



Analysis of employment change in response to hurricane landfalls

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Received: 24 June 2019 – Discussion started: 9 July 2019

Revised: 12 November 2019 – Accepted: 25 November 2019 – Published: 7 February 2020

Abstract. Hurricanes cause extensive harm to local economies, and in some cases the recovery may take years. As an adequate, skilled, and trained workforce is a prerequisite for economic development and capacity building, employment plays an important role in disaster reduction and mitigation efforts. The statistical relationship between hurricane landfalls and observed changes in employment at the county level is investigated. Hurricane impact is classified into temporary and permanent categories. In the former category, the level of economic activities is lowered following a hurricane landfall but quickly recovers to the pre-storm norm. In contrast, the permanent shift alters the mean value of the data and results in lasting losses in future years. The results show that Hurricane Katrina produced significant permanent impact on Orleans County, Louisiana. Chambers and Fort Bend counties experienced a significant temporary impact due to the landfall of Hurricane Ike. The results are further discussed through a qualitative analysis of various social, economic, and engineering factors in these affected communities. The findings support the notion that a higher resilience level leads to quicker recovery after a disaster. However, the underlying data-generating processes are characterized and tested in a more detailed manner.

1 Introduction

Natural hazards are an ongoing part of human history, which are caused by nature rather than by man (for example, an earthquake, flood, or hurricane), and coping with them is a critical element of how resource use and human settlement

have evolved (Adger, 2005). It is estimated that during the period of 2006 to 2016, natural disasters affected more than 3 billion people, resulted in over 750 000 deaths, and cost more than USD 600 billion around the world (Hallegatte et al., 2017). Globally, 1.2 billion people, or 23 % of the world's population, live within 100 km from the coasts (Nichols and Beavers, 2003), and the percentage is likely to increase to 50 % by 2030. Many of these coastal areas have high exposure to hurricanes, tsunamis, earthquakes, and other disasters.

Based on statistics from the Congressional Budget Office, the annualized economic losses due to hurricanes in the United States are estimated at USD 28 billion. The top state contributing to that sum is Florida (55 %), followed by Texas (13 %) and Louisiana (9 %). Hurricane Katrina was the costliest storm by far at USD 160 billion (in 2019 dollars).

In the aftermath of hurricanes, disruptions to business activities and supply chains, as well as the failure of infrastructures, often result in the redistribution of resources (Chow and Elkind, 2005; Kaisera et al., 2009; Comfort and Haase, 2006; Sword-Daniels et al., 2015). The capability to produce goods and services may be lost and the natural rate of employment may drop, making for higher levels of unemployment (Ewing, 2009; Schulte in den Bäumen et al., 2015). During the subsequent recovery phase, affected communities engage in debris cleanup and redevelopment designed to quickly restore local employment and other economic activities to pre-storm levels (Burton, 2015). An increasing frequency of disasters can lead to investment deficiency and economic recession, which may result in a decline in employ-

ment (NBER, 2009; Klomp, 2014). The process of economic recovery may require months or even years (Mel and McKenzie, 2011). As an example, US economic growth slowed to 2.6 % in the quarter after Hurricane Katrina compared to the previous quarter's 3.6 %. Hurricane Katrina produced a 19 % effect on US oil production, which caused the oil price to rise by USD 3 a barrel, and the gas price reached USD 5 a gallon (Amadeo et al., 2015). To date, researchers have identified several general classes of elements that could explain the connection between disaster impact and economic performance (Ewing et al., 2005, 2006, 2007, 2009; Tompkins, 2005; Cutter et al., 2008).

Employment has been shown as a key driver of economic activities as well as a major social concern. Local area employment provides a measure of labor market conditions, and firms gain insight into output performance by adjusting employment to match the changes in demand (ILO, 2008). In Australia, more than a week after the landfall of Tropical Cyclone Debbie in 2017, flooding was still widespread in North Queensland, which caused a significant effect on the local economy. Due to the disruption of the supply chain, the local community experienced significant job and income losses (Lenzen et al., 2019). In New Zealand, worker employment status was adversely affected by the disaster, and workers were less likely to work at the same company; most of them migrated to other regions in unaffected areas in New Zealand (Fabling and Grimes, 2016). The study focusing on the 2004 Indian Ocean tsunami demonstrates the importance of employment to evaluate post-disaster recovery programs (Jordan et al., 2015).

Employment is associated with the level of preparedness for disaster and the ability to take proactive actions. Higher employment in a county, for example, often translates into higher resilience and quicker recovery process through purchasing insurance and upgrading houses (Mayunga, 2007; Xie et al., 2014). Previous research has focused on analyzing the elements of vulnerability and disaster recovery, highlighting the importance of employment status for speeding up the recovery process after a disaster strikes a community (Frazier et al., 2014; Stewart et al., 2014; FEMA, 2018). In addition, the literature related to displacement following the landfall of hurricanes in general suggests that employment instability is an important component of displacement. The overwhelming reason given by migrants was job seeking or relocation for employment (Chaganti and Waddel, 2015; Sterett, 2015; Meléndez and Hinojosa, 2017). Therefore, examining the changes in employment following the landfall of a hurricane would not only represent the health of the business environment but also indicate the state of broad economic recovery. Disasters also provide opportunities to study the economic dimensions of large-scale shifts.

The research presented in this paper is focused on analyzing temporary (i.e., transitory) and permanent impacts of hurricanes on affected communities. More specifically, we examine the disruption of employment and investigate the sta-

tistical relationship between hurricane landfalls and observed changes in local employment. In some counties the time series are lowered following a hurricane landfall before quickly returning to the pre-storm level. In contrast, other counties experience permanent shifts in the mean value and sustain long-lasting losses. Understanding the dynamic response of employment to hurricanes can help local communities assess their future risk to hurricanes and devise effective mitigation measures.

The remainder of the paper is organized as follows. In Sect. 2, we describe two historical hurricanes in the study. In Sect. 3, data specifications of employment for affected counties are presented. In Sect. 4, we introduce the Auto-Regressive Integrated Moving Average (ARIMA) model and discuss its application to the data. Results are discussed in Sect. 5, and a qualitative explanation of the results is presented in Sect. 6. Concluding remarks and future extensions are given in Sect. 7.

2 Hurricanes under study

Hurricanes often bring highly detrimental consequences when they make landfall in urban areas (Voogd, 2004). Two historical hurricanes – Hurricane Ike and Hurricane Katrina – are selected in this study because they produced a big impact on the densely populated areas of New Orleans, Louisiana, and Houston, Texas, respectively.

On the morning of 13 September 2008, Hurricane Ike, as the fourth most destructive hurricane in the United States, made final landfall at Galveston island as a Category 2 hurricane with maximum sustained winds nearing 110 mph (175 km h^{-1}) and then moved onto the mainland, which covered over 425 miles of the Texas coastline (Berg, 2009). It was the first hurricane to hit the Houston area since the landfall of Hurricane Jerry in 1989. Hurricane Ike ripped through the Houston area, and the eye of the storm passed over Harris County, TX. In the Houston metropolitan statistical area (MSA), the fourth largest city in the US, at least 20 people died due to the landfall of Hurricane Ike. Nearly 2900 units were deemed unfit for living, with losses exceeding USD 208 million. The storm led to minor damage for about 251 000 residential homes. The total damage cost was estimated at around USD 4.6 billion (Harris County Texas, 2009). According to the estimation of the US Department of Energy, about 2.6 million customers experienced power failure in Texas and Louisiana. Due to the high winds of Hurricane Ike, many windows in the city's tallest building in downtown Houston were broken (Berg, 2008).

Hurricane Katrina made its final landfall as a Category 3 hurricane near the Pearl River at the Louisiana–Mississippi border. Hurricane Katrina's high winds combined with its enormous size at landfall caused tremendous storm surges along the Gulf Coast area. The hurricane severely impacted or destroyed business buildings and residential homes in New

Table 1. Historical hurricane tracks for Hurricane Ike (2008) and Hurricane Katrina (2005).

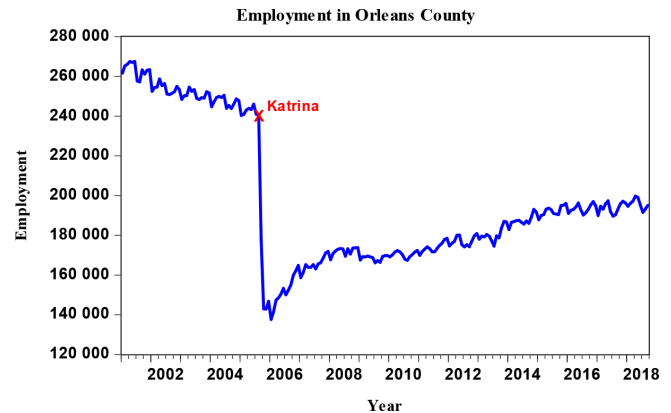
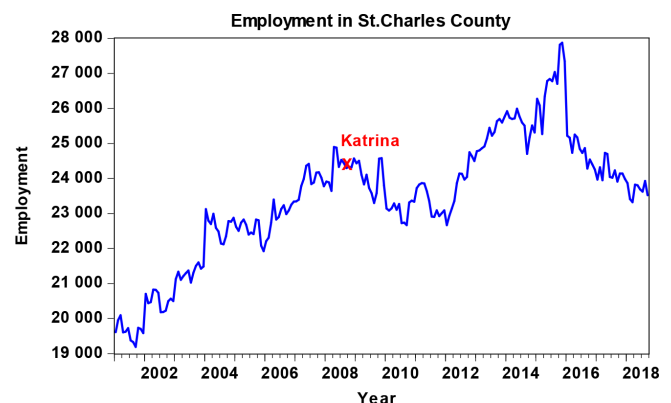
Hurricane Katrina				
Date and time	Longitude	Latitude	Wind speed (kt)	Pressure (mbar)
26, 18:00	24.9	82.6	85	968
27, 12:00	24.4	84.7	100	942
28, 12:00	25.7	87.7	145	909
29, 06:00	28.2	89.6	125	913
Hurricane Ike				
10, 18:00	24.2	85.8	85	958
12, 18:00	27.5	93.2	95	954
13, 12:00	30.3	95.2	85	959
14, 12:00	37.6	91	40	987

Orleans and some other heavily populated areas (Knabb and Rheme, 2005 and USDI and USDC, 2006). Approximately 80 % of New Orleans flooded, and the depth of the flood was up to 20 ft (6.1 m) following the landfall of the hurricane. The total economic damage from Hurricane Katrina is around USD 160 billion (in 2019 dollars), nearly 2 times the cost of the previously most expensive hurricane, Hurricane Andrew (Zhang and Peacock, 2009).

3 Data specification for hurricanes and employment

A brief introduction of the data used in the empirical analysis and some initial observations for the hurricane periods will be presented in this section. Hurricane-relevant parameters such as wind speed, central pressure, and radius were considered important atmospheric factors for assessing and predicting the physical damage caused by hurricanes (Zhang and Wang, 2003). Storm parameter data are obtained from the National Hurricane Center (NHC) for two hurricanes including latitude, longitude, wind speed, and pressure. Sample storm-track data for Hurricane Katrina and Hurricane Ike are shown in Table 1. In addition to physical damage, hurricanes also pose a risk to the local employment market and economic situation (Zhang and Peacock, 2009).

The population in New Orleans declined from over 400 000 to near zero in less than a week after Hurricane Katrina swept the Gulf of Mexico (Vigdor, 2007). The number of layoff events in Louisiana and Mississippi increased greatly and rapidly in September 2005 soon after Hurricane Katrina (Brown et al., 2006). The number of workers and the number of firms operating in New Orleans were also reduced. The subsequent rebuilding process was hindered by absent employees, many of whom had homes that were destroyed or family members requiring urgent care. It has been previously reported that employees who experience injury from a disaster may be more likely to be absent from work in the weeks following the event (Byron and Peterson, 2002). In

**Figure 1.** Monthly employment time series in Orleans County before and after Hurricane Katrina.**Figure 2.** Monthly employment time series in St. Charles County before and after Hurricane Katrina.

September 2005, Mickey Driver, a spokesperson for Chevron stated, “we are trying to find out where they’ve (our employees) gone, what their current situation is and what we can do to help them”. An organization’s ability to recover from a disaster can be weakened due to a lack of employee access to work (Kroll et al., 1991). Monthly employment data for the counties within Houston MSA and New Orleans MSA are obtained from the Bureau of Labor Statistics (<http://www.bls.gov>, 30 October 2019).

Figure 1 shows the monthly employment time series in Orleans County. The red X marker denotes the month in which Hurricane Katrina made landfall. The MSA lost more than 80 000 jobs (or 33 %) immediately after Katrina, gained some back during the initial month of recovery, and then lost again during the recession. Casual observation indicates that Hurricane Katrina was a contributing factor responsible for such a major reduction in employment.

Figure 2 presents the historical monthly employment data in St. Charles County. It is clear at first glance that the storm led to an initial drop in employment (2000 jobs or 8 %), but the magnitude was not as severe as in Orleans County. The

ensuing trajectory was also markedly different, with a long expansion after the Great Recession.

Figure 3 presents the historical monthly employment data for five counties within the Houston MSA. Again, the red X marker denotes the month when Hurricane Ike made landfall. Compared to Hurricane Katrina, it is not apparent whether or not Ike led to a drop in employment as the five counties appear to have been in the midst of a decline (or a period of slowing growth) preceding the storm. However, it does appear that there is an abatement in cyclical behavior (i.e., volatility) in the post-storm period and perhaps even an uptick in Brazoria County.

4 Methodology for quantifying hurricane impact

The ARIMA (Auto-Regressive Integrated Moving Average) model of time series mainly includes three parameters: p , d , and q . The process of determining the integral numbers of auto-regressive p , integrated d , and moving average q could identify the patterns of the model. It generally started with finding an accurate value of parameter d because it provides important information about the order of the time series being investigated; p is the number of auto-regressive terms that describes the number of lag observations included in the model. For example, in a model with three auto-regressive terms, $p = 3$ indicates that the current date of observation depends on three previous period observations. The value of q represents the moving average term, which is only related to the random errors that occurred in past time periods. For example, a model with one moving average term suggests that the current date of observation is determined by the preceding random shock to the series. If a parameter equals a value of 0, this indicates to not use that element of the model.

Two common unit root tests are implemented to test the stationarity of the respective time series and to identify the value of d in the model. The Phillips and Perron (1988) and augmented Dickey–Fuller (ADF) tests are applied in our study to analyze the stationarity of employment variables in different counties; if d equals 0, this indicates that the time series is stationary in levels. If not, the first (or second, third, etc.) difference of the time series will be examined until the time series is shown as stationary time series data.

The results of the ADF unit root test suggest that each series of employment in different counties is nonstationary in levels, but it is stationary in the first difference. The PP unit root test presents the same result as the ADF test. Therefore, the first difference of each sequence is used as input to identify the ARIMA model in order to compare the results of each county. Box–Jenkins methodology (Maddala, 1988) is involved in the identification and estimation of ARIMA (p , 1, q), which applies partial autocorrelations and autocorrelations of stationary time series data to obtain the best fit of time series data. The values of p and q are determined by

choosing the minimum value of the Akaike information criterion (AIC).

The ARIMA model with intervention analysis is mainly applied to estimate the impact caused by specific external events such as natural hazards and policy change (Enders, 2009). Baade et al. (2007) use the ARIMA model with intervention analysis to estimate the Hurricane Andrew impact on taxable sales in the respective cities. This technique has been widely used in many fields of research ranging from evaluating the impact of the financial crisis on Nigerian crude oil export (Adubisi and Jolayemo, 2015) to assessing the effects of Federal Emergency Management Agency (FEMA) policy changes on employment in hurricane-stricken cities (Ewing and Kruse, 2002). Intervention analysis offers a formal test to evaluate several patterns of distortion (changing the mean function or trend) as a result of external shock.

Table 2 presents the results of ARIMA model selection based on standard Box–Jenkins methodology with the Akaike information criterion. Consequently, the first difference in each series is used as input to identify the values of p and q in the ARIMA model; thus, the results for hurricane impact on different counties can be compared.

Intervention analysis is carried out in the following steps. We first identify the ARIMA model for each county before the month of hurricane landfall. A binary (intervention) variable with a value of 1 or 0 is defined as an intervention variable; a value of 1 flags the hurricane periods (either the month of hurricane landfall or the entire post-hurricane period accordingly) and takes the value 0 at other times. Then, the model with the intervention variable is reestimated for the whole time series of data (i.e., pre- and post-hurricane period). The effect of hurricanes on employment can be understood by examining the magnitude and statistical significance of coefficients on intervention variables.

Two types of intervention variables are added to the ARIMA model separately to evaluate the hurricane impact on employment at the county level. The “temporary” impact of a hurricane may be captured by the intervention variable that equals 1 in the month of hurricane landfall and 0 at other times. The “permanent” effect of the hurricane may be modeled by the intervention variable that equals 1 from the month of hurricane landfall through the end of the sample period and 0 elsewhere. Note that the latter represents a changing mean or trend in the growth rate of employment. Equation (1) shows the ARIMA model with intervention analysis:

$$\Delta y_t = c + a_1 \Delta y_{t-1} + \dots + a_p \Delta y_{t-p} + e_t + b_1 e_{t-1} + \dots + b_q e_{t-q} + \beta D, \quad (1)$$

where D is the intervention variable (i.e., temporary or permanent), β is the associated coefficient, c is a constant term, p is the number of lags on the auto-regressive term, a_1, \dots, a_p represents the coefficients for the AR model, and b_1, \dots, b_q represents the coefficients of the MA part in the model.

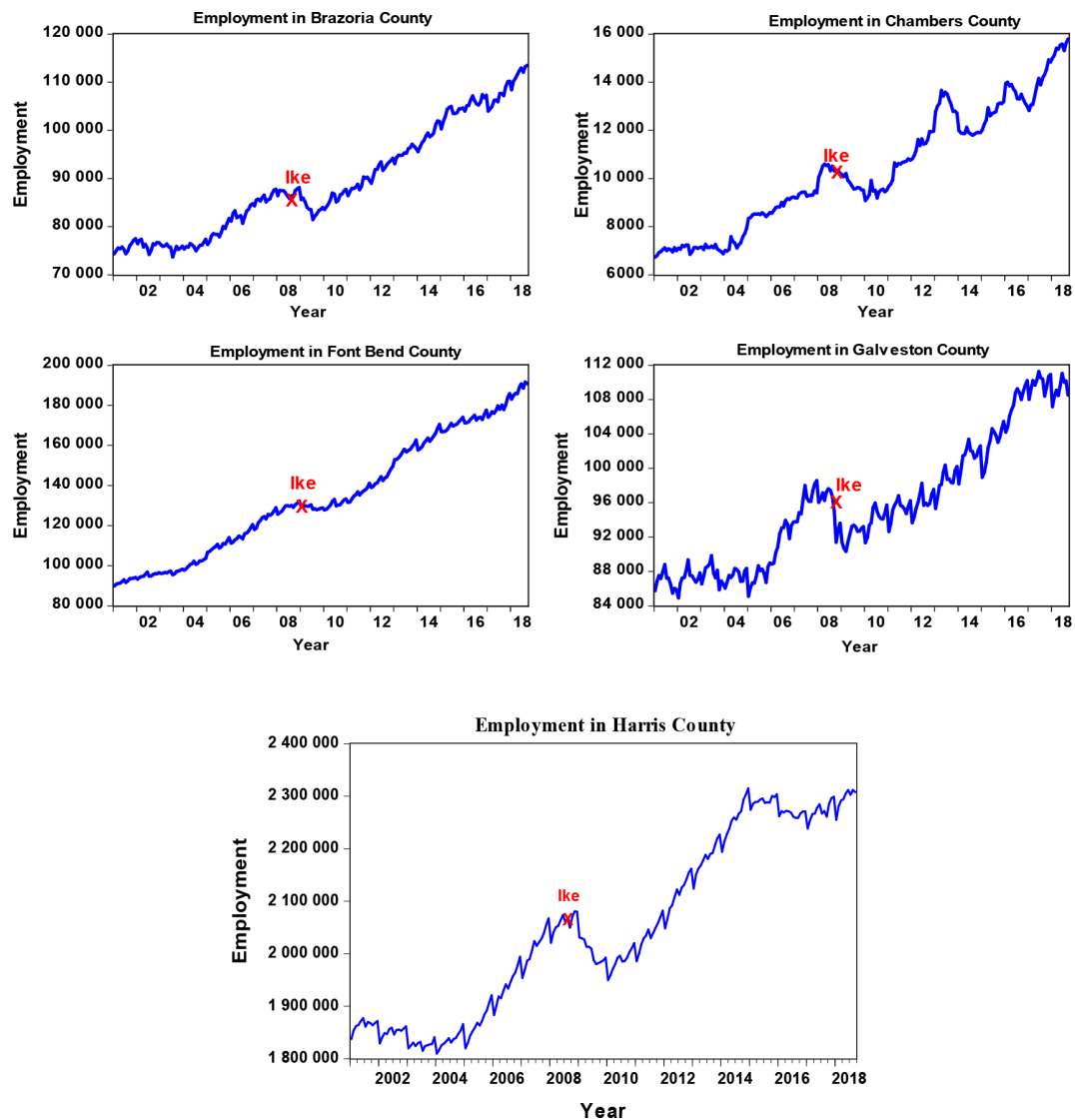


Figure 3. Monthly employment time series in five counties within Houston MSA before and after Hurricane Ike.

Table 2. ARIMA model selection.

Hurricane name	County	ARIMA model	Adjusted R^2	F statistic
Hurricane Katrina	Orleans	(0, 1, 3)	0.672650	28.05442
	St. Charles	(1, 1, 3)	0.548294	18.19573
Hurricane Ike	Brazoria	(2, 1, 3)	0.302821	11.41402
	Chambers	(2, 1, 3)	0.362174	12.12940
	Fort Bend	(0, 1, 2)	0.534298	12.91547
	Galveston	(2, 1, 2)	0.428823	15.30493
	Harris	(1, 1, 2)	0.478316	28.94065

There are several points worth noting in the ARIMA intervention model. The design of the ARIMA intervention method focuses on the time series relationship between a specific variable and an event (especially the time period of the occurrence of the event) and isolates the effects of changes in the time series behavior of the variable before and after the event. In addition, an appropriately defined ARIMA model can achieve this without adding additional control variables, and these variables are effectively handled in the error term (Enders, 2009). Excessive specification (i.e., adding irrelevant or statistically redundant control variables) leads to multicollinearity, and standard errors often result in lower accuracy in the time series models. Therefore, diagnostic tests are conducted on residual errors to determine that (1) they perform well (normal, constant variance) and (2) the error items do not contain additional information that can be used to improve the prediction accuracy of the model. In general, the ARIMA model has ideal characteristics, with fewer and better error terms. Results for the temporary effect are presented in Table 3, and the permanent effect results are shown in Table 4. Statistical significance at the 5 % level is indicated by a double asterisk (**).

The adjusted R^2 represents the extent of the total variance of the dependent variable that can be explained by the independent variable, and the estimated number of independent variables is also considered. The adjusted R^2 values reported in Table 3 are fully within the acceptance range of the model specified in the first difference. The F statistic tests the null hypothesis that all coefficients except the constant term are equal to zero. The results for F statistics shown in the tables below indicate that the null hypothesis is rejected, which proves the rationality of the existence of the model.

Hurricane Ike produced a significant temporary impact in Chambers County and Fort Bend County as the employment growth rate slowed down by 8.2 % in Chambers County and 4.3 % in Fort Bend County. In contrast, a permanent change in the mean growth rate is found to be significant in Orleans County where the mean growth rate slowed down by 8.6 %.

Figures 4 and 5 further illustrate the temporary and permanent impacts that hurricanes have on communities. The shaded area in these figures represents the post-storm period. Actual and forecast values are shown, as are the (1 standard deviation from the mean) upper and lower bounds for the forecast (or confidence bands). A temporary reduction from Hurricane Ike occurred in Chambers County where employment dropped by 8.1 % but recovered within 2 years (see Fig. 4) when the series reentered the areas shown within the confidence bands. In contrast, it took Orleans County about 7 years (2005 through 2012) to return to the pre-storm employment level following Hurricane Katrina. These two cases present a clear difference in timescale in terms of how local employment recovered from hurricanes.

Furthermore, others have found that long-term recovery from disasters usually takes 3 to 5 years (Webb et al., 2002; Marks, 2015). Therefore, we define the threshold for the per-

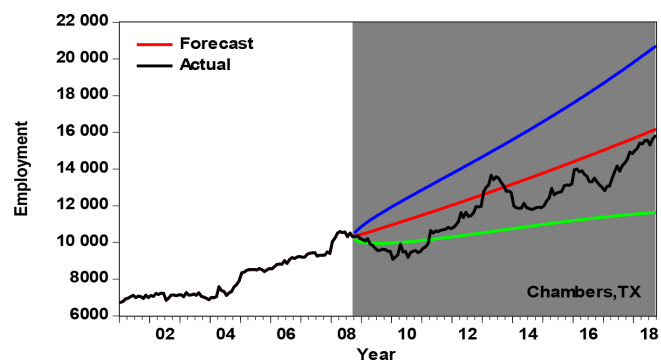


Figure 4. Temporary effects of Hurricane Ike in Chambers County.

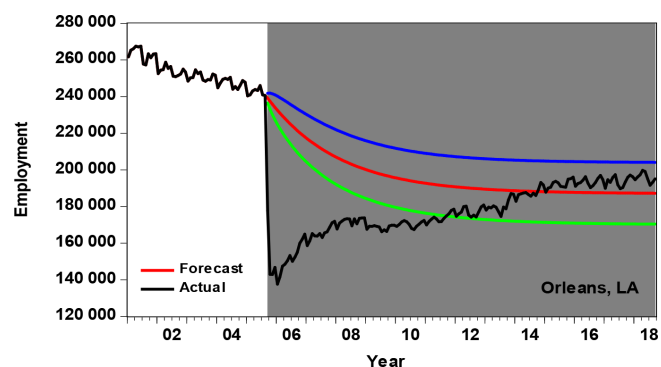


Figure 5. Permanent effects of Hurricane Katrina in Orleans County.

manent effect in this study as 3 years or longer. In other words, if it takes 3 years or more for employment to return to within the forecast confidence bands, the impact will be considered permanent. Otherwise, it will be considered a temporary impact.

Further investigations are conducted in relation to the changing tendency of various types of employment in Houston MSA and New Orleans MSA following the landfall of hurricanes. Monthly employment data extracted from the Bureau of Labor Statistics in the construction, retail sale, wholesale, and utilities industries of Houston MSA and New Orleans MSA are shown in Figs. 6 and 7 below. The shaded areas represent the post-hurricane period, and the X indicates the month that Hurricane Ike or Hurricane Katrina made landfall.

Construction employment in Houston MSA increased slightly immediately following the landfall of Hurricane Ike. Employment data in the other three industries (retail sales, wholesale, and utilities) present a decreasing tendency following the landfall of Hurricane Ike, and employment in retail sales, wholesale, and utilities shows an increasing tendency until the beginning of 2010 (which is 1.5 years after the landfall of Hurricane Ike).

Unlike employment in Houston MSA, employment in four industries in New Orleans MSA presents a huge drop im-

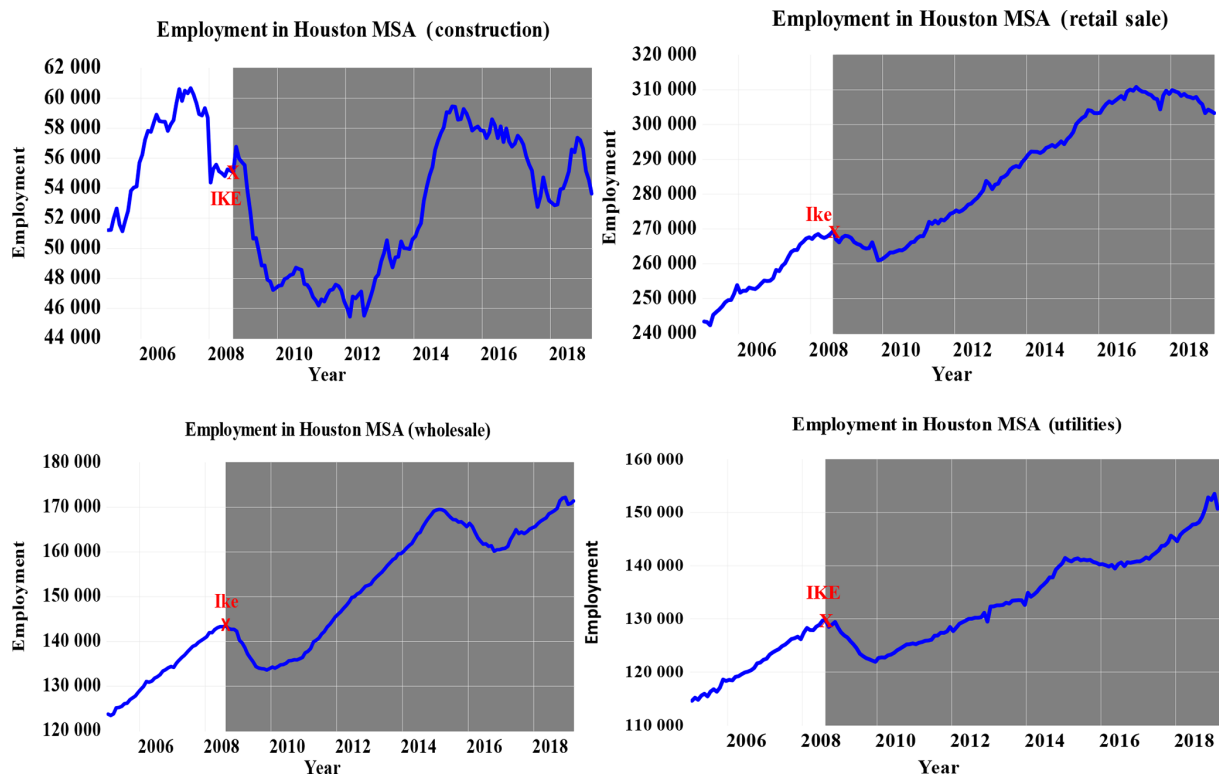


Figure 6. Monthly employment in four industries for Houston MSA.

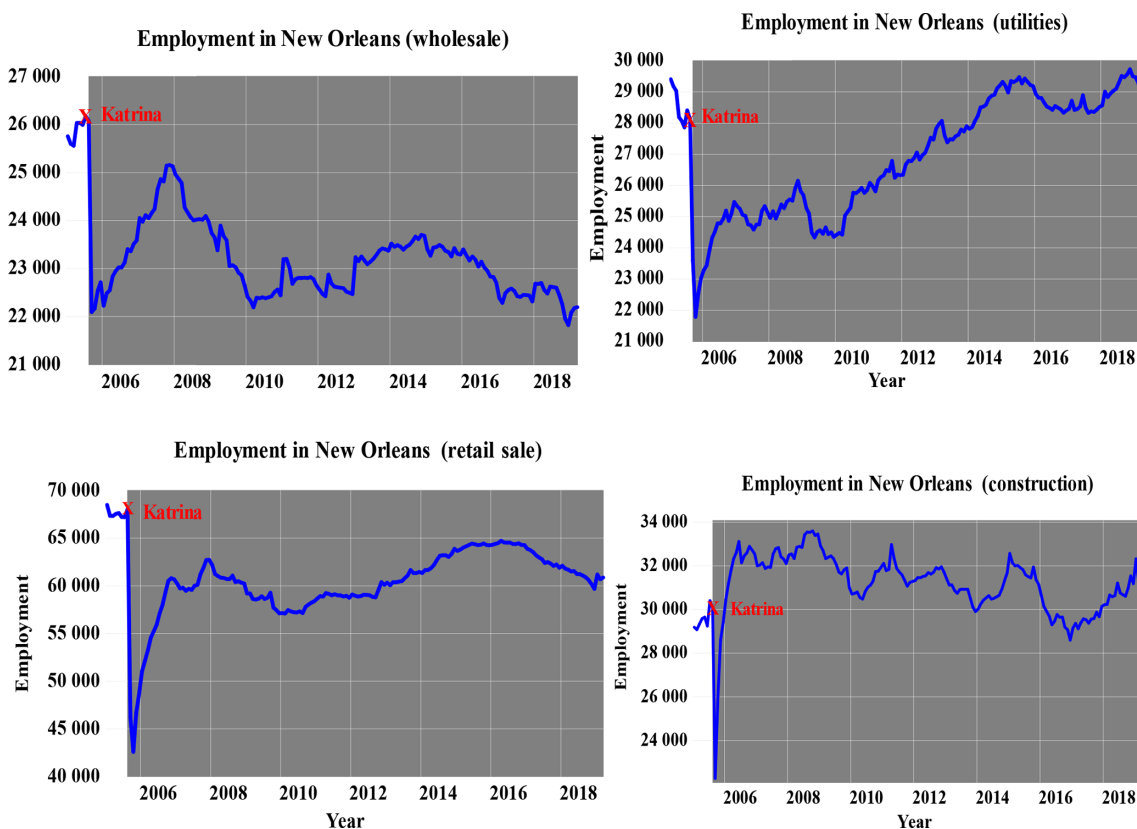


Figure 7. Monthly employment in four industries for New Orleans MSA.

Table 3. Results of temporary impact for employment. Statistical significance at the 5 % level is indicated by a double asterisk (**)

Hurricane	County	Temporary		Adjusted R^2	F statistic
		P value	β		
Hurricane Katrina	Orleans	0.8609	0.005476	0.521029	47.76391
	St. Charles	0.7781	−0.003473	0.274538	7.856402
Hurricane Ike	Brazoria	0.3020	−0.001221	0.416745	31.35297
	Chambers	0.0000**	−0.081789**	0.342465	15.52769
	Fort Bend	0.0387**	−0.043339**	0.350011	19.28911
	Galveston	0.65491	−0.217338	0.318773	18.22978
	Harris	0.18665	0.001188	0.256785	9.798675

Table 4. Results of permanent impact for employment. Statistical significance at the 5 % level is indicated by a double asterisk (**)

Hurricane	County	Permanent		Adjusted R^2	F statistic
		P value	β		
Hurricane Katrina	Orleans	0.0000**	−0.08653**	0.5692541	30.89562
	St. Charles	0.2882	−0.003649	0.387652	10.76492
Hurricane Ike	Brazoria	0.3020	−0.001221	0.386158	19.22739
	Chambers	0.3942	−0.003558	0.257711	10.99645
	Fort Bend	0.1407	−0.002233	0.278219	15.99100
	Galveston	0.9467	−0.003265	0.378517	19.06807
	Harris	0.2271	−0.057741	0.339228	20.68832

mediately following the landfall of Hurricane Katrina. Only employment in utilities shows a long-term increasing tendency starting from 2007, which is 2 years after the landfall of Hurricane Katrina. Employment in wholesale, retail sales, and construction has a short-term quick increase, and it then presents a fluctuating trend; employment in wholesale and retail sales was not back to the pre-disaster level until 2019.

5 Qualitative explanation of the results

Based on the analysis above, Hurricane Ike produced a significant but temporary impact on employment in Chambers County, while Galveston, Harris, and Brazoria counties did not experience any significant impact. The following question is then raised: what has contributed to a community's ability to withstand and recover from disaster?

We attempt to address this question through the prism of resilience. Disaster resilience is defined as the capacity or ability of a community to anticipate, prepare for, respond to, and recover quickly from the impacts of a disaster (Foster, 2006). According to Walker et al. (2006), adaptability is mainly controlled by all forms of capital, as well as the amount of government and the number of institutions in the system. The capital in a system represents fundamental components for a resilience study of the entire community, e.g., social, human, economic, physical, and natural, which are

referred to as elements of resilience. The evaluation of community resilience is a complex process due to the dynamic interactions among people, the community, society, and the environment (Foster, 2006; Pelling et al., 2017). Several indicators have been applied to assess community resilience under each element of resilience as shown in Table 5.

Hurricane Ike made a direct hit in Galveston but failed to produce any significant impact on its employment. A possible explanation for this is that while Galveston County is highly susceptible to hurricanes and tropical storm-force winds, it has experienced several hurricanes in the past and may have adapted accordingly (e.g., Hurricane Alicia in 1983, Hurricane Allison and Hurricane Jerry in 1989). Several emergency studies suggest that community resilience could be built through the adoption of social media (Dufty, 2012). Through a warning system, the community could promote effective action to respond to disaster (Tasic and Amir, 2016). Thanks to advanced weather monitoring systems, the National Hurricane Center (NHC) correctly predicted that Hurricane Ike would hit Galveston (FEMA, 2008). This triggered a mandatory evacuation for Brazoria (located to the south of Galveston County) and Galveston counties. Residents who followed the order took necessary steps to protect themselves, their families, and their property. As a result, residents in these two counties by and large were better prepared for Hurricane Ike than those living in other counties. Morss and Hayden (2010) interviewed 49 residents affected

Table 5. Framework for evaluating resilience (Mayunga, 2007).

Element of resilience	Indicator of resilience	Explanation
Social capital	Trust, norms, and networks	Facilitates coordination and cooperation. Facilitates access to resources.
Economic capital	Income, savings, and investment	Reduces poverty. Increases capacity, e.g., insurance speeds the recovery process.
Human capital	Education, health skills, knowledge–information	Increases knowledge and skills to understand community risks. Increases ability to develop and implement risk reduction strategies.
Physical capital	Housing, public facilities, business–industry	Communication, transportation, and evacuation.
Natural capital	Resource stocks, land and water ecosystem	Sustains all forms of life. Increases protection from storms and floods. Protects the environment.

by Hurricane Ike approximately 5 weeks after landfall; 90 % of interviewees said they prepared their residences before the landfall of Hurricane Ike. Only five reported that they did not prepare specifically for Ike. However, all five residents who did not prepare suffered heavy losses, most of which were caused by flooding. This further supports the conclusion that better preparation could enhance the resilience of affected counties.

Harris County, the biggest county within Houston MSA, has a highly diversified economy. Cutting-edge technologies allow the energy industry to continue to power the Houston region's growth, while research and development breakthroughs regularly occur at the world's largest medical complex – the Texas Medical Center – which adds to regional prosperity. It also has a growing population represented by all major racial and ethnic groups. Harris County's well-developed financial infrastructure, skilled workforce, good labor relations, and diverse population attract many international companies. All of these factors in turn could be responsible for raising its capability to resist external shocks like Hurricane Ike and recover more quickly in the aftermath.

Unlike Harris County, Chambers County is very rural and has a population of just over 26 000. Hurricane Ike damaged its utilities and critical infrastructures, including power lines, substations, and water and sewer plants. The estimated loss was USD 12.1 billion (TEES, 2009). At the same time, the storm disrupted many of its economic engines, including the University of Texas Medical Branch (UTMB), the ports and waterways, agricultural and natural resources, and the tourist industries (USHUD, 2009). The UTMB at Galveston recorded an employment decline during this time, largely due to the effects of Hurricane Ike, which damaged several buildings.

According to Abel et al. (2006), the ability to self-organize is the foundation of resilience. A need exists for local systems to be interconnected and connected to a larger national system in order to deal with disturbances. It is also important that these local networks maintain self-reliance, or the ability to subsist without the larger system (Baker and Refsgaard, 2007). This can be accomplished through establishing trust among the population through networks and institutions, their leaders, and the information disseminated to the community (Nkhata et al., 2008; Longstaff and Yang, 2008). Building networks is an essential element in disaster reduction, and the resilience level of a community heavily depends on the established networks of people from different sectors (Chatterjee et al., 2016). Collaboration among networks can greatly improve the resilience of a community. The management method frequently taken by the New Orleans government was a command and control approach that targeted a specific variable and reduced resilience by ignoring other parts of the system (Gunderson, 2009).

Lastly, it is worth noting that a hurricane's impact does not permeate all elements of a community on an equal basis. A previous analysis of the same two hurricanes on building permits (Cui et al., 2015) reveals that a significant temporary impact was evident in Orleans, Chambers, Fort Bend, Harris, Liberty, and Montgomery, while a significant permanent impact was evident only in St. Charles. We suggest that three counties – Orleans, Chambers, and Fort Bend – were the least resilient among their peers and suffered the most during these two hurricanes.

6 Concluding remarks and future research

The results from this empirical study illustrate the impact of hurricanes on local employment. An interesting finding

is that, regardless of the storm, the effects are limited to either being temporary or permanent in nature. In the temporary impact case, the level of employment is lowered following a hurricane landfall but quickly recovers to the pre-storm norm. In contrast, the permanent impact shifts the mean value of the time series data and persists for a longer period of time. The results may be explained through the five forms of capital used to evaluate the resilience of an affected community. The comparison among communities identifies strengths and weaknesses in these various forms of capital and their contribution to recovery. Understanding the empirical results in the context of social, economic, human, physical, and natural capital provides local officials with insight and possible actions to ensure the outcomes can be significantly improved.

Hurricane Harvey highlights the idea that people are a critical link in the effort to build community resilience (Savio, 2018). Business owners need to form a recovery plan in which several aspects of human capital are considered. For example, could employees continue working safely during recovery? Can they work remotely? Are they trained in disaster preparedness? For businesses relying on local customers, will they be able to access goods and services?

Future work in this area of study should target two main unresolved issues. The first one is to examine employment across different demographic groups stratified by factors like income, age, and race at the local scale, which is critical for planning, mitigation, and recovery from hurricanes. The goal is to identify the distributional and disproportionate impacts of hurricanes in various subpopulations so that policies and programs could be tailored for their specific needs. The second issue is to improve our understanding of fundamental factors and underlying processes of disaster recovery. To that end, we need to extend the analysis to other socioeconomic settings. For example, a cross-country panel data set can be used to analyze critical drivers of community resilience in developed and developing countries.

The methodology presented in this paper could be considered an entry point to addressing the complex problems related to disaster resilience. Focused, limited-scope empirical studies like ours play a major role in bridging the knowledge gaps and catalyzing innovations.

Data availability. The data are publicly accessible, and a description of the data is presented in Sect. 3. Monthly employment data for the counties within Houston MSA and New Orleans MSA are obtained from the Bureau of Labor Statistics (<https://data.bls.gov/cgi-bin/dsrv?en>; U.S. Bureau of Labor Statistics, 2002–2018).

Author contributions. YC was responsible for model development, calculation, plotting figures, and writing. DL was responsible for data specification and revising the paper. BE was responsible for giving guidance on model development, result discussion, and the conclusion.

Competing interests. The authors declare that they have no conflict of interest.

Acknowledgements. This material is partially based upon work in part supported by the National Science Foundation under grants CMMI-1000251 and CMMI-1131392. Any opinions, findings, and conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the National Science Foundation.

Financial support. This research has been supported by the National Science Foundation (grant nos. CMMI-1000251 and CMMI-1131392).

Review statement. This paper was edited by Sven Fuchs and reviewed by one anonymous referee.

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