The Economic Aftermath of Hurricanes Harvey and Irma

Jim Lee
Texas A&M University-Corpus Christi

August 2019

Abstract:
This paper estimates the economic impacts of Hurricanes Harvey and Irma of 2017, with a focus on the local labor markets. Data from 90 counties of the federally declared disaster regions in Texas and Florida reveal a strong relationship between direct economic damage and localized measures of storm intensity, such as wind speeds, rainfall amounts, and storm surge levels. The impact of the storms on unemployment and employment of the disaster counties dissipated within six months, and then recovery supported in part by federal relief programs boosted employment and wage growth primarily through expansion in construction and service-oriented activities. Regressions with spatial effects show that following a hurricane strike, employment and wages moved in the opposite directions between a disaster county and its neighboring counties.

Keywords: disaster, economic impacts, policy response, recovery, spatial effects

1. Introduction

In 2017, the United States experienced a historic year of natural disasters. Hurricane Harvey made landfall on the Texas Gulf Coast in late August. According to the National Oceanic and Atmospheric Administration (NOAA), this Category 4 tropical storm cost at least $125 billion in economic damage, second only to Hurricane Katrina. Within two weeks apart, Hurricane Irma, once a Category 5 storm, swept across the Florida peninsula, causing an economic toll estimated at $50 billion (Blake and Zelinsky, 2018; Cangialosi, Latto, and Berg, 2018; NOAA, 2018).

Most economists would agree that major storms like Harvey and Irma immediately depressed economic activity in the affected areas. Yet little is known about the size and duration of the impact, and what drives the subsequent recovery. One reason is that economy-wide findings are necessarily non-experimental. Because the timing and the paths of the tropical storms are not predictable well in advance, storm events are widely regarded as exogenous shocks (Belasen and Polachek, 2009). However, it difficult to identify the causal effects of these shocks because there are always confounding factors that likely make observations of post-disaster economic activity not directly informative. Chang and Rose (2012) point out a myriad of local factors, ranging from the specific economic landscape to the extent of government economic stimulus, which mask the transition from economic impact to recovery.

Following the hurricane strikes, U.S. Congress approved two disaster relief funding bills that appropriated a total of $34.5 billion. In early 2018, Congress passed a two-year budget that included another $90 billion for recovery from natural disasters in 2017, including Hurricane Maria that hit Puerto Rico in September and California wildfires in December. The total federal spending in response to the 2017 disasters at over $130 billion was a U.S. historical record. An aggressive federal policy response, especially at this magnitude, would likely dwarf potential the near-term impact of the two catastrophes on the local economies.

The objective of this paper is to empirically estimate the immediate impacts of the two hurricanes in 2017 as well as the efficacy of subsequent disaster relief programs. With a focus on near-term movements of local labor markets in aggregate as well as by industry, we seek to better understand the macroeconomic context in which we analyze the transmission of economic shocks associated with the two events. Out study departs from the related literature (e.g., Vigdor, 2008; Belasen and Polachek, 2008, 2009) in three directions. First, following Strobl (2011), we measure the relative strengths and potential destruction of the storms using directly observed weather data, such as wind speeds, rainfall amounts, and storm surge levels. In contrast to previous studies that measure an overall hurricane intensity based on the five intensity levels of the Saffir-Simpson Scale (e.g., Belasen and Polachek, 2008, 2009), such data allow us to capture different destructive impacts of the storms on each affected community in addition to their intensity.

The second innovation of this paper is the geographical scope of the study. In response to Harvey, the Federal Emergency Management Agency (FEMA) declared 41 counties in the southern and southeastern parts of Texas as a Disaster Region (DR-4332) that is eligible for Individual Assistance programs. For Irma, the Disaster Region (DR-4337) consists of 49 counties that encompass nearly the entire state of Florida except the Panhandle. The treatment group in this study consists of these 90 disaster counties in Texas and Florida. Despite the massive sizes of both hurricanes, the extent of destruction varied widely across those counties. Panels of cross-sectional data will enable us to differentiate the disaster impact on the hardest-hit counties from other, less affected counties (Wooldridge, 2002).

The third distinction of this paper is the consideration of spatial effects in estimating disaster impacts and federal policy responses. Our panel regression models account for not only dynamics over time, or temporal effects, but also spillover effects across counties. Belasen and Polachek (2009) show that historically wage earnings increased in Florida counties directly hit by a hurricane but decreased in their neighboring counties. Looking at business recovery patterns after Hurricane Katrina, LeSage et al. (2011) and Tierney (2007) also find that the decision of affected businesses to reopen depended on whether their neighboring businesses were open or not. Given such findings of spatial interactions in business and community recovery, conventional econometric models that ignore geographic spillovers yield biased and inconsistent estimates (Elhorst, 2010). Empirical evidence on panel regressions with spatial effects will potentially provide insight into how federal relief funds should be allocated in response to hurricane events.

The rest of the paper is organized as follows. The next section provides an overview of the post-storm economic conditions and reviews the strand of recent literature on labor market responses to disaster events. The third section describes the empirical methodology and our sample data. The fourth section details our econometric results and compare our inferences with findings in the existing literature. The final section contains a summary and conclusion.

2. Background

The two hurricanes in 2017 set historic records for natural disasters. Harvey made U.S. landfall in Aransas County on August 25, with maximum wind gusts over 130 miles per hour and storm surge as high as 12 feet. For that particular Texas Gulf Coast region, Harvey was primarily a wind event. During the next five days, the storm stalled over southeastern parts of Texas, bringing record amounts of rainfall over 60 inches that caused widespread flooding to Houston and its surrounding areas in the states of Texas and Louisiana. According to NOAA, Harvey was the second "costliest" natural disaster in the United States, next to Hurricane Katrina of 2005. While economic costs of Katrina came mostly from storm surge, devastation from Harvey was largely due to flooding near the Houston area along the upper Texas coast. Harvey could have been the costliest hurricane ever if the eye of the storm had passed the city of Corpus Christi instead of much less densely populated communities in the Coastal Bend region.

According to FEMA, Harvey caused $2.4 billion in damage to a total of more than 290,000 homes in Texas, with nearly 17,000 homes destroyed. At least 160,000 structures were flooded in Harris and Galveston counties alone. While the majority of damaged properties were in neighborhoods around the Greater Houston metro area, the "ground-zero" communities in the Coastal Bend region where Harvey made landfall faced disproportionately more property losses, particularly from wind damage.

Hurricane Irma hit the Florida Keys on September 10, 2017, within two weeks after Harvey's landfall. According to the National Weather Service, Irma was the strongest hurricane ever observed in the Atlantic Ocean with sustained winds of 185 miles per hour for 37 hours at its peak. After the storm was downgraded to Category 1 after making U.S. landfall, it headed north along Florida's west coast with strong winds, storm surge and heavy rains over the entire peninsula.

According to NOAA, Irma's economic toll was $50 billion, but this would have soared to $300 billion should it hit the Miami metro area directly. In the Florida Keys, about one-quarter of homes were totally destroyed, and about half of homes within its Monroe County were damaged, according to FEMA. Irma could have caused destruction comparable to Harvey. Other than being away from the more densely populated areas in southeastern Florida, the state has responded to the relatively high frequency of hurricane activity by reinforcing building codes that make structures most resilient to wind and flood damage in the United States (Institute of Business and Home Safety, 2018).

FEMA is the primary federal agency in the U.S. for funding assistance following a natural disaster. By the end of 2018, the agency had dispensed nearly $20 billion in disaster relief programs to the affected communities in Texas and Florida. The funds were in the form of Individual Assistance to residents and homeowners, Small Business Administration (SBA) disaster loans, and the National Flood Insurance Program (NFIP) claim payments to flood policyholders. In addition, FEMA had obligated $1.5 billion to local authorities for Public Assistance program to rebuild community infrastructure. Reconstruction activity has also been supported by other government agencies, particularly the Economic Development Administration and Texas General Land Office, but the majority of these funds had yet been distributed by the end of 2018.

In addition to government aid, disaster survivors rebuild their homes and businesses with insurance claims. Because of the widespread flooding around the Houston area, NFIP paid out nearly $9 billion to Texas residents, more 10 times the amount to Florida residents. On the contrary, proportionally more residents had private insurance in Florida than in Texas, resulting in nearly twice the total amount of insurance claim payments from Florida residents ($11 billion vs. $6 billion). In Texas, the Texas Windstorm Insurance Association (TWIA) provides most windstorm insurance policies to the coastal areas. In the wake of Harvey, TWIA made $1.6 billion in insurance payouts for property damages, 90% of which were from policyholders in the three counties near the landfall. Reconstruction activities funded by insurance payments and federal aid typically create a so-called "silver lining" following a natural disaster. The influx of external transfer payments and grants helps replace destroyed capital stock, which includes housing, business and infrastructure, and raises regional spending.

In addition to property damage as part of direct economic costs, Harvey and Irma wreaked havoc on the local economies of the hard-hit areas. In the month immediately following Harvey's landfall, Aransas County's unemployment rate soared to a historic high for the area above 10%. Similarly, unemployment in Monroe County in Florida, where Irma made landfall, nearly doubled from the pre-storm level. Yet even for these hardest-hit counties, devastation on the overall economic activity appeared to dissipate rather quickly. Lee (2019) reports that more than half of local businesses in Aransas County and its surrounding areas were reopened within six months of Harvey. By the end of 2018, less than 10% of businesses remained closed. Those business establishments were mostly hotels and motels that sustained structural damage.

Against this background, this paper aims at investigating changes in the labor markets of hurricane affected areas on the road to full recovery. A large body of literature on the macroeconomic impacts of natural disasters concerns long-term economic growth among affected countries (e.g., Toya and Skidmore, 2007; Strobl, 2012; Cavallo et al., 2013; Klomp and Valckx, 2014). It is now too soon to tell what the long-term economic consequences of Hurricanes Harvey and Irma will be after two years as it typically takes much longer time for the economy to reach a new steady state. Nevertheless, it is interesting to shed light on the immediate impact of the storms on the local economies and the effects of subsequent federal policy responses. As Lee (2019) asserts, the early phase of recovery is informative about how resilient an area is to natural disasters, and what shapes recovery in the long run.

The study of disaster impact and recovery is inevitably subject to a confluence of factors other than the disaster shocks. As Cavallo et al. (2013) point out, it is difficult to control for the myriad of variables that differentiate one area from another, such as the political environment, stage of development, and other institutional factors. Although our empirical work below suggests considerable heterogeneity among even counties within the same state, disparities in institutions and the political environment within the two disaster regions should be neglectible.

3. Literature Review

3.1 Economic Modeling

Studies of the economic impact of natural disasters as disruptive events generally follow one of the two broad approaches: economic modeling and econometric analysis. The workhorse of economic modeling is typically either an input-output (IO) type model or a computable general equilibrium model. Building on the foundation of general equilibrium, these models describe how an exogenous shock is propagated across different sectors of the economy.

IO models are built with a matrix that describes how different sectors of an economy interact with each other. It is easy to understand how the shocks spread through the economy through the set of economic transactions underlying these models. Standard IO models treat a disruptive event as a shock to final demand. Without additional shocks, the economy gradually returns to a new equilibrium.

A well-known example of IO model applications is HAZUS (HAZards US), which is used by FEMA to evaluate of economic impacts of hurricanes, floods, and earthquakes. The software estimates *direct* economic losses from a given disaster using geographic information systems (GIS) technology to measure capital stock losses (structure, contents, and inventory damage) and income losses (e.g., wage and rental incomes) due to business interruptions and property losses. For the Texas region where Hurricane Harvey made landfall, HAZUS estimates total direct economic losses at \$2.5 billion, \$2.1 billion of which represents capital stock losses and \$0.4 billion income losses (FEMA, 2017a). For Florida counties in the wake of Hurricane Irma, HAZUS' estimated economic losses are $14.2 billion, with $12.7 billion in capital stock losses and $1.5 billion in income losses (FEMA, 2017b).

The major limitations of IO analysis arise from its fixed coefficients associated with the assumptions of fixed technology, wages and prices (Rose and Casler, 1996). Computable general equilibrium (CGE) models relax these assumptions by allowing for changes in consumers and producers' optimal decisions, including input substitution and market adjustments (Rose, 2004). In contrast to IO models, standard CGE models' assumptions of frictionless markets and completely adaptive behavior might overestimate the ability of businesses and the economy as a whole to rebound from a major disruptive event. As for IO models, these models still require knowledge about the values of elasticities and other structural parameters for calibration, which tend to be difficult for local or regional-level models.

Economic modeling for disaster analysis has been extended to explore temporal and spatial effects. Notably, Regional Economic Modeling Inc. (REMI) provides a multiregional perspective through equations for interregional trade by industry, and migration of residents and labor between regions (Treyz, 1993). Property damage from a disaster is captured by a decline in capital stock that leads to reductions in the flow of goods and services as in the case of business interruptions. The time-series nature of this model also allows researchers to explore the dynamic aspect of disaster impacts. The Texas Comptroller of Public Accounts (2018) has applied REMI to estimate the impact of Harvey on the state of Texas. During the first year, the estimated economic losses are $16.8 billion, which is partially offset by a gain of $13 billion due to increased spending and rebuilding activity. Beyond the first year, economic gains exceed losses.

3.2 Econometric Analysis

Economic models like HAZUS and REMI are potentially fruitful for generating *ex ante* forecasts that, among others, guide policymakers' decisions on allocating relief funds in response to a disaster event. Instead we are interested in discerning how the local economies have responded to the historic catastrophes in 2017 in light of observable *ex post* data. To this end, we apply econometric models to historical, time-series data. The empirical techniques in this study fall under the general framework of an event study.

The econometric literature on natural disasters' impact on the local economy is growing. Despite the obvious physical destruction caused by these events, disruption in regional economic activity is typically found to be temporary and evidence of the impact is often counterintuitive. Ewing, Kruse and Thompson (2003, 2004) show that the tornadoes that hit Nashville in 1988 and Fort Worth in 2000 slowed down local employment growth, but the adverse effects were limited to certain industries, such as trade and manufacturing. Ewing, Kruse and Thompson (2009) also find that employment growth in fact rose in Oklahoma City after being hit by a major tornado in 1999. Belasen and Polachek (2008, 2009) look at 19 hurricanes hitting Florida between 1988 and 2005. They find that employment dropped and wage earnings rose in the directly-hit counties, but their neighboring counties experienced a decline in earnings.

Hurricane Katrina, which directly hit the states of Louisiana and Mississippi in 2005, has prompted a large number of impact studies. Despite being the "costliest" natural disaster in U.S. history, this event's impact on local unemployment dissipated in a few months. According to Brown, Mason and Tiller (2006), and Vigdor (2008), New Orleans' unemployment rate began to fall below the national average as the reduction in its supply of labor exceeded the reduction in demand. The metro area's overall employment and wages rose, but the gains were mostly concentrated in the construction, accommodation, and food services industries.

Despite the severity of property damage, the initial shock wrought by a catastrophic event is soon offset by rebuilding efforts financed by external sources. With hindsight, it is natural to expect the economic impact of Hurricanes Harvey and Irma to be transitory. Still it is interesting to characterize the recovery trajectories of the affected areas in order to understand the nature of community resilience to disasters. Moreover, these two historic events generated rich data for evaluating the impact of government disaster relief programs.

4. Empirical Methodology

4.1 Generalized Difference-In-Difference Model

The relatively large sample from the two storm events combined forms the basis of a quasi-experimental setup for our empirical work. The "treatment" sample consists of 90 counties: 41 Texas counties of the Harvey federally declared disaster region DR-4332, and 49 Florida counties of the Irma federally declared disaster region DR-4337. In this paper, the corresponding "control" sample consists of other counties in the same states of the two disaster regions. As such, the labor market outcomes that we look at are the differences in the dynamics of the disaster counties and other counties in the same state after the storm events. [1]

To quantify the response of labor market outcome measures, we apply a dynamic differences-in-differences (DID) approach. The DID approach has gained popularity in event studies, and the dynamic specification allows us to explicitly capture the effects of a shock on labor markets over time, particularly the transitional dynamic before reaching a

[1] As discussed below, the quasi-experimental approach also allows us to evaluate the robustness of our findings in the paper with other control samples, including all U.S. counties.

new steady state equilibrium. Following Hobijn, Nechio and Shaprio (2019), we quantify this dynamic using the following regression equation:

$$y_{i,t+\tau} - y_{i,t-1} = \alpha_i + \boldsymbol{D}_i \boldsymbol{\beta}_\tau + \boldsymbol{C}_i \boldsymbol{\gamma}_\tau + \varepsilon_{i\tau}. \quad (1)$$

where $i \in \{1,\ldots, N\}$ refers to a specific county, t refers to the time period of a hurricane strike, and $\tau \in \{1,\ldots, 16\}$ is the time horizon measured by the number of months over which we measure the impact of an hurricane event. The terms α, $\boldsymbol{\beta}$'s, and $\boldsymbol{\gamma}$'s are unknown parameters, and ε_{it} is an independently and identically distributed (i.i.d.) error term. The coefficients of interest are the estimates of $\boldsymbol{\beta}_\tau$, which trace out the path of $y_{i,t+\tau}$ for the disaster counties relative to the control sample in the τ months following the hurricanes. So, the time horizon τ essentially represents the sum of monthly changes in local labor markets, given the cumulative effect of the shock on variable $y_{i,t+\tau}$ by time $t + \tau$.

Equation (1) differentiates the treatment sample (disaster counties) from the control samples (non-disaster counties) using the dummy variable $\boldsymbol{D}_i$. The most popular specification in the related literature is a dummy variable (e.g., Belasen and Polachek, 2008, 2009), which equals one if county i belongs to one of the two federally declared disaster regions. As an alternative to the binary dummy variable, we incorporate a set of weather data that serve as destruction proxies particularly for tropical storms. The alternative time-invariant variables in $\boldsymbol{D}_i$ are localized wind speed, storm surge, and rainfall data associated with the two individual hurricanes. It is well documented that disaster impacts vary by storm intensity. These directly observed weather data more precisely capture the various aspects of storm damage to individual counties than the aggregate Saffir-Simpson Scale levels, as commonly used in previous studies (e.g., Burrus, Dumas and Farell, 2002; Strobl, 2011; Belasen and Polachek, 2008, 2009).

The variables in term $\boldsymbol{C}_i$ control for inherent characteristics of individual counties that affect their vulnerability to a given disaster or how fast their economies will bounce back from the shock. As described in the Section 4.3 below, we consider the Baseline Resilience Indicators for Communities (BRIC), which have been developed and updated by the Hazards and Vulnerability Research Institute at University of South Carolina (Cutter, Ash and Emrich, 2014). This project was funded by FEMA. BRIC essentially identify how ready a community is to respond to a disaster and how well the community will subsequently recover.

To estimate equation (1), we apply a generalized version of DID analysis outlined in Belasen and Polachek (2008, 2009). This generalized DID procedure controls for state trends ($\bar{y}_i$) by comparing the counties directly affected by a hurricane with the unaffected counties within the same state. Under this approach, the dependent variable y_i in (1) is transformed by subtracting the state average $\bar{y}_{it}$ from the value for a county, $\tilde{y}_{it} = y_{it} - \bar{y}_{it}$, so that the dependent variable of equation (1) becomes $z_{i\tau} = \tilde{y}_{i,t+\tau} - \tilde{y}_{i,t-1}$.

In equation (1), the intercept α_i is a time-invariant variable that captures the effect of unobserved heterogeneity, or unique characteristics of each county in the sample. Given the cross-sectional and time-series dimensions of our dependent variables, we can accommodate heterogeneity among counties by running panel regressions that stack county-specific observations over time:

$$z_\tau = \alpha + \boldsymbol{X\beta} + \varepsilon_\tau. \tag{2}$$

where z_τ=$(Y_{1\tau}, \dots, Y_{N\tau})'$, α=$(\alpha_1, \dots, \alpha_N)'$, $\boldsymbol{X}_\tau$=$(\boldsymbol{D}_1, \dots, \boldsymbol{D}_N; \boldsymbol{C}_1, \dots, \boldsymbol{C}_N)'$, and ε_τ=$(\varepsilon_{1\tau}, \dots, \varepsilon_{N\tau})'$. Conditional on the specification of the intercept α, equation (2) can be estimated as a fixed- or random-effects model. In the fixed-effects model, a binary dummy variable is introduced for each county as a measure of the intercept that varies across the sample. In the random-effects model, the intercept α is treated as a random variable that is i.i.d. distributed with zero mean and variance σ_α^2. Moreover, the two random variables in this random-effects model, α_i and $\varepsilon_{i\tau}$, are assumed to be independent of each other.

As described below, most of the regressors in $\boldsymbol{Z}_\tau$ are time-invariant, so that they are swept away in the standard fixed-effects model that is based on the within estimator of the coefficients on the time-varying regressors. Although the fixed-effects model can still control for the effects of variables whose values do not change over time, we will apply the random-effects model in order to obtain estimates for the effects of these time-invariant variables. Another advantage of the random-effects over the fixed-effects method is to avoid the substantial loss of degrees of freedom associated with the large number of dummy variables, each of which represents one of the N counties in the sample.

4.2 Spatial Models

Although we attempt to explicitly control for cross-sectional heterogeneity with regressors, such as the BRIC indicators, failing to completely capture spatial-specific effects raises the risk of obtaining biased estimation results associated with omitted variables in a cross-sectional model. As reported below, we indeed find strong evidence of spatial effects in our estimated models. As such, we follow the spatial econometric literature (e.g., Anselin, 1988) and model spatial interaction effects with an $N \times N$ spatial weight matrix $\boldsymbol{W}$, which describes the spatial arrangement of the counties (spatial units) in the sample. The spatial lag model corresponding to equation (1) describes how the dependent variable of county i is affected by the dependent variable observed in neighboring or nearby counties:[2]

[2] In addition to the spatial lag of the dependent variable, the model may include spatial lags of independent variables, leading to the so-called spatial Durbin model (LeSage and Pace, 2009). Inclusion of these lag terms does not alter the overall results that we report for the more parsimonious spatial models presented in this paper.

$$z_{i\tau} = \alpha_i + \rho \boldsymbol{W} z_{i\tau} + \boldsymbol{D}_i \boldsymbol{\beta}_\tau + \boldsymbol{C}_i \boldsymbol{\gamma}_\tau + \varepsilon_{i\tau}. \tag{3}$$

where ρ $(0 \leq \rho \leq 1)$ is called the spatial autoregressive coefficient that measures the strength of spatial autocorrelation, and $\boldsymbol{W}$ contains elements W_{ij}'s (i and $j = 1, \ldots, N$) that are pre-specified, non-negative constants.

By convention, the diagonal elements of $\boldsymbol{W}$ are set to zero (i.e., $W_{ij} = 0$ if $i = j$), because no county can be viewed as its own neighbor. The other elements take the value of either $1/m_i$ or zero, where m_i is the number of counties as county i's neighbors. All elements in the ith row of $\boldsymbol{W}$ that are not associated with the neighboring counties take the value of zero. For ease of interpretation, $\boldsymbol{W}$ is row-normalized such that the elements of each row sum to unity. The spatial lag model potentially depicts the condition that the labor market of one county is affected by the labor market of its neighboring counties. The presence of the spatially lagged dependent variable generates feedback effects as each county is also a neighbor of its neighbors.

An alternative to a spatially lagged dependent variable is the spatial error model, in which the dependent variable depends on the observed local characteristics while the error terms are correlated across counties:

$$z_{i\tau} = \alpha_i + \boldsymbol{D}_i \boldsymbol{\beta}_\tau + \boldsymbol{C}_i \boldsymbol{\gamma}_\tau + \omega_{i\tau}, \tag{4}$$
$$\omega_{i\tau} = \delta \boldsymbol{W} \omega_{i\tau} + \varepsilon_{i\tau}. \tag{5}$$

where $\omega_{i\tau}$ is the spatially autocorrelated error term and δ is called the spatial autocorrelation coefficient. This spatial error model depicts situations in which unobserved factors or "common shocks" lead to similar or diverging outcomes across different counties. If $\delta \neq 0$, the ordinary least squares (OLS) estimator yields inefficient, albeit unbiased, coefficient estimates (LeSage and Pace, 2009).

The spatial lag and spatial error models, as represented by equations (3) to (5), can also be applied to panel data depicted by equations (2). In this paper, we estimate the spatial panel data models with random effects using a maximum likelihood (ML) estimator described in Elhorst (2003, 2010). To evaluate the validity of the spatial lag and spatial error models, we apply the robust Lagrange Multiplier (LM) tests proposed by Anselin et al. (1996). The robust versions of LM tests take into account the existence of one type of spatial dependence does not bias the test for the other type of spatial dependence. The tests are applied to the residuals of the estimated model without spatial effects, and the test statistics follow a χ^2 distribution with one degree of freedom.

4.3 Data

4.3.1 Dependent Variables

The key dependent variable of our regression models is represented alternatively by three measures of local labor market performance: the unemployment rate, the aggregate employment level and disaggregated levels by industry, and the average weekly wage earnings per worker. County-level unemployment and employment data are obtained from the U.S. Bureau of Labor Statistics' (BLS) monthly Local Area Unemployment Statistics (LAUS) program. Monthly data of average weekly wage levels draw on BLS Quarterly Census of Employment and Wages (QCEW). This quarterly database also contains monthly employment levels for 14 two-digital-level economic sectors classified by the National American Industry Classification System (NAICS). All labor market time series consist of seasonally adjusted data using the X11 method to remove seasonal regularities. These three alternative measures of the dependent variable represent the percentage point difference between the values of a county in the sample and its state-wide average. This specification allows us to estimate the differential impacts of a hurricane shock on these variables over different horizons.

Unemployment paints an incomplete picture of the local labor market especially in the wake of a disaster. First, the unemployment rate may in fact decline because displaced residents and out-migration reduce the size of the local labor force, which is the total number of employed and unemployed residents. The overall unemployment rate also masks changes in the industry mix that affects shifts in wages and possibly economic development in the long run (Xiao and Feser, 2014).

Between 2017 and 2018, Aransas County topped the nation in population loss of 6.5%, due mostly to out-migration. Meanwhile, Monroe County lost 2.1% of its pre-storm population. From this perspective, we supplement observations in unemployment rates with employment data. Different movements between the unemployment rate and employment growth reflect changes in the labor force. An additional advantage of employment data is their availability at a disaggregate level by industry in addition to county-wide level data. Observed changes in employment of different industries shed light on the key drivers of economic recovery from the disasters. As a complement to employment, we also look at changes in wage earnings over time to shed light on how changes in the labor market of the hard-hit counties affected the labor markets in their neighboring areas.

Figures 1 to 3 plot the unemployment rate, the overall employment level, and weekly wage level for each of the 41 disaster counties in Texas. The observation period spans between January 2014 and December 2018. The vertical gridlines delineate the timing of Hurricane Harvey in August 2017. Figures 4 to 6 plot the corresponding data for the 49 disaster counties in Florida. The vertical gridlines delineate the timing of Hurricane Irma in September 2017. An abrupt surge in the unemployment rate is apparent for some counties, particularly Aransas, Refugio, and San Patricio Counties in Texas, and Monroe County in Florida. A comparison of the unemployment time series across the sample indicates that those coastal counties directly hit by one of the two storms faced disproportionately adverse economic impacts.

Evidence of the hurricanes' impacts on local employment and wages is less visible. The hurricane shock is most striking in Monroe County, Florida, which lost more than 10% of jobs during the month of landfall in September 2017. Identifying the shock to employment is difficult for a large number of counties, which experienced cyclical patterns since 2014 instead of steady long-term growth. Most plots for wages, by comparison, show relatively steady uptrends. However, their post-hurricane patterns diverge across the sample: Wages in some counties continued to follow their upward trends while wages in some other counties slowed down or even declined.

In each plot, a dash line depicts the post-hurricane data constructed using the statewide average as the benchmark. The vertical distance between the solid line and the dash line essentially captures the differences in the rates of changes between the county and the state since the hurricane strike. Specifically for unemployment, the dash line depicts the county unemployment rate during the month immediately before the hurricane landfall plus subsequent changes in the statewide unemployment rate. As unemployment of both Texas and Florida states continued their downward trends across much of the observation window through December 2018, most "counterfactual" unemployment rates declined throughout the post-hurricane period. Despite their downtrends, some "actual" unemployment rates declined at a faster pace than their corresponding counterfactual rates.

In plots of employment and wage levels, the dash lines show what if the county's post-hurricane employment and wage levels changed at the same percentages as for its statewide averages. The post-hurricane statewide employment and wage levels followed their upward trends established since 2014. The patterns for the disaster counties are, however, mixed. As a result, the actual employment and wage levels were higher for some counties but lower for others than their statewide or counterfactual trends.

In this paper, we follow the standard intervention analysis, in which we explore changes in time series based on *a priori* knowledge about the timing of an intervention or exogenous shock. However, Figures 1 to 6 reveal only mixed evidence about any meaningful impact on the local economies of the disaster regions. To further explore the statistical significance of the shocks induced by the two storms, we employ the conventional structural break analysis that detects a possible structural break in a time series with *a priori* unknown break dates.

Tables A1 and A2 in the Appendix list the Andrews-Quandt (Andrews, 1993) and Andrews-Ploberger (Andrews and Ploberger, 1994) test statistics, which are respectively the maximum and the geometric average of Lagrange Multiplier (LM) statistics.[3] Reinforcing the observations in Figures 1 to 6, the structural break test statistics are not statistically significant for the majority of time series. The break dates are only identified under the alternative hypothesis. The timing of some identified break points does not match the hurricane event.

We also apply the same tests for non-disaster counties in the states of Texas and Florida. As shown at the bottom of the tables, the overall test results for the disaster counties are not noticeably different from the results for their non-disaster counterparts as the control sample. The test structural break test statistics together highlight the importance of differentiating the localized intensity of a hurricane like Harvey and Irma, with a footprint that covers a relatively large number of counties. Not all counties in or

[3] The tests for structural change have been extended to multiple breaks using the Bai and Perron (2003) method. Results from those multiple break tests add little insight into detection of structural changes in our time series data.

near the path of the same storm are equally affected. It is therefore crucial to differentiate areas that face disproportionately more damage than other disaster areas.

Table 1 displays summary statistics of the cross-sectional data for regressions. The table first lists the statistics for labor market variables within the first month of the hurricane strike and the final month of the observation period (December 2018). For the unemployment rate, the impact is represented by the post-hurricane change in the county unemployment rate that is above the corresponding change in the statewide unemployment rate, i.e., the vertical distance between the solid and dash lines in Figures 1 and 4. The first month of the impact horizon is set as September 2017 for both hurricanes.

Harvey's impact was felt the most in Aransas County, which experienced an immediately increase in the unemployment rate that was 3.9 percentage points above the statewide change from the August. In Monroe County, Florida, the unemployment rate also rose 1.68 percentage points in September above the statewide change from the pre-Irma level. Particularly for Texas, the mean and median are both positive in the first month but negative in the 16th month, meaning that a typical disaster county experienced a faster post-Harvey improvement in unemployment than its state did. The Florida sample shows much smaller deviations from the state partly because of a substantially larger share of counties in the disaster region.

Below the statistics for unemployment are corresponding summary statistics for local employment and wage impacts. The measure of local employment impact in a specific month following a hurricane is the difference in the percentage change of county employment since the hurricane event and the corresponding percentage change of statewide employment. The percentage change in employment is approximated as the difference of the log employment level over the specified time horizon. We apply the same procedure to compute monthly wage impacts through the end of the observation period.

Overall, the summary statistics indicate considerable disparities in employment and wage growth patterns following the hurricane events. The hardest hit communities, such as Refugio County in Texas and Monroe County in Florida, experienced the largest employment loss during the first month. By December 2018, the typical disaster county still experienced relatively lower employment growth. As for employment, disparity in wage growth across the sample appears to rise over time.

4.3.2 Explanatory Variables

We measure the potential damage from Hurricanes Harvey and Irma using three storm destruction proxies: average sustained peak wind speeds, rainfall totals, and storm surge heights. We construct county-wide data with observations from NOAA's contour maps and data at various reporting locations (Blake and Zelinsky, 2018; Cangialosi, Latto and Berg, 2018). The maps in Figure A1 of the Appendix show the data by county. Table 1 further lists the summary statistics. The average and median wind speeds were higher for Irma than Harvey, but Harvey brought a greater amount of rainfall on average. Since storm surge affects mainly coastal areas, a large number of inland disaster counties experienced no storm surge impact.

As for most event studies, one source of concern is heterogeneity in the cross-sectional sample. The set of control variables in regression models, $\boldsymbol{C}_i$, capture time-invariant heterogeneity among counties within the sample. In this paper, we consider a set of Baseline Resilience Indicators for Communities scores, which reflect individual communities' resilience to natural disasters. Cutter (2016) provides an overview of the concept of disaster resilience and elements in its measures.

With a total of 49 individual indicators, the BRIC index provides a comprehensive view of the socioeconomic aspects of a local community that might affect its resilience to natural hazards, especially in the context of how vulnerable its economy is to a given shock as well as how it would respond to and recover from a disaster event in both the short and long terms (Cutter, Ash and Emrich, 2014). Last updated in 2015, the BRIC index is made up of six broad categories of disaster resilience at the county level: social (10 variables), economic (8 variables), community capital (7 variables), institutional (10 variables), infrastructural (9 variables), and environmental hazards (5 variables).

In our preliminary analysis, the estimates for the social, economic and community capital indicators are statistically significant in at least some of the regressions, and other indicators (infrastructural, institutional, and environmental) are mostly statistically significant. For this reason, we include the social, economic and infrastructural BRIC indicators as control variables in all regression models presented in this paper.

Variables in the social category includes educational attainment, transportation and physician access, health insurance, and mental health support. Communities with higher levels of educational attainment, more English speakers, fewer retirees, higher rates of health insurance coverage, and more access to physical and mental health resources receive higher social resilience scores. The indicators of economic resilience reflect local economic vitality, diversity, income equality. Higher economic resilience scores are given to communities with more owner-occupied housing units, more large businesses, and a smaller income gap. The indicators of community capital resilience reflect how inclined and prepared local residents are to assist their fellow residents. Counties with a higher percentage of voters, more civic organizations, and more Red Cross volunteers receive a higher score in community capital resilience.

Table 1 contains summary statistics of the three BRIC indexes. In contrast to other variables in the table, the standard deviations seem relatively small. This observation is in line with Cutter and Derakhshan (2018), who find clustering patterns in BRIC scores among counties in different broad regions of the United States. Nevertheless, the differences between the ranges of the scores within the sample are considerable. In particular, Harris and Miami-Dade Counties, which are respectively the most populated counties in Texas and Florida, face the least community capital resilience.

Among the studies on business recovery from natural disasters, LeSage et al. (2011), Xiao and Van Zandt (2011), and Lee (2019) show spatial clustering patterns in the business reopening decisions. Xiao and Nilawar (2013) find overall economic spillovers from counties directly hit by Hurricane Katrina to their neighboring counties. With a focus on local labor markets, Belasen and Polachek (2008, 2009) find that hurricanes that hit Florida lowered employment and wage growth in disaster counties, but the effects were the opposite in their neighboring counties.

4.3.3 Direct Impacts

Before we estimate indirect economic impacts using labor market indicators as the alternative dependent variables, we consider a few measures of direct economic losses. The variables considered as the percentage of homes damaged within a county, the amount of physical losses per capita, the amount of federal funds per capita, and the total amount of disaster relief funds per capita. The amount of federal funds consists of the amount of FEMA grants for Individual Assistance and Public Assistance, NFIP, and the amount of SBA Disaster Loans. The total disaster relief funds are the sum of these federal funds and private insurance payments.

Data for the number of damaged homes, the amount of physical losses, and federal funds by county are drawn from FEMA's Data Feeds. Data for private insurance payments by county are obtained from the Texas Department of Insurance and the Florida Office of Insurance Regulation.[4] The share of damaged homes is computed as the number of damaged

---

[4] The data from FEMA Data Feeds is accessible at https://www.fema.gov/data-feeds; the data source for Texas Department of Insurance is https://www.tdi.texas.gov/reports/documents/harvey-dc-12102018.pdf;

homes divided by the total pre-hurricane housing units within a county. For comparison, all nominal values are divided by the pre-hurricane population. Data for housing units and population are obtained from the 2016 Census.

Orange County sustained the highest share (43%) of damaged homes in Texas due largely to flood damage. In Florida, the extent of damaged homes was as high as 31% in Monroe County. Table 1 shows the summary statistics of the direct impact data as of December 2018. The disaster relief funds per capita and insurance payouts were highly correlated with the extent of physical losses, with the largest amounts going to the counties where the hurricane made landfall (i.e., Aransas, Collier and Monroe).

5. Empirical Findings

5.1 Direct Economic Impacts

Table 2 shows the results of regressions that relate the four alternative measures of direct economic losses to different potential damage proxies of Hurricanes Harvey and Irma. Except for the percentage of damaged homes, all dependent variables are expressed as logarithmic levels of the nominal values pre-divided by the pre-hurricane county population. The first explanatory variable, TX, is a dummy variable that takes the value of one for a county in Texas and zero otherwise. All estimates are positive, meaning higher direct property damage and disaster relief aid for Texas counties than for Florida counties, conditional on various measures of storm intensity.

The other explanatory variables in Table 2 are key aspects of tropical storms and their interaction terms.[5] All variables are expressed in logarithmic terms. The coefficient

---

and the data source for Florida Office of Insurance Regulation is https://www.floir.com/Office/HurricaneSeason/HurricaneIrmaClaimsData.aspx.

[5] In line with Strobl (2011), we have considered the inclusion of exponential terms of the regressors to explore nonlinear effects. The squared term of the wind variable is statistically significant in some regressions.

estimates for the wind speed and rainfall variables are statistically meaningful. The storm surge variable alone is statistically significant at the 10% level in the regression for damaged homes, but the estimate is negative. However, the coefficient estimate for interaction term of wind and storm surge is also statistically significant but positive. This means that the impact of storm surge on homes must be conditional on its interaction with wind speeds. Storm surge would have reduced the extent of home damage only if wind gusts were mild or absent, which was not the case for most counties except those on the upper eastern coastline of Florida.

The coefficient estimates for the interaction term of the wind and rain variables are all negative. This means that the effects of wind and rain are not limited to the coefficient estimates of those two variables alone, but they also depend on the estimates of their interaction term. As shown in Figure A1 of the Appendix, counties that faced highest wind speeds tended to receive less precipitation (i.e., southwest portion of the Texas disaster region and western Florida coast).

The R^2 statistics as measures of overall goodness-of-fit suggest that the regression models explain between 34% and 62% of variation of the cross-sectional data in the alternative dependent variables. The notably high R^2 (0.62) for the regression on federal funds suggests that allocations of federal disaster relief funds among disaster counties were highly correlated with the key proxies of storm damage.

5.2 Labor Market Impacts

In this subsection, we present regression results for the alternative labor market variables that capture the economic impacts of Hurricanes Harvey and Irma. Table 3 lists the

---

Since this paper focuses on indirect economic impacts instead of direct impacts, we only present results in Table 2 that are comparable to those in tables that follow.

coefficient estimates for the first month following the storm ($\tau = 1$) and the end of the observation window ($\tau = 16$). As discussed in Section 4.1 above, the value of the unemployment variable at a given post-hurricane period is expressed as the percentage point difference between the change in the county unemployment rate from the pre-hurricane rate (i.e., the rate during the month immediately before the hurricane strike) and the corresponding change in the statewide unemployment rate. Instead of percentage terms for the unemployment variable, the employment and wage variables are log transformation of the natural levels. In other words, these two variables represent the percentage change of county employment and wages, respectively, over a given post-hurricane period that is above or below the statewide average.

All regressions include a state dummy variable to capture possible different effects between Texas and Florida counties, and three BRIC indicators. These BRIC indicators control for inherent characteristics of individual counties that potentially affect the impact of the storm on the local economy and how they recover over time. The other BRIC indicators are not statistically significant in preliminary regressions and thus have been excluded.

For comparison purposes, panel A of Table 3 presents regression results using a dummy variable, DR, to capture the disaster shock to disaster counties. This is a popular specification in the related literature (e.g., Belasen and Polachek, 2008, 2009). The dummy variable takes the value of one for one of the 90 disaster counties and zero otherwise. The regressions are run for a total of 321 counties in the states of Texas and Florida. The results indicate that disaster counties tended to experience a 0.39 percentage points higher unemployment rate, 1% lower employment growth, and 0.5% higher wage growth immediately following a hurricane strike. While the impact on unemployment and employment reversed 16 months later, wage growth of disaster counties was 3% higher than other counties. The coefficient estimates for the state dummy variable take the same signs as those for the disaster dummy variables. These results underscore the greater storm impact on Texas than Florida.

The coefficient estimates for the BRIC indicators are largely not statistically meaningful for the first month following the storms. For the final month of the observation period, all three estimates are negative and statistically significant in the unemployment regression. Whenever the coefficients are statistically significant in the employment or wage regression, the estimates are positive. The results over a long post-storm horizon reflect the role that community resilience and mitigation efforts play in the way a county recovers from a disaster shock.

In panel B of Table 3, the regression models consider the three key measures of tropical storm damages instead of a single binary dummy variable. Because no corresponding weather data exist for non-disaster counties, the sample is limited to the 90 disaster countries only. The key variables of interest are the three proxy measures of storm damage. According to the estimation results, counties that sustained more damage from winds and rainfall tended to experience higher unemployment and lower employment growth immediately after the storm. By the end of the observation period, however, these counties faced relatively lower unemployment. As in Table 2 above, the coefficient estimates for the storm surge variable alone are opposite to the other two storm variables. Again, the estimated impact of storm surge must be interpreted along with its interaction with wind gusts.

Coefficient estimates for the state dummy variables are comparable to their counterparts in panel A. However, the estimates at the end of the regression period are no longer statistically significant, meaning no meaningful difference between counties in the two states further away from the storm events. On the other hand, the BRIC indicators for social, economic, and community capital resilience appear to continue to play a role in determining labor market dynamics in month 16.

As complements to the estimation results in Table 3, Figures 7 and 8 trace out the coefficient estimates for the direct measures of storm damage from period $\tau = 1$ (September 2017) through $\tau = 16$ (December 2018). The shaded bands represent the 95% confidence intervals around the point estimates. Figure 7 shows the dynamics of estimates for DR. Accordingly, a hurricane's adverse impact on the unemployment rate and employment growth dissipates in about six months. Wage earnings among disaster counties, however, persistently rise in comparison with their counterparts.

Figure 8 shows the estimated labor market impacts of damage from wind, rainfall, and storm surge. For unemployment, the wind variable alone is not meaningfully different from zero after two months, but the effect of its interaction with storm surge lingers for another eight months. The amount of rainfall appears to inflict a persistent impact on employment growth. The effects of rainfall's interaction with wind gusts were also statistically significant as long as nine months. The interactive effects of wind and storm surge on unemployment and employment also persist for about one year. Most estimates of wage impacts, however, are not qualitatively meaningful over the entire observation period.

We have presented the dynamics impacts that Hurricanes Harvey and Irma generated on the labor markets of disaster counties. To understand the key drivers of the observed changes in labor markets, we apply the same regression models as shown in Table 3 to county employment of 14 individual industries instead of their aggregate levels. Figures 9 to 14 plot sequential coefficient estimates for the storm impact variables corresponding to those in Figure 8. According to those figures, the construction industry is particularly vulnerable to wind damage, but it recovers rather quickly. The "other services" sector, which includes household support and building maintenance services, also appears to perform relatively better with a hurricane strike, especially when it involves wind and rain damage.

Wholesale trade appears to be the only sector that benefit from wind and rain damage throughout the entire observation window. This finding arises from the fact that this sector includes trade in machinery and emergency equipment, which are required for emergency response. On the contrary, the estimates for retail trade are mixed, depending on the type of storm damage. On the one hand, retail establishments are vulnerable to structural and content damages. On the other hand, retail sales typically rise due to emergency response following a disaster and subsequent rebuilding activities.

Mixed evidence is also found in the hospitality sector, which includes accommodations and food and drinking places. A wind or flood event alone raises hospitality employment due largely to displaced residents and an influx of emergency crews from the rest of the United States. Estimates for their interactions appear to be qualitatively significant and positive after half a year when reconstruction and community recovery begin to take shape.

5.3 Disaster Relief

Model estimation results in the previous subsection suggest that any observed storm impact on local labor market performance might have been undermined by rebuilding activity. In the wake of Hurricanes Harvey and Irma, economic recovery in the disaster regions has been accelerated by disaster relief assistance and reconstruction activities supported by the federal government and philanthropic organizations (e.g., Rebuild Texas Fund, Red Cross). The cumulative total amounts of FEMA aid to the two disaster regions rose from slightly less than $1 billion in October 2017 to over $18 billion by December 2018. From this perspective, it would be interesting to unravel the effects of federal aid in a disaster county's post-hurricane recovery process.

To empirically investigate the role that federal disaster programs played in the local labor markets, we augment the regression models presented in the previous subsection with a regressor that captures the government programs. As described in Section 4.3 above, we measure this variable by the logarithmic level of the monthly cumulative total of federal funds per capita that are allocated to individual disaster counties beginning October 2017.

However, the model estimation results in Table 2 show strong evidence that allocations of federal disaster funds per capita across disaster counties depended on the extent of direct economic damage. In other words, the federal aid variable is most likely an endogenous rather than exogenous variable as assumed in conventional regression models. In this situation, an OLS model cannot consistently estimate the causal effect of federal aid on the dependent variables. To alleviate this drawback, we obtain consistent estimates with the instrumental variable (IV) estimator (Wooldridge, 2002). The specific instrument is a time-invariant variable of total hurricane-related property losses based on the logarithmic transformation of FEMA's estimates for individual counties, as presented in Section 4.3 above.[6] The weak instrument test for the validity of property losses as an instrumental variable is 65.67. This $\chi^2(1)$ statistic rejects the null hypothesis at the 1% confidence level and thus lends support to the property losses variable as a valid instrument.

We apply IV estimation to the same model presented in panel B of Table 3 above, along with the federal aid variable as an additional regressor. Because it takes time between relief fund distributions and construction activity to begin, this variable enters the regressions with a three-month lag. The instruments consist of the property loss variable

[6] As expected, the F-tests for the validity of the property damage variable as a relevant instrument for federal aid are statistically significant at the 1% confidence level. The Wu-Hausman tests for consistency in the OLS regressions also provide strong evidence for endogeneity in the federal aid variable.

and all regressors other than federal aid. Figure 15 plots the cumulative impacts of federal disaster programs in 2018, as represented by the coefficient estimates for the federal relief funds on the three alternative labor market indicators. According to the plots, federal aid as an external source for funding rebuilding efforts immediately reduced unemployment and added employment in the disaster counties. As evident in Figures 9 to 14, the construction, wholesales and other services sectors were likely the drivers of employment growth in the local labor markets. The impact on the unemployment rate and employment growth leveled off in late 2018, but wage continued to grow due to strong labor demand.

Next, we leverage both time-series and cross-sectional aspects of our county-level data to estimate the effects of federal disaster aid with panel regressions. Table 4 displays estimation results of the panel IV models estimated with random effects. The models consist of 16 monthly panels, each of which has a cross-section of 90 disaster counties. In addition to the federal funds variable as described above, the regressors include all the weather-related variables (wind, rainfall, storm surge, and their interaction terms) and the three BRIC indicators (social, economic, and community capital). As for the cross-sectional IV regressions, the instruments include the log level of property losses per capita and all independent variables in the main regression equation.

The first column of each panel of the three alternative dependent variables displays panel IV estimation results for without spatial effects. The key variable of interest is the federal funds variable. The coefficient estimates are consistent with the cross-sectional evidence presented in Figure 15. According to the estimation results, a one-percent increase in federal disaster aid reduced unemployment by 2.76 percentage points, raised employment growth by 3% and wage growth by 4%. Coefficient estimates for all other regressors also align with expectations in the sense that the local labor markets are vulnerable to storm damage, but they tend to perform better if the community is more resilient to disasters.

Nevertheless, under the panel setting that spans the entire 16 months of the post-hurricane window, estimates for the BRIC indicators are not qualitatively meaningful for explaining unemployment dynamics.

Below the coefficient estimates are a number of statistics for testing our model specifications. The Breusch-Pagan (BP) statistics for testing heterogeneity in the OLS regressions of the pooled sample are distributed as $\chi^2(1)$. The test results indicate strong evidence of heterogeneity across counties in the sample. Estimations with the random-effects model as opposed to the alternative fixed-effects model are evaluated by the corresponding LM test statistics. The statistically insignificant statistics provide support for the random-effects model for handling cross-sectional heterogeneity. The null hypothesis under the Wu-Hausman (WH) exogeneity test, also distributed as $\chi^2(1)$, is that estimation without IV's generates consistent estimates. The test statistics are significant at the 10% confidence level or higher, lending support to the application of IV estimation.

However, the LM statistics for testing the two types of spatial effects are statistically significant. The LM tests are based on the specification of a spatial weight matrix $\boldsymbol{W}$, as discussed in Section 4.2. The spatial weights in $\boldsymbol{W}$ are specified using the queen definition of contiguity, which considers two counties are neighbors if they share borders as small as one point or corner. In the Texas disaster region (DR 4332), there are 23 counties (including five parishes in the neighboring state of Louisiana) that are considered neighbors of the 41 counties but are located outside that region. In the Florida disaster region (DR 4337), there are 6 such neighbors in the states of Florida and Georgia. As such, the full sample for the specification of $\boldsymbol{W}$ also includes those 29 counties.

Given strong evidence of spatial heterogeneity, we next extend the panel IV model to the spatial regressions described in Section 4.2 above. The estimation results with both spatial autoregressive lags and spatial errors are displayed in the second column of the three vertical panels. Interestingly, the absolute sizes of coefficient estimates in the unemployment and employment equations tend to be larger as compared to their non-spatial counterparts. Corresponding to this finding are the positive estimates for the spatial lag or autoregressive variable. When spatial spillover effects are accounted for, the effect on federal funds on the local labor markets is greater. As a county's unemployment tends to be lower when unemployment is also lower in its neighboring county, reconstruction activity funded by the federal government will induce a greater impact on unemployment if spatial interactions are accounted for.

While the coefficient estimate for the spatial error term is also positive in the unemployment equation, the estimate is negative in the employment and wage equations. These negative estimates suggest that some unobserved factors lead to negative interactions in the employment and wage dynamics between two neighboring counties. The coefficient estimate for the spatial lag term, $\boldsymbol{W}z_{i\tau}$, is also negative in the wage equation.

5.4 Discussion

The two hurricanes in 2017 have provided a wealth of data for us to better understand how local communities respond to natural disasters like Harvey and Irma through observations on their labor markets. Our first key empirical finding is on the differential impacts between wind and water damage from a hurricane strike. Interestingly, damage from storm surge alone is found to be less devastating to the local economy than damage from winds or rainfall.

Hurricane Irma swept across the western half of the Florida state, while storm surge was especially high among its eastern coastal counties. As storm surge might have inflicted relatively less structural damage than winds or rainstorms, eastern Florida counties tended to perform relatively better in the wake of Irma. Similarly, storm surge was relatively higher to the east of the area where Harvey made landfall. These observations are consistent with Belasen and Polachek (2008, 2009), who find opposite effects on employment and wage earnings between Florida counties directly hit by a hurricane and their neighboring counties. In addition to geographical shifts of labor force, we can explain the differential effects through unique characteristics of a typical tropical storm.

The second major finding arises from regressions with sectoral employment. Observations on employment dynamics by industry allowed us to identify specific shocks. As in Belasen and Polachek (2008), we have found positive shocks in the construction, wholesales and other service sectors. We have also found these shocks following a hurricane event to be associated with rebuilding efforts funded in large part by the federal government, among other external funding sources. This evidence explains why economic disturbance created by a natural disaster appears to be short-lived, as well documented in the related literature (e.g., Ewing, Kruse and Thompson, 2003, 2004, 2009; Belasen and Polachek, 2008, 2009).

The third major finding arises from regressions that explicitly estimate the federal government's responses to the two hurricane events. According to the empirical results, property damage from a hurricane led to lower labor demand in the affected counties, but massive federal relief aid has accelerated economic recovery at least in the short run. While the long-term impacts of federal relief and reconstruction programs remain to be seen, Ewing, Kruse and Thompson (2003) find that the economy of an area hit by tornadoes appears to be better off as time passes. Positive shocks arise from post-disaster reconstruction efforts that promote productivity improvements by replacing damaged capital stock and infrastructure and adopting new technologies.

The fourth and last major finding stems from the presence of spatial effects between the disaster counties and their nearby areas. Local economies within a region tend to move in the same direction in response to common aggregate demand shocks. Negative shocks to labor demand following the two hurricanes in 2017 immediately led to higher unemployment and lower employment growth. The estimated spatial panel models confirm positive spatial interactions in these two variables.

According to Belasen and Polachek (2008, 2009), hurricanes in Florida generate opposite wage and employment shocks between hardest-hit counties and their neighbors. Following a catastrophe like Harvey or Irma, displaced residents flee the devastated area and they likely settle in nearby areas. Between July 2017 and July 2018, Aransas County lost 6.5% of its population and Monroe County lost 2.1%, due mostly to outmigration. Harris County of Texas, part of the Houston metro area, lost a total of 43,669 domestic residents due to net out-migration. During that period, the eight counties that surround Harris County gained a combined total of 34,655 residents due to domestic migration flows. Corresponding shifts in the labor supply would likely raise wages in the hardest hit counties and lower wages in their neighboring counties.

We explicitly estimated interactions between neighboring counties using a model that incorporates both spatial autoregressive lags and errors. Estimates for the spatial lag term reveal the effect of a labor demand shock, while estimates for the spatial error term appear to reflect the effects of labor supply shifts across counties. Empirical evidence on spatial spillovers in the disaster region implies that the efficacy of federal disaster responses is higher than otherwise.

On the other hand, FEMA's temporary relocation programs for displaced residents following Hurricanes Harvey and Irma appeared to have generated unintended effects on the labor markets of the disaster communities and their neighboring areas. As Greenberg, Lahr and Mantell assert (2007), an understanding of the spatial or geographical aspect of a region is important for policymakers' design of disaster mitigation and resilience programs.

Moreover, disparate experiences among counties within the disaster regions bear implications for policymakers that make decisions on disaster relief fund allocations. A hurricane's impact on the local economy does not intensify until property damage reaches a certain level. This makes it difficult for policymakers to effectively facilitate local economic recovery across a relatively broad federally declared disaster region.

Even though our empirical results overall reinforce several key findings in the related literature, it is instructive to evaluate the robustness of our study. Ideally, in an experiment, the treated and control samples are, on average, identical in the absence of the treatment, namely the hurricane event in our case. Although the generalized DID method used in this study aims at controlling for pre-hurricane trends, it does not account for differential effects of the disasters in the post-disaster period. More resilient counties may react to a given disaster shock differently than less resilient counties. Differences in characteristics of the disaster counties could potentially convolute the empirical evidence.

Another key aspect of the time-series econometric approach is the sensitivity to historical trends in the economy. The impact of a disruptive event is measured as the difference between the historical data with the baseline or counterfactual forecast. As such, inferences are potentially sensitive to how the baseline is constructed typically using historical data. In addition to the empirical strategies described in this paper, we alleviate the concern of robustness by applying alternative methods to control for pre-disaster trends and unobserved heterogeneity, including the synthetic control approach suggested by Abadie, Diamond, and Hainmueller (2010), common factor approach (Pesaran, 2006; Bai, 2009), and univariate ARIMA forecasts.

Particularly under the synthetic control method, the sample for specifying the comparison group, or so-called "donor pool," consists of all 3,142 counties and equivalents in the United States. The synthetic control group is constructed as a convex combination of the data-generating processes that closely resembles the data-generating processes of the treated group (i.e., disaster counties) in the pre-hurricane period beginning in January 2014. The lagged values of the time series are used for their predictors. The data under the common factor approach are generated using all data series within a disaster county's own state. This approach is similar to using the statewide averages, but the common factor is a measure of a latent variable behind the movements of the pre-hurricane data in all counties of the same state. The ARIMA forecasts, by comparison, are generated based on the time-series model that best characterizes the data-generating process over the pre-hurricane period.

Figure A2 in the Appendix shows the data outcomes for two hardest-hit counties, Aransas and Monroe, as a sample. The series labeled as "state trend" are used for model regressions in this study. Although the post-disaster data observations generated by these alternative methods tend to cluster together, observed differences with the "state trend" observations, especially for employment data, can potentially affect the quantitative aspects of our empirical findings. It is, nevertheless, apparent that the qualitative results are not likely to be particularly sensitive to the specific type of data specification.

In addition to alternative specifications of the "baselines" for empirical investigation, our regression approach could be extended to other aspects of the local economy. Several studies (e.g., Dahlhamer and Tierney, 1998; Tierney, 2007; Le Sage et al., 2011; Xiao and Van Zandt, 2012; Lee, 2019) investigate the reopening rate of businesses in a disaster region over time. Baade, Baumann and Matheson (2007) look at recovery in the overall business conditions following Hurricane Katrina through changes in the local sales volumes. One avenue of future research would be to apply our empirical model to business data.

6. Conclusion

Short term responses in communities devastated by natural hazard have received little attention from the economics literature. To fill this gap, we have investigated local economic responses to Hurricanes Harvey and Irma of 2017 with a focus on the labor markets. Data from the 90 counties of the federally declared disaster regions in Texas and Florida reveal a strong relationship between direct economic damage and localized measures of storm intensity, such as wind speeds, rainfall amounts, and storm surge levels.

The impact of the storms on unemployment and employment of the disaster counties dissipated within six months, and then recovery supported in part by federal relief programs boosted employment and wage growth primarily through expansion in construction and service-oriented activities. Regressions with spatial effects show that following a hurricane strike, employment and wages moved in the opposite directions between a disaster county and its neighboring counties.

One of the innovations in our study is the spatial as well as temporal context of the empirical research. The regression results shed light on the dynamic responses of the local economies of the disaster regions and the role that federal relief aid plays in short-term recovery. As the scope of this paper is confined to within two years following the disaster events, a natural next step is to evaluate the performance of the disaster regions over a longer time horizon.

References

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. (2010) "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program," Journal of the American Statistical Association, 105(490), 493–505.

Andrews, Donald W.K. (1993) "Tests for Parameter Instability and Structural Change with Unknown Change Point," *Econometrica*, 61, 821-856.

Andrews, Donald W. K., and Werner Ploberger. (1994) "Optimal Tests When a Nuisance Parameter is Present Only Under the Alternative," *Econometrica*, 62, 1383-1414.

Anselin, Luc. (1988) *Spatial Econometrics: Methods and Models.* Kluwer Academic Publishers, Dordrecht, NL.

Anselin, Luc, A.K. Bera, R. Florax, and M.J. Yoon. (1996) "Simple Diagnostic Tests for Spatial Dependence," *Regional Science and Urban Economics*, 26, 77-104.

Baade, Robert A., Robert Baumann, and Victor Matheson. (2007) "Estimating the Economic Impact of Natural and Social Disasters, with an Application to Hurricane Katrina," *Urban Studies*, 44(11), 2061-2076.

Bai, Jushan. (2009) "Panel Data Models with Interactive Fixed Effects," *Econometrica*, 77(4), 1229-1279.

Bai, Jushan, and P. Perron (2003) "Computation and Analysis of Multiple Structural Change Model," *Journal of Applied Econometrics*, 18(1), 1-22.

Belasen, Ariel R., and Solomon W. Polachek. (2008) "How Hurricanes Affect Employment and Wages in Local Labor Markets," *American Economic Review: Papers and Proceedings*, 98, 49–53.

Belasen, Ariel R., and Solomon W. Polachek. (2009) "How Disasters Affect Local Labor Markets: The Effects of Hurricanes in Florida," *Journal of Human Resources*, 44, 251-276.

Blake, Eric S., and David A. Zelinsky. (2018) *National Hurricane Center Tropical Cyclone Report: Hurricane Harvey (AL092017)*, National Hurricane Center, May 9. Accessed online: https://www.nhc.noaa.gov/data/tcr/AL092017_Harvey.pdf

Brown, Sharon P., Sandra L. Mason, and Richard B. Tiller. (2006). “The Effect of Hurricane Katrina on Employment and Unemployment,” *Monthly Labor Review*, 129(August), 52–69.

Burrus, R.T., C.F. Dumas, and C.H. Farrell. (2002) “Impact of Low-Intensity Hurricanes on Regional Economic Activity,” *Natural Hazards Review*, 3(3), 118-125.

Cangialosi, John P., Andrew S. Latto, and Robbie Berg. (2018) *National Hurricane Center Tropical Cyclone Report: Hurricane Irma (AL112017)*, National Hurricane Center, June 30. Accessed online: https://www.nhc.noaa.gov/data/tcr/AL112017_Irma.pdf

Cavallo, Eduardo, Sebastian Galiani, Ilan Noy, and Juan Pantano. (2013) “Catastrophic Natural Disasters and Economic Growth,” *Review of Economics and Statistics*, MIT Press, 95(5), 1549-1561.

Chang, Stephanie E., and Adam Z. Rose. (2012) “Towards a Theory of Economic Recovery from Disasters,” *International Journal of Mass Emergencies and Disasters*, 32(2), 171-181.

Cutter, Susan L. (2016) “The Landscape of Disaster Resilience Indicators in the USA,” *Natural Hazards*, 80(2), 741-758.

Cutter, Susan L., Kevin D. Ash, and Christopher T. Emrich. (2014) “The Geographies of Community Disaster Resilience,” *Global Environmental Change*, 29, 65-77.

Cutter, Susan L., and Sahar Derakhshan. 2018. “Temporal and Spatial Change in Disaster Resilience in US Counties, 2010-2015,” *Environmental Hazards*, forthcoming.

Dahlhamer, James M. and Kathleen J. Tierney. (1998) “Rebounding from Disruptive Events: Business Recovery Following the Northridge Earthquake,” *Sociological Spectrum*, 18, 121-141.

Elhorst, J. Paul. (2003) “Specification and Estimation of Spatial Panel Data Model,” *International Regional Science Review*, 26(3), 244-268.

Elhorst, J. Paul. (2010) “Spatial Panel Data Models,” In Fischer, Manfred M. and Arthur Getis (eds.), *Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications*, Berlin Heidelberg: Springer, 377-405.

Ewing, Bradley, Jamie B. Kruse, and Mark Thompson. (2003) "A Comparison of Employment Growth and Stability Before and After the Fort Worth Tornado," *Environmental Hazards*, 5, 83–91.

Ewing, Bradley, Jamie B. Kruse, and Mark Thompson. (2004) "Employment Dynamics and the Nashville Tornado," *Journal of Regional Analysis and Policy*, 34, 47–59.

Ewing, Bradley, Jamie B. Kruse, and Mark Thompson. (2009) "Twister! Employment Responses to the 3 May 2009 Oklahoma City Tornado," *Applied Economics*, 41, 691–702.

Federal Emergency Management Agency. (2017a) *Hurricane Harvey, HAZUS: Estimated Damage and Economic Losse*s, August 26.

Federal Emergency Management Agency. (2017b) *Hurricane Irma, Hazus: Estimated Damage and Economic Losses Based on Final Wind Observations*, September 12.

Greenberg, Michael R., Michael Lahr, and Nancy Mantell. (2007) "Understanding the Economic Costs and Benefits of Catastrophes and Their Aftermath: A Review and Suggestions for the U.S. Federal Government," *Risk Analysis*, 27(1), 83-96.

Hobijn, Bart, Fernanda Nechio, and Adam Hale Shapiro. (2019) "Using Brexit to Identify the Nature of Price Rigidities," Federal Reserve Bank of San Francisco Working Paper 2019-13. https://doi.org/10.24148/wp2019-13.

Insurance Institute of Business and Home Safety. (2018) *Rating the States: 2018*.

Klomp, Jeroen, and Kay Valckx. (2014) "Natural Disasters and Economic Growth: A Meta-Analysis," *Global Environmental Change*, 26, 183-195.

Lazzaroni, Sara, and Peter A.G. van Bergeijk. (2014) "Natural Disasters' Impact, Factors of Resilience and Development: A Meta-Analysis of the Macroeconomic Literature," *Ecological Economics*, 107(C), 333-346.

Lee, Jim. (2019) "Business Recovery from Hurricane Harvey," *International Journal of Disaster Risk Reduction*, 34, 305-315.

LeSage, James P., and R. Kelley Pace. (2009) *Introduction to Spatial Econometrics*. New York: Taylor and Francis Group/CRC Press.

LeSage, James P., R. Kelley Pace, Nina Lam, Richard Campanella, and Xingjian Liu. (2011) "New Orleans Business Recovery in the Aftermath of Hurricane Katrina," *Journal of the Royal Statistical Society*, Series A (Statistics in Society), 174(4), 1007-1027.

National Oceanic and Atmospheric Administration. (2018) *Service Assessment: August/ September 2017 Hurricane Harvey*, June.

Pesaran, M. Hashem. (2006) "Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure," *Econometrica*, 74(4), 967-1012.

Rose, Adam. (2004) "Economic Principles, Issues, and Research Priorities in Hazard Loss Estimation." In Okuyama, Y. and Chang, S. (Eds.), *Modeling Spatial and Economic Impacts of Disasters*, (13-36). Springer: Berlin.

Rose, Adam, and Stephen Casler. (1996) "Input-Output Structural Decomposition Analysis: A Critical Appraisal," *Economic Systems Research*, 8(1), 33-62.

Skidmore, Mark, and Hideki Toya. (2002) "Do Natural Disasters Promote Long-Run Growth?" *Economic Inquiry*, 40(4), 664–687.

Strobl, Eric. (2011) "The Economic Growth Impact of Hurricanes: Evidence from U.S. Coastal Counties," *Review of Economics and Statistics*, 93(2), 575-589.

Strobl, Eric. (2012) "The Economic Growth Impact of Natural Disasters in Developing Countries: Evidence from Hurricane Strikes in the Central American and Caribbean Regions," *Journal of Development Economics*, 97(1), 130-141.

Texas Comptroller of Public Accounts. (2018) "A Storm to Remember: Hurricane Harvey and the Texas Economy," *Fiscal Notes*, February.

Tierney, Kathleen J. (2007) "Businesses and Disasters: Vulnerability, Impacts, and Recovery'. In H. Rodriguez, E.L. Quarantelli, and R. Dynes (eds.) *Handbook of Disaster Research*. Springer, New York, NY, 275-296.

Toya, Hideki, and Mark Skidmore. (2007) "Economic Development and the Impacts of Natural Disasters," *Economics Letters*, 94(1), 20-25.

Treyz, George. (1993) *Regional Economic Modeling: A Systematic Approach to Economic Forecasting and Policy Analysis*, Boston, MA: Kluwer Academic Publishers.

Vigdor, Jacob. (2008) “The Economic Aftermath of Hurricane Katrina,” *Journal of Economic Perspectives*, 22(4), 135-154.

Wooldridge, Jeffrey M. (2002) *Econometric Analysis of Cross Section and Panel Data*, Cambridge, Mass.: MIT Press.

Xiao, Yu, and Edward Feser. (2014) “The Unemployment Impact of the 1993 US Midwest Flood: A Quasi-Experimental Structural Break Point Analysis,” *Environmental Hazards*, 13(2), 93-113.

Xiao, Yu, and Uttara Nilawar. (2013) “Winners and Losers: Analysing Post-Disaster Spatial Economic Demand Shift,” *Disasters*, 37(4), 646-668.

Xiao, Yu, and Shannon Van Zandt. (2011) “Building Community Resiliency: Spatial Links between Household and Business Post-Disaster Return,” *Urban Studies*, 49(11), 2523-2542.

Figure 1. Texas County Unemployment

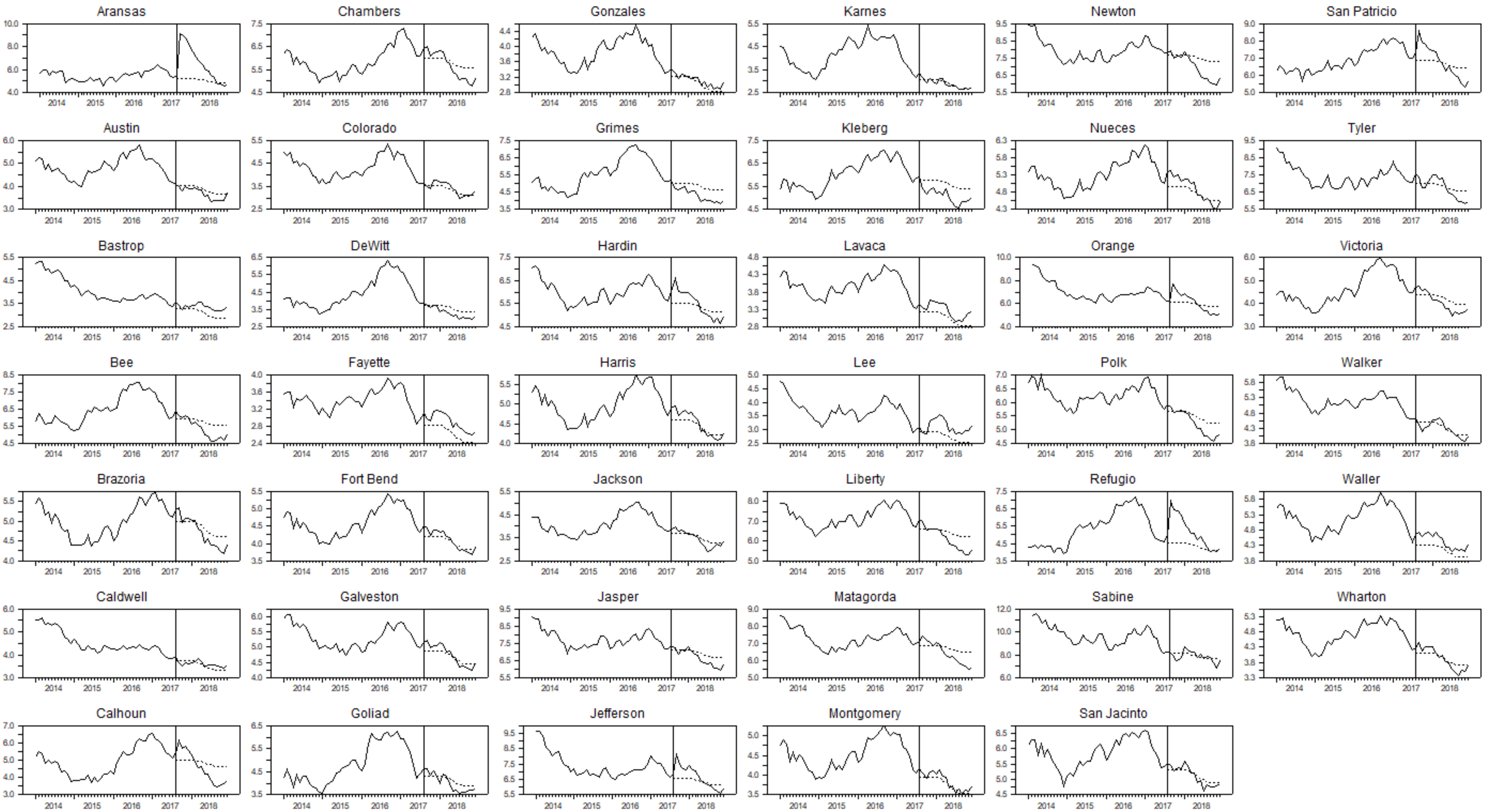


Figure 2. Texas County Employment

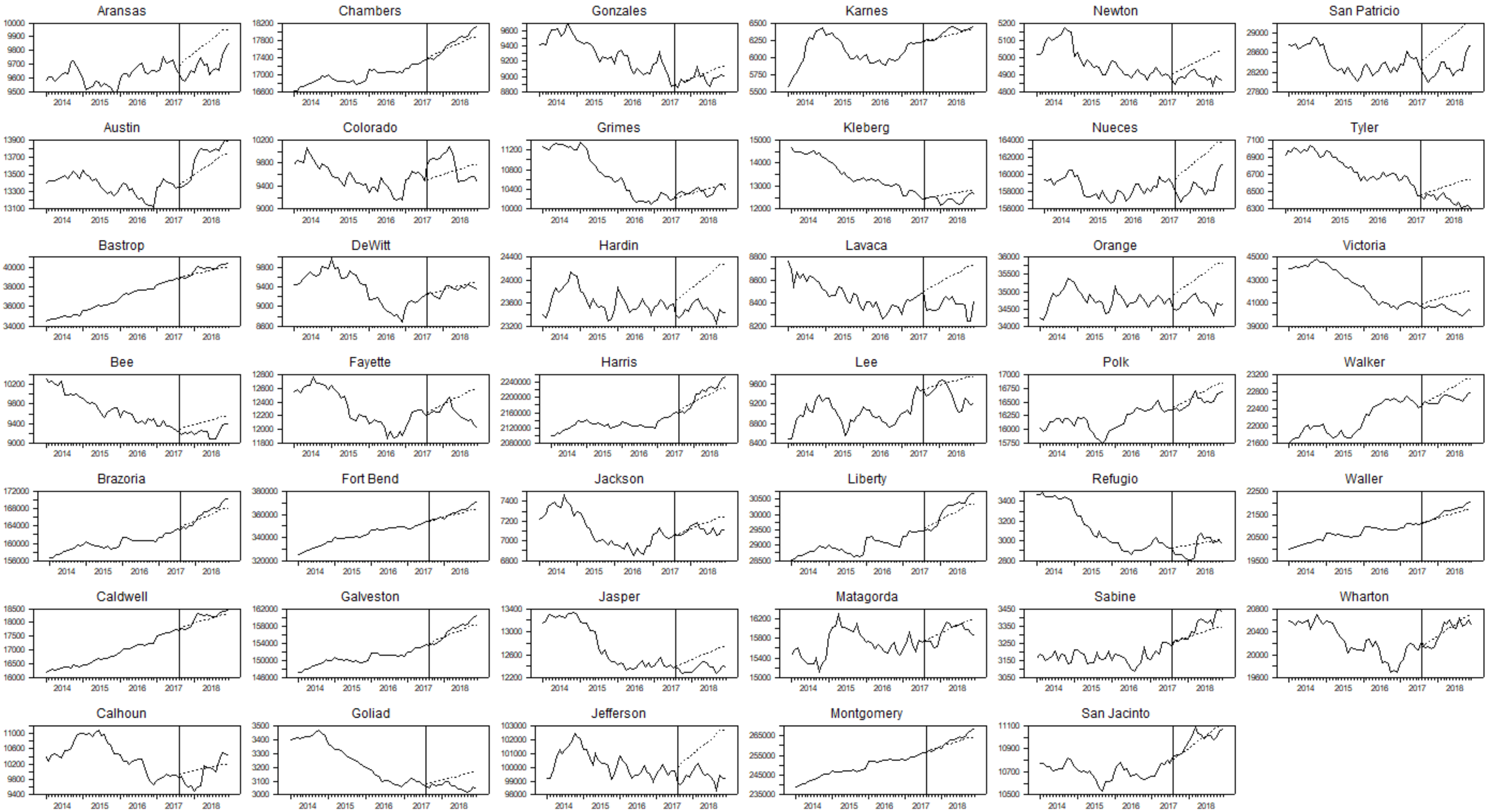


Figure 3. Texas County Wages

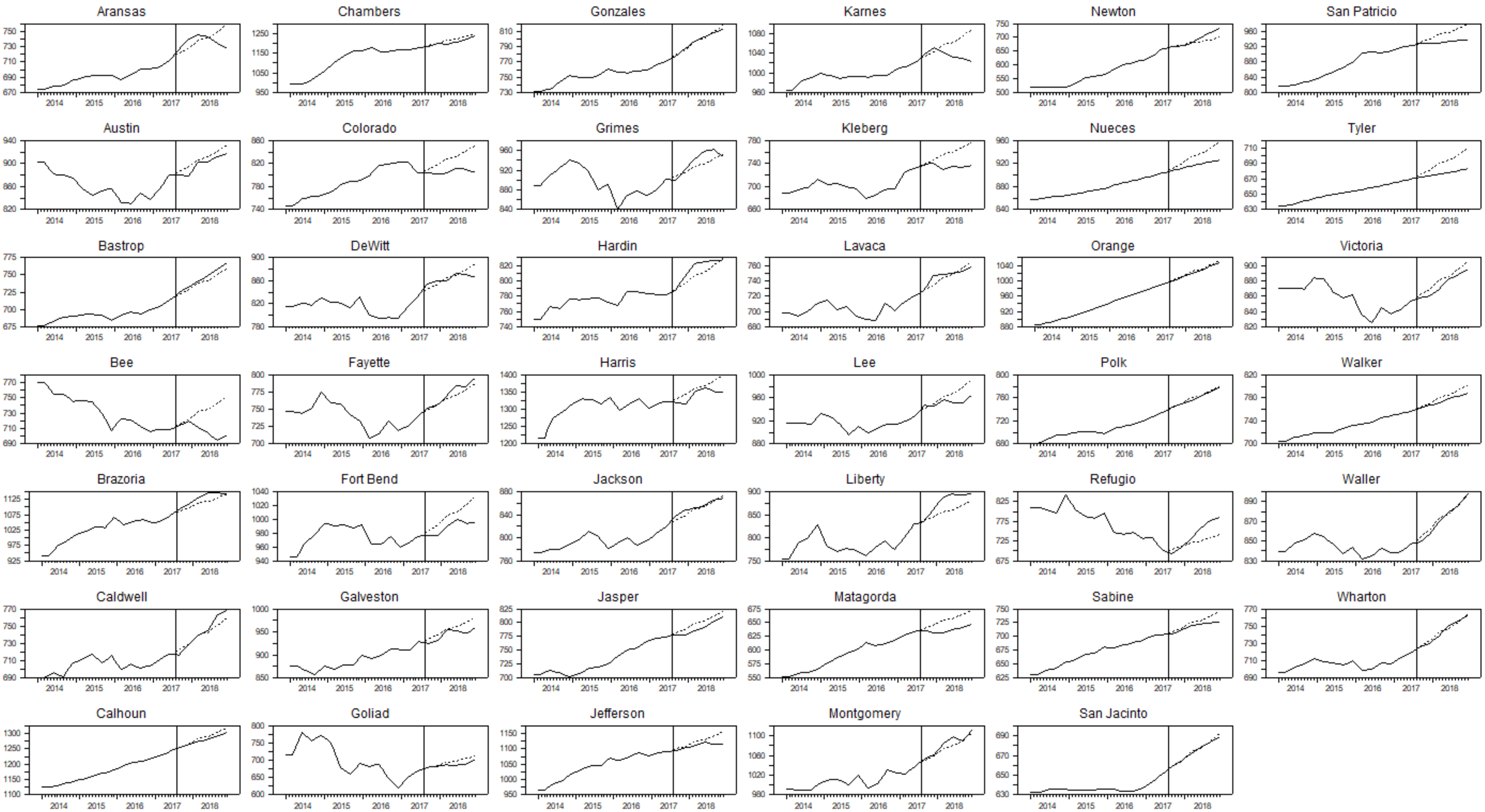


Figure 4. Florida Unemployment

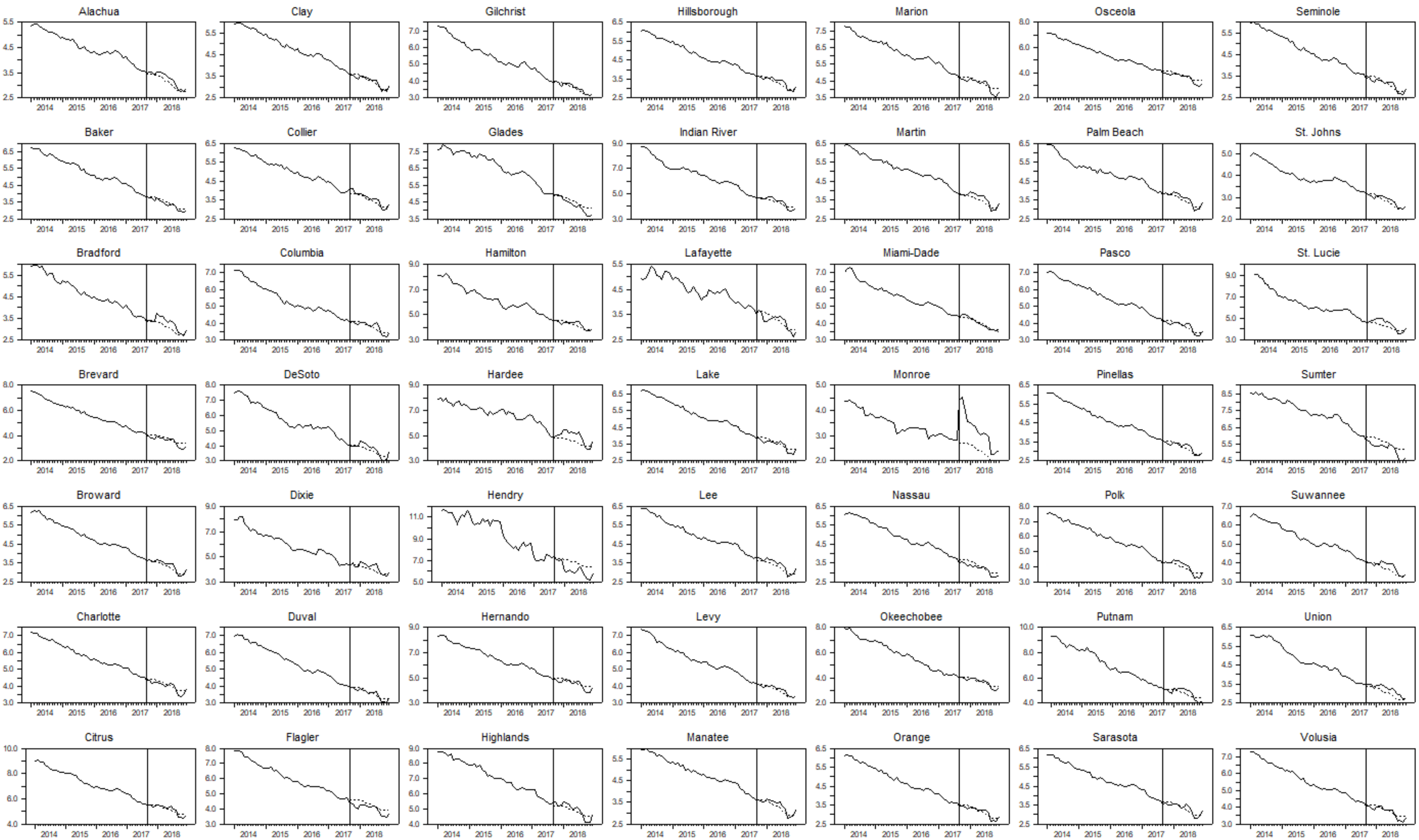


Figure 5. Florida County Employment

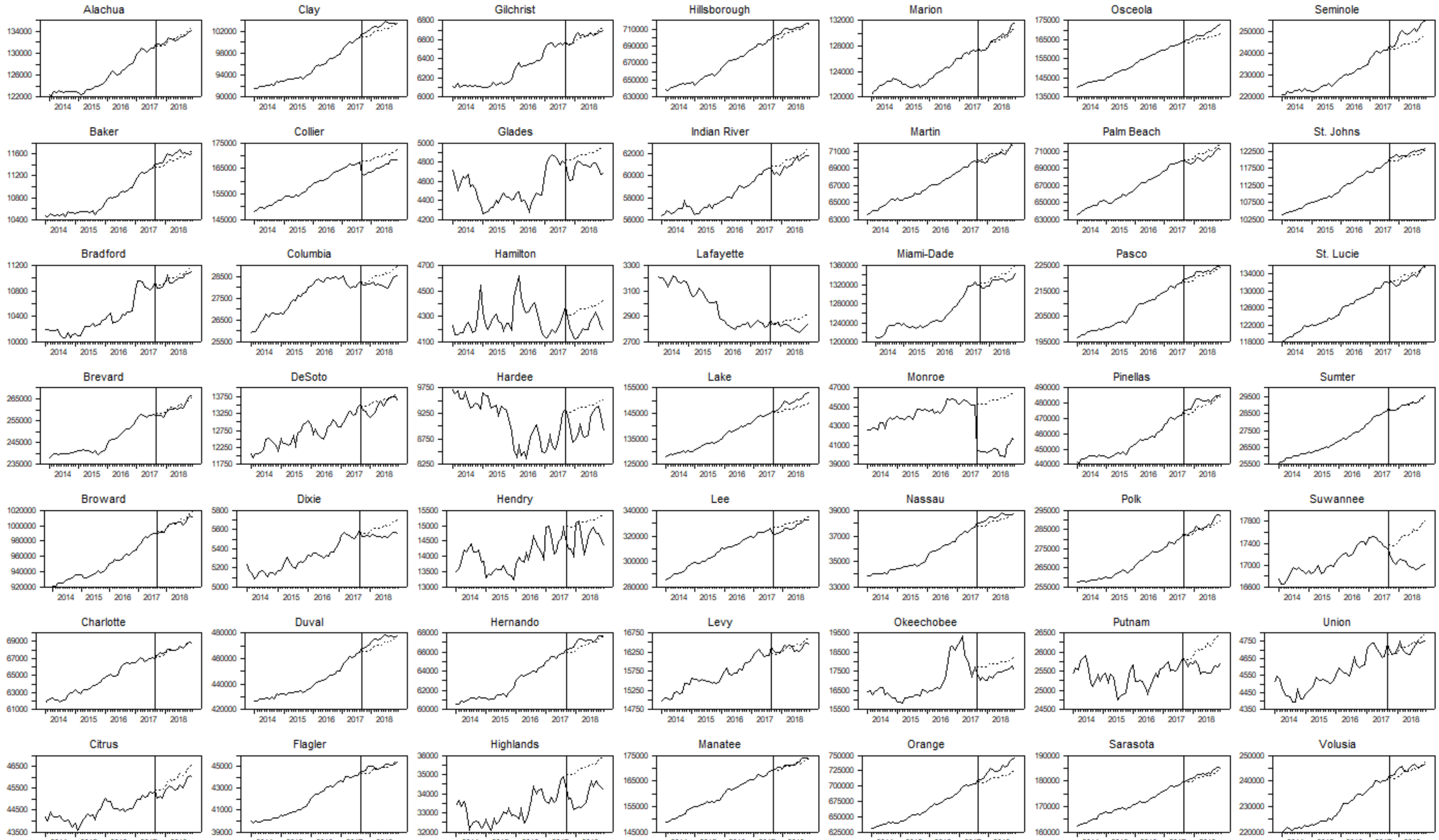


Figure 6. Florida County Wages

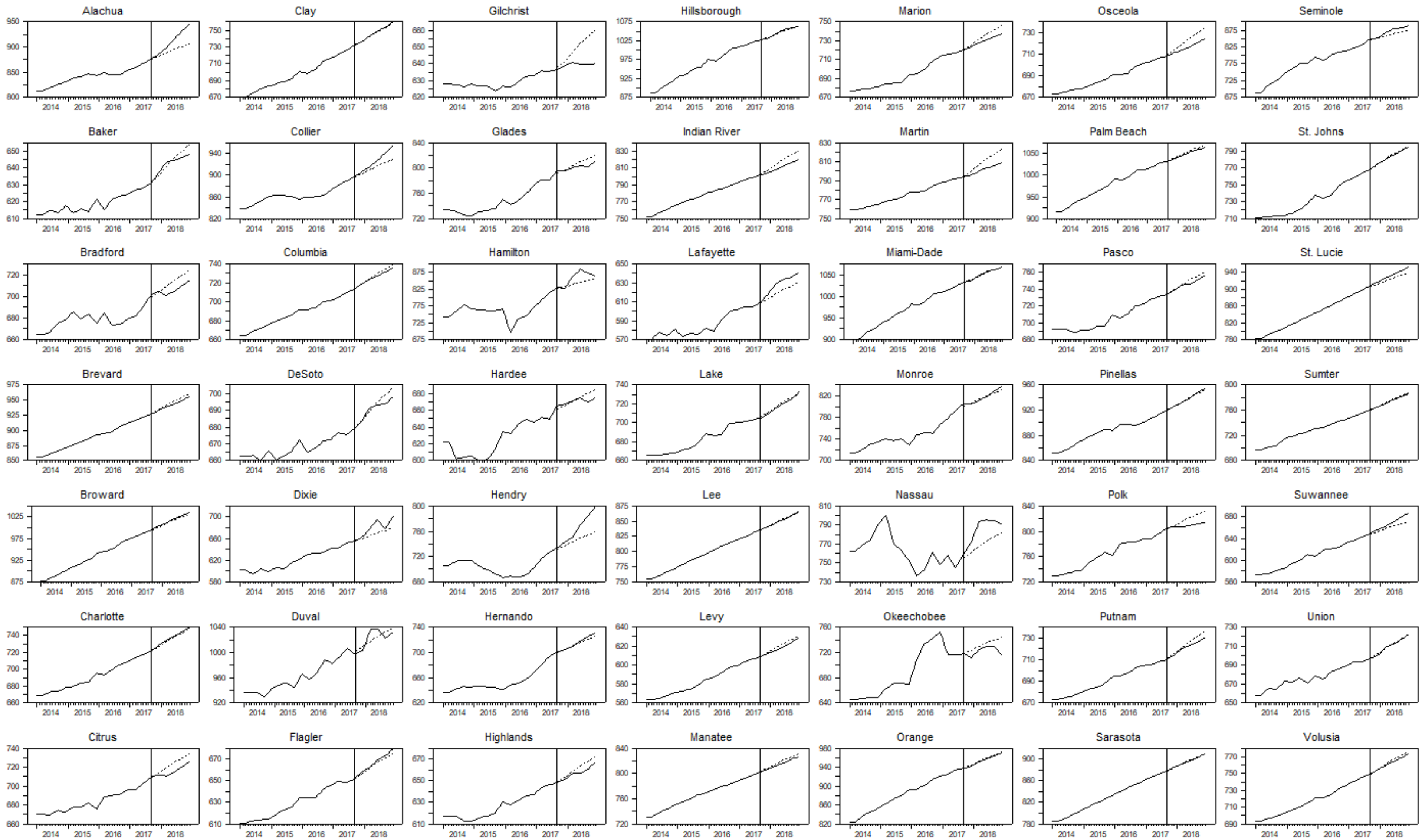


Figure 7. Estimated Impacts for DR

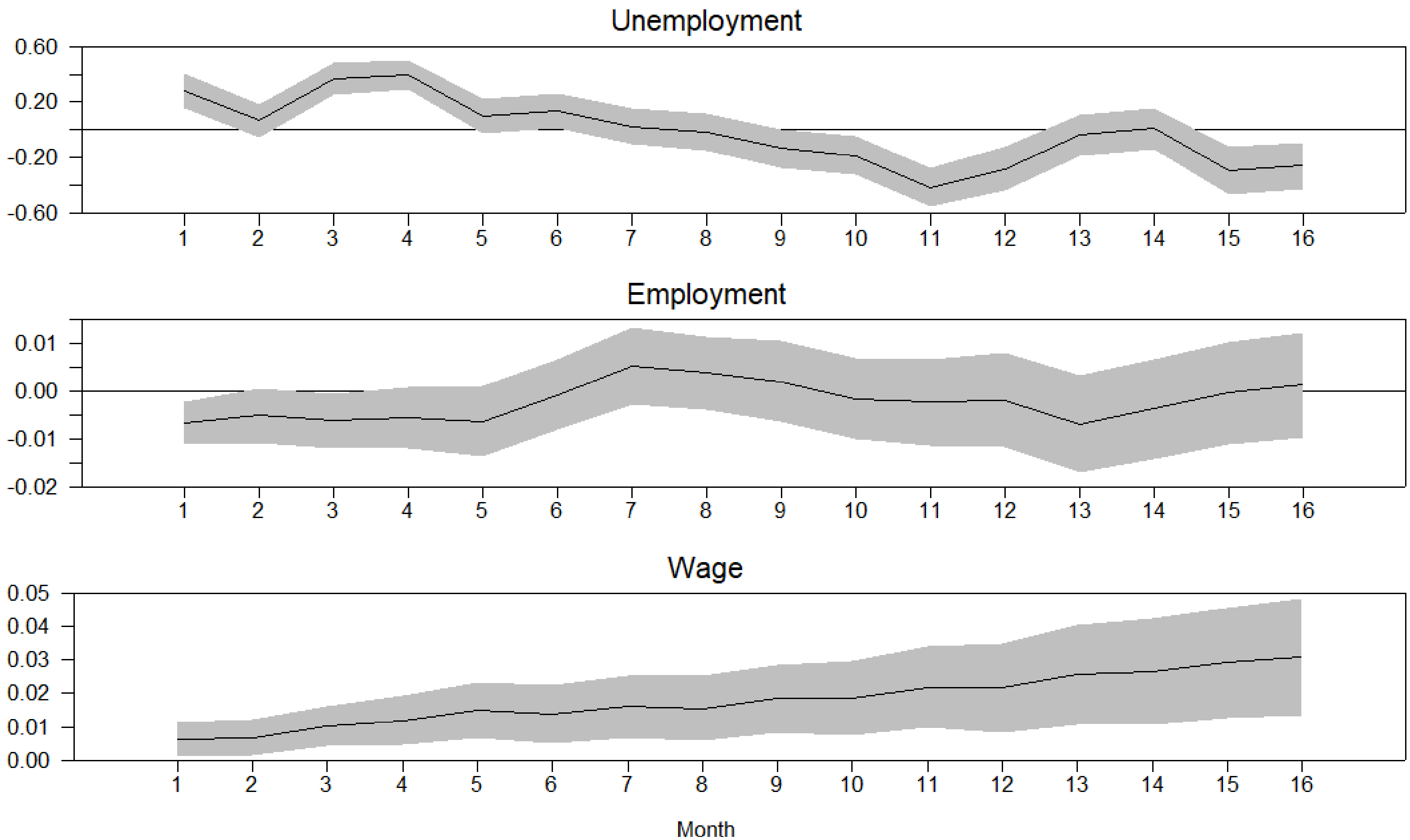


Figure 8. Estimated Impacts for Storm Destruction Variables

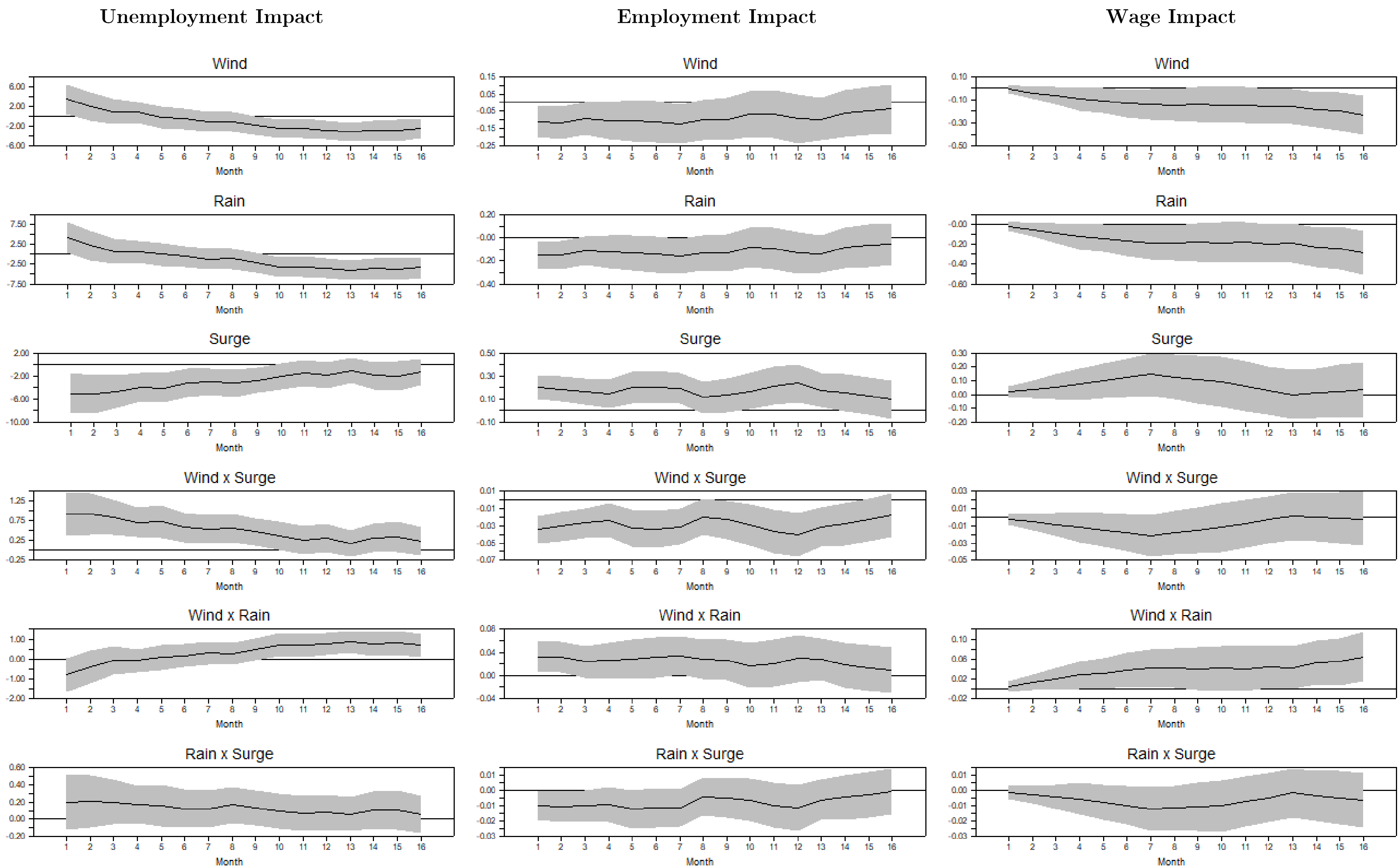


Figure 9. Estimated Employment Impacts of Wind by Industry

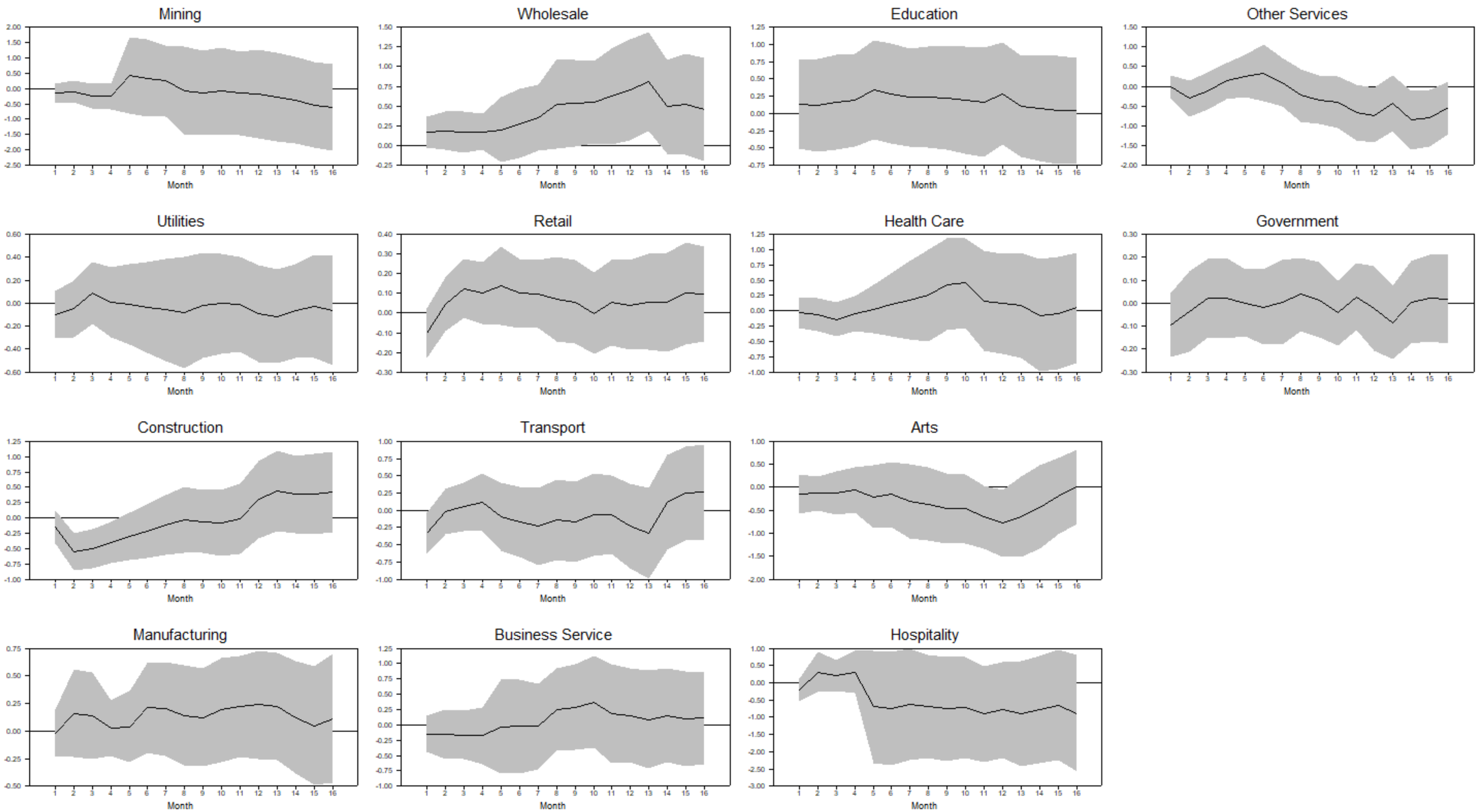


Figure 10. Estimated Employment Impacts of Rain by Industry

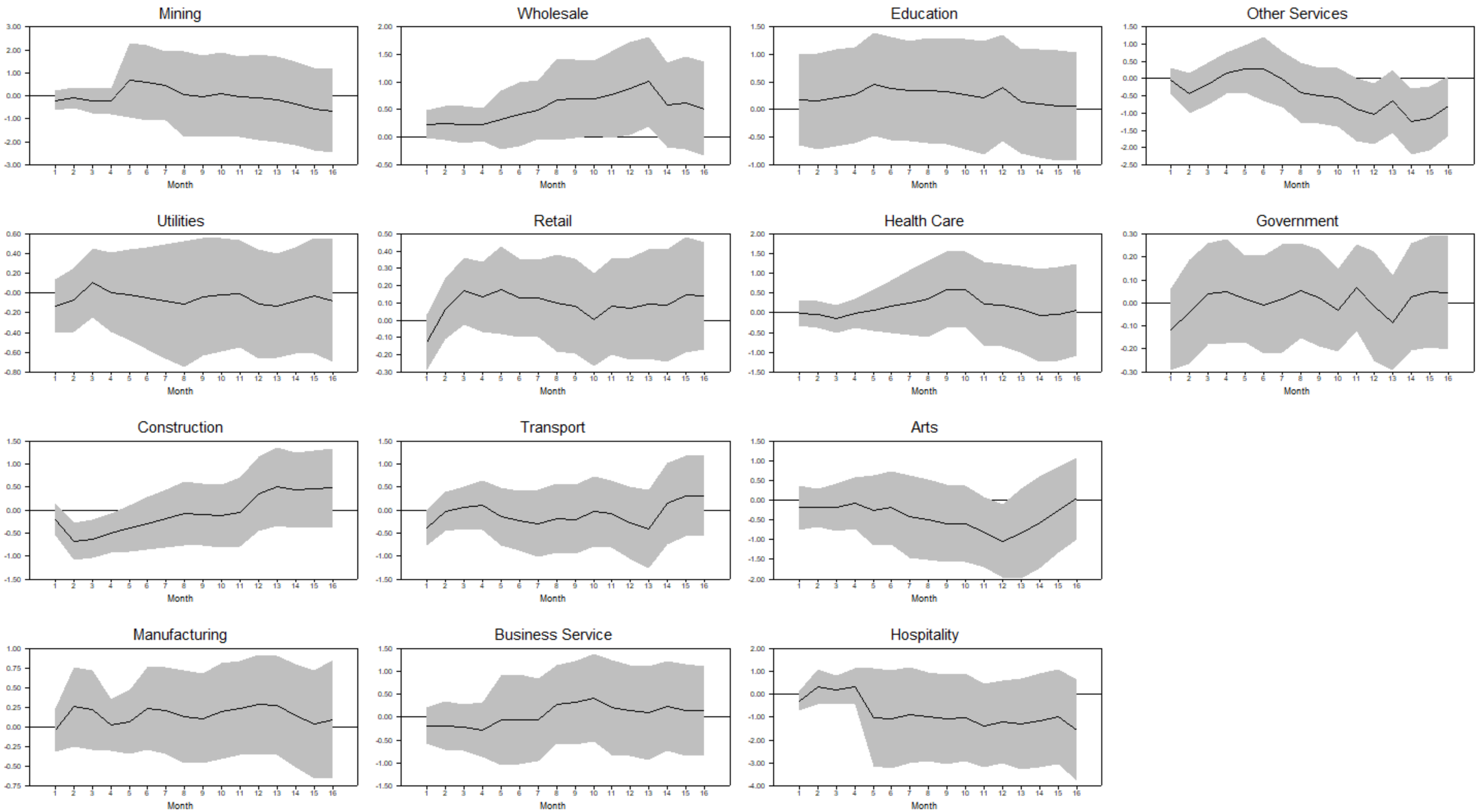


Figure 11. Estimated Employment Impacts of Surge by Industry

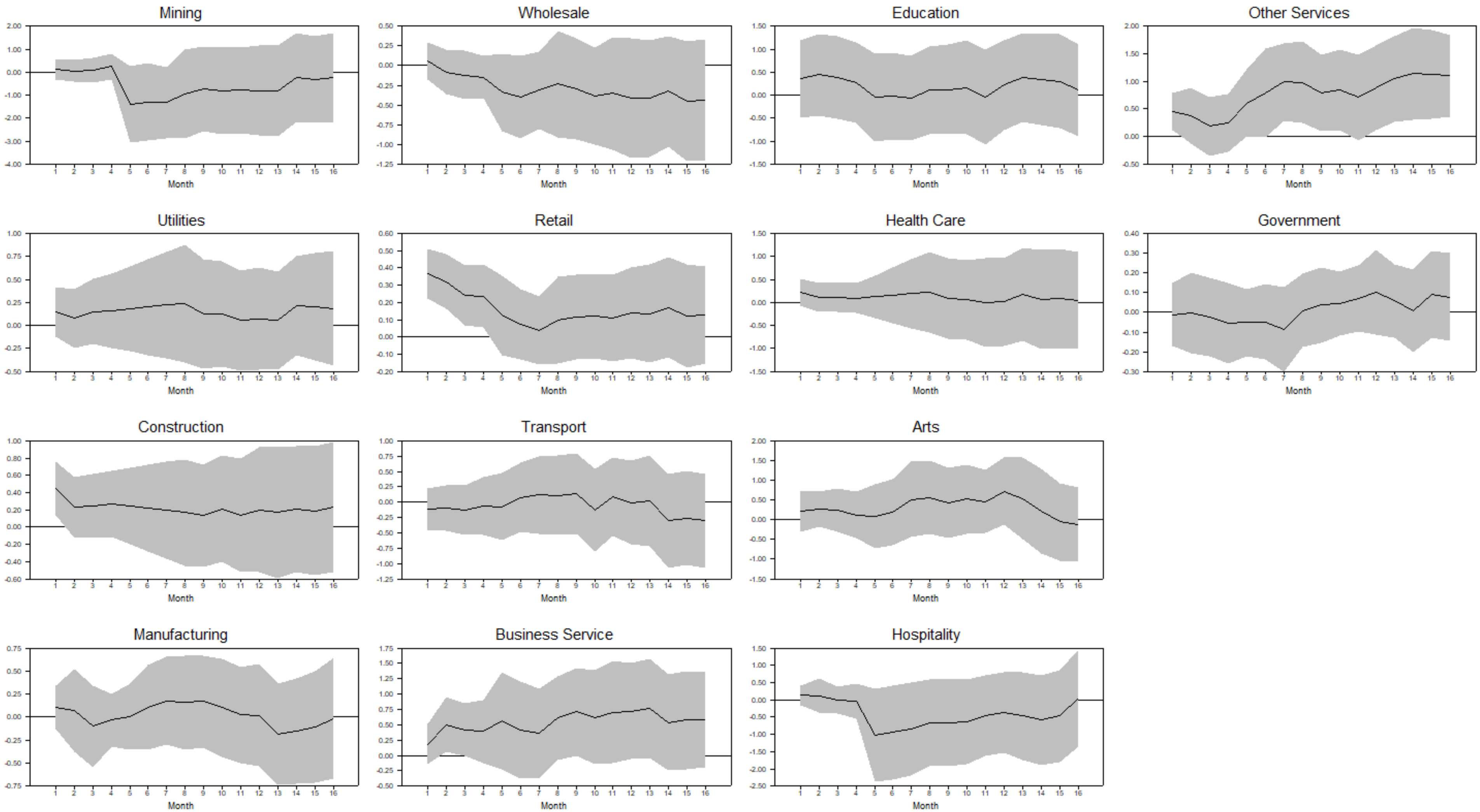


Figure 12. Estimated Employment Impacts of Wind × Surge by Industry

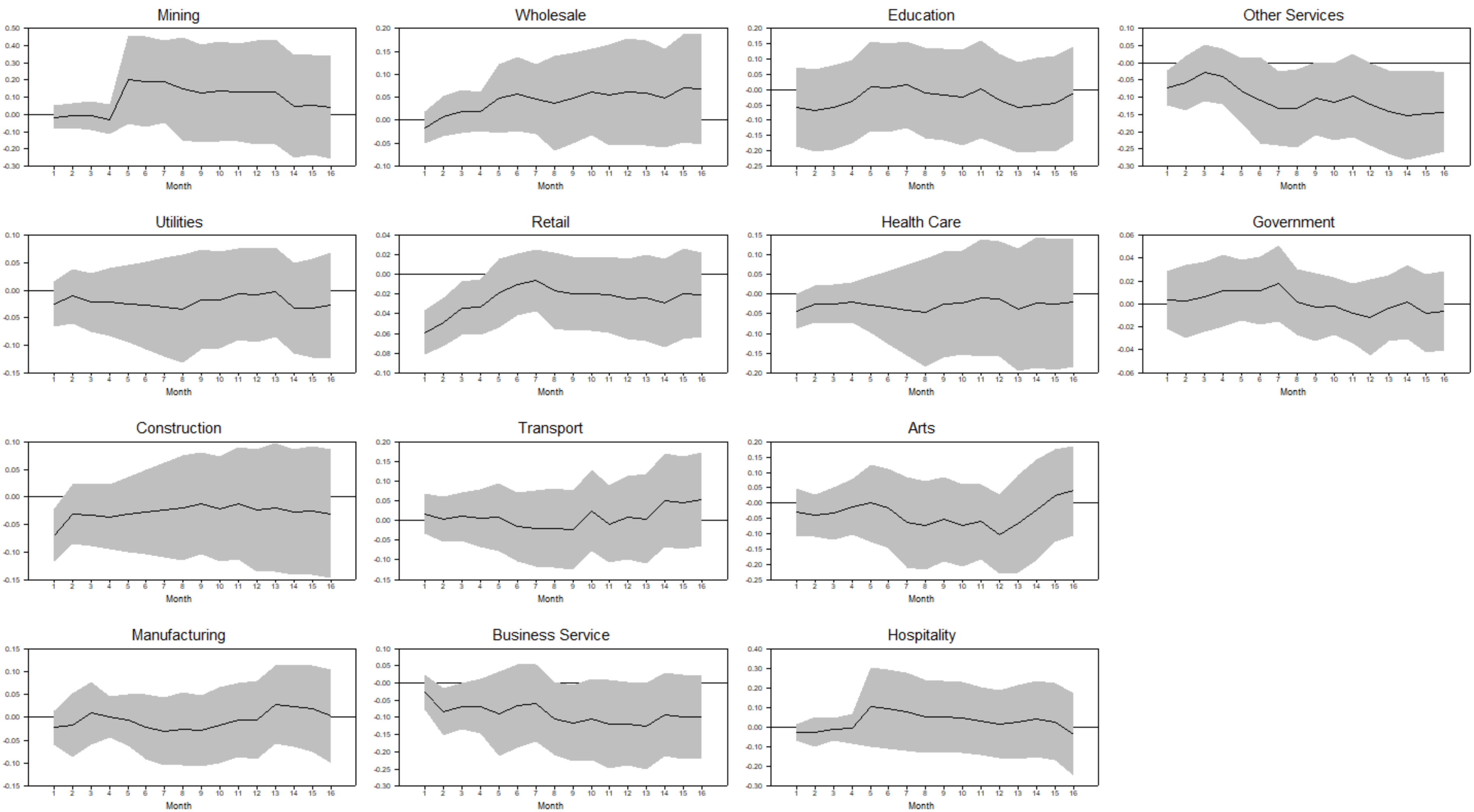


Figure 13. Estimated Employment Impacts of Wind × Rain by Industry

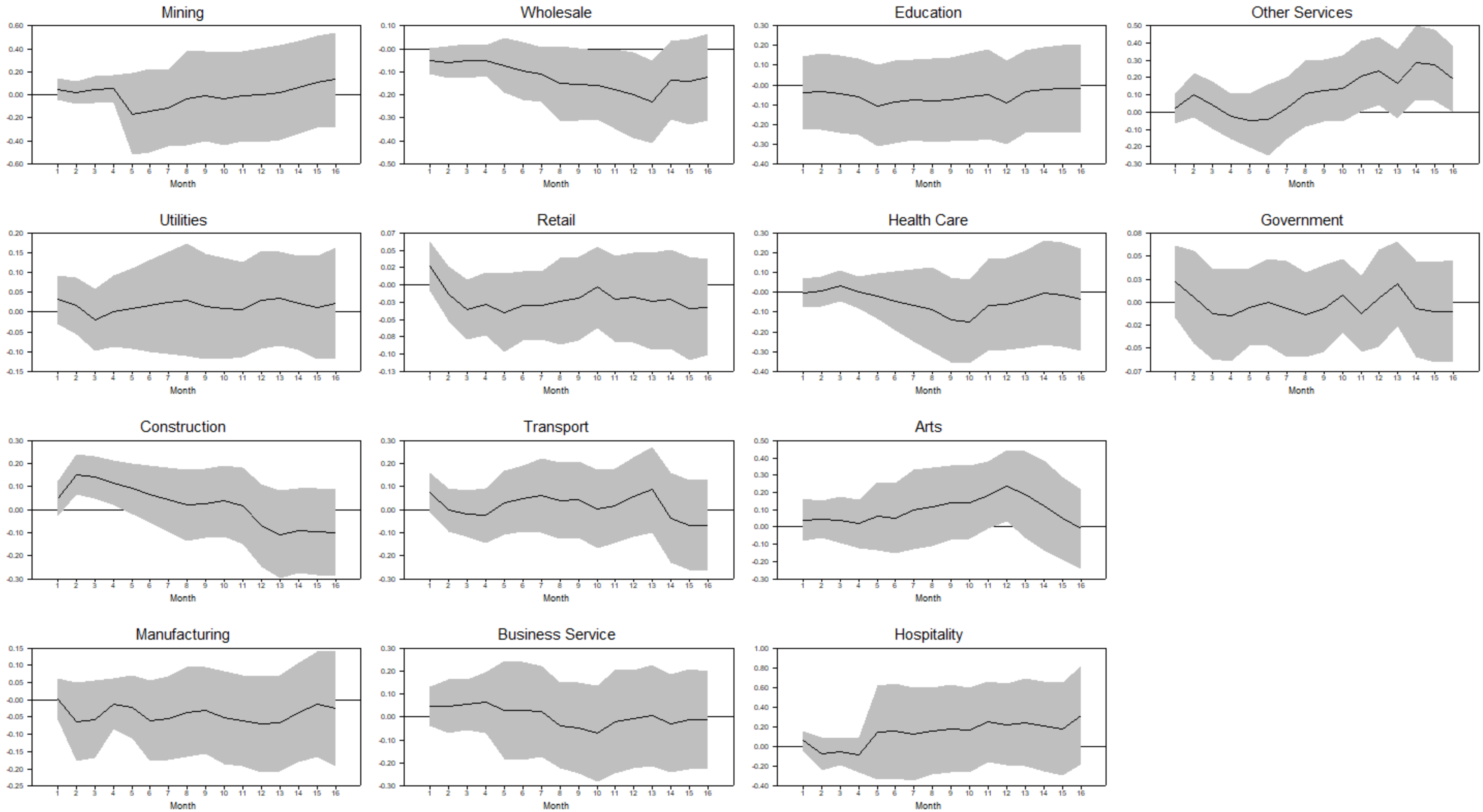


Figure 14. Estimated Employment Impacts of Rain × Surge by Industry

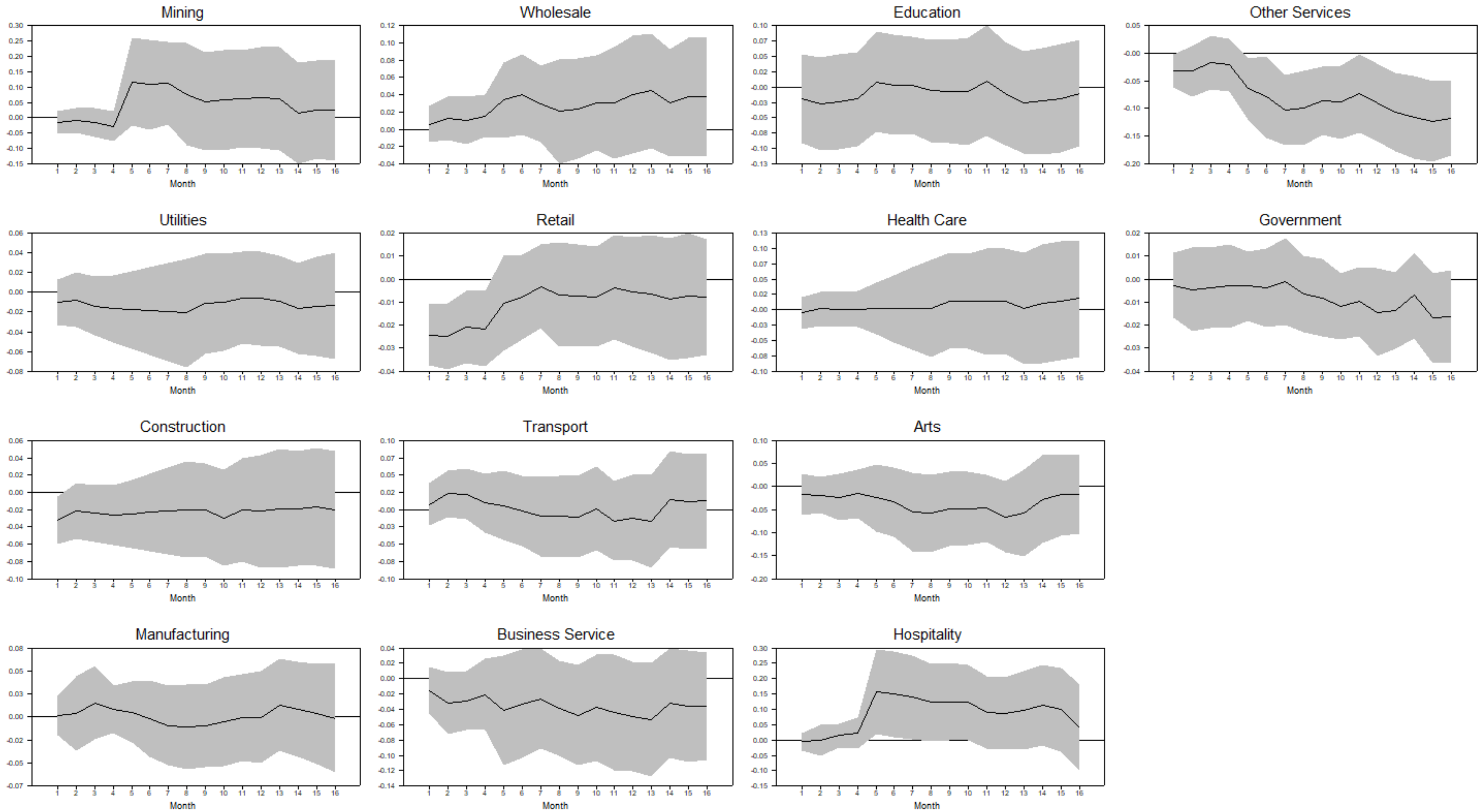
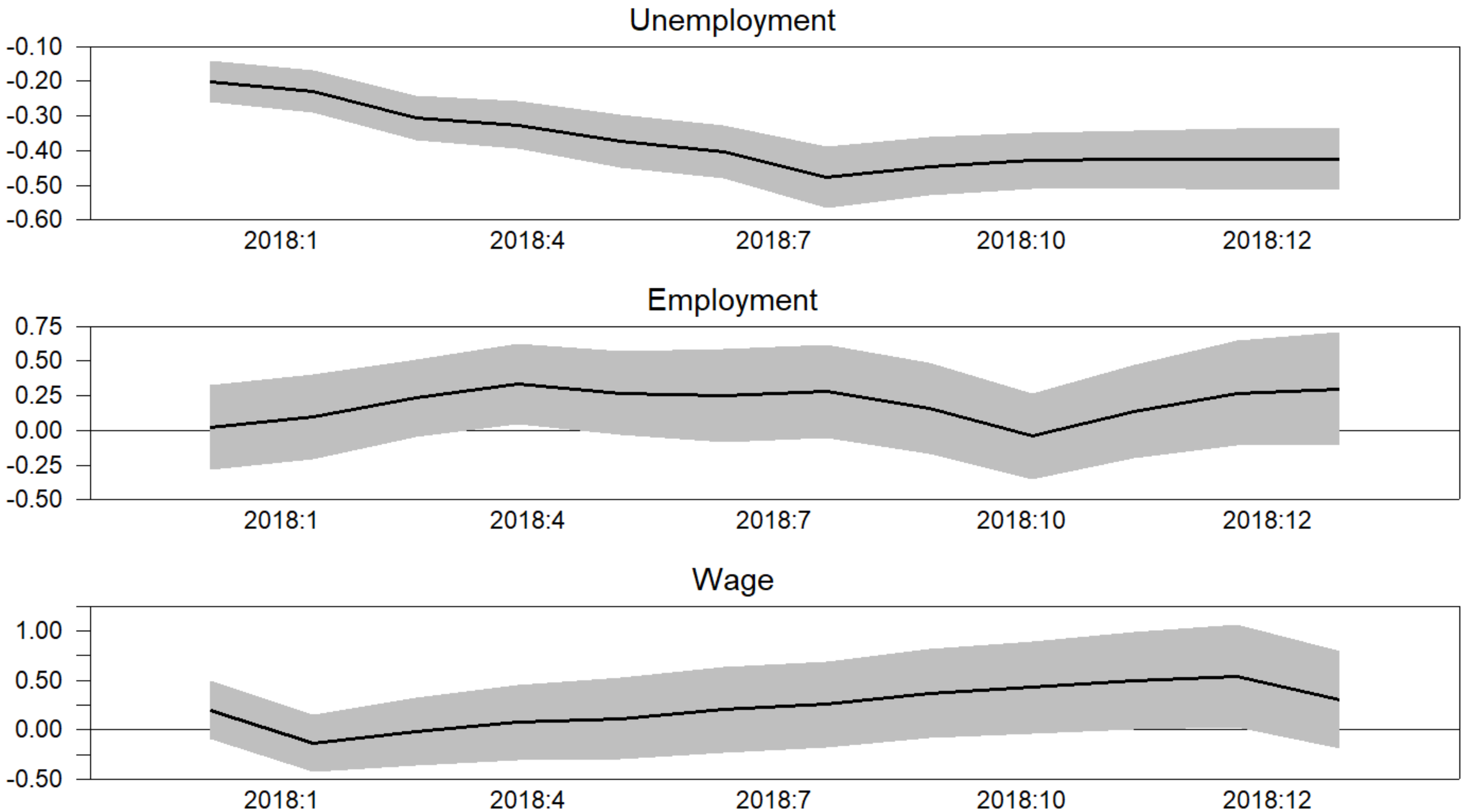


Figure 15: Estimated Impacts of Federal Relief Funds



Notes: Coefficient estimates for employment and wage variables have been pre-multiplied by 100.

Table 1: Summary Statistics for Disaster Counties

	Texas (Obs. = 41)							Florida (Obs. = 49)						
	Mean	Median	Std. Dev.	Min.	County	Max.	County	Mean	Median	Std. Dev.	Min.	County	Max.	County
Labor Market Indicators:														
Unemployment Impact τ=1 (%)	0.46	0.24	0.79	-0.39	Kleberg	3.9	Aransas	-0.02	-0.06	0.27	-0.26	Hardee	1.68	Monroe
Unemployment Impact τ=16 (%)	-0.17	-0.17	0.4	-1.01	Newton	0.6	Lee	-0.04	-0.01	0.22	-0.86	Hendry	0.38	Monroe
Employment Impact τ=1 (%)	-0.5	-0.3	0.96	-2.54	Refugio	3.38	Colorado	0.09	0.45	1.92	-11.04	Monroe	3.79	Hardee
Employment Impact τ=16 (%)	-1.09	-1.21	2.24	-5.65	Lee	2.55	Sabine	-0.89	-0.38	2.37	-11.08	Monroe	3.05	Osceola
Wage Impact τ=1 (%)	0.69	0.55	0.72	-0.14	Hardin	3.22	Goliad	0.07	-0.01	0.44	-1.07	Duval	1.24	Lee
Wage Impact τ=16 (%)	0.54	0.36	2.83	-5.97	Colorado	8.69	Liberty	-0.23	-0.35	2.34	-11.25	Polk	5.36	Hendry
Storm Intensity:														
Wind (miles per hour)	51.98	50	20.79	30	Hardin	130	Aransas	79.9	80	12.39	60	Dixie	120	Monroe
Rain (inches)	21.54	18.59	12.75	5	Bee	53.08	Jefferson	11.42	11.03	1.28	10	Indian River	16.01	St. Lucie
Surge (feet)	0.85	0	1.83	0	Austin	6.78	Harris	1.72	0	2.03	0	Alachua	7.78	Nassau
Resilience Indicators:														
BRIC Social	0.64	0.64	0.04	0.54	Sabine	0.71	Brazoria	0.62	0.63	0.04	0.51	Sumter	0.70	Alachua
BRIC: Economic	0.43	0.44	0.03	0.37	Bee	0.51	Chambers	0.44	0.44	0.02	0.36	Glades	0.49	Clay
BRIC: Community Capital	0.36	0.36	0.04	0.27	Harris	0.44	Refugio	0.29	0.29	0.04	0.19	Miami-Dade	0.36	Bradford
Direct Impact Measures:														
% Damaged Homes	0.12	0.09	0.12	0	Caldwell	0.47	Orange	0.08	0.07	0.05	0.02	Hamilton	0.31	Monroe
Physical Losses Per Capita ($)	1,557	560	3,769	47	Matagorda	23,037	Lee	722	469	888	158	Lafayette	5,373	Collier
Federal Funds Per Capita ($)	1,216	429	2,365	24	Kleberg	12,614	Aransas	245	107	680	49	Lafayette	4,846	Monroe
Disaster Funds Per Capita ($)	2,392	764	5,670	64	Kleberg	33,624	Aransas	902	549	1,371	188	Lafayette	9,187	Collier

Table 2: Regressions for Direct Impacts

	% Damaged Homes			Physical Losses			Federal Funds			Disaster Funds		
Constant	-2.96	(2.77)	*	-25.58	(2.15)	**	-48.26	(4.10)	*	-43.34	(4.01)	*
TX	0.07	(3.14)	*	0.71	(2.77)	*	1.51	(5.94)	*	0.96	(4.12)	*
Wind	0.58	(2.51)	*	5.62	(2.19)	**	9.89	(3.88)	*	9.21	(3.94)	*
Rain	0.70	(2.34)	**	6.07	(1.81)	***	12.31	(3.70)	*	10.56	(3.46)	*
Surge	-0.43	(1.66)	***	-2.58	(0.89)		-2.88	(1.01)		-1.32	(0.51)	
Wind × Surge	0.08	(2.02)	**	0.62	(1.37)		0.67	(1.50)		0.43	(1.05)	
Wind × Rain	-0.13	(2.01)	**	-1.00	(1.35)		-2.25	(3.07)	*	-1.90	(2.83)	*
Rain × Surge	0.01	(0.46)		-0.11	(0.42)		-0.08	(0.32)		-0.20	(0.84)	
R^2	0.34			0.43			0.62			0.59		
Observations	90			90			90			90		

Notes: Except for the percentage of damaged homes, all dependent variables are expressed as logarithmic levels of the nominal values pre-divided by the county population. Except for the dummy variable TX, all independent variables are expressed in logarithmic terms. Absolute t-statistics are listed in parentheses. *, **, and *** represent significance at the 1%, 5%, and 10% statistical levels, respectively.

Table 3: Labor Market Impact Regressions

	Period τ = 1			Period τ = 16		
	Unemployment	Employment	Wage	Unemployment	Employment	Wage
Panel A:						
Constant	-0.93 (2.74)*	0.01 (0.51)	0.01 (1.00)	-2.75 (5.87)*	-0.03 (0.94)	0.001 (0.02)
TX	0.28 (4.57)*	-0.007 (2.98)*	0.01 (2.38) **	-0.26 (3.05)*	0.001 (0.24)	0.01 (2.17)**
DR	0.39 (7.44)*	-0.01 (3.88)*	0.005 (2.04) **	-0.32 (4.41)*	0.005 (1.65)***	0.03 (2.90)*
BRIC: Social	0.78 (1.42)	-0.02 (0.82)	0.04 (1.77) ***	-2.94 (3.89)*	0.11 (2.29)**	0.30 (3.69)*
BRIC: Economic	-0.05 (0.08)	0.03 (1.18)	0.09 (3.38) *	-1.71 (1.96)***	-0.03 (0.52)	0.38 (4.10)*
BRIC: Community	0.43 (1.01)	0.003 (0.17)	-0.002 (0.01)	-1.51 (2.56)**	0.11 (2.78)*	-0.06 (0.97)
Adjusted R^2	0.15	0.04	0.06	0.15	0.02	0.07
Observations	321	321	321	321	321	321
Panel B:						
Constant	-18.76 (2.58)**	0.56 (2.59)**	0.07 (0.80)	10.76 (2.20)**	0.12 (0.34)	1.14 (2.74)*
TX	0.54 (3.01)*	-0.01 (1.09)	0.01 (2.44)**	-0.16 (1.31)	0.01 (1.07)	-0.001 (0.11)
Wind	3.46 (2.32)**	-0.11 (2.54)**	-0.01 (0.61)	-2.50 (2.49)**	-0.04 (0.54)	-0.23 (1.62)
Rain	4.17 (2.15)**	-0.15 (2.59)**	-0.02 (0.72)	-3.24 (2.49)**	-0.05 (0.57)	-0.28 (1.54)
Surge	-5.00 (2.87)*	0.20 (3.91)*	0.02 (0.76)	-1.30 (1.11)	0.09 (1.16)	0.03 (0.33)
Wind × Surge	0.91 (3.39)*	-0.03 (4.37)*	-0.003 (0.76)	0.23 (1.25)	-0.02 (1.44)	-0.002 (0.15)
Wind × Rain	-0.81 (1.89)***	0.03 (2.53)**	0.004 (0.77)	0.69 (2.38)**	0.01 (0.45)	0.06 (2.61)**
Rain × Surge	0.19 (1.21)	-0.01 (2.12)**	-0.001 (0.74)	0.06 (0.53)	-0.001 (0.09)	-0.01 (0.72)
BRIC: Social	-0.43 (0.28)	-0.05 (1.19)	0.02 (0.79)	-1.39 (1.94)***	0.05 (0.64)	0.04 (0.40)
BRIC: Economic	0.18 (0.07)	0.04 (0.62)	0.08 (2.70)*	0.85 (0.53)	0.23 (2.01)**	0.23 (1.66)***
BRIC: Community	0.51 (2.43)**	-0.05 (1.20)	0.003 (0.14)	-0.44 (0.46)	0.15 (2.23)**	-0.09 (1.10)
Adjusted R^2	0.47	0.30	0.25	0.12	0.18	0.05
Observations	90	90	90	90	90	90

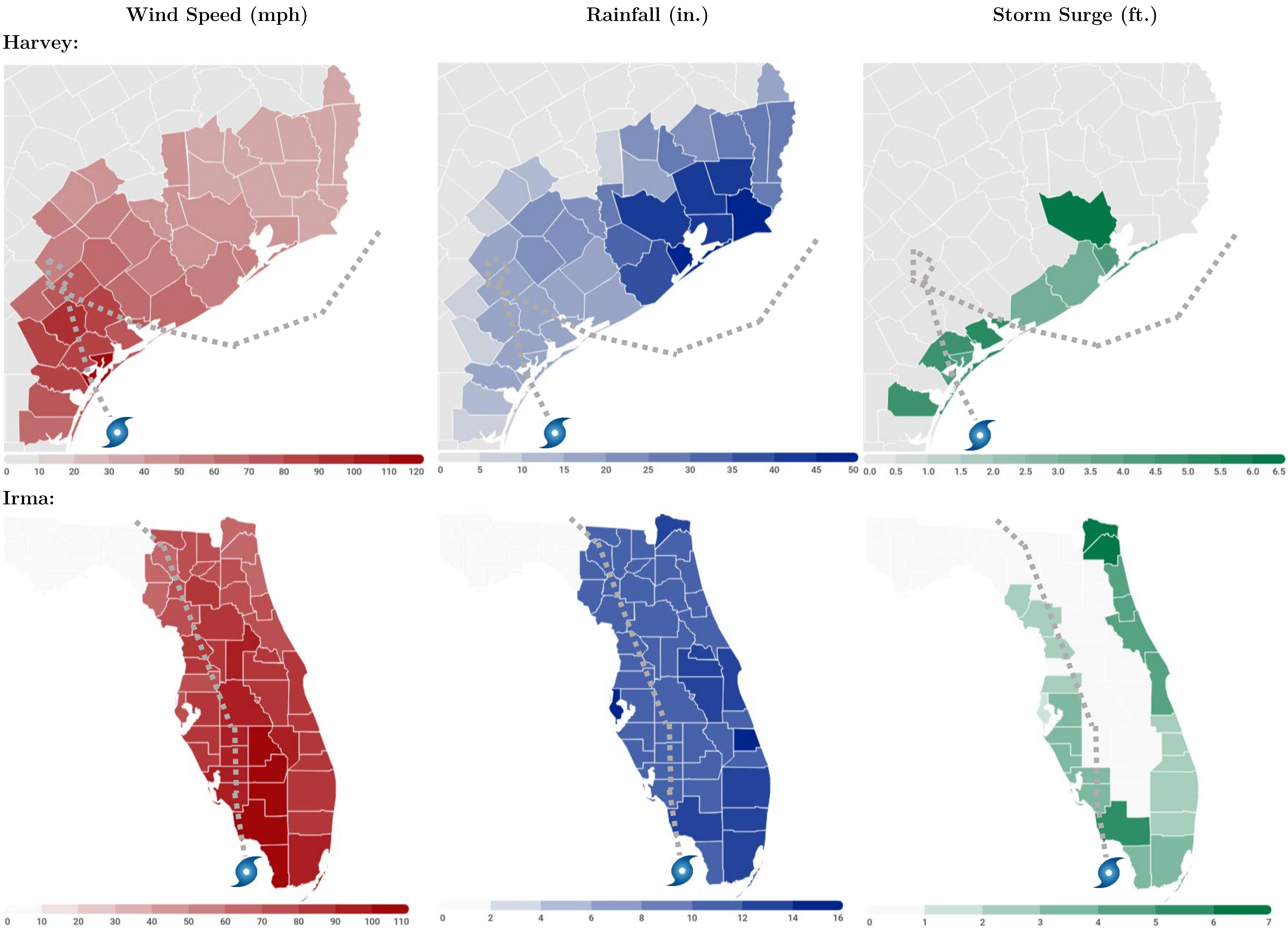
Notes: Absolute t-statistics listed in parentheses are computed using heteroskedasticity-robust standard errors. *, **, and *** represent significance at the 1%, 5%, and 10% statistical levels, respectively.

Table 4. Panel IV Estimations for Federal Relief Funds with Random Effects

	Unemployment		Employment		Wage	
	No Spatial	Spatial	No Spatial	Spatial	No Spatial	Spatial
Constant	11.58 (0.14)	19.51 (0.97)	1.20 (1.16)	1.34 (1.23)	3.16 (2.30) *	2.11 (2.59) *
TX	-0.08 (0.85)	-0.23 (1.91) **	0.002 (0.38)	0.005 (2.64) *	0.01 (2.53) *	0.02 (2.74) *
Wind	6.02 (2.13) **	9.13 (2.02) **	-0.56 (2.20) **	-0.60 (2.25) **	-0.72 (2.29) **	-0.93 (2.21) **
Rain	6.85 (1.75) ***	9.93 (1.98) **	-0.62 (2.18) **	-0.67 (2.22) **	-0.71 (2.17) **	-1.07 (2.59) *
Surge	8.23 (2.77) *	-6.37 (1.88) ***	-0.50 (2.52) *	0.22 (1.19)	-0.11 (0.18)	0.25 (1.13)
Wind × Rain	6.73 (0.02)	4.66 (1.02)	0.28 (1.17)	0.30 (1.20)	0.34 (2.18) **	0.49 (1.62)
Wind × Surge	3.22 (2.95) *	2.58 (2.21) **	-0.19 (2.76) *	-0.09 (1.36)	0.03 (0.19)	-0.08 (1.07)
Rain × Surge	0.46 (1.61)	0.26 (0.51)	-0.03 (1.14)	-0.01 (0.37)	0.02 (0.15)	-0.03 (1.04)
BRIC: Social	-0.04 (1.58)	-0.04 (0.04)	0.02 (0.05)	0.02 (0.07)	0.16 (0.97)	0.05 (0.83)
BRIC: Economic	0.03 (0.08)	-0.24 (0.16)	0.16 (1.75) ***	0.10 (1.17)	0.24 (2.41) *	0.21 (2.08) **
BRIC: Community	0.09 (0.09)	0.32 (0.40)	0.11 (2.04) **	0.07 (1.65) ***	0.01 (0.23)	-0.05 (0.99)
Federal Funds	-2.76 (1.94) **	-5.23 (2.52) *	0.03 (3.71) *	0.11 (2.49) *	0.04 (2.77) *	0.04 (2.36) *
BP Heterogeneity Test	135.08 *	232.87 *	174.03 *	205.41 *	73.27 *	70.18 *
LM: Random Effects	1.68	1.43	0.78	0.69	1.71	1.75
WH Exogeneity Test	21.48 *	17.74 *	6.81 *	2.74 ***	42.00 *	36.16 *
Spatial Lag		0.35 (3.65) *		0.21 (2.67) *		-0.23 (2.19) **
Spatial Errors		0.38 (2.55) *		-0.43 (3.02) *		-0.29 (2.39) *
LM: Spatial Lag	9.12 *		7.82 *		3.46 **	
LM: Spatial Error	6.14 *		9.19 *		2.80 ***	
Observations	1,440	1,904	1,440	1,904	1,440	1,904

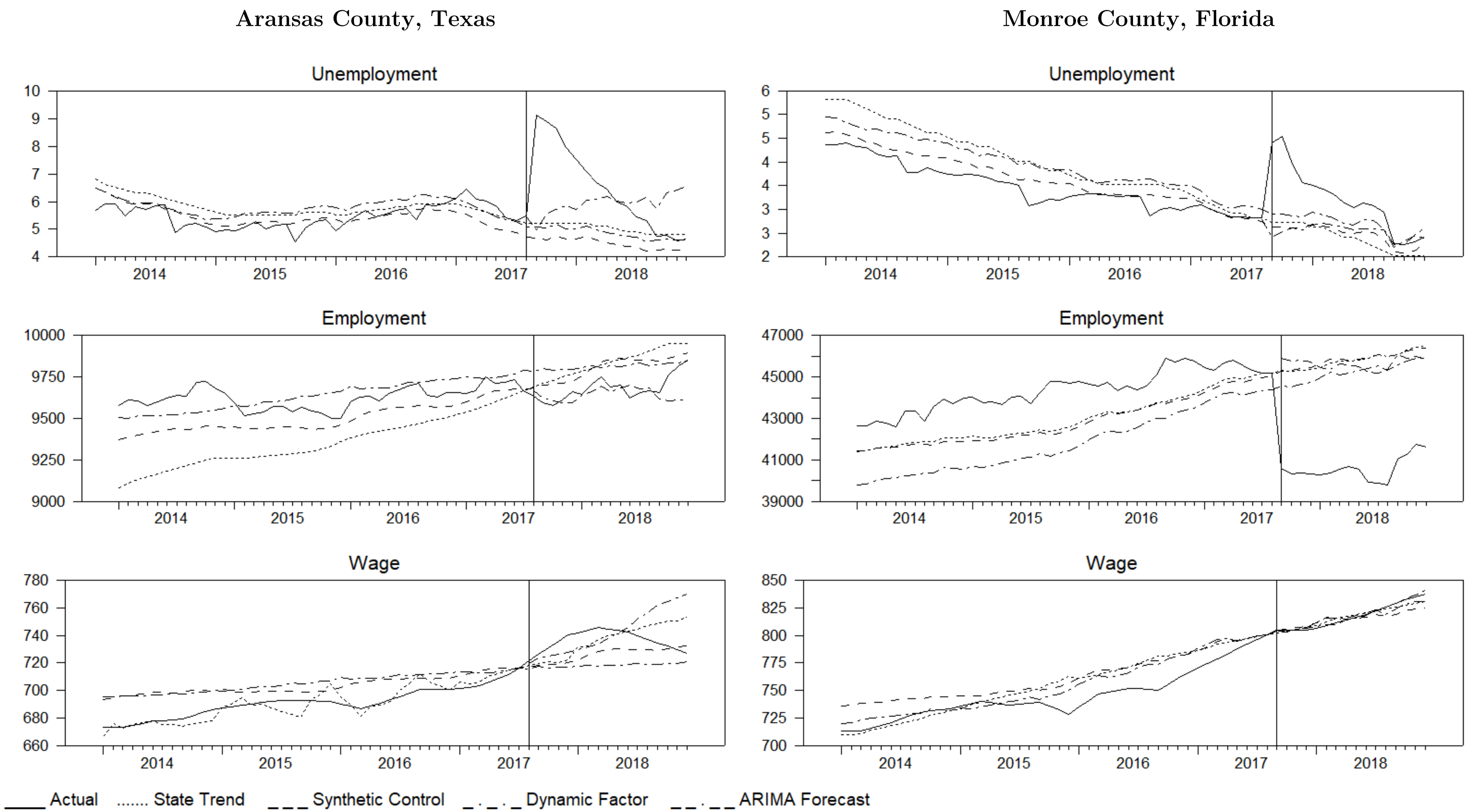
Notes: Absolute t-statistics listed in parentheses. *, **, and *** represent significance at the 1%, 5%, and 10% statistical levels, respectively.

Appendix: Figure A1. Weather Data by County



Sources: National Oceanic and Atmospheric Administration, and National Weather Service, 2017-2018.

Appendix: Figure A2. Alternative Methods for Impact Measures



Appendix: Table A1. Structural Break Tests for Texas Disaster Counties

	Unemployment					Employment					Wage				
County:	AQ	*p*-value	AP	*p*-value	Break Date	AQ	*p*-value	AP	*p*-value	Break Date	AQ	*p*-value	AP	*p*-value	Break Date
Aransas	10.40	***0.07***	3.75	***0.03***	2017:09	4.20	0.69	0.91	0.58	2018:06	17.45	***0.00***	5.85	***0.00***	2017:12
Austin	8.71	0.16	2.22	0.14	2016:09	5.51	0.48	1.54	0.30	2017:12	8.67	0.16	2.26	0.14	2016:12
Bastrop	7.16	0.28	1.42	0.34	2014:08	3.42	0.82	0.62	0.77	2017:12	13.73	***0.02***	4.09	***0.02***	2016:09
Bee	8.16	0.19	2.43	0.11	2017:02	7.71	0.23	2.19	0.15	2014:07	10.26	***0.09***	2.76	***0.08***	2016:03
Brazoria	4.20	0.69	1.25	0.40	2018:02	8.61	0.16	2.40	0.12	2016:12	15.96	***0.01***	6.15	***0.00***	2017:03
Caldwell	7.09	0.29	1.46	0.32	2017:03	3.32	0.84	0.66	0.74	2017:12	8.26	0.19	2.42	0.11	2016:03
Calhoun	6.60	0.34	1.49	0.31	2017:11	6.38	0.36	1.72	0.24	2018:03	9.42	0.12	2.81	***0.08***	2016:09
Chambers	4.38	0.66	1.24	0.41	2018:02	8.63	0.16	2.59	***0.10***	2016:12	4.02	0.72	1.06	0.50	2016:05
Colorado	7.43	0.25	1.84	0.21	2017:02	3.47	0.82	0.54	0.83	2018:05	14.66	***0.01***	5.05	***0.01***	2017:03
DeWitt	10.11	***0.09***	2.69	***0.09***	2016:09	6.13	0.40	1.51	0.31	2016:12	12.93	***0.03***	4.38	***0.02***	2016:12
Fayette	6.48	0.35	1.81	0.22	2017:02	5.99	0.41	1.37	0.36	2015:01	7.04	0.29	2.08	0.17	2016:03
Fort Bend	5.61	0.47	1.73	0.24	2014:07	8.72	0.16	2.91	***0.07***	2018:01	7.81	0.22	2.55	0.10	2016:12
Galveston	5.62	0.46	1.34	0.37	2018:02	8.50	0.17	2.34	0.13	2016:12	4.47	0.65	1.36	0.36	2017:12
Goliad	7.50	0.25	1.80	0.22	2014:09	14.44	***0.02***	4.80	***0.01***	2014:10	12.30	***0.04***	3.56	***0.04***	2016:12
Gonzales	7.24	0.27	2.03	0.17	2017:02	9.13	0.13	2.30	0.13	2017:03	21.91	***0.00***	9.12	***0.00***	2016:12
Grimes	9.21	0.13	2.32	0.13	2016:12	8.94	0.14	2.58	***0.10***	2015:03	8.16	0.19	2.63	***0.09***	2016:03
Hardin	7.24	0.27	1.82	0.22	2018:04	12.07	***0.04***	3.26	***0.05***	2014:12	11.48	***0.05***	3.34	***0.04***	2017:09
Harris	5.39	0.50	1.50	0.31	2017:02	12.21	***0.04***	3.72	***0.03***	2017:10	7.01	0.29	1.99	0.18	2017:12
Jackson	6.33	0.37	1.69	0.25	2016:10	10.25	***0.09***	2.72	***0.08***	2014:09	9.60	0.11	3.02	***0.06***	2016:12
Jasper	9.17	0.13	2.60	***0.10***	2018:01	7.13	0.28	2.49	0.11	2015:06	17.03	***0.01***	7.41	***0.00***	2017:12
Jefferson	8.12	0.20	1.72	0.24	2017:09	8.70	0.16	2.30	0.13	2014:12	7.52	0.24	2.11	0.16	2016:03
Karnes	7.25	0.27	1.95	0.19	2016:12	7.87	0.22	2.37	0.12	2014:07	15.43	***0.01***	4.92	***0.01***	2017:12
Kleberg	6.94	0.30	1.67	0.26	2014:06	11.55	***0.05***	3.10	***0.06***	2014:10	9.61	0.11	2.91	***0.07***	2016:12
Lavaca	7.70	0.23	1.87	0.21	2017:02	10.74	***0.07***	2.82	***0.07***	2013:12	9.02	0.14	2.53	0.10	2016:06
Lee	6.62	0.34	1.30	0.38	2017:02	6.90	0.31	1.76	0.23	2014:02	7.85	0.22	2.31	0.13	2016:03
Liberty	6.88	0.31	2.39	0.12	2017:02	7.39	0.26	1.65	0.26	2017:12	11.45	***0.05***	4.34	***0.02***	2016:12
Matagorda	8.04	0.20	2.35	0.12	2018:02	8.10	0.20	1.74	0.24	2014:10	8.54	0.17	2.64	***0.09***	2016:09
Montgomery	5.93	0.42	1.76	0.24	2017:02	8.02	0.20	2.44	0.11	2017:02	9.15	0.13	2.32	0.13	2016:03
Newton	10.12	***0.09***	2.63	***0.09***	2018:01	8.97	0.14	2.50	0.11	2014:12	9.73	0.11	3.29	***0.05***	2018:03
Nueces	4.84	0.59	1.36	0.36	2018:04	3.70	0.78	0.64	0.76	2018:06	10.91	***0.07***	3.07	***0.06***	2016:09
Orange	7.36	0.26	1.64	0.27	2017:09	12.82	***0.03***	3.64	***0.03***	2014:12	24.52	***0.00***	8.78	***0.00***	2016:09
Polk	7.89	0.21	2.46	0.11	2014:06	10.24	***0.09***	3.21	***0.05***	2015:09	8.74	0.16	2.82	***0.08***	2016:09
Refugio	10.61	***0.07***	2.55	***0.10***	2016:10	10.59	***0.08***	3.09	***0.06***	2018:03	22.88	***0.00***	8.56	***0.00***	2017:09
Sabine	8.14	0.20	1.95	0.19	2017:02	11.59	***0.05***	4.02	***0.02***	2017:01	9.04	0.14	3.12	***0.05***	2016:03
San Jacinto	6.02	0.41	1.53	0.30	2014:07	9.63	0.11	2.85	***0.07***	2017:02	21.01	***0.00***	9.11	***0.00***	2016:09
San Patricio	7.89	0.21	2.11	0.16	2017:09	9.37	0.12	2.21	0.14	2014:12	9.25	0.13	3.14	***0.05***	2016:09
Tyler	8.31	0.18	2.06	0.17	2018:04	7.45	0.25	2.17	0.15	2017:04	14.74	***0.01***	5.25	***0.01***	2017:09
Victoria	4.89	0.58	1.62	0.27	2014:07	17.01	***0.01***	5.29	***0.01***	2015:01	8.72	0.16	2.42	0.12	2016:06
Walker	8.11	0.20	2.03	0.17	2017:02	8.10	0.20	1.77	0.23	2015:09	6.91	0.30	2.27	0.14	2016:09
Waller	7.63	0.24	1.83	0.22	2017:03	5.66	0.46	1.25	0.40	2015:01	8.49	0.17	2.71	***0.08***	2016:03
Wharton	6.87	0.31	1.78	0.23	2017:02	5.13	0.54	1.13	0.46	2018:02	10.26	***0.09***	3.60	***0.03***	2016:03
DR Median	7.30	0.26	1.81	0.22		8.50	0.17	2.34	0.13		9.60	0.11	3.02	0.06	
Non-DR Median	7.31	0.26	1.75	0.24		7.98	0.21	2.22	0.14		10.07	0.09	3.06	0.06	

Notes: DR denotes the Disaster Region. AQ and AP denote Andrews-Quandt test and Andrews-Ploberger test statistics, respectively. The regression model is ARIMA(1,0,1) for unemployment, and ARIMA(1,1,1) for employment and wages. Due to trimmings at endpoints, tests are effectively run for the monthly data between January 2014 and August 2018.

Appendix: Table A2. Structural Break Tests for Florida Disaster Counties

	Unemployment					Employment					Wage				
County:	AQ	*p*-value	AP	*p*-value	Break Date	AQ	*p*-value	AP	*p*-value	Break Date	AQ	*p*-value	AP	*p*-value	Break Date
Alachua	6.46	0.60	1.41	0.62	2018:08	13.83	***0.02***	4.09	***0.02***	2015:03	17.17	***0.00***	6.90	***0.00***	2016:09
Baker	8.48	0.35	1.82	0.45	2018:08	13.30	***0.02***	3.69	***0.03***	2015:09	11.49	***0.05***	3.17	***0.05***	2016:03
Bradford	4.98	0.80	1.10	0.77	2018:08	4.70	0.61	1.40	0.34	2016:12	8.41	0.18	2.44	0.11	2017:03
Brevard	9.30	0.27	3.03	0.16	2018:07	8.79	0.15	2.03	0.18	2015:09	5.69	0.45	1.28	0.39	2014:05
Broward	5.70	0.71	1.57	0.55	2018:08	6.70	0.33	1.44	0.33	2017:12	8.66	0.16	2.47	0.11	2014:05
Charlotte	10.07	0.21	3.07	0.15	2018:08	3.55	0.80	0.78	0.66	2013:10	8.14	0.20	2.04	0.17	2015:12
Citrus	6.48	0.60	1.53	0.57	2018:08	11.25	***0.06***	3.48	***0.04***	2015:09	8.53	0.17	1.51	0.31	2015:12
Clay	7.22	0.50	1.58	0.54	2018:08	11.74	***0.05***	2.92	***0.07***	2015:09	4.42	0.66	0.99	0.53	2016:03
Collier	5.40	0.75	1.59	0.54	2018:08	5.88	0.43	1.12	0.46	2017:04	20.87	***0.00***	7.16	***0.00***	2016:09
Columbia	5.55	0.73	1.23	0.71	2018:08	8.63	0.16	2.09	0.16	2013:06	6.79	0.32	1.59	0.28	2015:12
DeSoto	6.35	0.61	1.67	0.51	2014:09	7.04	0.29	2.04	0.17	2015:07	10.25	***0.09***	2.58	***0.10***	2016:03
Dixie	5.66	0.71	1.23	0.71	2018:07	6.76	0.32	1.71	0.25	2016:09	5.97	0.42	1.48	0.31	2018:06
Duval	6.16	0.64	1.76	0.47	2018:07	12.23	***0.04***	3.17	***0.05***	2016:12	7.83	0.22	2.02	0.18	2017:12
Flagler	7.13	0.51	2.01	0.38	2018:08	9.16	0.13	2.20	0.15	2014:01	8.57	0.17	2.11	0.16	2015:12
Gilchrist	5.75	0.70	1.16	0.74	2014:05	10.69	***0.07***	3.10	***0.06***	2015:10	14.54	***0.01***	4.86	***0.01***	2015:09
Glades	11.21	0.14	3.96	***0.07***	2015:07	6.28	0.38	1.26	0.40	2016:12	14.35	***0.02***	4.71	***0.01***	2016:06
Hamilton	6.93	0.53	1.67	0.51	2014:04	6.17	0.39	1.53	0.30	2016:01	15.08	***0.01***	5.50	***0.01***	2016:03
Hardee	7.29	0.49	2.26	0.31	2018:07	5.39	0.50	1.52	0.30	2016:06	11.91	***0.04***	3.63	***0.03***	2015:06
Hendry	6.14	0.64	1.75	0.48	2015:12	7.58	0.24	1.51	0.31	2016:12	25.14	***0.00***	9.52	***0.00***	2016:09
Hernando	8.08	0.39	2.19	0.33	2018:08	10.05	***0.09***	2.66	***0.09***	2015:09	25.74	***0.00***	9.44	***0.00***	2016:09
Highlands	9.77	0.23	3.40	0.11	2018:08	10.75	***0.07***	2.95	***0.07***	2016:05	9.65	0.11	2.63	***0.09***	2015:12
Hillsborough	6.08	0.65	1.48	0.59	2018:08	8.33	0.18	2.09	0.16	2015:09	6.07	0.40	1.30	0.39	2014:05
Indian River	7.93	0.41	2.83	0.19	2018:07	4.72	0.61	1.21	0.42	2013:10	9.37	0.12	2.95	***0.07***	2014:12
Lafayette	6.66	0.57	1.62	0.53	2018:08	8.65	0.16	2.27	0.14	2015:12	9.83	0.10	2.75	***0.08***	2016:03
Lake	12.81	***0.08***	4.16	***0.06***	2018:08	3.89	0.75	0.66	0.75	2015:09	12.96	***0.03***	3.60	***0.03***	2015:12
Lee	8.42	0.35	1.73	0.48	2018:08	2.70	0.93	0.75	0.68	2018:06	12.72	***0.03***	3.64	***0.03***	2014:05
Levy	5.34	0.76	1.69	0.50	2018:08	6.79	0.32	1.95	0.19	2014:04	17.53	***0.00***	5.61	***0.01***	2016:09
Manatee	12.66	***0.08***	3.53	***0.10***	2018:08	3.68	0.78	0.77	0.67	2018:06	13.91	***0.02***	4.54	***0.01***	2014:05
Marion	11.73	0.12	4.08	***0.06***	2018:08	9.46	0.12	1.97	0.19	2014:06	11.66	***0.05***	3.71	***0.03***	2016:09
Martin	7.88	0.41	2.41	0.27	2018:08	2.63	0.94	0.40	0.94	2014:10	6.33	0.37	1.58	0.29	2015:12
Miami-Dade	4.37	0.88	1.20	0.72	2014:12	13.63	***0.02***	3.64	***0.03***	2014:11	4.21	0.69	0.84	0.62	2014:06
Monroe	14.21	***0.05***	5.66	***0.05***	2017:08	2.75	0.92	0.61	0.78	2017:08	12.02	***0.04***	3.11	***0.06***	2015:12
Nassau	6.40	0.61	1.14	0.75	2018:08	9.58	0.11	2.65	***0.09***	2015:09	10.22	***0.09***	2.63	***0.09***	2017:06
Okeechobee	8.27	0.37	2.36	0.28	2014:07	6.54	0.34	2.10	0.16	2017:03	14.10	***0.02***	4.23	***0.02***	2016:12
Orange	5.40	0.75	1.29	0.68	2018:08	3.94	0.74	0.64	0.75	2015:09	7.49	0.25	1.40	0.34	2015:12
Osceola	6.21	0.63	1.85	0.44	2018:08	4.19	0.70	0.63	0.76	2014:12	7.97	0.21	2.39	0.12	2015:12
Palm Beach	6.37	0.61	2.07	0.37	2018:08	5.75	0.45	0.96	0.55	2015:09	9.71	0.11	2.17	0.15	2015:12
Pasco	10.71	0.17	3.60	***0.09***	2018:08	7.73	0.23	1.86	0.21	2015:09	9.34	0.12	2.78	***0.08***	2015:12
Pinellas	9.38	0.26	2.98	0.16	2018:08	11.26	***0.06***	2.72	***0.08***	2015:09	12.11	***0.04***	4.07	***0.02***	2016:09
Polk	10.25	0.20	3.16	0.14	2018:08	6.74	0.32	1.52	0.30	2015:10	12.04	***0.04***	3.71	***0.03***	2014:12
Putnam	10.03	0.21	2.20	0.33	2014:01	7.29	0.27	1.75	0.24	2016:07	7.68	0.23	1.93	0.19	2015:12
Sarasota	8.90	0.30	2.40	0.27	2018:08	3.99	0.73	0.74	0.69	2016:09	18.67	***0.00***	6.07	***0.00***	2014:05
Seminole	6.84	0.55	1.72	0.49	2018:08	5.61	0.47	1.16	0.45	2017:11	8.11	0.20	1.82	0.22	2015:06
St. Johns	8.89	0.31	1.96	0.40	2018:08	9.41	0.12	2.00	0.18	2015:09	13.62	***0.02***	4.65	***0.01***	2015:12

Appendix: Table A2 (cont'd). Structural Break Tests for Florida Disaster Counties

	Unemployment					**Employment**					**Wage**				
County:	AQ	*p*-value	AP	p-value	Break Date	AQ	*p*-value	AP	*p*-value	Break Date	AQ	*p*-value	AP	*p*-value	Break Date
St. Lucie	15.11	***0.03***	4.83	***0.03***	2015:11	4.19	0.70	0.80	0.65	2014:10	5.78	0.44	2.42	0.11	2014:05
Sumter	13.99	***0.05***	4.20	***0.05***	2018:08	6.43	0.36	1.45	0.33	2014:08	4.17	0.70	1.11	0.47	2014:12
Suwannee	5.23	0.77	1.55	0.56	2018:08	8.65	0.16	2.05	0.17	2017:09	6.61	0.34	1.87	0.21	2015:09
Union	7.40	0.47	1.62	0.53	2018:08	7.51	0.25	2.40	0.12	2016:12	7.05	0.29	1.75	0.24	2016:03
Volusia	5.97	0.67	1.58	0.55	2018:08	8.76	0.15	2.01	0.18	2014:06	6.76	0.32	1.73	0.24	2015:12
DR Median	7.21	0.50	1.82	0.45		7.04	0.29	1.86	0.21		9.65	0.11	2.63	0.09	
Non-DR Median	6.42	0.60	1.73	0.48		8.75	0.16	2.12	0.16		12.11	0.04	3.39	0.04	

Notes: DR denotes the Disaster Region. AQ and AP denote Andrew-Quandt test and Andrews-Ploberger test statistics, respectively. The regression model is ARIMA(1,0,1) for unemployment, and ARIMA(1,1,1) for employment and wages. Due to trimmings at endpoints, tests are effectively run for the monthly data between January 2014 and August 2018.