in Orlando. Using a synthetic control approach, the authors find that aggregate employment increased and that this increase was particularly marked in construction and retail 12 months after the shock. Earnings fell slightly in the construction sector, which employs migrant labor to a greater extent. Yet, this fall was offset by a growth in earnings in retail and hospitality. Finally, Groen et al. (2020) look at the long-term effects of Hurricanes Katrina and Rita on earnings outcomes. Using a difference-in-difference approach, they find that, due to job losses, quarterly earnings in affected regions declined (although modestly) in the first year following the strike. However, from 2006 through 2012, wages rose substantially. Consistent with other studies, results differ by industry and are particularly marked for construction workers, whereas tourism, health care, and professional services bear substantial losses.

Our study differs from these papers in several aspects. First and foremost, we evaluate the average labor market response of directly affected jurisdictions. In contrast, these studies focus on very different sub-groups of the population – i.e. evacuees or incumbent workers in regions that are not directly hit by the hurricane but experienced in-migration. This is an important distinction as the labor market response of directly affected regions may differ substantially from neighboring areas. Relatedly, these studies use migration as a proxy for the disaster shock, while we use a measure that captures wind exposures and is exogenous by construction. Importantly, using in-migration implies that the authors exclusively focus on the labor supply aspect of the shock in indirectly affected areas. This paper seeks to be more general and is interested in the labor markets effects associated with disaster damages, the direct need for rebuilding, and the resulting changes in the industrial structure. Finally, we consider all of the counties in Puerto Rico and all of the hurricanes that occurred over the sample period. This is markedly different than the aforementioned papers, which limit themselves to one hurricane and a few counties at a time, making their results less generalizable.

Closer to our paper are Belasen and Polachek (2008, 2009). Using quarterly data, they explore the employment and wage effects of hurricanes across counties in Florida for the period 1988–2005. Belasen and Polachek (2008) also perform an additional analysis across five broad sectors (such as Manufacturing and Services). In both papers, the authors rely on categorical measures of hurricanes and adopt a generalized difference-in-difference (GDD) approach. They find that earnings respond positively and employment falls over time following a hurricane. In a more recent study, Deryugina (2017) uses a difference-in-differences method to estimate the fiscal costs of US hurricanes. Estimates imply that in the ten years following the shock, extra transfers from non-disaster social insurance programs to affected counties average $780-$1,150 per capita per hurricane in present value. This result suggests that the fiscal costs of hurricanes are substantial and underestimated when considering disaster aid alone. To examine the channels behind this result, Deryugina (2017) also provides estimates of the impact of US hurricanes on other county-level outcomes and finds that while average earnings and population remain unchanged, the employment rate drops temporarily.

The contribution of our work relative to these papers is threefold. First, we focus on a different geographic area. So far, the literature on the labor markets impacts of natural disasters has largely focused on the United States, despite the fact that the lion's share of natural disasters is concentrated in developing countries. As pointed out in Hsiang and Jina (2014), countries that are frequently and perpetually exposed to hurricanes suffer permanent losses that accumulate over time, resulting in larger long-run income penalties. By focusing on Puerto Rico, we provide novel evidence on the short-run employment effects in a lower-income setting, which has been understudied.

Second, we use a different measure of storm exposure. Belasen and Polachek (2008, 2009) both rely on categorical measures of hurricanes defined by two sub-groups reflecting low and high intensities according to the Saffir–Simpson scale. Similarly, Deryugina (2017) measures hurricane exposure with an indicator variable. Instead, we propose a continuous treatment that allows to account for differences in storm exposure even within categories of the Saffir–Simpson scale. This distinction is an important one because the type of damages inflicted by storms can differ substantially depending on wind intensities and this is likely to matter for industrial adjustments. For instance, one might expect the tourism sector to respond already at relatively low wind intensities while the construction sector may only boom following havoc. The use of a continuous treatment is even more relevant as we study adjustments across detailed classification of industries, unlike Belasen and Polachek (2008), which analyze broad sectors. Our results highlight that even within narrowly defined sectors, different industries experience different employment dynamics in the aftermath of a natural disasters. Moreover, the use of this detailed set of industries allows us to unveil the importance of input–output linkages as a driving mechanism of the employment effects of natural disasters.

Third, our empirical approach is different and uses local projections. Following the seminal work by Jorda (2005), local projections have been used in the literature to investigate the dynamic effects of shocks on the economy. Examples of this literature include Auerbach and Gorodnichenko (2013), Jorda and Taylor (2016), and Leduc and Wilson (2013), who look at fiscal policy shocks. Ottonello and Winberry (2020) investigate the effects of monetary shocks, while Barattieri and Cacciatore (2020) study trade policy shocks in the presence of network effects. To the best of our knowledge, this paper is among the first studies to use local projections to examine the economic impacts of hurricanes. In a recent paper, Roth Tran and Wilson (2021) also perform local projections on county-level U.S. data over the period spanning 1980–2017 to look at the response of local economies following natural disasters. Impulse response functions indicate that natural disasters, measured using an indicator variable equaling one in the case of positive damages, lead to a rise in total and per-capita personal income as of 8 years out. While we share a similar methodology, we concentrate on a different type of shock, i.e. hurricanes, using a continuous exposure index to examine employment adjustments across industries. Moreover, while Roth Tran and Wilson (2021) exclude Puerto Rico, our analysis provides some evidence of the labor market responses in a lower income setting.

3. Data

In this Section we introduce our measure of exposure to hurricanes, obtained using satellite data, and the data on Puerto Rican employment dynamics taken from the Bureau of Labor Statistics (BLS).

3.1. Wind speed at the county level

We use satellite data from the National Oceanic and Atmospheric Administration (NOAA) Tropical Prediction Center. We look at the storms' best tracks in the Caribbean Sea over the period 1995–2017 to construct the maximum wind speed associated with each hurricane H hitting Puerto Rican county c, i.e. w_{cH}. A best track contains the full history of a hurricane, with information at 6-hour intervals on latitude, longitude, date, and wind speed at its eye.

First, we linearly interpolate the storms' best tracks at every kilometer. For each interpolated kilometer, we compute the set of coordinates for the position of the eye (landmark h) and the wind speed at the eye, V_h. For each county that falls in the vortex associated with a landmark h, we use the HURRECON model (see Boose et al., 1994, 2001, 2004) to compute the sustained wind velocity at the county's centroid, w_{ch}.[3]

In order to improve the precision of our measure and obtain a good proxy of the impact of hurricanes on economic activity, we do

[3] More details about the HURRECON model are provided in Appendix A.

not use the simple geometrical centroid of each county. Instead, using population data from the 2010 Census at the block level and the geometrical centroid of each census block, we construct a population-weighted centroid for each of the 78 counties of Puerto Rico. This correction allows us to compute the maximum wind speed affecting populated areas and to give less weight to strong winds hitting forests or other areas with no economic activity.

Finally, we obtain one measure of windspeed per county and hurricane by retaining the maximum windspeed to which a county was exposed:

$$w_{cH} = \max_{h \in H}\{w_{ch}\}.$$

3.2. Counties exposure to hurricanes

In this section, we describe how we construct S_{ct}, the index of exposure to hurricanes for county c at time t (where time can be at monthly or quarterly frequency). Following Bernabe et al. (2022), Pelli et al. (2022), Pelli and Tschopp (2017), and Yang (2008), our index of exposure is obtained in the following way:

$$S_{ct} = \sum_{H} x_{cHt} \quad \text{where} \quad x_{cHt} = \frac{(w_{cHt} - 33)^3}{(w^{max} - 33)^3} \quad \text{if} \quad w_{cHt} > 33 \tag{1}$$

where x_{cHt} represents the maximum windspeed affecting county c during storm H at time t relative to the sample maximum (the term w^{max}). We normalize x_{cHt} with respect to the maximum wind speed observed in order to obtain a measure included between zero and one. The cubic powers account for the force exerted by winds on physical structures (see the technical HAZUS manual of the Federal Emergency Management Agency (FEMA) of the US Department of Homeland Security and Emanuel, 2005).[4] We use a threshold of 33 knots, which defines a tropical storm according to the Simpson and Riehl scale.[5,6]

Fig. 1 shows examples of our measure of exposure, S_{ct}, for four major hurricanes that hit Puerto Rico over the years. Each hurricane is represented with a different color and within each color, darker shades reflect stronger exposures. On the left side of the figure, we show the best track for each of the four hurricanes, while, on the right side, we show the exposure index, S_{ct}, for each of the four months concerned. This figure underlines the large extent of geographical and time variation at our disposal for identification. Hurricane Jeanne, for instance, mostly hit the western part of Puerto Rico (the counties most affected were *municipios* “Aguada”, “Aguadilla” and “Cabo Rojo”). On the contrary, hurricanes Irene and Maria hit the eastern part of the island much more severely. *Municipios* “Vieques”, “Yabucoa” and “Culebra” were the counties most affected by hurricane Irene, while *municipios* “Culebra”, “Fajardo” and “Luquillo” were the counties most affected by hurricane Maria. Finally, hurricane Georges mostly hit the central part of the island. The counties most affected were *municipios* “Catano”, “Aibonito”, and “Toa Alta”. In Appendix B, we list the 23 hurricanes and tropical storms that hit Puerto Rico in our sample period.

Table 1 presents summary statistics of the exposure index, S_{ct}, across Puerto Rican counties and for the period 1995–2017 using monthly (top panel) and quarterly (bottom panel) data. Not surprisingly, when zero exposures are accounted for, monthly exposures exhibit a smaller average. When computed using positive exposures only, the average monthly and quarterly exposures are similar.

[4] In Section 6, we experiment with a variety of alternative specifications of counties exposure to hurricanes.

[5] In one robustness check, we increase the threshold from 33 knots to 64.

[6] By definition, $S_{ct} \in (0, \sum_H)$, with a value of 0 indicating zero county exposure to hurricanes (i.e. winds in county c are below the threshold) and with $\sum_H$ indicating the number of storms hitting a county at time t. This is because in the cases when more than one hurricane hits Puerto Rican counties at the same time t, we sum x_{cHt} over hurricanes.

Table 1
Summary statistics of hurricane exposures.

Variable	Mean	Std. dev.	Min.	Max.	N
Monthly data:					
S_{ct}	0.004	0.057	0	1.645	21294
S_{ct} if $S_{ct} > 0$	0.084	0.242	3.34e−10	1.645	1063
Quarterly data:					
S_{ct}	0.013	0.098	0	1.645	7098
S_{ct} if $S_{ct} > 0$	0.092	0.253	3.34e−10	1.645	961

Notes: S_{ct} is our disaster shock measure, computed from Eq. (1). Roughly 5% of our observations have positive exposures to the disaster shock. This is due to the fact that our baseline specification includes not only hurricanes but also tropical storms, i.e. events with windspeeds exceeding 33 knots.

Finally, Fig. 2 presents boxplots of the exposure index. The boxplots describe S_{ct} by county using monthly data for the period 1995–2017. Counties with $S_{ct} > 0$ between 1995 and 2017 are listed in alphabetical order. The top (bottom) panels include (exclude) outliers. The white line is the median. The left edge of the box is the first quartile ($Q1$ or 25th percentile) and the right edge the third quartile ($Q3$ or 75th percentile). The end of the left (right) whisker is the 1st percentile (99th percentile). The circles outside of the box capture outliers. The boxplots highlight the substantial variation in exposures both across counties and over time.

3.3. Puerto rico employment data

We use employment data from the Quarterly Census of Employment and Wages (QCEW) by the Bureau of Labor Statistics of the United States (BLS). The QCEW contains monthly data on employment and quarterly data on wages at the county and county–industry level. To the best of our knowledge, this level of detail is impossible to find in developing countries. We focus our attention on employment in the private sector. To give a broad idea of the economic structure of the Puerto Rican economy, during our sample period, the private sector employed on average 674,800 people. Of those workers, 18.4% were employed in Retail Trade (NAICS 44-45), 17.2% in Manufacturing (NAICS 30), 9.7% in Health care and social assistance (NAICS 62), 9.1% in Accommodation and Food Services (NAICS 72), 8.7% in the Administrative and Waste services (NAICS 46), and 7.1% in Construction (NAICS 23). In terms of employment dynamics, manufacturing has witnessed a secular decline. Most services display an increase over time, while the construction sector seems characterized by an inverted U-shaped dynamics.

Within the manufacturing sector, the most important industries in terms of average employment in our sample period are NAICS 325 (“Chemical manufacturing”), NAICS 311 (“Food manufacturing”), and NAICS 315 (“Apparel manufacturing”). While (unsurprisingly) apparel manufacturing employment displays a negative trend, chemical manufacturing employment shows an inverted-U shape. We also use the Local Area Unemployment Statistics from the BLS to get county-level data at monthly frequency on the number of unemployed and the total labor force. In Appendix C, we provide tables and graphs with more details on the structure of the Puerto Rican economy, as well as a table of summary statistics.

4. Empirical strategy

Armed with the exogenous exposure to hurricanes illustrated in the previous section, we explore the dynamic employment effects using local projections. After the seminal contribution by Jorda (2005), local projections have become a tool used in many settings, as discussed in the Introduction. The approach consists of running a sequence of predictive regressions of a variable of interest on a shock for different prediction horizons. The sequence of regression coefficients traces the dynamic response of the variable of interest to the shock. The main

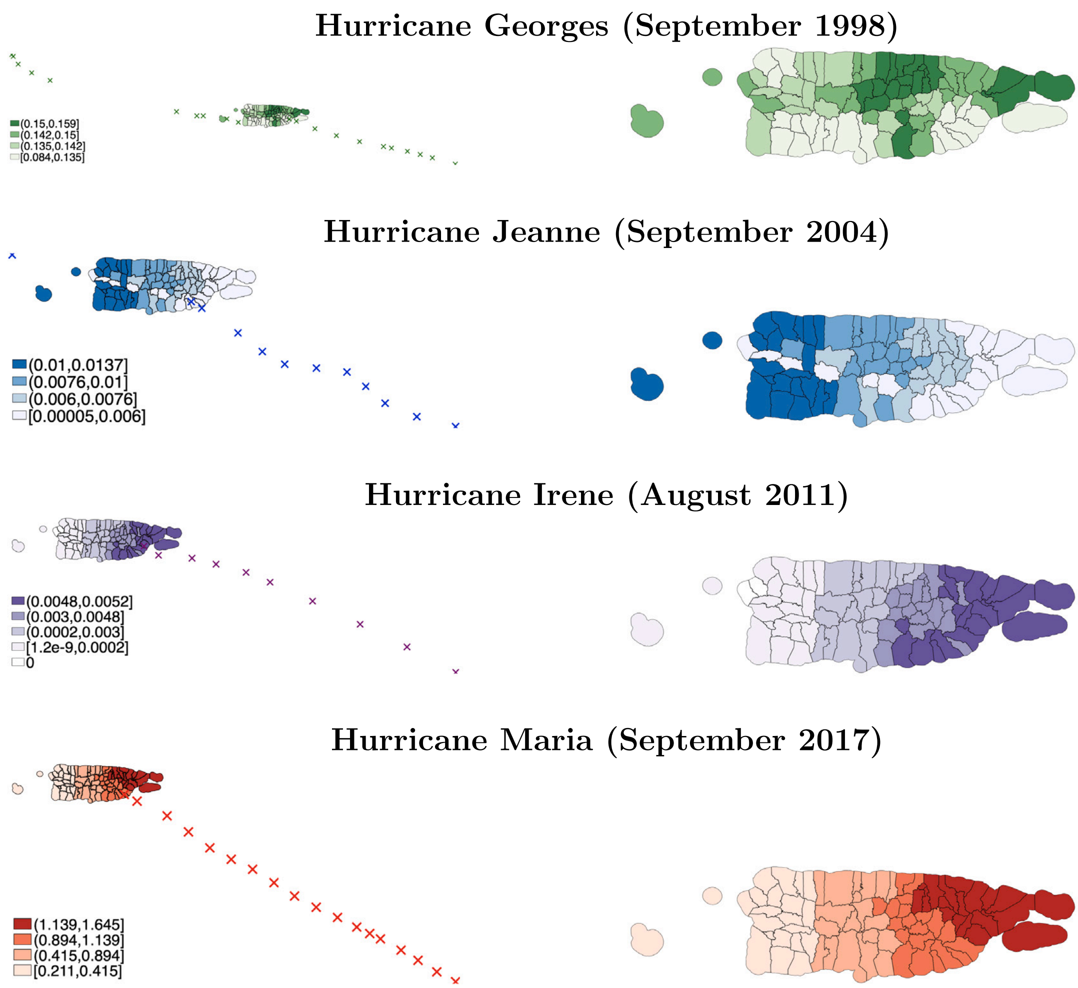

Fig. 1. County exposure to hurricanes — Examples.
Note: The left panels show the best tracks of hurricanes Georges, Jeanne, Irene, and Maria respectively. Each cross represents the position of the eye of the hurricane at 6-hours intervals. All these four hurricanes made landfall in Puerto Rico. Note however that making landfall is not a necessary condition for the island to be impacted, as some areas further away from the eye of the hurricane may experience strong winds and thus have positive exposures. The right panels zoom in on the island and show, for each county, the values taken by the storm index S_{ct} during the month the hurricane stroke. Color shades indicate positive exposures, with darker shades displaying stronger exposures.

advantages of this approach are that local projections do not impose potentially inappropriate dynamic restrictions (as panel VARS do), they are robust to misspecification of the data-generating process, and they can be estimated in a simple univariate framework. As argued by Dube et al. (2022), local projections also offer a simple tool to solve the problem of dynamic heterogeneous treatment effects that can arise in difference-in-difference approaches with multiple treatments. Moreover, this method is direct, clear, simple, easy to code and compute, and is transparent and flexible in its handling of treated and control units. Finally, it is not specific, but extremely general, including notably its ability to control for pre-treatment values of the outcome and of other covariates (Dube et al., 2022).

In our context, we will explore variation at the county–time level, at the county–industry–time level, and at the industry–time level. First, we run the following k-step ahead panel predictive regressions:

$$\Delta X_{c,t+k} = \alpha^k + \gamma_1^k S_{ct} + \sum_p \beta_p \Delta X_{c,t-p} + \delta_t + \eta_c + \epsilon^1_{c,t+k}, \quad (2)$$

where $\Delta X_{c,t+k}$ is the cumulative growth of our variable of interest from time $t-1$ to time $t+k$ (that is, $\Delta X_{c,t+k} \equiv \log X_{c,t+k} - \log X_{c,t-1}$). Notice that this definition of our dependent variables implies that our results are cumulative up to period k. X_c represents employment, unemployment, the labor force (for each county c at monthly frequency) or the average weekly wage (for each county c at quarterly frequency). S_{ct} is our measure of disaster shocks, varying at county level for each month (or quarter). Our main object of interest is γ_1^k, representing the average response of X_c at horizon k to a disaster shock at time t. $\sum_p \Delta X_{c,t-p}$ controls for past values of the one-period growth of the variable of interest, which in this context is akin to controlling for potential pre-trends.[7] δ_t and η_c represent time and counties fixed effects. Our sample period runs from 1995M1 to 2019M11. We have data for a panel for 78 counties (GEO).

The richness of our data allows us to also exploit the county–industry–time variation for average employment and wage outcomes.[8] Our second specification is therefore the following:

$$\Delta X_{ic,t+k} = \alpha^k + \gamma_2^k S_{ct} + \sum_p \beta_p \Delta X_{ic,t-p} + \nu_{ic} + \nu_{it} + \epsilon^2_{ic,t+k}, \quad (3)$$

X_{ic} represents employment, (for each county c and industry i at monthly frequency) or the average weekly wage (at quarterly frequency). All of the other variables are defined as in Eq. (2). Now, we can introduce county–industry specific fixed effects (ν_{ic}), together with industry–time fixed effects (ν_{it}). As before, our sample period runs from

[7] We selected $p = 6$ for monthly data and $p = 2$ for quarterly data. Notice that since $\Delta X_{c,t-p} \equiv \log X_{c,t-p} - \log X_{c,t-p-1}$, we are not inserting in the regression lagged values of the dependent variable.

[8] Unemployment and the labor force are concepts only defined at the county level.

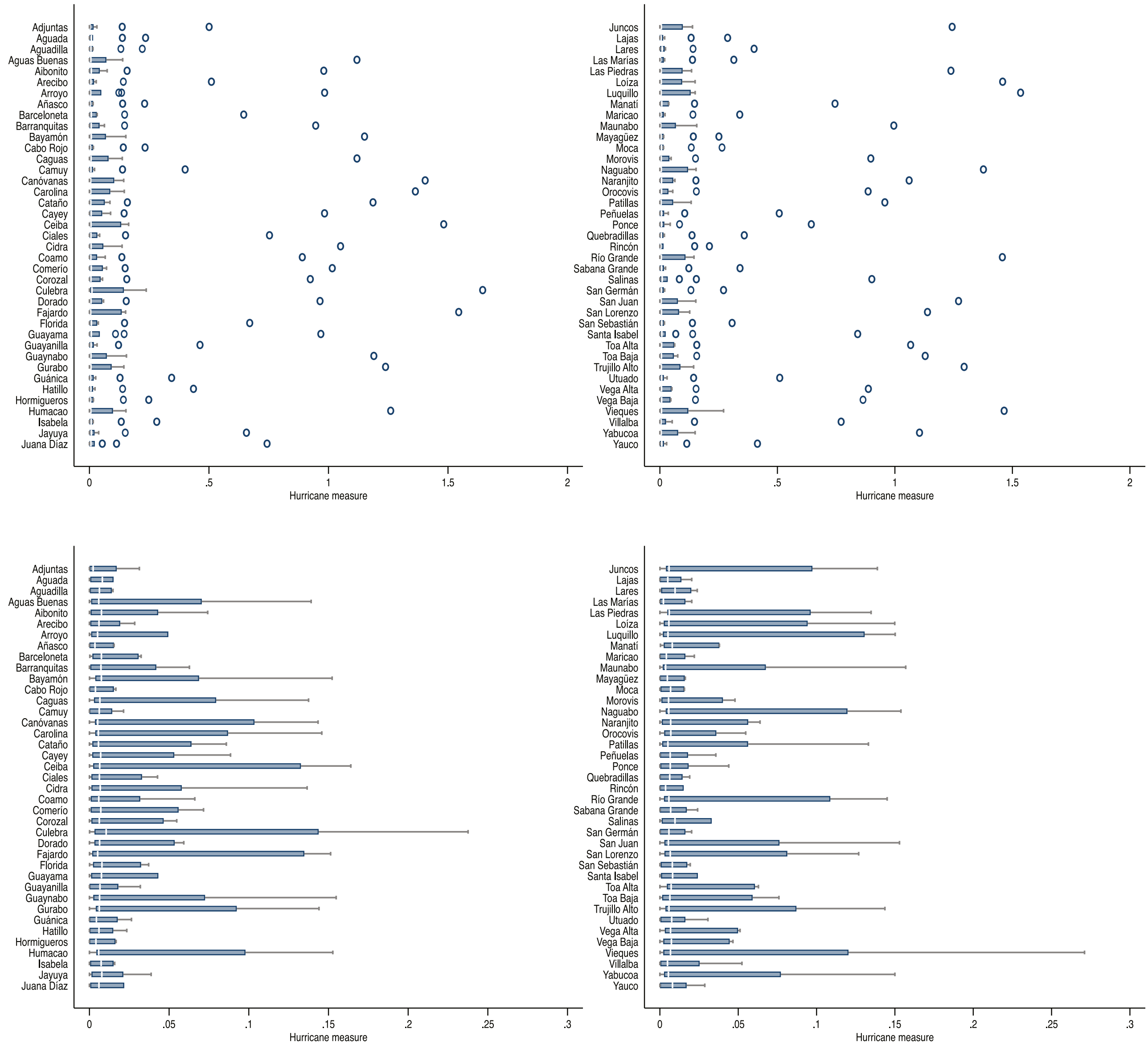

Fig. 2. Storm exposure by county for $S_{ct} > 0$, monthly Data,1995–2017.
Note: The top and the bottom panel show disaster shock exposure by county over the period 1995–2017. The top (bottom) panels include (exclude) outliers. The white line within each blue box represents the median. The left edge of the box is the first quartile ($Q1$ or 25th percentile) and the right edge the third quartile ($Q3$ or 75th percentile). The end of the left (right) whisker is the 1st percentile (99th percentile). The circles outside of the box capture outliers.

1995M1 to 2019M11. We have data for a panel for 78 counties (GEO) and 70 3-digits industries (NAICS). The advantage of using these more detailed data is the possibility to control for a richer set of fixed effects. The main disadvantage is that using county-by-industry level variables implies dealing with a lot of reported zeros. These observations are about 40% of the total. This is the reason for which we present first the county level analysis, where this problem is absent. There is a further 8% of observations where the reported zeros reflect non-disclosure due to anonymity concerns at this very fine level of disaggregation. We can detect those instances because they correspond to industry–county–time observations reporting zero employment or wages but a non-zero number of establishments. On those 8% of the observations, we apply a linear interpolation.[9] In the next Section we will present our baseline results excluding the zeros, both with and without applying the linear interpolation.[10]

[9] Note that the interpolation is only performed on the 8% of industry–county–time employment and wage observations where the reported zeros reflect non-disclosure due to anonymity concerns.

[10] When we exclude the zeros and do not apply the linear interpolation, we exclude all the zeros (which amounts to 48% of the original sample). In the appendix (Fig. D.2) we also show results obtained when including the zeros. We essentially include all the zeros in the case where we include the zeros and do not perform the linear interpolation. Impulse response functions of employment follow a pattern broadly similar to the baseline results. For wages, although the estimates remain imprecise for most of the quarters, including zeros and using non-interpolated data causes the wage responses to flip sign from positive to negative. If the data are interpolated, wage results remain

Finally, we explore the dynamic employment effects across industries and run the following specification for each industry separately:

$$\Delta X_{i,t+k} = \alpha^k + \gamma_i^k S_t + \sum_p \beta_p \Delta X_{i,t-p} + \delta_m + \epsilon^3_{i,t+k}, \tag{4}$$

In this case, we do not exploit the variation at the county level, but only at the industry level.[11] X_i represents the employment for each industry i at monthly frequency. Since we run Eq. (4) separately by industry, the constant term α^k captures industry fixed effects. S_t is an aggregate measure of exposure to disaster, computed as a population-weighted average of S_{ct}. Our object of interest is γ_i^k, representing the response of X_i at horizon k to a disaster shock at time t. We also insert in the regression controls for pre-trends ($\sum_p \Delta X_{i,t-p}$). While we cannot use a full set of time fixed effects (which would absorb all the variation in S_t), we insert monthly dummies (δ_m), to control for potential seasonal effects. Finally, since we run Eq. (4) by industry, controls and seasons may have differential effects across industries.

For the panel regressions, we cluster the standard errors at the county level. For the industry-level regressions, we use Newey–West corrected standard errors to account for the potential presence of autocorrelation and heteroskedasticity.

5. Results

In this Section, we report impulse responses following a disaster shock. This means that we plot the coefficients γ_1^k, γ_2^k or γ_i^k at different horizons k. We consider a two years horizon. Therefore, at monthly frequency k ranges from 0 to 24, while at quarterly frequency k ranges from 0 to 8.[12] We rescale the coefficients so that we report the response to the "average" hurricane recorded. In order to obtain the response to an average hurricane, we multiply the coefficients by the value reported in Table 1 for the mean of S_{ct} if $S_{ct} > 0$, i.e. 0.084. We also report 95% confidence intervals.

Fig. 3 reports our first main results. In the first two rows, we report the coefficients obtained from Eq. (2). As the Figure shows, after the "average" hurricane, employment falls on average by about 0.5% after about six months. The effects are statistically significant. At the same time, we also find a significant increase in the number of unemployed, suggesting that the drop in employment is partly absorbed by a rise in unemployment. The labor force, on average, does not display significant changes in the aftermath of a disaster shock, which could suggest that, on average, out-migration flows may be offset by new labor market entrants. The response of average weekly wages is positive after six months, but it is not statistically significant.

Our results on employment are in line with the existing literature. For instance, Belasen and Polachek (2008, 2009) show that employment falls over time, reaching a growth rate of about 4% lower than that of the control group. While our results also point towards a decline in employment, effects emerge only at the beginning of the second quarter, peak after six months and disappear thereafter, indicating that the employment effects of hurricanes are temporary. Interestingly, although not entirely comparable, the result that employment effects are temporary is consistent with Roth Tran and Wilson (2021)'s findings on damages of different kind of disasters. The authors find that, after a sharp decline and a recovery period of up to one year out, employment gradually reverts to the no-disaster counterfactual, within approximately 14 months.

Furthermore, our findings indicate that, albeit imprecisely estimated, the average wage response to the hurricane shock is positive between the first and fourth quarters. Belasen and Polachek (2008, 2009) also find that earnings respond positively within the first quarter of the strike, yet the effect appears to extend over a longer period of time; twenty-four months later, earnings end up at a level that is 0.4% above the growth of unaffected counties. Similarly, Roth Tran and Wilson (2021) find that average weekly wages of workers increase continuously in the aftermath of natural disasters, which may be consistent with an increase in hourly wages and/or a rise in weekly hours worked.

In the third and fourth row of Fig. 3, we report the results we obtain from Eq. (3) for employment and average weekly wages. In the third row, we report the results obtained without using the linear interpolation for the 8% of the observations, while in the fourth row we use the interpolation. As the Figure shows, the results are very similar to our baseline specification.[13]

We then move to explore whether these average effects masks heterogeneous responses across industries. Using specification (4), we find that industries can be divided into three main groups. A first group of industries, which we call "strengthened", are the industries that experience an increase in employment following a disaster shock. We report a selection of those industries in the first three rows of Fig. 4.

In the first row, the Figure illustrates a clear (and sensible) boom in construction: in industries NAICS 236 ("Construction of buildings"), NAICS 237 ("Heavy and civil engineering constructions") and NAICS 238 ("Special trade contractors"), employment grows by 2%–5% after 6 months following the "average" hurricane. In the second row of Fig. 4, we report three manufacturing industries that experience an expansion in employment after a disaster shock: NAICS 331 ("Primary metal manufacturing"), NAICS 332 ("Fabricated metal product manufacturing"), and NAICS 337 ("Furniture Manufacturing"). Interestingly, the increase appears delayed in the case of furniture manufacturing. Finally, three service sector industries that see an increase in employment after a hurricane are reported in the third row in Fig. 4: NAICS 442 ("Furniture and home furniture stores"), NAICS 444 ("Building material and garden supply stores"), and NAICS 561 ("Administrative and support services").

A second group of industries, which we label "weakened" industries, instead experience a fall in employment following a disaster shock. We report a selection of those industries in the last three rows of Fig. 4. The fourth row reports the results for primary and manufacturing weakened industries: NAICS 111 ("Crop production"), NAICS 112 ("Animal production and aquaculture"), and NAICS 323 ("Printing and related support activity"). In the fifth row, we report the results obtained from industries in the retail sector: NAICS 448 ("Clothing stores"), NAICS 451 ("Sport, book and music stores"), and NAICS 452 ("General merchandise stores"). In the sixth row of Fig. 4, we can also see how transportation and accommodation are negatively affected by a disaster shock: NAICS 487 ("Scenic and Sightseeing transportation"), and NAICS 712 ("Museums, Historical Sites, Zoos and Parks"), and NAICS 721 ("Accommodation"). Employment declines in these industries are potentially driven by a decline in demand in tourism, a particularly vulnerable sector that heavily depends on weather and climatic conditions. In fact, the attractiveness of an area may decline substantially when damages inflicted by natural disasters extend to its cultural heritage and landscape.

similar to the baseline estimates. Importantly, however, results on wages are inconclusive whether including or excluding the zeros.

[11] We therefore avoid the problem of interpolating the data.

[12] This is also the reason why we look at outcome variables data until 2019, and exposure to hurricane until 2017.

[13] In the appendix, Fig. D.1 shows that the results are similar even if we alternatively include just county-industry specific fixed effects together with time fixed effects or industry–time fixed effects together with county fixed effects. Moreover, Fig. D.2 shows how the results reported in the third and fourth row of Fig. 3 are qualitatively similar if the zeros are not eliminated, both using and not using the linear interpolation.

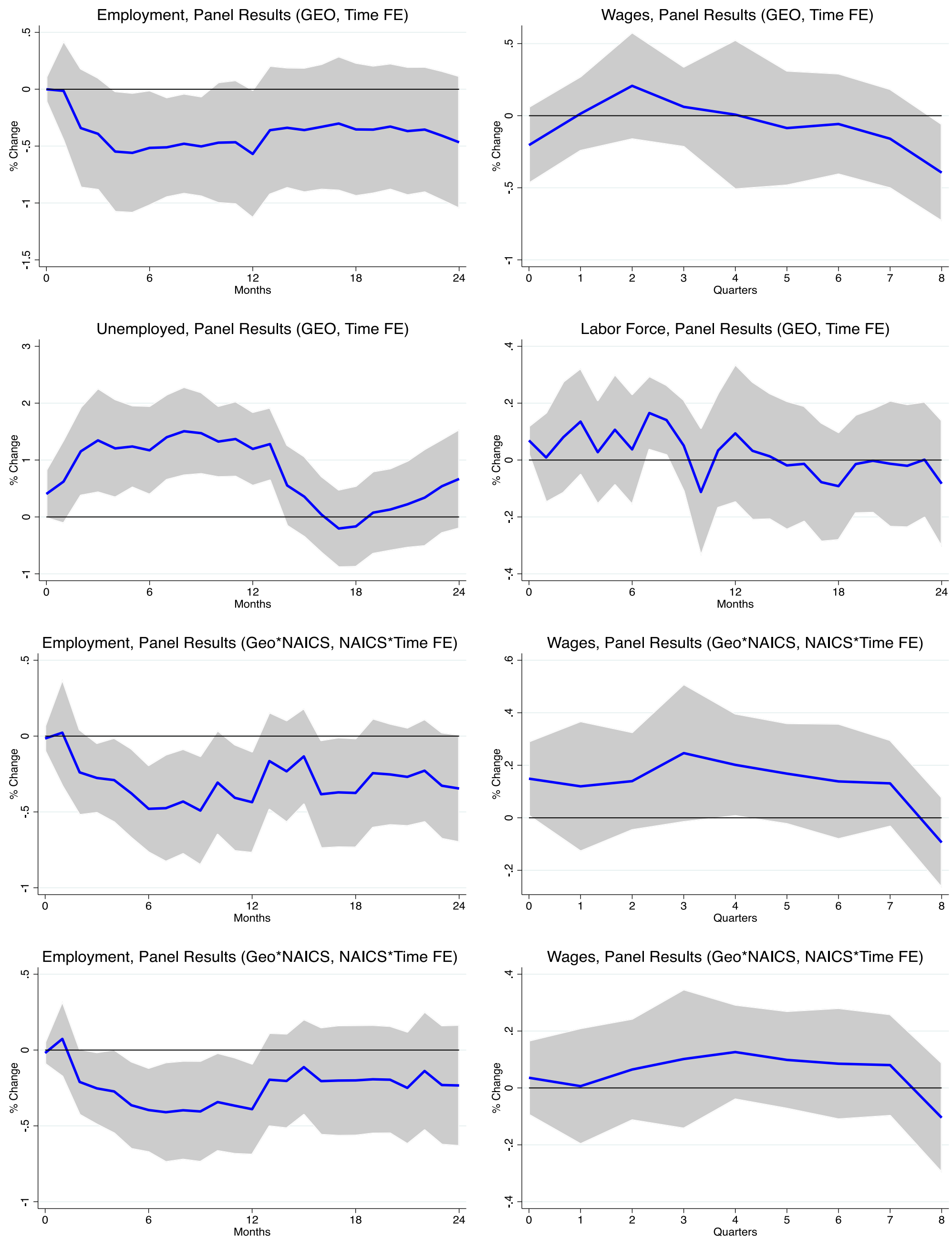

Fig. 3. Employment effects of natural disasters: Panel results.
Note: First and second row: dynamic effects of hurricanes at time t on employment, average weekly wages, unemployed and labor force at different horizons exploiting county–time variation. Third row: dynamic effects of hurricanes at time t on employment, average weekly wages, at different horizons exploiting county–industry–time variation without linear interpolation. Fourth row: dynamic effects of hurricanes at time t on employment, average weekly wages, at different horizons exploiting county–industry–time variation with linear interpolation. Shaded areas are confidence bands at 95%. The shock used to generate these IRFs is the average hurricane over our sample, with value 0.084.

Finally, a third group of industries, which we call "neutral", are industries where the employment does not seem to react in a significant way to a disaster shock. A synthetic way to have a complete picture for all of the 70 industries included in our sample is offered by Table 2, which lists all of the industries and their classification into "strengthened" (S), "weakened" (W) or "neutral" (N) for a particular time horizon (12-months). We also report the size of the coefficient (γ_i) and its standard error.[14]

As shown by Table 2, the heterogeneity in the employment response to natural disasters can be found even within 2-digits sectors. We consider the example of Transportation (Sector NAICS 48). Two industries within these sectors are featured among the group of "strengthened"

[14] As explained in the previous Section, we rescale them to represent the impact of the "average" hurricane.

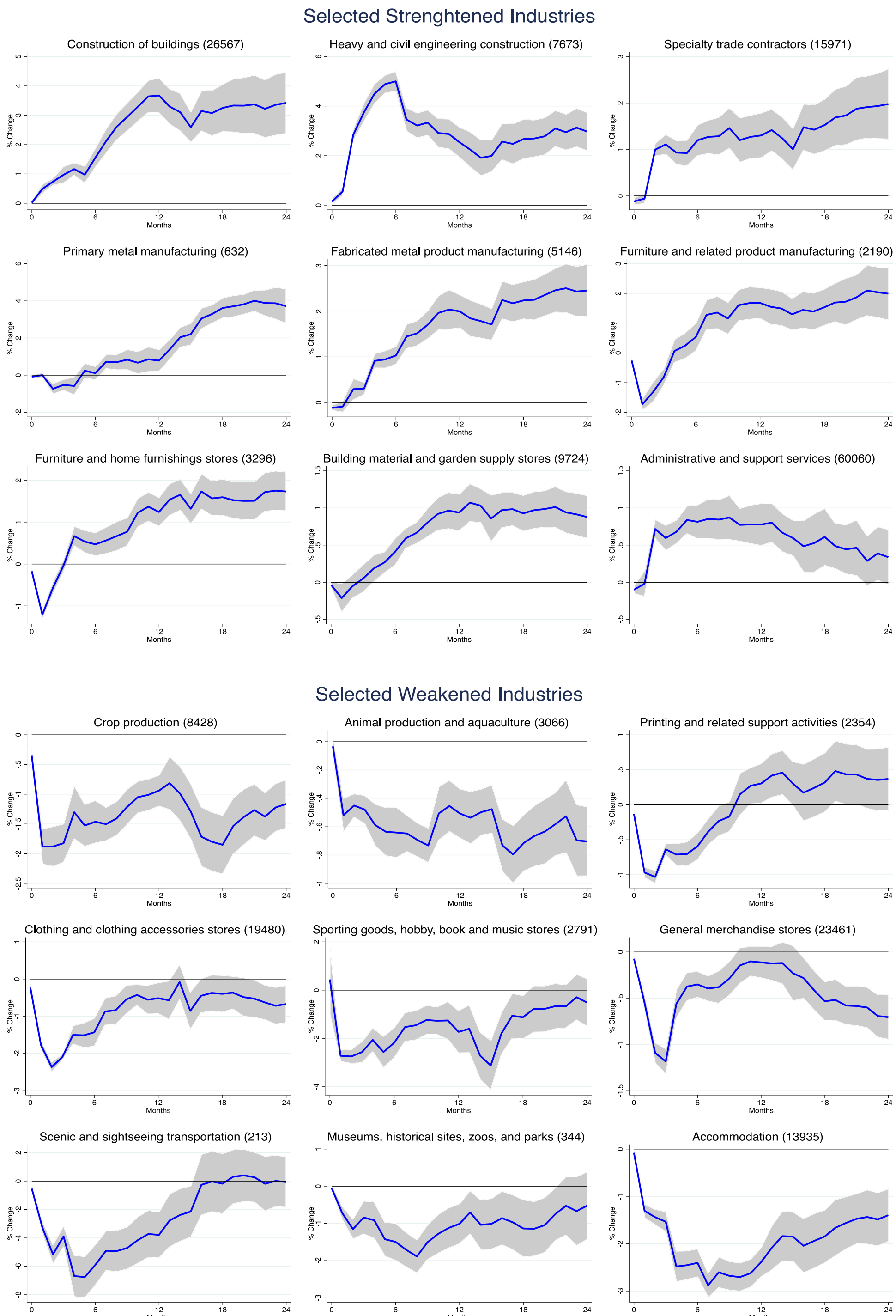

Fig. 4. Employment effects of natural disasters: Selected industries.
Note: Dynamic effects of hurricanes at time *t* on employment at different horizons exploiting industry–time variation. Numbers in parenthesis represent the average industry employment over the period 1995–2019. Shaded areas are confidence bands at 95%. The shock used to generate these IRFs is the average hurricane over our sample, with value 0.084.

industries: NAICS 484 (“Truck transportation”) and NAICS 488 (“Support activities for transportation”). Two industries are classified as “neutral”: NAICS 481 (“Air transportation”) and NAICS 483 (“Water transportation”). Two other industries are instead classified as “weakened”: NAICS 485 (“Transit and ground passenger transportation”) NAICS 487 (“Scenic and sightseeing transportation”). This particular example shows the importance of using detailed industry data to better gauge the employment effects of natural disasters.

In Appendix E, we propose a Table where we report the classification (S, N, or W) also for different time horizons (3, 6, 12, 18, 24 months) for each industry, thus giving a simple way to better grasp the dynamic employment effects of disaster shocks in each of the 70 industries.

Discussion and Mechanisms. The positive effects in the construction sector are consistent with other studies and indicate an intense process of repairing and rebuilding following the shock. For instance, Strobl and Walsh (2009) estimate that U.S. county employment in construction increases by about 25 per cent in the aftermath of hurricanes. Similarly, for all kinds of disasters, Roth Tran and Wilson (2021) find that after a short decline at the time of the event, construction employment recovers and rises sharply within one year, reaching levels about 1.2% higher than in the absence of the disaster. Thereafter, construction employment keeps rising. Belasen and Polachek (2008) also find positive employment and earning responses in the construction sector, although their estimates of the employment response are imprecisely estimated. In the specific context of Hurricanes Katrina and Rita, Groen et al. (2020) find positive earnings responses in the construction sector, both in the short and the long run.

As discussed above, our results highlight the importance of analyzing the employment response to hurricanes across detailed industries. This is particularly true for the transport and the manufacturing sectors, which both account for a large share of employment, and, as indicated in Table 2, exhibit differential responses across industries.[15] Hence, our results suggest that a sectoral analysis may lead to an aggregation bias, which may, to some extent, explain why Belasen and Polachek (2008) find statistically insignificant employment effects in the manufacturing sector. Moreover, the authors estimate negative employment effects in the transport sector. Our findings imply that this result could be driven by two industries, *Transit and ground passenger transportation* and *Scenic and sightseeing transportation*.

Some of the heterogeneity we found across industries, witnessed in Fig. 4 and Table 2, appears very sensible and almost self-evident: a disaster shock generates a construction boom and negatively affects retail, transport, and accommodation industries. To shed more lights on our results, we investigate a potential transmission mechanism of natural disaster shocks to employment at detailed industry level: input–output linkages. The construction boom, for instance, could trigger the increase in employment in some of its important suppliers, such as the manufacturing of metals and of furniture. The same construction boom might also explain the increase in employment in furniture stores and garden supply stores, which materializes only after a few months. To formally test this hypothesis, we downloaded the 2020 BEA Input–Output table for the US at NAICS-3 digits, and for each industry we computed the share of output sold to the construction sectors. We concentrate on the strengthened industries that we could match with the Input–Output data (excluding the construction sectors).[16] Fig. 5 illustrates a plot of the coefficients from Table 2 against the share of construction sectors as buyers of the industry output. The relation is starkly positive and statistically significant. The univariate regression has an $R^2 = 0.61$. Using data from the NBER-CES Manufacturing Industry Database, we verified that this correlation is robust also after controlling for the industry's labor share and the skill composition of its labor force.[17] We conclude that input–output linkages are likely to play a key role in the transmission of disaster shocks to employment across different industries.

Finally, we notice that the lack of impact of hurricanes on the employment in many important manufacturing sectors (which might at first appear surprising) is consistent with what Pelli et al. (2022) find using firm-level data for India, where hurricanes appear to have a large impact on manufacturing firms' capital, but no significant effects on employment.

6. Robustness

In order to check the robustness of our results, we experiment both with the use of different measures of exposure to natural disasters and with a different specification of the local projection. First, we increase the threshold from 33 to 64 knots in Eq. (1). Second, we use a different way of computing the wind speed, based on the classic formula of Deppermann (1947). Third, we substitute the population-weighted centroid with the geographical centroid of each county when computing the maximum windspeed affecting county c during hurricane H. Fourth, for the industry-level results, we build a measure of exposure that is industry-specific. Lastly, we control both for past hurricanes and for the hurricanes occurring between period t and horizon h in the local projections.

64 Knots Threshold A storm officially becomes a hurricane only when its windspeed crosses the threshold of 64 knots. Yet, the literature agrees that, especially in low and middle income countries, even winds below 64 knots already generate significant destruction (see for instance Pelli et al., 2022; Pelli and Tschopp, 2017; Yang, 2008). For this reason, in our baseline results we consider winds starting at 33 knots. In this first robustness test, we limit ourself to hurricanes and exclude tropical storms by changing the threshold used in Eq. (1) from 33 to 64 knots, which defines a category 1 hurricanes according to the Simpson and Riehl scale. Figs. F.1 and F.2 in Appendix F report the equivalent of the analysis presented in Figs. 3 and 4. The results are qualitatively similar to the baseline. Not surprisingly, however, the effect found are larger, since we focus now only on the most powerful hurricanes.

Depperman Formula The meteorological literature proposes several ways in which to calculate the wind field of a hurricane. They differ on the number of parameters used and on how they intervene in the formula. In this robustness test, we use an alternative model to generate the wind field, i.e. to compute w_{ch}, the wind speed at each county c for each landmark h. Here, we use the classical Depperman formula instead of the HURRECON model (Deppermann, 1947).

The Depperman formula describes sustained wind velocity at any point in the specific case of each population-weighted centroid in the following way:

$$w_{ch} = V_h \cdot \left(\frac{D_{ch}}{26.9978} \right) \text{ if } D_{ch} \leq 26.9978$$

$$w_{ch} = V_h \cdot \left(\frac{26.9978}{D_{ch}} \right)^{0.5} \text{ if } D_{ch} > 26.9978.$$

D_{ch} is the radial distance of each county centroid from the landmark h and V_h the wind speed at the landmark h. The number 26.9978 (50 km) corresponds to Simpson and Riehl radius of maximum wind speed. In general, the radius of maximum wind speed is computed using the gap between the barometric pressure between the center and the outskirts of the storm. Given the high number of missing measures of barometric pressure in the data, we follow Simpson and Riehl (1981) and Hsu and Zhongde (1998) and use the average radius of maximum windspeed (50 km) for all hurricanes. Figs. F.3 and F.4 in Appendix F report the equivalent of the analysis presented in the Figs. 3 and 4. The results are very similar to the baseline.

Geographical Centroids In the baseline specification, we weigh the centroid of each county by population. One could argue that there is no guarantee that economic activity is located close to population centers. For this reason, in this robustness check, we use the simple geographical centroid of each county instead of the population weighted one.

[15] For example, Table 2 clearly indicates that not all industries in the manufacturing sector respond in a similar way. *Fabricated metal product manufacturing* is classified as a strengthened industry while *Plastics and rubber products manufacturing* and *Beverage and tobacco product manufacturing* appear to be neutral and weakened industries, respectively.

[16] We also omit the industries 323, "Printing and related support activity" and 512, "Motion picture and sound recording industries", which are classified as "strengthened" only at the 12-months horizon, as shown in Appendix E.

[17] For each of the 9 manufacturing industries in Fig. 5, we computed the labor share as the average share of wage payments in the value added over the period 1995–2018. The composition of the labor force is measured using the average share of non-production workers to total workers over our sample period.

Table 2
Industry results: 12-months horizon.

NAICS	Industry name	12-months coefficient	12-months standard error	Average employment	12-months classification
	Strengthened industries				
236	Construction of buildings	3.67	0.31	26567	S
237	Heavy and civil engineering construction	2.54	0.32	7673	S
238	Specialty trade contractors	1.30	0.25	15971	S
321	Wood product manufacturing	1.45	0.21	392	S
322	Paper manufacturing	0.39	0.16	1678	S
323	Printing and related support activities	0.30	0.15	2354	S
324	Petroleum and coal products manufacturing	0.81	0.37	1115	S
325	Chemical manufacturing	0.34	0.10	25624	S
331	Primary metal manufacturing	0.78	0.30	632	S
332	Fabricated metal product manufacturing	2.00	0.19	5146	S
333	Machinery manufacturing	0.46	0.21	2387	S
334	Computer and electronic product manufacturing	0.72	0.24	10088	S
337	Furniture and related product manufacturing	1.68	0.27	2190	S
423	Merchant wholesalers, durable goods	0.34	0.12	12792	S
442	Furniture and home furnishings stores	1.24	0.18	3296	S
444	Building material and garden supply stores	0.94	0.13	9724	S
445	Food and beverage stores	0.18	0.07	26557	S
484	Truck transportation	0.63	0.14	3337	S
488	Support activities for transportation	0.58	0.16	4651	S
492	Couriers and messengers	2.19	0.19	1166	S
512	Motion picture and sound recording industries	2.02	0.57	2234	S
561	Administrative and support services	0.78	0.15	60060	S
	Neutral industries				
221	Utilities	−0.58	0.42	262	N
311	Food manufacturing	0.15	0.14	14054	N
315	Apparel manufacturing	0.84	0.55	11792	N
326	Plastics and rubber products manufacturing	0.32	0.20	2682	N
327	Nonmetallic mineral product manufacturing	0.27	0.33	3355	N
335	Electrical equipment and appliance mfg.	−0.16	0.17	6494	N
336	Transportation equipment manufacturing	0.08	0.19	1698	N
339	Miscellaneous manufacturing	0.14	0.14	11822	N
424	Merchant wholesalers, nondurable goods	0.09	0.10	17488	N
441	Motor vehicle and parts dealers	0.08	0.15	12582	N
443	Electronics and appliance stores	0.25	0.36	3971	N
447	Gasoline stations	−0.06	0.08	5285	N
452	General merchandise stores	−0.11	0.09	23461	N
454	Nonstore retailers	−0.32	0.18	1195	N
481	Air transportation	−0.04	0.36	2757	N
483	Water transportation	0.57	1.00	887	N
493	Warehousing and storage	0.45	0.24	1876	N
517	Telecommunications	0.15	1.57	8812	N
524	Insurance carriers and related activities	−0.04	0.11	12069	N
531	Real estate	0.00	0.19	9410	N
562	Waste management and remediation services	−0.01	0.22	3153	N
622	Hospitals	−0.04	0.12	27872	N
711	Performing arts and spectator sports	−0.55	0.31	1026	N
722	Food services and drinking places	−0.08	0.17	51870	N
811	Repair and maintenance	0.29	0.16	5614	N
813	Membership associations and organizations	0.11	0.13	4286	N
	Weakened industries				
111	Crop production	−0.94	0.13	8428	W
112	Animal production and aquaculture	−0.51	0.09	3066	W
312	Beverage and tobacco product manufacturing	−0.69	0.16	3276	W
425	Electronic markets and agents and brokers	−1.40	0.18	1156	W
446	Health and personal care stores	−0.57	0.11	15237	W
448	Clothing and clothing accessories stores	−0.52	0.21	19480	W
451	Sporting goods, hobby, book and music stores	−1.73	0.45	2791	W
453	Miscellaneous store retailers	−2.54	0.29	4784	W
485	Transit and ground passenger transportation	−0.59	0.23	1503	W
487	Scenic and sightseeing transportation	−3.79	0.83	213	W
511	Publishing industries, except internet	−1.46	0.18	3346	W
515	Broadcasting, except internet	−0.99	0.19	2220	W
518	Data processing, hosting and related services	−0.86	0.32	1830	W
522	Credit intermediation and related activities	−0.45	0.13	17650	W
611	Educational services	−0.54	0.17	24942	W
621	Ambulatory health care services	−0.60	0.08	28825	W
623	Nursing and residential care facilities	−0.74	0.12	4552	W
624	Social assistance	−0.53	0.21	9457	W
712	Museums, historical sites, zoos, and parks	−1.01	0.28	344	W

(*continued on next page*)

Table 2 (*continued*).

NAICS	Industry name	12-months coefficient	12-months standard error	Average employment	12-months classification
713	Amusements, gambling, and recreation	−1.30	0.27	2160	W
721	Accommodation	−2.39	0.16	13935	W
812	Personal and laundry services	−0.70	0.19	5620	W

Notes: We show strengthened (with a positive and statistically significant coefficient), neutral (with a coefficient not statistically significant) and weakened (with a negative and statistically significant coefficient) industries at the 12-months horizon.

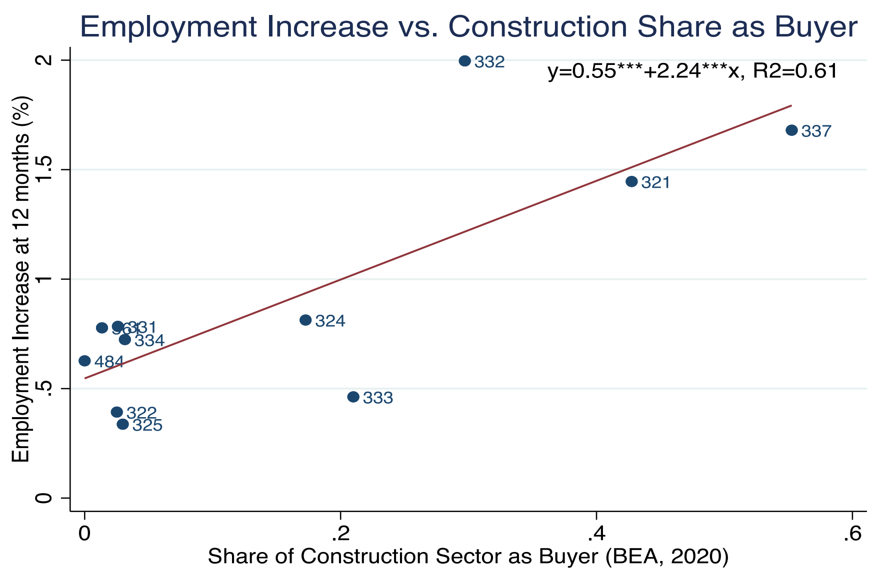

Fig. 5. Employment effects of natural disasters: Mechanism.
Note: The figure plots the coefficients from Table 2 against the share of the construction sector as buyer of each industry output. The figure also show the equation of the fitted line. The relation is positive and statistically significant, with an $R^2 = 0.61$.

Figs. F.5 and F.6 in Appendix F report the equivalent of the analysis presented in Figs. 3 and 4. The results are again very similar to those reported in the baseline.

Industry-Specific Measure of Exposure to Hurricanes While industries may not be located close to population centers (as we saw in the previous robustness check), they may also be concentrated in specific counties. Fig. F.7 in Appendix F reports the equivalent of the analysis presented in Fig. 4. In this case, though, we do not build the aggregate exposure to hurricanes as a population-weighted average (which, in Eq. (4), is by definition identical for each industry). Instead, we compute here an industry-specific measure of exposure to hurricanes that for each industry takes a weighted average of the county-level measure of exposure S_{ct} using as weights the average weights of employment in each county for each industry. This results in a measure of exposure that varies by industry. In practice, these measures are all very correlated. Therefore, not surprisingly, the results presented in Fig. F.7 are very close to those of Fig. 4.

Different Specification of the Local Projection Our baseline specification may be affected by the possibility of having several subsequent hurricanes. Figs. F.8 and F.9 in Appendix F report the equivalent of the analysis presented in Figs. 3 and 4, now using a different specification for the local projections. In order to capture the effect of hurricanes happening at time t on the outcome variables at horizon k, we now control for both the past values of the measure of exposure and the leads of the measure from period 1 to period k. This guarantees that the results we found are not confounding previous or subsequent hurricanes relative to the one happening at time t.

7. Conclusion

In this paper, we study the short-run, dynamic employment effects of natural disasters. Using monthly data for 70 3-digits NAICS industries and 78 Puerto Rican counties over the period 1995–2019, we find an average decline in employment following a disaster shock, which masks an extensive heterogeneity at the industry level. A part of this heterogeneity can be explained by input–output linkages. We are persuaded that the key qualitative insights we provide are valid also for other contexts, such as developing countries, where data limitations make impossible the type of analysis performed in this paper.

Moreover, the fact that some industries contract and some others expand following natural disasters suggests a new potential concept of resilience: *adaptability-driven employment resilience*, defined as the potential opportunity for workers to reallocate from the contracting industries to the expanding ones in the aftermath of a natural disaster. Greater mobility can be achieved by enhancing the transferability of workers' skills across jobs. Concretely, this would entail educating workers in acquiring the set of skills that are typically needed in the industries that expand post-disaster. This does not mean training people to switch across two distant industries such as retail and construction. Rather, this means preparing them to switch between jobs that involve similar tasks or relatively close skills.

To see this, consider for example the six industries related to transport - i.e. Truck transportation (484), Support activities for transportation (488), Transit and ground passenger transportation (485), Scenic and sightseeing transportation (487), Air transportation (481), and Water transportation (483). Our results indicate that not all of these industries are affected in the same way by a hurricane (see Fig. 6): employment in "Truck transportation", "Support activities for transportation" and "Water transportation" expand; employment in "Transit and passenger transportation" and "Scenic and sightseeing transportation" are affected negatively, while "Air transportation" seems unresponsive. *Adaptability-driven employment resilience* would prepare people involved in passenger transportation to be able to quickly switch to truck transportation through specific courses during their vocational training. Unfortunately, while these types of switches may already be happening, our data do not allow us to trace individual movements. Yet, facilitating them would help reduce people's unemployment spells and speed up recovery in the aftermath of a hurricane.

The importance of these potential reallocations (or especially lack thereof) is witnessed by Sathyendrakajan et al. (2012), who surveyed construction firms in Sri Lanka. The lack of skilled workers was cited as the most important challenge faced by these firms during the post-disaster reconstruction efforts.

The IMF (2019) proposed a three-pillar "disaster resilience strategy" based on structural, financial, and post-disaster (and social) resilience. Adaptability-driven employment resilience could be an important building block of the post-disaster (and social) resilience. It could be achieved by introducing new and different vocational training programs, aimed at endowing workers with a set of heterogeneous skills needed for quick and potentially temporary reallocations across different industries. As explained by the OECD (2010): "Vocational Education and Training (VET) can play a central role in preparing young people for work, developing skills of adults, and responding to the labour market needs of the economy".

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Alessandro Barattieri reports financial support was provided by Social Sciences and Humanities Research Council of Canada. Martino Pelli reports financial support was provided by Social Sciences and Humanities Research Council of Canad and by the Swiss National Science Foundation. Jeanne Tschopp reports financial support was provided by Social Sciences and Humanities Research Council of Canada and by the Swiss National Science Foundation.

Data availability

Data will be made available on request.

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Appendix A. HURRECON model

The HURRECON model (see Boose et al., 1994, 2001, 2004) describes sustained wind velocity at any point within a hurricane's vortex using information on the track, size, intensity, and cover type (land or water) of a hurricane. In the case of this paper, we use this model to compute sustained wind velocity at each population-weighted county centroid[18]:

$$w_{ch} = F\left[V_h - S(1-\sin T)\frac{V_f}{2}\right]\left[\left(\frac{R_m}{R}^{B} e^{1-\left[\frac{R_m}{R}\right]^{B}}\right)\right]^{1/2}$$

where F is a scaling parameter for the effect of friction set at 0.8, since all the point of interest to us are situated on land (this parameter is usually set equal to 1 for points over water and to 0.8 for points over land); V_h is the wind velocity at the eye at landmark h, which we linearly interpolate from the best track data; S is a scaling parameter for the asymmetry due to the forward motion of the storm, set to 1 (i.e. peak wind speed on the right side minus peak wind speed on the left side equals the forward velocity of the hurricane – V_f, as defined in Boose et al. (2001)); T is the clockwise angle between the forward path of the hurricane and a radial line connecting the eye of the hurricane to the population-weighted centroid of a county; V_f is the forward velocity of the hurricane, i.e. the speed at which the hurricane is moving forward; R_m is the radius of maximum winds, obtained from the best track data; R is the radial (or Euclidean) distance from the center of the hurricane to the population-weighted centroid of a county; and B is a scaling parameter controlling for the shape of the wind profile curve (usually included between 1.2 and 1.5, and set at 1.35).

The parameters of this equation, adapted from Holland's equation for the cyclostrophic wind (Holland, 1980), have been set following Boose et al. (2004) that parameterized and validated the model for Puerto Rico.

Appendix B. Hurricanes list

We report below the names of the 23 hurricanes and storms we use in our baseline specification, together with the year and month when they hit Puerto Rico and the maximum category they reached according to the Simpson and Riehl scale. We also report the number of people that these hurricanes have affected overall, the number of fatalities and the estimated damages. Blanks correspond to missing values (see Table B.1).

Appendix C. Puerto Rico employment and labor force

In this Section, we report summary statistics of both monthly and quarterly Puerto Rico employment data (Table C.1), as well as the structure of Puerto Rico private employment using NAICS 2-digits industries (Table C.2) and the structure of Puerto Rican private manufacturing employment using NAICS 3-digits industries (Table C.3). We present average figures across our sample period. In Table C.4 we show the labor force for each county in Puerto Rico in 1995, its share in the total labor force, and the percentage change of labor force in each county over the period 1995–2019. Finally, in Figs. C.1 and C.2 we report instead the dynamics over time of employment in selected industries.

Appendix D. Alternative specifications

See Figs. D.1 and D.2.

Appendix E. Industry heterogeneous dynamics

Table E.1 reports for each of the 70 NAICS industries included in our analysis the classification into Strengthened ("S"), Neutral ("N"), or Weakened ("W") for different time horizons (3, 6, 12, 18, 24 months).

Appendix F. Robustness figures

See Figs. F.1–F.9.

[18] Velocity and wind direction are measured relative to the surface of the Earth, and angles are measured in degrees.

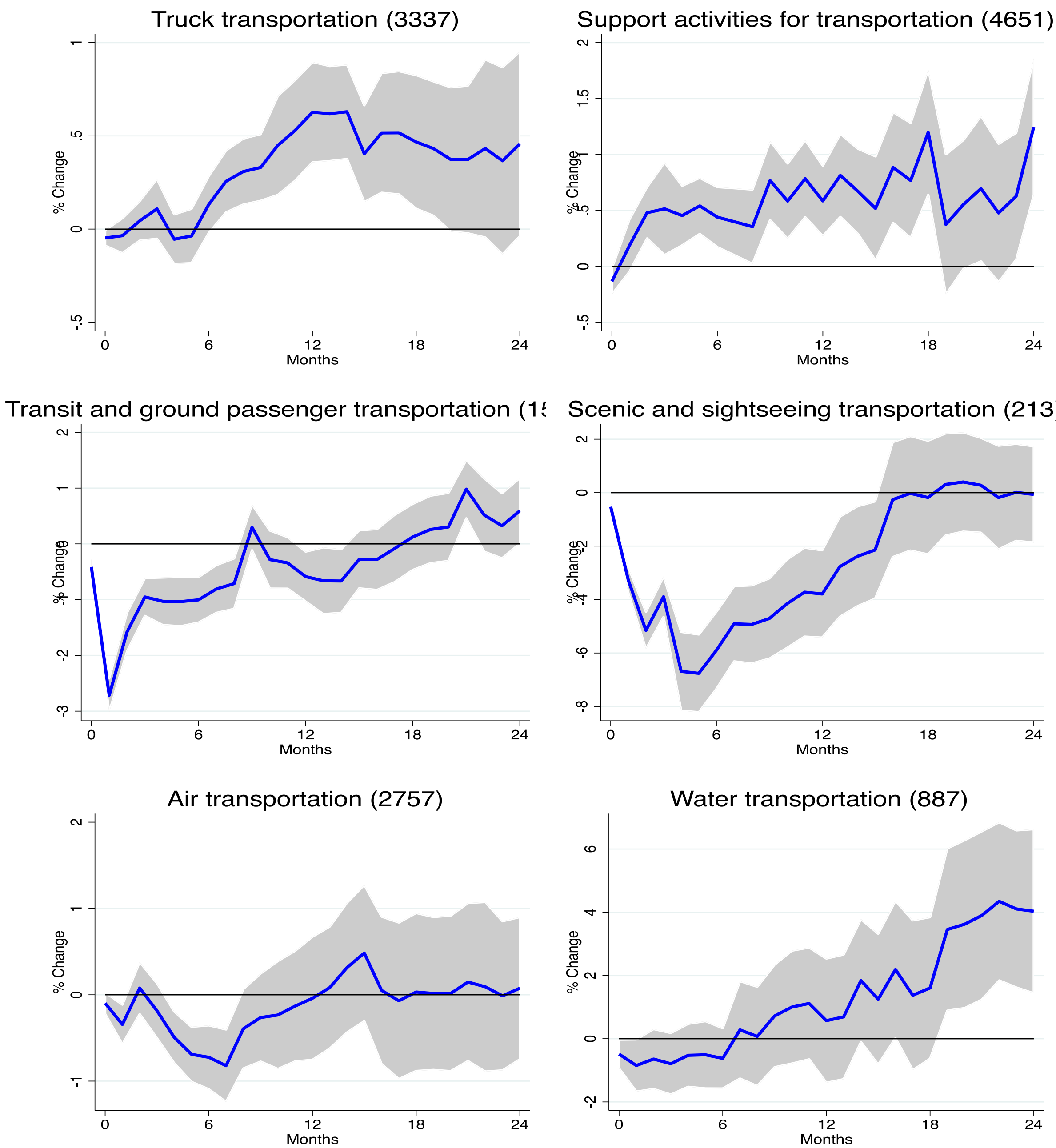

Fig. 6. Employment Effects of hurricanes: Transport Industries.
Note: Industry results for selected Transport Industries. Dynamic effects of hurricanes at time t on employment at different horizons exploiting industry–time variation. Numbers in parenthesis represent the average industry employment over the period 1995–2017. Shaded areas are confidence bands at 95%.

Table B.1
Hurricanes.

Name	Year	Month	Category	People affected	Total fatalities	Total damages
Luis	1995	9	4	98,000		339,684,000
Marilyn	1995	9	4		1	169,842,000
Bertha	1996	7	2–3			
Hortense	1996	9	4	57,315	18	825,028,000
Georges	1998	9	3			2,778,505,000
José	1999	10	TS			
Lenny	1999	11	4		1	233,058,000
Debby	2000	8	1			
Keith	2000	10	3			
Dean	2001	8	1			
Jeanne	2004	9	3	3,500	2	137,022,000
Frances	2004	9	4			
Dean	2007	5	5			
Olga	2007	12	TS			
Omar	2008	10	4		1	
Earl	2010	8	4			
Irene	2011	8	3	2,271	1	575,291,000
Karen	2013	10	TS			
Gonzalo	2014	10	4			
Danny	2015	8	3			
Erika	2015	8	TS			
Irma	2017	9	5		2	
Maria	2017	9	5	750,000	64	71,798,241,000

Note: *Category* refers to the category corresponding to the maximum windspeed reached by the hurricane according to the Saffir–Simpson wind scale. *TS* stands for tropical storm. Data on *People affected*, *Total fatalities*, and *Total damages* come from the EM-DAT database (https://public.emdat.be).

Table C.1
Summary statistics of Puerto Rico employment data.

Variable	Mean	Std. dev.	Min.	Max.	N
Monthly data:					
$\Delta EMPL_{ct}$	−0.00018	0.046	−1.177	0.973	21,175
$\Delta UNEMPL_{ct}$	−0.00075	0.092	−0.536	0.693	21,175
ΔLAB_FORCE_{ct}	−0.00021	0.025	−0.333	0.400	21,175
$\Delta EMPL_{cit}$	0.00019	0.110	−3.951	4.357	441,050
$\Delta EMPL_{it}$	0.00010	0.050	−0.931	1.069	25,087
Quarterly data:					
$\Delta WAGE_{ct}$	0.00410	0.105	−0.580	0.613	6,982
$\Delta WAGE_{cit}$	0.00503	0.132	−2.377	1.490	142,817

Notes: $\Delta EMPL_{ct}$ is the employment growth at county level, $\Delta UNEMPL_{ct}$ the growth of unemployed at county level, ΔLAB_FORCE_{ct} is the labor force growth at county level, $\Delta WAGE_{ct}$ is the average wage growth at county level. $\Delta EMPL_{cit}$ and $\Delta WAGE_{cit}$ are the employment and average wage growth at county–industry level. $\Delta EMPL_{it}$ is the average employment growth at industry level.

Table C.2
Private employment structure.

NAICS2	Sector name	Av. employment (count)	Empl. share
11	Agriculture, forestry, fishing and hunting	12,560	1.86%
21	Mining, quarrying, and oil and gas extraction	1000	0.15%
22	Utilities	240	0.04%
23	**Construction**	**48,130**	**7.13%**
30	**Manufacturing**	**116,020**	**17.20%**
42	Wholesale trade	30,420	4.51%
44–45	**Retail trade**	**123,740**	**18.34%**
48–49	Transportation and warehousing	16.58	2.46%
51	Information	16,810	2.49%
52	Finance and insurance	29,570	4.38%
53	Real estate and rental and leasing	13,040	1.93%
54	Professional and technical services	24,880	3.69%
55	Management of companies and enterprises	12,230	1.81%
56	**Administrative and waste services**	**59.11**	**8.76%**
61	Educational services	23,900	3.54%
62	**Health care and social assistance**	**65.83**	**9.76%**
71	Arts, entertainment, and recreation	3,360	0.50%
72	**Accommodation and food services**	**61.40**	**9.10%**
81	Other services, except public administration	15,220	2.26%
99	Unclassified	690	0.10%
	TOTAL	**674,800**	**100.00%**

Notes: **Av. Employment (count)** reports average employment over our study period (1995–2019).

Table C.3
Manufacturing employment structure.

NAICS3	Industry name	Av. employment (count)	Empl. share
325	Chemical manufacturing	25,360	21.9%
311	Food manufacturing	14,840	12.8%
315	Apparel manufacturing	14,820	12.8%
339	Miscellaneous manufacturing	12,280	10.6%
334	Computer and electronic product manufacturing	10,430	9.0%
335	Electrical equipment and appliance mfg.	6,700	5.8%
332	Fabricated metal product manufacturing	5,070	4.4%
327	Nonmetallic mineral product manufacturing	3,390	2.9%
312	Beverage and tobacco product manufacturing	3,250	2.8%
316	Leather and allied product manufacturing	3,020	2.6%
326	Plastics and rubber products manufacturing	2,930	2.5%
323	Printing and related support activities	2,320	2.0%
333	Machinery manufacturing	2,310	2.0%
337	Furniture and related product manufacturing	2,200	1.9%
336	Transportation equipment manufacturing	1,820	1.6%
322	Paper manufacturing	1,780	1.5%
324	Petroleum and coal products manufacturing	1,210	1.0%
314	Textile product mills	960	0.8%
331	Primary metal manufacturing	650	0.6%
321	Wood product manufacturing	420	0.4%
313	Textile mills	230	0.2%
	TOTAL	**116,020**	**100.0%**

Notes: **Av. Employment (count)** reports average employment over our study period (1995–2019).

Table C.4
Labor force, by county.

County name	Labor force 1995	Labor force share	Δlabor force 1995–2019
San Juan Municipio	155752	12.70%	−14.87%
Bayamun Municipio	82662	6.74%	−23.86%
Carolina Municipio	74477	6.07%	−19.28%
Ponce Municipio	57516	4.69%	−23.38%
Caguas Municipio	53565	4.37%	−11.16%
Guaynabo Municipio	39202	3.20%	−5.66%
Mayagez Municipio	35054	2.86%	−45.33%
Toa Baja Municipio	32573	2.66%	−10.85%
Arecibo Municipio	30831	2.51%	−26.92%
Trujillo Alto Municipio	26903	2.19%	−0.85%
Aguadilla Municipio	21250	1.73%	−36.09%
Humacao Municipio	19350	1.58%	−10.70%
Vega Baja Municipio	18018	1.47%	−30.23%
Toa Alta Municipio	17819	1.45%	40.25%
Rio Grande Municipio	16599	1.35%	3.13%
Cayey Municipio	15825	1.29%	1.99%
Canuvanas Municipio	15594	1.27%	2.72%
Cabo Rojo Municipio	15133	1.23%	−9.44%
Cidra Municipio	14295	1.17%	6.68%
Aguada Municipio	14134	1.15%	−18.04%
Isabela Municipio	14118	1.15%	−11.96%
San Sebastian Municipio	13541	1.10%	−26.33%
San German Municipio	13417	1.09%	−32.17%
Fajardo Municipio	13102	1.07%	−13.43%
Juana Diaz Municipio	12901	1.05%	14.93%
Yauco Municipio	12774	1.04%	−24.31%
Manati Municipio	12763	1.04%	−9.14%
Moca Municipio	12375	1.01%	−16.04%
Yabucoa Municipio	11830	0.96%	−27.20%
Juncos Municipio	11605	0.95%	6.79%
San Lorenzo Municipio	11105	0.91%	6.96%
Guayama Municipio	10985	0.90%	4.75%
Hatillo Municipio	10960	0.89%	18.48%
Vega Alta Municipio	10791	0.88%	−9.94%
Aibonito Municipio	10685	0.87%	−46.35%
Gurabo Municipio	10338	0.84%	53.70%
Aoasco Municipio	10236	0.83%	−15.13%
Las Piedras Municipio	9780	0.80%	14.57%
Dorado Municipio	9763	0.80%	27.56%
Catano Municipio	9490	0.77%	−19.59%
Camuy Municipio	9477	0.77%	−0.87%
Corozal Municipio	9308	0.76%	−2.76%
Coamo Municipio	9184	0.75%	8.99%
Morovis Municipio	9173	0.75%	−13.56%
Lajas Municipio	8779	0.72%	−48.87%
Aguas Buenas Municipio	8373	0.68%	−23.54%
Sabana Grande Municipio	8363	0.68%	−30.23%
Salinas Municipio	8363	0.68%	−14.19%
Loiza Municipio	8133	0.66%	3.09%
Utuado Municipio	8115	0.66%	−19.10%
Lares Municipio	8083	0.66%	−12.60%
Quebradillas Municipio	7579	0.62%	−22.58%
Barranquitas Municipio	7439	0.61%	0.84%
Barceloneta Municipio	7408	0.60%	−22.96%
Guayanilla Municipio	7342	0.60%	−39.62%
Naranjito Municipio	7030	0.57%	1.43%
Pequelas Municipio	7009	0.57%	−18.66%
Hormigueros Municipio	6791	0.55%	−21.16%
Naguabo Municipio	6528	0.53%	22.00%
Luquillo Municipio	6163	0.50%	3.29%
Santa Isabel Municipio	6029	0.49%	47.95%
Orocovis Municipio	5801	0.47%	−12.25%
Gunica Municipio	5738	0.47%	−35.09%
Villalba Municipio	5715	0.47%	25.96%
Rincon Municipio	5630	0.46%	−18.59%
Ceiba Municipio	5584	0.46%	−37.13%
Patillas Municipio	5559	0.45%	−20.01%
Adjuntas Municipio	5501	0.45%	−22.17%
Arroyo Municipio	5208	0.42%	−7.76%
Comerlo Municipio	5147	0.42%	−4.90%
Ciales Municipio	4889	0.40%	−24.96%
Jayuya Municipio	3834	0.31%	13.43%
Maunabo Municipio	3100	0.25%	−8.02%
Las Marias Municipio	3043	0.25%	−10.85%
Vieques Municipio	2609	0.21%	4.86%

(*continued on next page*)

Table C.4 (*continued*).

County name	Labor force 1995	Labor force share	Δlabor force 1995–2019
Florida Municipio	2573	0.21%	25.70%
Maricao Municipio	2143	0.17%	−9.44%
Culebra Municipio	746	0.06%	13.64%
TOTAL	**1226600**	**100.00%**	**−11.1%**

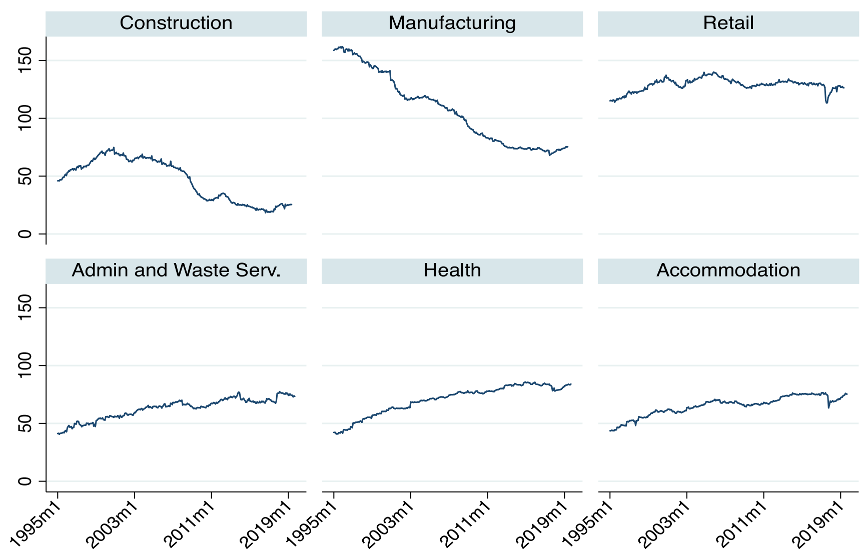

Fig. C.1. Private employment dynamics (in thousands).

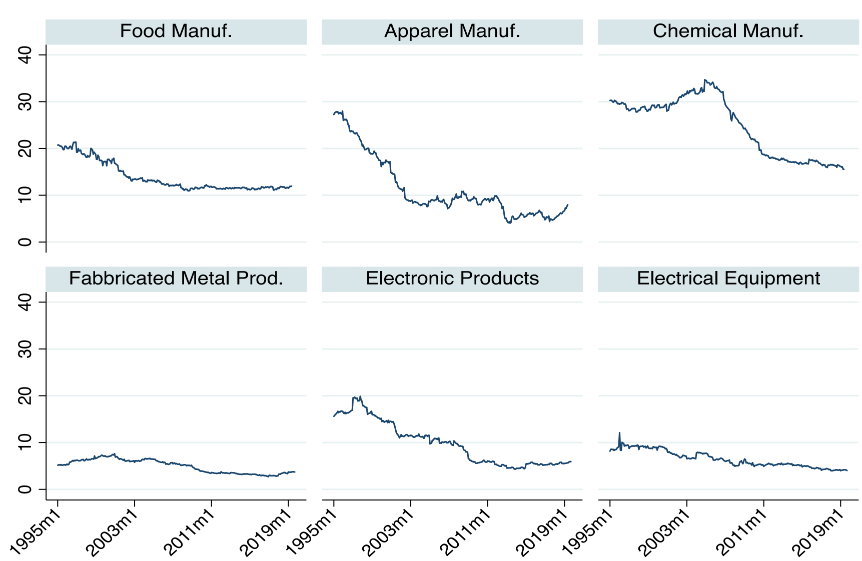

Fig. C.2. Manufacturing employment dynamics (in thousands).

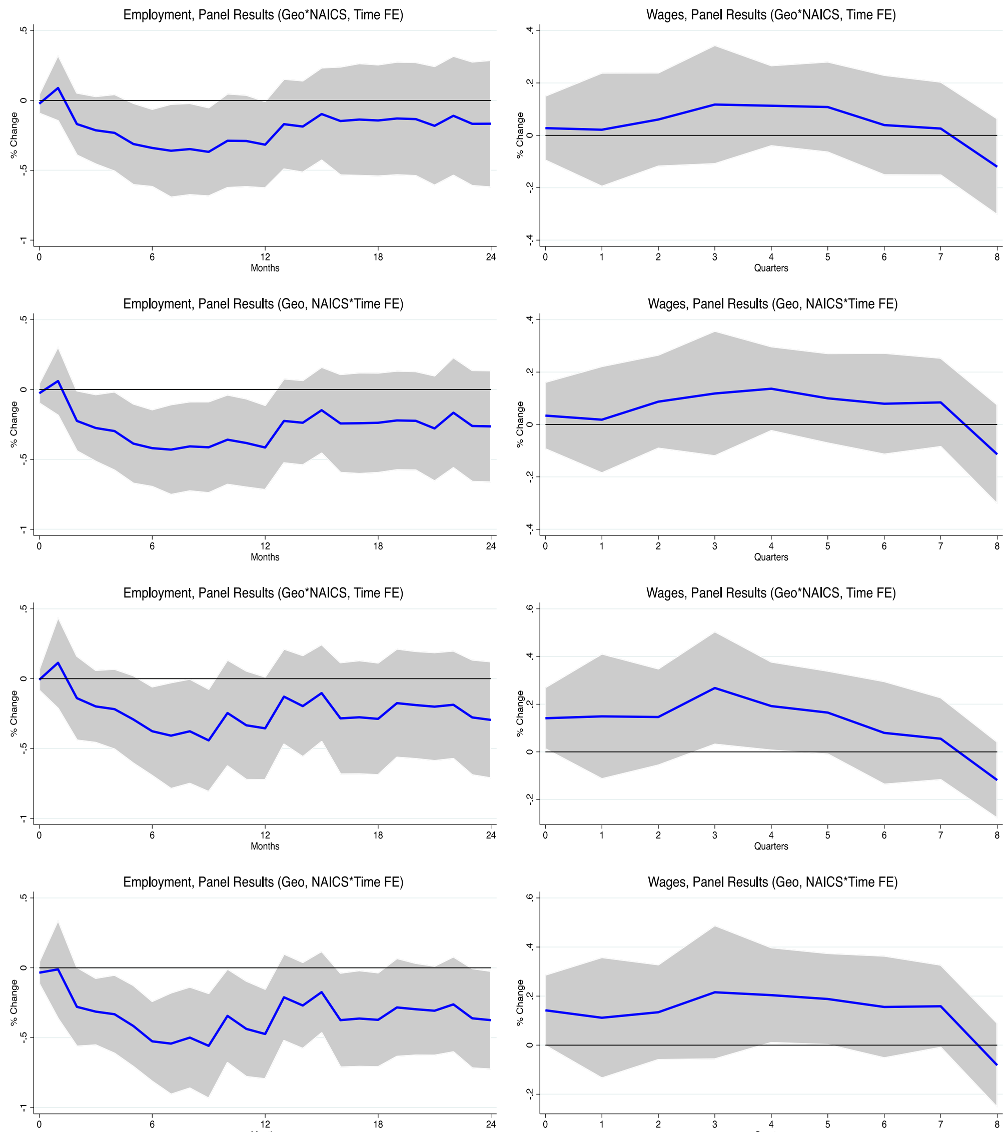

Fig. D.1. Alternative set of fixed effects.
Note: Panel results controlling for alternative sets of fixed effects. First and second row: dynamic effects of hurricanes at time *t* on employment, average weekly wages, at different horizons exploiting county–industry–time variation without and with linear interpolation using county*industry and time fixed effects. Third and fourth row: dynamic effects of hurricanes at time *t* on employment, average weekly wages, at different horizons exploiting county–industry–time variation without and with linear interpolation using county and industry*time fixed effects. Shaded areas are confidence bands at 95%.

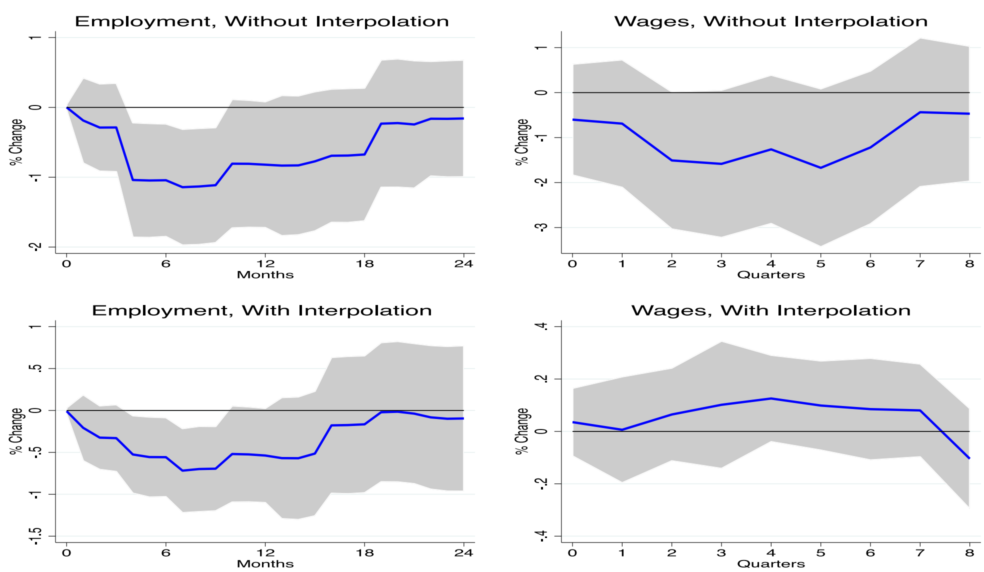

Fig. D.2. Including Zeros.

Note: Panel results including zeros. First row: dynamic effects of hurricane at time *t* on employment, average weekly wages, at different horizons exploiting count-y-industry–time variation without linear interpolation using county*industry and industry*time fixed effects. Second row: dynamic effects of hurricanes at time *t* on employment, average weekly wages, at different horizons exploiting county–industry–time variation with linear interpolation using county*industry and industry*time fixed effects. Shaded areas are confidence bands at 95%.

Table E.1
Classification of industries at different horizons.

NAICS	Industry	Baseline model Classification at month 3,6,12,18,24	64-Knots threshold Classification at month 3,6,12,18,24	Deppe formula Classification at month 3,6,12,18,24	Non-weighted centroids Classification at month 3,6,12,18,24
111	Crop production	WWWWW	WWWWW	WWWWW	WWWWW
112	Animal production and aquaculture	WWWWW	WWWWW	WWWWW	WWWWW
221	Utilities	WNNWN	WNWWW	WNNWN	WNNWN
236	Construction of buildings	SSSSS	SSSSS	SSSSS	SSSSS
237	Heavy and civil engineering construction	SSSSS	SSSSS	SSSSS	SSSSS
238	Specialty trade contractors	SSSSS	SSSSS	SSSSS	SSSSS
311	Food manufacturing	WNNNN	WNNSS	WNNNN	WNNNN
312	Beverage and tobacco product manufacturing	NNWNN	NNWNN	NNWNN	NNWNN
315	Apparel manufacturing	NNNSS	NNSSS	NNNSS	NNNSS
321	Wood product manufacturing	WWSSS	WWSSS	WNSSS	WWSSS
322	Paper manufacturing	NNSSN	NSSSN	NNSSN	NNSSN
323	Printing and related support activities	WWSNN	WWSNN	WWNNN	WWSNN
324	Petroleum and coal products manufacturing	NNSSS	NNSSS	NNSSS	NNSSS
325	Chemical manufacturing	NSSSN	NSSSN	NSSSN	NSSSN
326	Plastics and rubber products manufacturing	SNNSS	SNNSS	SNNSS	SNNSS
327	Nonmetallic mineral product manufacturing	NNNNN	NNNNN	NNNNN	NNNNN
331	Primary metal manufacturing	WNSSS	WNSSS	WNSSS	WNSSS
332	Fabricated metal product manufacturing	SSSSS	SSSSS	SSSSS	SSSSS
333	Machinery manufacturing	NNSSS	NNSSS	NNNNS	NNSSS
334	Computer and electronic product manufacturing	NNSSS	WNSSS	NNSSS	NNSSS
335	Electrical equipment and appliance mfg.	NWNNN	NWNNN	NWNNN	NWNNN
336	Transportation equipment manufacturing	WWNSS	WWNSS	WWNSS	WWNSS
337	Furniture and related product manufacturing	WSSSS	WSSSS	WSSSS	WSSSS
339	Miscellaneous manufacturing	NNNNN	NNNNS	NNNNN	NNNNN
423	Merchant wholesalers, durable goods	WNSSS	WWSSS	WNSSS	WNSSS
424	Merchant wholesalers, nondurable goods	WNNNS	WNNNS	WNNNS	WNNNS
425	Electronic markets and agents and brokers	WWWWW	WWWWW	WWWWW	WWWWW
441	Motor vehicle and parts dealers	WWNSS	WWNSS	WNNNS	WWNSS
442	Furniture and home furnishings stores	NSSSS	NSSSS	NSSSS	NSSSS
443	Electronics and appliance stores	WNNNN	WWNNS	WNNNN	WNNNN
444	Building material and garden supply stores	NSSSS	NSSSS	NSSSS	NSSSS
445	Food and beverage stores	WWSSN	WWSSN	WWSSN	WWSSN
446	Health and personal care stores	WWWWW	WWWWW	WWWNN	WWWWW
447	Gasoline stations	WWNNN	WWNSS	WWNNN	WWNNN
448	Clothing and clothing accessories stores	WWWNW	WWWWW	WWNNN	WWWNW
451	Sporting goods, hobby, book and music stores	WWWWN	WWWWW	WWWWN	WWWWN
452	General merchandise stores	WWNWW	WWNWW	WWNWW	WWNWW
453	Miscellaneous store retailers	WWWWW	WWWWW	WWWWW	WWWWW
454	Nonstore retailers	WWNSS	WWWSS	WWNSS	WWNSS
481	Air transportation	NWNNN	WWNNN	NWNNN	NWNNN
483	Water transportation	NNNNS	WNNNS	NNNNS	NNNNS
484	Truck transportation	NNSSN	SSSSS	NNSSN	NNSSN
485	Transit and ground passenger transportation	WWWNS	WWWNS	WWWNN	WWWNS
487	Scenic and sightseeing transportation	WWWNN	WWWNN	WWWNN	WWWNN
488	Support activities for transportation	SSSSS	SSSSS	NSSSS	SSSSS
492	Couriers and messengers	NSSSS	WSSSS	NSSSS	NSSSS
493	Warehousing and storage	SNNSS	SNSSS	SNNSS	SNNSS
511	Publishing industries, except internet	WNWWS	WNWWS	WNWWS	WNWWS
512	Motion picture and sound recording industries	WNSWW	WNSWW	WNSWW	WNSWW
515	Broadcasting, except internet	WWWNW	WWWWW	WWWNN	WWWNW
517	Telecommunications	WWNNN	WWWWW	WWNNN	WWNNN
518	Data processing, hosting and related services	WNWNN	WWWNN	NNWNN	WNWNN
522	Credit intermediation and related activities	WWWWW	WWWWW	NWWWW	WWWWW
524	Insurance carriers and related activities	WNNSS	WNNSS	WNNNN	WNNSS
531	Real estate	NNNNN	NWNNS	NNNNN	NNNNN
561	Administrative and support services	SSSSN	SSSSN	SSSSN	SSSSN
562	Waste management and remediation services	SSNNN	SSNNN	SSNNN	SSNNN
611	Educational services	WWWWW	WWWWW	WWWWW	WWWWW
621	Ambulatory health care services	WWWWW	WWWWW	WWWWW	WWWWW
622	Hospitals	NWNNN	SWNNN	NWNNN	NWNNN
623	Nursing and residential care facilities	WWWWN	WWWWW	WWWWN	WWWWN
624	Social assistance	WWWNN	WWWNN	WWNNN	WWWNN
711	Performing arts and spectator sports	WWNNN	WWWNN	WWNNN	WWNNN
712	Museums, historical sites, zoos, and parks	WWWWN	WWWWW	WWWWN	WWWWN
713	Amusements, gambling, and recreation	WWWWN	WWWWN	WWWWN	WWWWN
721	Accommodation	WWWWW	WWWWW	WWWWW	WWWWW
722	Food services and drinking places	WWNNN	WWWNN	WWNNN	WWNNN
811	Repair and maintenance	WNNSS	WNNSS	WNNSS	WNNSS
812	Personal and laundry services	WWWNN	WWWWN	WWWNN	WWWNN
813	Membership associations and organizations	WWNNN	WWNNN	WWNNN	WWNNN

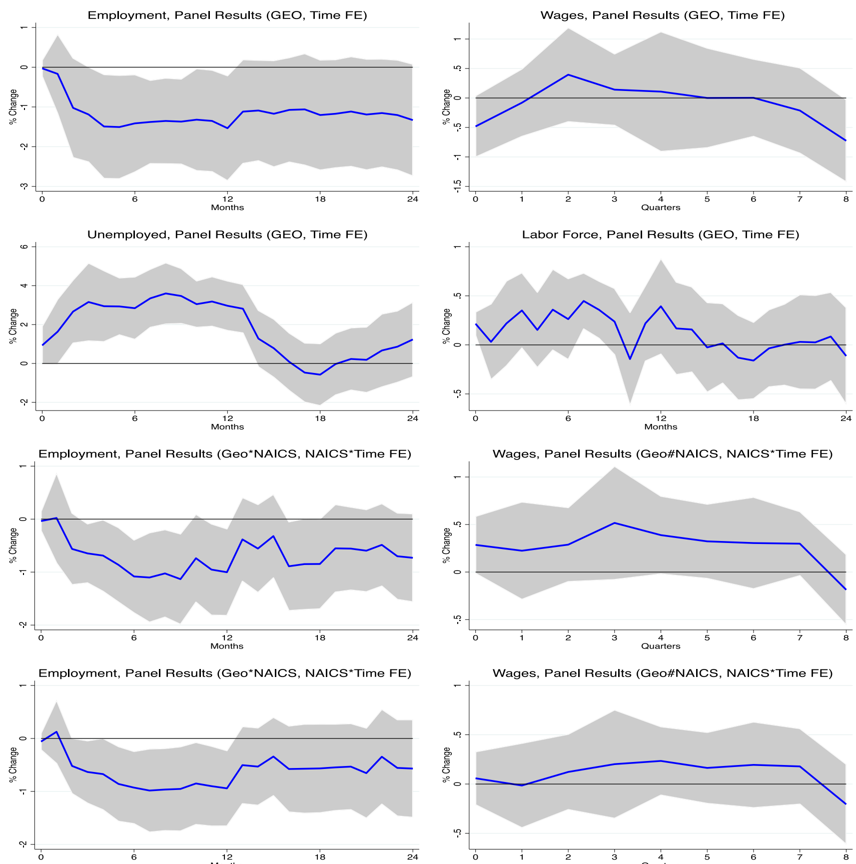

Fig. F.1. Panel results, 64-knots.

Note: Panel results with a different threshold (64-knots). First and second row: dynamic effects of hurricanes at time t on employment, average weekly wages, unemployed and labor force at different horizons exploiting county–time variation. Third row: dynamic effects of hurricanes at time t on employment, average weekly wages, at different horizons exploiting county–industry–time variation without linear interpolation. Fourth row: dynamic effects of hurricanes at time t on employment, average weekly wages, at different horizons exploiting county–industry–time variation with linear interpolation. Shaded areas are confidence bands at 95%.

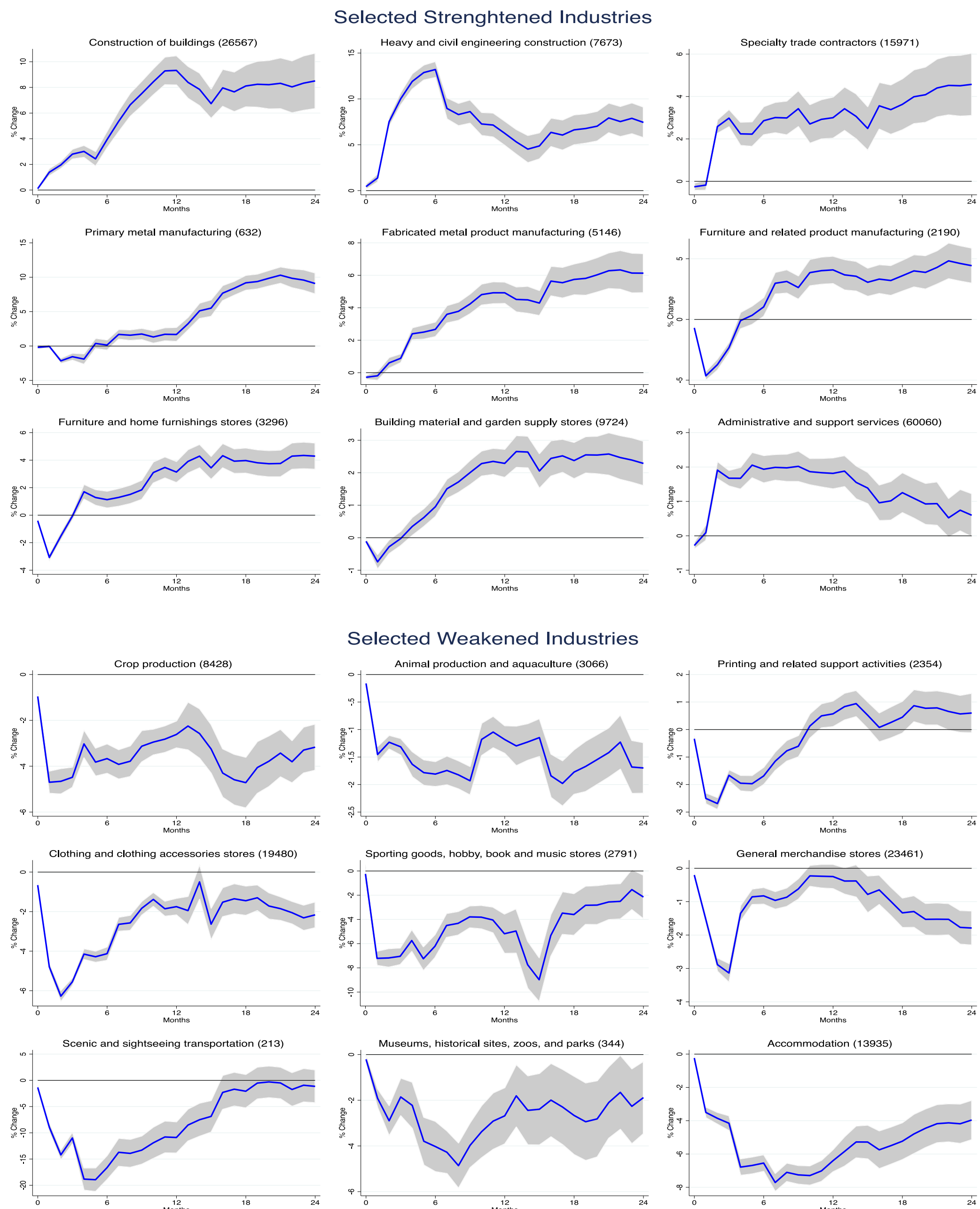

Fig. F.2. Selected industries, 64-knots.
Note: Industry results with a different threshold (64-knots). Dynamic effects of hurricanes at time *t* on employment at different horizons exploiting industry–time variation. Numbers in parenthesis represent the average industry employment over the period 1995–2017. Shaded areas are confidence bands at 95%.

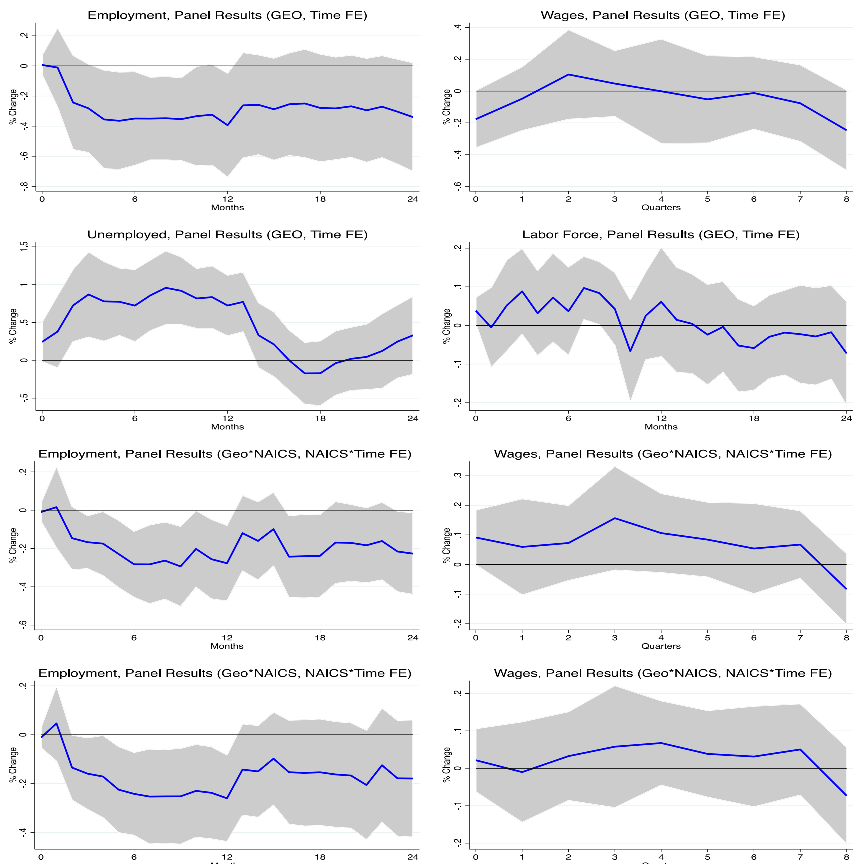

Fig. F.3. Panel results, Depperman.

Note: Panel results with a formula for the wind speed (Depperman). First and second row: dynamic effects of hurricanes at time t on employment, average weekly wages, unemployed and labor force at different horizons exploiting county–time variation. Third row: dynamic effects of hurricanes at time t on employment, average weekly wages, at different horizons exploiting county–industry–time variation without linear interpolation. Fourth row: dynamic effects of hurricanes at time t on employment, average weekly wages, at different horizons exploiting county–industry–time variation with linear interpolation. Shaded areas are confidence bands at 95%.

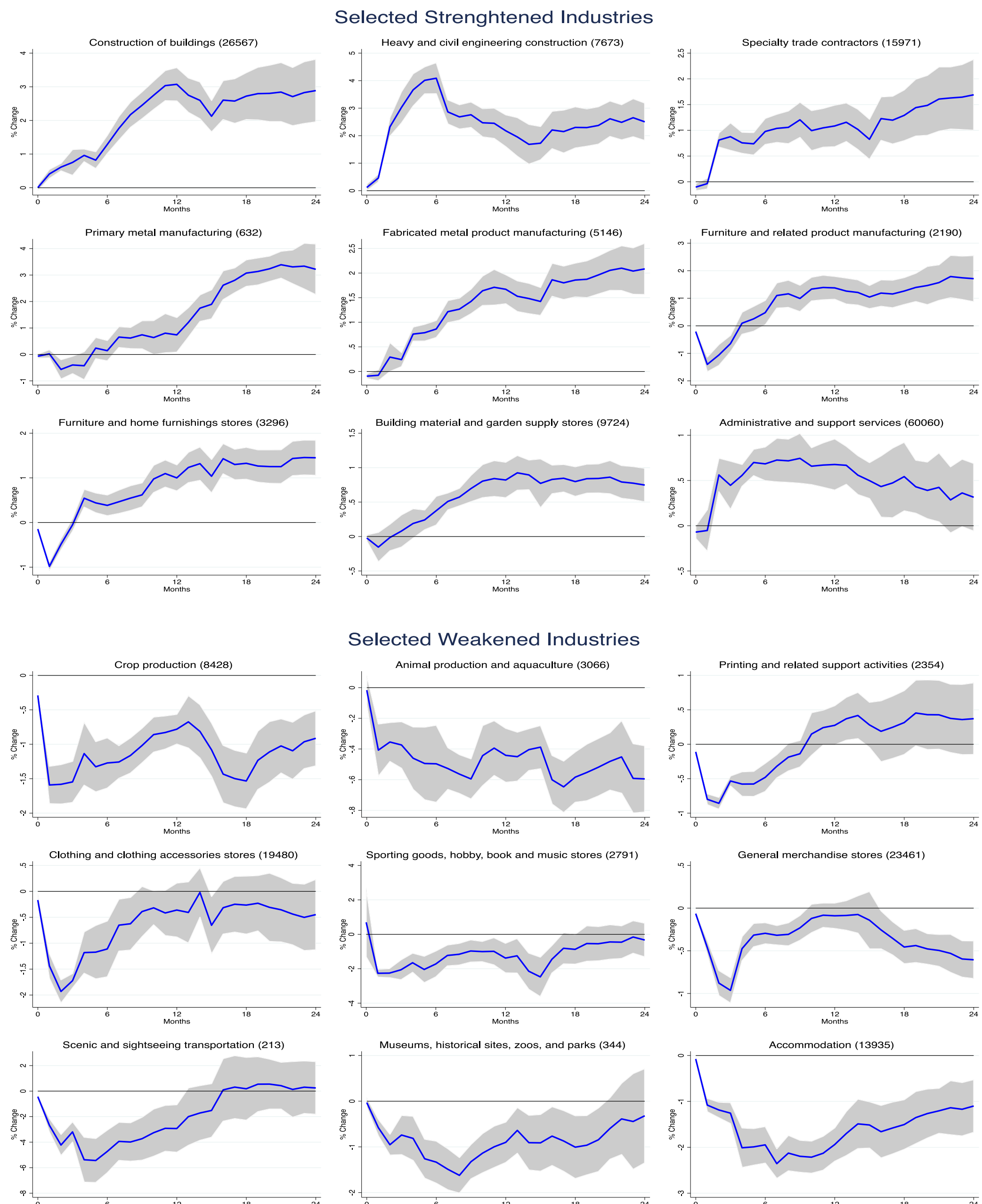

Fig. F.4. Selected industries, Depperman.
Note: Industry results with a formula for the wind speed (Depperman). Dynamic effects of hurricanes at time t on employment at different horizons exploiting industry–time variation. Numbers in parenthesis represent the average industry employment over the period 1995–2017. Shaded areas are confidence bands at 95%.

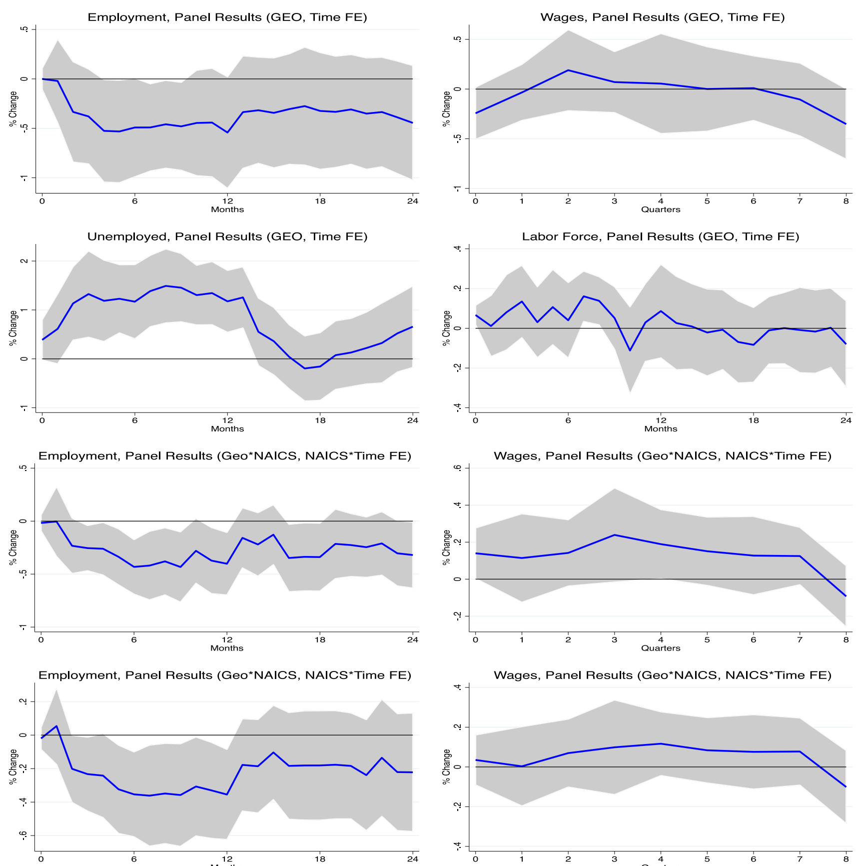

Fig. F.5. Panel results, unweighted centroids.

Note: Panel results with distance from geographical centroids (Unweighted). First and second row: dynamic effects of hurricanes at time t on employment, average weekly wages, unemployed and labor force at different horizons exploiting county–time variation. Third row: dynamic effects of hurricanes at time t on employment, average weekly wages, at different horizons exploiting county–industry–time variation without linear interpolation. Fourth row: dynamic effects of hurricanes at time t on employment, average weekly wages, at different horizons exploiting county–industry–time variation with linear interpolation. Shaded areas are confidence bands at 95%.

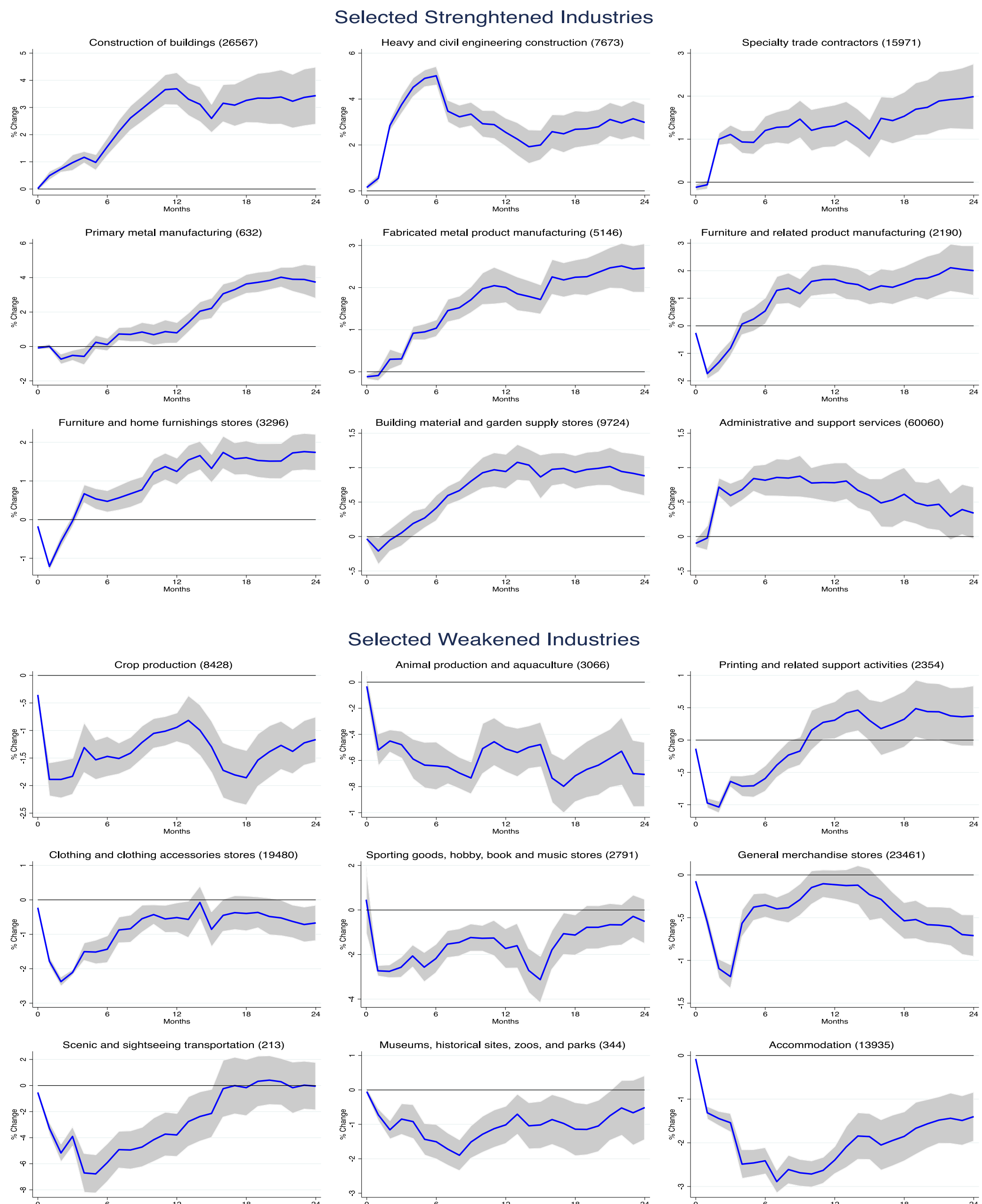

Fig. F.6. Selected industries, unweighted centroids.
Note: Industry results with distance from geographical centroids (Unweighted). Dynamic effects of hurricanes at time *t* on employment at different horizons exploiting industry–time variation. Numbers in parenthesis represent the average industry employment over the period 1995–2017. Shaded areas are confidence bands at 95%.

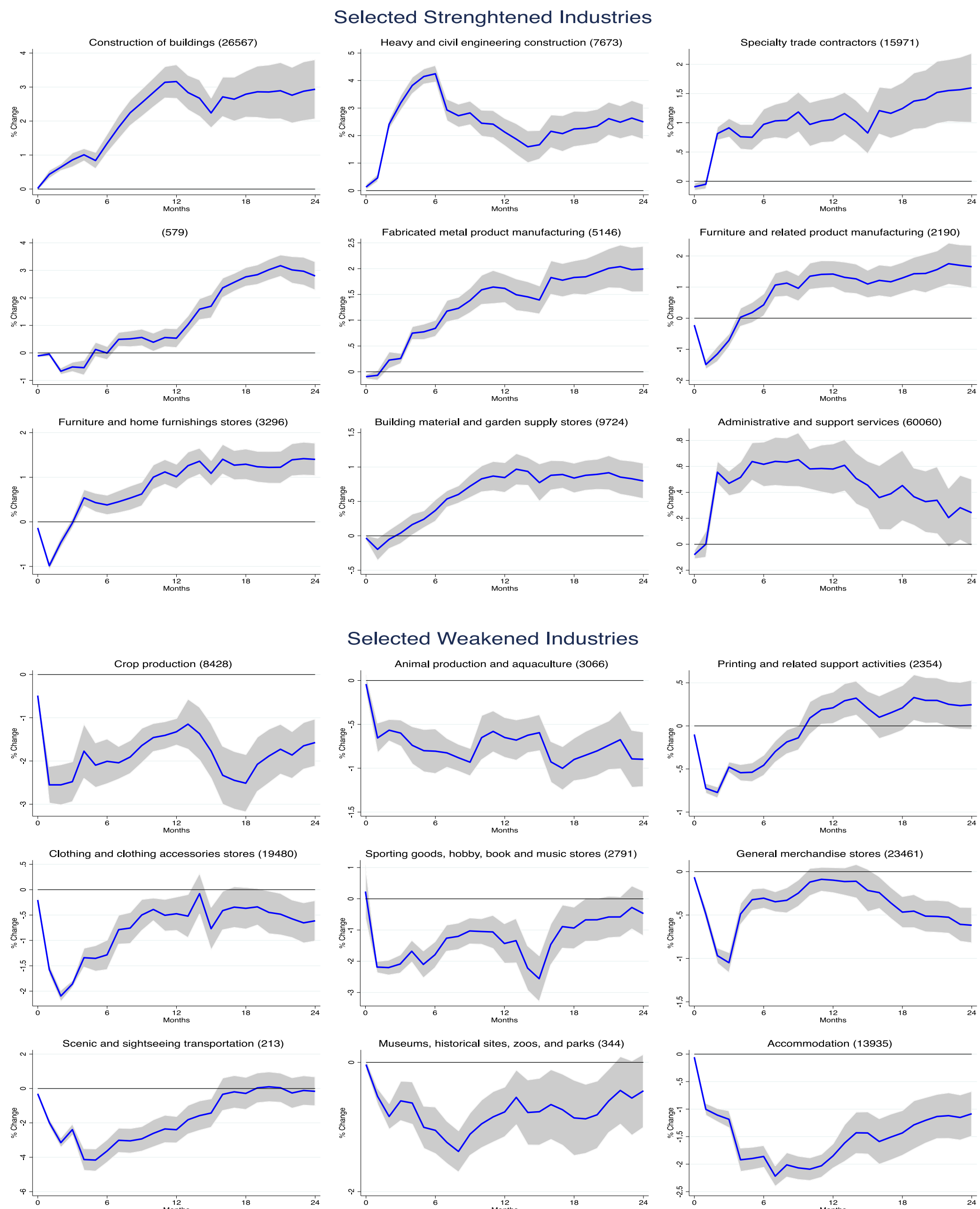

Fig. F.7. Selected industries, industry-specific storm measure.
Note: Industry results with industry-specific exposure measure. Dynamic effects of hurricanes at time *t* on employment at different horizons exploiting industry–time variation. Numbers in parenthesis represent the average industry employment over the period 1995–2017. Shaded areas are confidence bands at 95%.

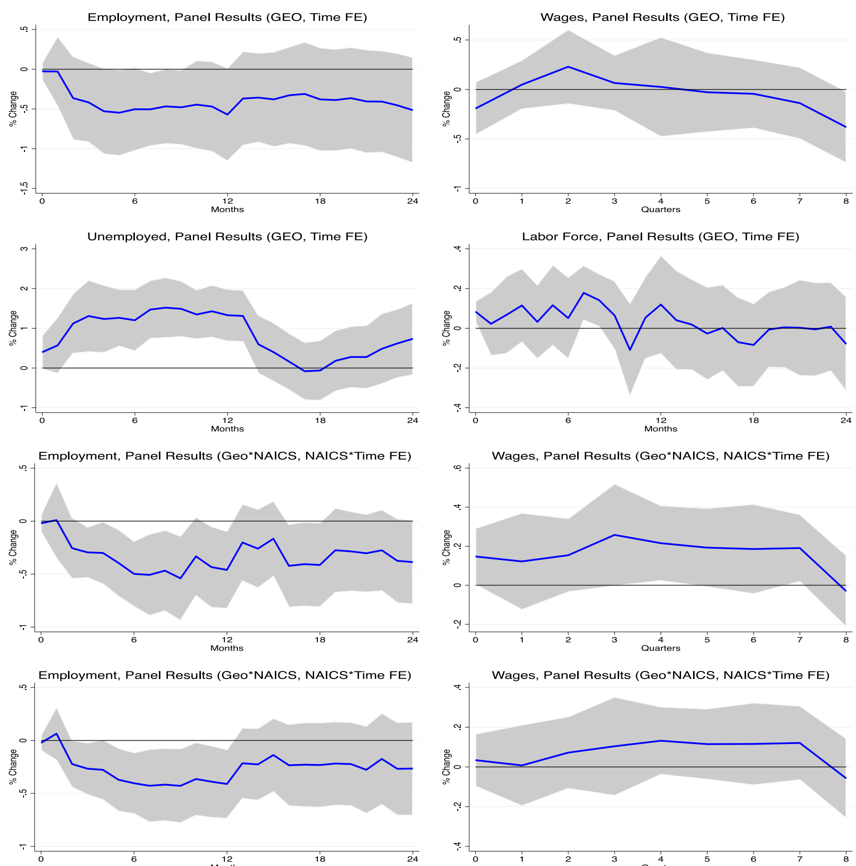

Fig. F.8. Panel results, different controls.

Note: Panel results controlling for lags and leads of exposure measure (Different Controls). First and second row: dynamic effects of hurricanes at time t on employment, average weekly wages, unemployed and labor force at different horizons exploiting county–time variation. Third row: dynamic effects of hurricanes at time t on employment, average weekly wages, at different horizons exploiting county–industry–time variation without linear interpolation. Fourth row: dynamic effects of hurricanes at time t on employment, average weekly wages, at different horizons exploiting county–industry–time variation with linear interpolation. Shaded areas are confidence bands at 95%.

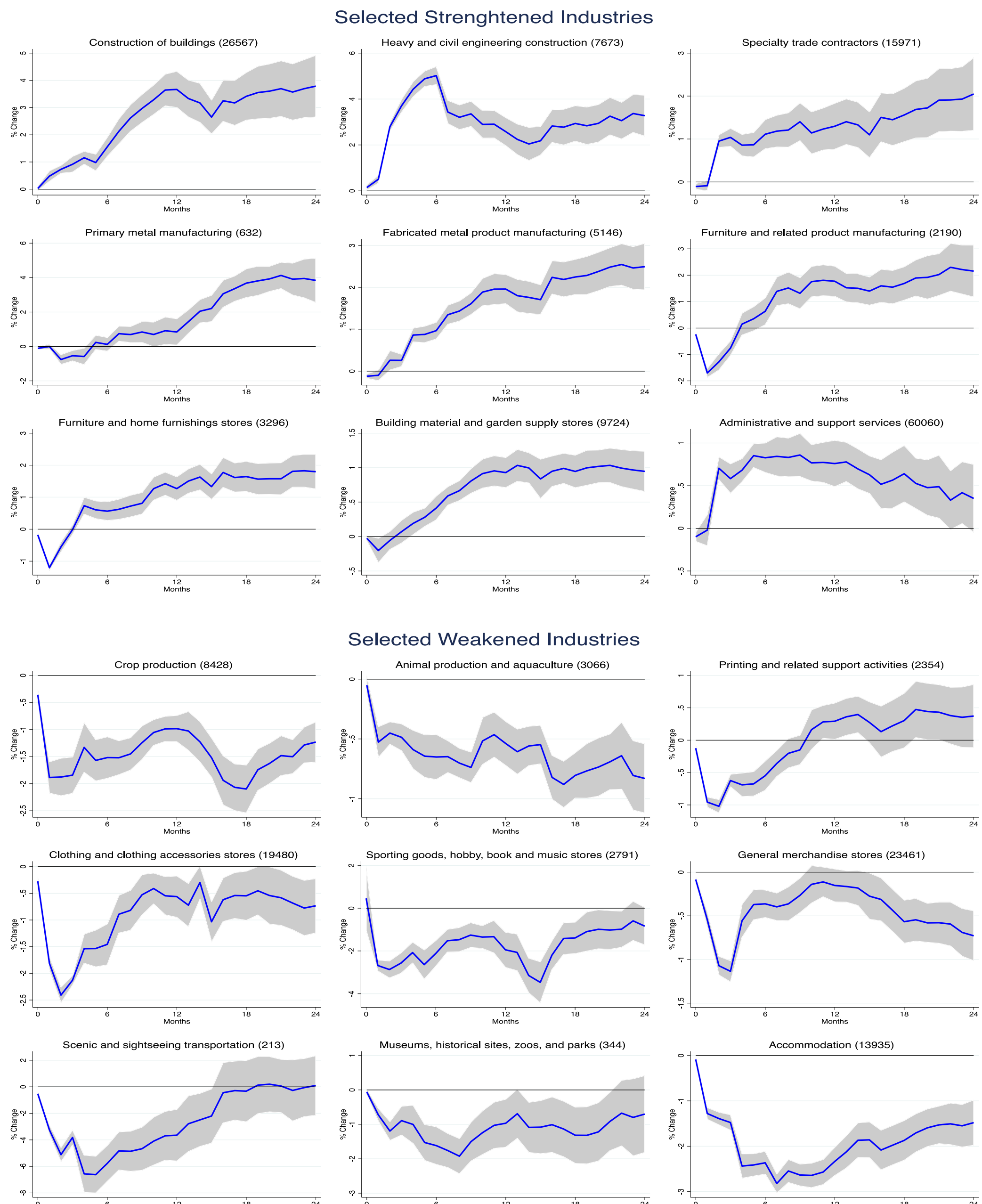

Fig. F.9. Selected industries, different controls.

Note: Industry results controlling for lags and leads of exposure measure (Different Controls). Dynamic effects of hurricanes at time *t* on employment at different horizons exploiting industry–time variation. Numbers in parenthesis represent the average industry employment over the period 1995–2017. Shaded areas are confidence bands at 95%.

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