Storm Surge to Demand Surge: Exploratory Study of Hurricanes, Labor Wages, and Material Prices

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Abstract: Demand surge is understood to be a socioeconomic phenomenon associated with large-scale natural disasters. It is most commonly explained as higher repair costs resulting from higher labor wages and material prices after a large- versus small-scale disaster. This paper explores this explanation by developing quantitative models for the relative cost change of sets of repairs to residential and commercial properties damaged by Atlantic hurricanes in the southeast mainland United States. Cost data from 2002–2010 show that changes in the labor component drive the changes in total repair costs and that cost changes can vary notably by year and less so by geographic region. A series of multilevel regression models is then proposed to predict the relative cost changes by considering several combinations of the following explanatory variables: the largest wind speed at a city in a hurricane season; the number of tropical storms passing near a city in a hurricane season; and relative cost changes in the first two quarters of the year. For commercial properties in Florida, the data are sufficient to develop models with only linear and interacting explanatory variables. These models, however, show a large uncertainty in expected cost changes and a systematic underprediction for larger cost changes. For residential properties in Florida and both residential and commercial properties in other states on the Atlantic and Gulf of Mexico coasts, either the data are insufficient to develop robust models or a more complex model must be proposed for relative cost changes at these property types. **DOI:** 10.1061/(ASCE)NH.1527-6996.0000111.

CE Database subject headings: Natural disasters; Insurance; Reconstruction; Storm surges; Hurricanes; Damage; Costs.

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Introduction

Demand surge is understood to be a socioeconomic phenomenon of large-scale natural disasters: repair costs rise, locally and temporarily, through any of several possible demand- or supply-related mechanisms. As a result, the repair cost for a property damaged in a large event exceeds the repair cost for a similar property similarly damaged in a small event. Increased repair costs after past large-scale natural disasters have been reported in the range of 20–50%. For example, after the 1994 Northridge earthquake, insurers observed a 20% increase in the costs to settle claims (Kuzak and Larsen 2005, p. 113). Commercial catastrophe modelers estimated demand surge of 10–40% after Hurricane Katrina (Guy Carpenter and Co. 2005). The Australian Securities and Investments Commission (2007) reported that insurers saw reconstruction costs increase 50% after Cyclone Larry in 2006.

Institutions that indemnify properties exposed to natural disasters, such as insurers, reinsurers, and governments, pay the equivalent of billions of U.S. dollars in claims after large-scale natural disasters. These payments can be even larger as a result of demand surge. Anticipating whether demand surge is 20 versus 30 versus 50% can affect how insurers, reinsurers, and governments plan for and respond to large-scale natural disasters. Understanding the socioeconomic mechanisms of demand surge should result in better predictive models and is presumably a prerequisite to reducing its magnitude after future disasters.

Various groups have developed quantitative models for demand surge. The authors surveyed these models in Olsen and Porter (2010) and updated the summary in Olsen and Porter (2011b). The primary developers of demand-surge models are commercial catastrophe modelers, such as AIR Worldwide, RMS, and EQECAT. (Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. government.) These companies provide quantitative estimates of risk, usually resulting from natural hazards, for a single property or set of properties. Their clients are mostly insurance and reinsurance companies that are interested in anticipating their monetary losses in the event of a natural disaster. Although these models are proprietary, they generally multiply the ground-up loss—the loss at a property before applying insurance deductibles, copayments, or limits—by a factor, typically between 1.0 and 1.6. This multiplicative factor can be based on the expected loss to the insurance industry as a whole, the affected region, the type of peril, the type of property, or some combination of these.

In previous work, the authors proposed seven general descriptions of socioeconomic mechanisms that could result in increased repair costs after large- versus small-scale natural disasters (Olsen and Porter 2010). These explanations for demand surge followed from studies of the reconstruction periods after historical natural disasters, including earthquakes, hailstorms, cyclones, flooding, and wildfires, from the fourteenth, eighteenth, and nineteenth centuries through the present day, in Australia, the United States, the United Kingdom, and continental Europe. Although the circumstances contributing to increased reconstruction costs were unique to each disaster, there were common explanations for demand surge

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when the disasters were considered together. Briefly, the authors' explanations for demand surge involve the following factors: (1) the total amount of repair work; (2) the costs of reconstruction materials, labor, and equipment; (3) reconstruction timing; (4) construction contractor fees; (5) general economic conditions; (6) insurance claims handling; and (7) decisions of an insurance company.

The work described in this paper addresses part of the second proposed factor for demand surge, as well as the fifth factor to a limited extent. The change of reconstruction labor wages and material prices from before to after Atlantic hurricane seasons are studied by relating these cost changes to tropical storms and to wage and price changes in the first half of the calendar year. As discussed in Olsen and Porter (2010), increased cost of reconstruction labor and materials is the most common explanation for demand surge, and therefore, among the proposed factors, is a good first choice for an in-depth study.

Cost and Hazard Data

Although demand surge has been observed after disasters caused by many different types of natural hazards, precise data on reconstruction costs consistently measured after many disasters are not readily available. After some disasters, observers informally noted cost changes for specific lists of construction labor, materials, or equipment, but the lists are not consistent from one disaster to another. Construction cost-estimating firms routinely collect data for more comprehensive lists of construction costs at cities of many sizes throughout the world. Existing data from one such firm are used to compare the same labor-wage and material-price changes across several historical disasters. Thus, this study is limited by the frequency, locations, and choice of labor and materials collected by the cost-estimating firm.

The Atlantic hurricane seasons provide an opportunity to study demand surge quantitatively. The authors select 52 U.S. cities near the Atlantic or Gulf of Mexico coasts (Fig. 1) and collect data on labor and material costs in each city as well as the tropical storms affecting the cities. Each city is defined by the latitude and longitude values provided in the National Atlas of the United States (2003). The authors presume that each city's coordinates are near its city center and use no additional information about the city, such as population, incorporated area, or metropolitan area. The data are from two sources: *Xactimate 25* (labor and material costs) and the National Hurricane Center (hurricane tracks and intensities).

Labor and Material Costs

Xactware Solutions, a company based in Orem, Utah, collects pricing data on building repairs, contents replacement, and cleaning costs for more than 470 cities in the United States, Canada, the United Kingdom, and Ireland (Xactware 2011b, c). Xactware packages the pricing data into software appropriate for different applications. *Xactimate* is the software for estimating repair costs, and therefore claims, on property-insurance policies (Xactware 2011a). According to Xactware, "Eighty percent of insurance-repair contractors and 19 of the top 25—including 9 of the top 10—property insurers use *Xactimate* to calculate the cost of repairs" (Xactware 2012).

The authors collect a subset of the data *Xactimate* provides for each city. Xactware published cost data in the years 2002–2008 at the beginning of each quarter and, since 2009, publishes data at the beginning of each month. To use data from as many Atlantic hurricane seasons as possible, this study does not consider the monthly cost changes, only the cost changes reported from the beginning of one quarter to the beginning of another quarter. One author (K. A. Porter) chose sets of repair line items typically performed in reconstruction after hurricanes, based on his experience and judgment, for typical residential and commercial properties. The repair cost for the set is simply the sum of the costs for the individual line items. For residential properties, the set is 28 m^2 (300 sq ft) of composition shingle roofing; 9.3 m^2 (100 sq ft) of clay tile roofing; 3.7 m^2 (40 sq ft) of reglazing; 9.3 m^2 of installed drywall; 9.3 m^2 of carpet; and 19 m^2 (200 sq ft) of sealed and painted wood siding. For commercial properties, the set is 9.3 m^2 of three-ply roofing; 9.3 m^2 of gravel ballast roofing; 9.3 m^2 of PVC membrane roofing; 9.3 m^2 of metal roofing; 9.3 m^2 of glass curtain wall; 9.3 m^2 of installed drywall; 9.3 m^2 of carpet; and 9.3 m^2 of sealed and painted wood siding [see Olsen and Porter (2011a) for details of these repair line items]. These sets of repairs are not compared to actual insurance claims. The authors assume that the sets are consistent with the types of repairs needed after hurricanes and thus assume that the repair costs for these sets are highly correlated with insurance claims following these natural disasters.

For each line-item repair, *Xactimate* provides several types of costs. The total cost to make a repair is the remove and replace (R&R) cost, which is the sum of labor, material, and equipment costs; market conditions; labor burden (a markup resulting from any labor costs unique to that repair item or to account for the overhead to employ laborers); and taxes. Three of these costs are used: the total R&R cost, the material component cost (MAT), and the sum of regular labor and labor-burden component costs (LAB). Because distinct sets of repairs exist for residential (RES) and commercial (COM) properties, this study tracks a total of six sets of repair costs. Also, *Xactimate* reports market costs, the costs reported to Xactware in estimates of repair costs used to settle insurance claims, and hard costs, the costs reported by construction materials and equipment suppliers as well as construction contractors (Xactware 2009). This study considers only the market costs because these more directly represent the costs paid by insurance companies after past disasters [see Olsen and Porter (2011a) for analyses of the hard costs].

The *Xactimate* databases are not complete for all cities at all times. This is a particular problem for many Florida cities in October 2004. When a data point is missing, the authors linearly interpolate between the preceding and succeeding quarters (in the years 2002–2008) or months (2009–2010). The authors presume that a linear interpolation underestimates the actual wage or price because there must have been highly unusual conditions if Xactware was not able to use its routine procedures to report the data.

Hurricane Intensities

The National Hurricane Center provides observations of tropical storms, including latitude, longitude, maximum wind speed, and minimum central pressure. Specifically, this study uses the Extended

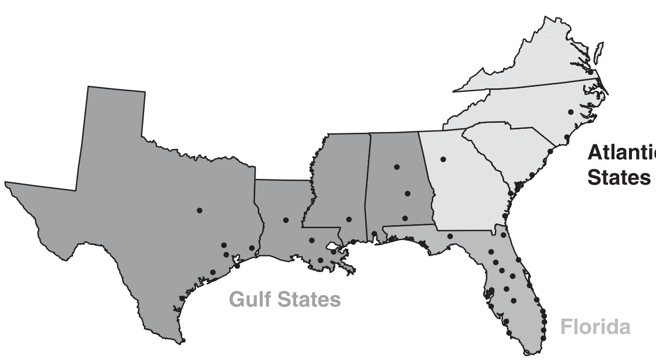

Fig. 1. Fifty-two cities near Atlantic and Gulf coasts with data from *Xactimate* and geographic regions used in this study

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Best Track File (Demuth et al. 2006). For each of the 52 cities, the authors first identify the storms that came within 200 km of the city in a given hurricane season; 200 km is used because it is small enough to exclude tropical storms not affecting a city but large enough to allow for multiple storms affecting a city in a hurricane season. The authors then apply the Holland Wind Profile (Holland 1980) at each observed point on the tropical storm's path, calculating the gradient wind speed at a city resulting from each observation at a known distance from the city center. (The gradient wind speed is defined as the wind speed in the absence of friction from the Earth's surface. It is the wind speed above the hurricane boundary layer, approximately 1–2 km above the surface, and the gradient wind speed is roughly 25% greater than the wind speed at the surface.)

The authors find the peak wind speed and the number of tropical storms affecting each city in the 2002–2010 hurricane seasons. If there is only one tropical storm affecting a city in a season, the study uses the maximum gradient wind speed at the city among those calculated for each observation on a tropical storm's path. If there is more than one such storm, the study uses the maximum gradient wind speed among the maximum wind speeds of the individual storms. The number of tropical storms affecting a city, or proximate storms, is a count of the tropical storms whose track in the Extended Best Track File came within 200 km of a city, irrespective of wind speed. The authors use wind speed and number of proximate storms as proxies for the demand for repair materials and services in that city. These proxies are used for lack of better data; there appear to be no well-documented, publicly available, and consistent records of actual total repair expenditures across multiple disasters.

Development of Models for Relative Cost Change

This section examines the relationship between cost changes in the *Xactimate* data and observed tropical storms during the 2002–2010 Atlantic hurricane seasons. The purpose of these models is to address several proposed explanations for demand surge caused by increased labor wages and material prices. The authors seek to establish (1) whether labor wages and material prices increase notably after large tropical storms compared with small storms or in the absence of a storm, and (2) whether wages and prices increase more when multiple tropical storms affect a city in a single hurricane season. Also, as mentioned in the Introduction section, the authors' previous research documented that underlying economic conditions have been proposed as a factor to explain demand surge. The authors use wage and price changes in the first two quarters of a calendar year as indicators of the economic conditions preceding and independent of the hurricane season.

The authors define a relative cost change as the difference between the final and initial costs for a time period divided by the initial cost. For the six sets of repair costs noted previously, the relative change in the costs of repairs during the following time periods is known: July 1 to January 1, Δ, (roughly from before to after the Atlantic hurricane season, which is officially from June 1 to November 30); and incrementally by quarter: January 1 to April 1, Δ_1; April 1 to July 1, Δ_2; July 1 to October 1; and October 1 to January 1. In this initial, exploratory study, the authors not attempt to associate cost changes in the third and fourth quarters with specific hurricanes.

First, the data are plotted to develop an initial understanding of possible explanatory variables for repair cost changes during the Atlantic hurricane season. Then, a series of quantitative models is proposed based on the *Xactimate* and Extended Best Track File (Demuth et al. 2006) data and the initial understanding. Finally, the best predictive models among those proposed are identified and discussed.

Data Exploration

Fig. 2 shows the relative market cost changes from July to the following January, denoted by Δ, for the six sets of repair costs as functions of the peak gradient wind speed of a proximate storm. Data plotted where the wind speed is none are for cities with no proximate storm. There are several obvious features in the plots.

For the R&R and labor component sets [Figs. 2(a–d)], the maximum cost change when there is no proximate storm is similar to the maximum cost change when there is at least one storm with gradient wind speed less than roughly 40 km/h. In other words, R&R and labor component costs can increase by 10–20% in the absence of a proximate tropical storm, and these cost changes exceed 20% only if there is at least one sufficiently intense tropical storm.

There is no apparent correlation between wind speed and the relative change in material component costs [Figs. 2(e and f)]. The range of material cost changes when there is no proximate storm is similar to the range when there is at least one storm, independent of wind speed. These cost changes are well within $\pm 20\%$ for residential properties and within $\pm 5\%$ for commercial properties.

The R&R and labor component cost changes are more strongly correlated than are the R&R and material component cost changes. Although separate plots of these correlations are not provided, Fig. 2 shows that the R&R and labor component cost changes are simultaneously large at high wind speeds and simultaneously small at low wind speeds. A similar statement cannot be made for the R&R and material component cost changes. Because the material component cost changes do not vary with wind speed, there is little correlation with the R&R cost changes, which do vary with wind speed. Thus, the labor component cost changes appear to drive the total R&R cost changes.

Data from different years and different states can be distinct. The residential, labor, and material costs most obviously show the differences between years. For example, the changes in the material costs in 2007 are clearly distinct from those in 2008 [Fig. 2(e)], and the changes in the labor costs in 2004 and 2005 are different [Fig. 2(c)]. On the scale used in Fig. 2, the differences among states are less obvious than those among years. The largest positive changes in the residential and commercial total and labor costs are exclusively from Florida in 2004. Observed, relative cost changes in the other states and years studied are never as large, implying that the circumstances causing cost changes in Florida in 2004 were unusual. Because data from different U.S. states and years can be distinguished, all data for a set of repair costs are not independently and identically distributed (i.i.d.) about any single curve. Thus, a regression methodology that makes this assumption about the data set as a whole cannot be applied.

Fig. 3 shows the distributions of relative market cost changes as functions of the number of proximate tropical storms. In this case, the authors consider the full data sets not separated by year or state. For the R&R and labor component costs [Figs. 3(a–d)], the median relative cost change appears to increase as the number of proximate storms increases. Also, the range of the cost changes increases with an increasing number of storms. For the material costs [Figs. 3(e and f)], the median relative cost change varies with the number of proximate storms, but there is no clear trend in these median values.

Grouping Data

As discussed in the previous section, the data for each of the six sets of repair cost changes are not i.i.d. about a single curve. This suggests that the data for all cities and all years within a single set of repair costs are not generated by a single process or, in other words, are not generated by a single underlying population. A single regression model might not be appropriate for all data points.

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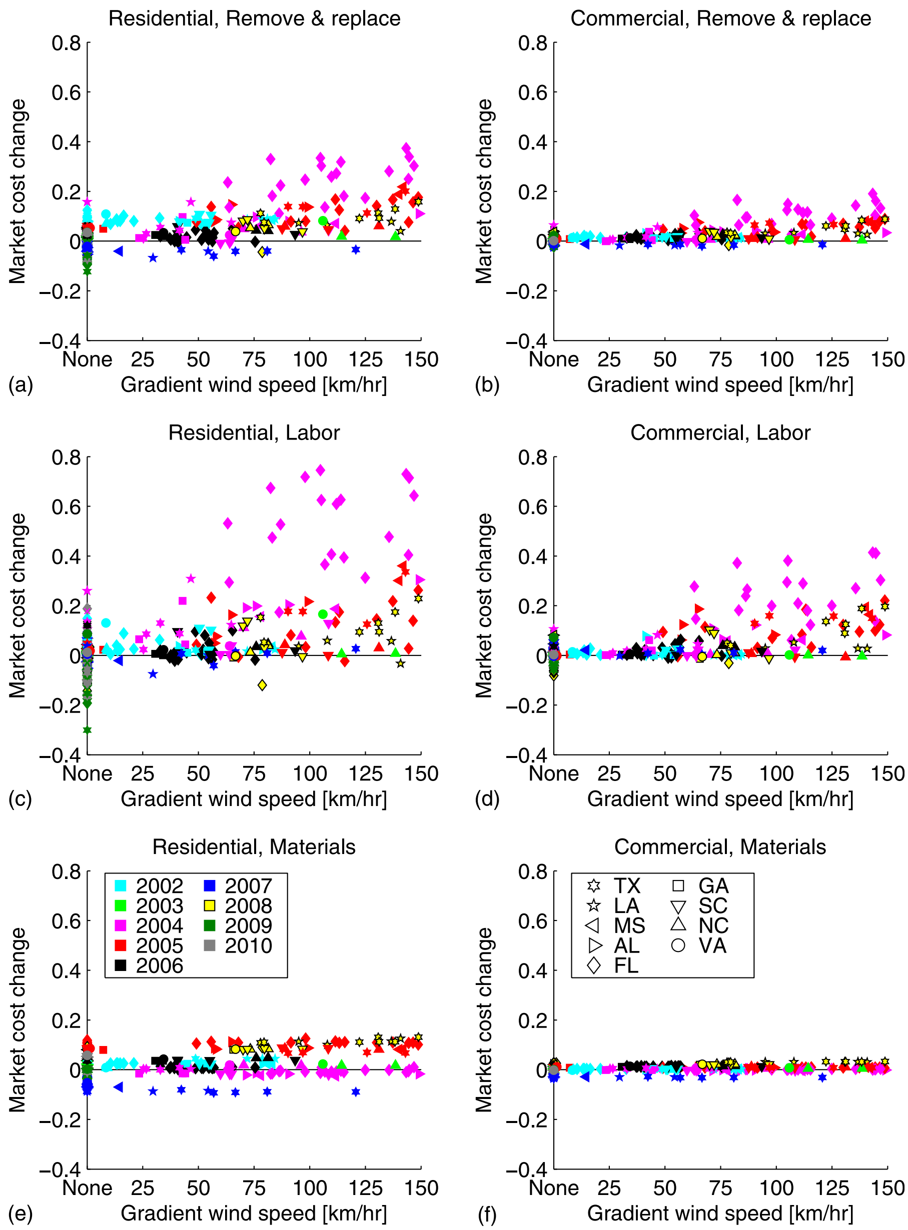

Fig. 2. (Color) Observed, relative, market cost change from July to January versus gradient wind speed for six sets of repairs (symbol colors represent different Atlantic hurricane seasons, and symbol shapes represent different U.S. states)

If the data are grouped instead, the groups might share the same functional relationship between the explanatory and response variables, but the parameter values of the models would differ among the groups. This approach to regression is known as multilevel, hierarchical, or mixed-effects modeling (e.g., Gelman and Hill 2007). The authors motivate the multilevel models proposed in the next section by inspecting groups of data in this section.

The findings of the previous section suggest that peak wind speed, the number of proximate storms, U.S. state, and year might all contribute to the observed variation in relative cost changes. Note that the statistical unit of analysis is different among these variables: peak wind speed, number of storms, and cost change are measured at each city, whereas the U.S. state and year apply to data from many cities, forming obvious groups of data. Although the data are available by U.S. state, the authors instead reagionalize the states as the Gulf States (17 cities, including Texas, Louisiana, Mississippi, and Alabama), Florida (25 cities), and the Atlantic states (10 cities, including Georgia, South Carolina, North Carolina, and Virginia). Fig. 1 indicates these regions. Groups defined by individual U.S. state have too little data, and the data from different states within a region are not obviously distinct. The geography of the southeastern United States suggested the three regions, but the authors do not perform formal hypothesis tests that these groups of states are better than any alternatives.

Fig. 4 shows the residential R&R data for relative cost change during an Atlantic hurricane season versus gradient wind speed, grouped by geographic region and year. The figure also shows simple linear regression models of the data with at least one proximate storm, as well as confidence bands for the mean relative cost change given a wind speed. These models serve as references for the following discussion of the data groupings; they are not the same as the multilevel models developed in the next section.

For any given year, no single line lies in the three confidence bands across regions, and for a given region, no single line lies in the

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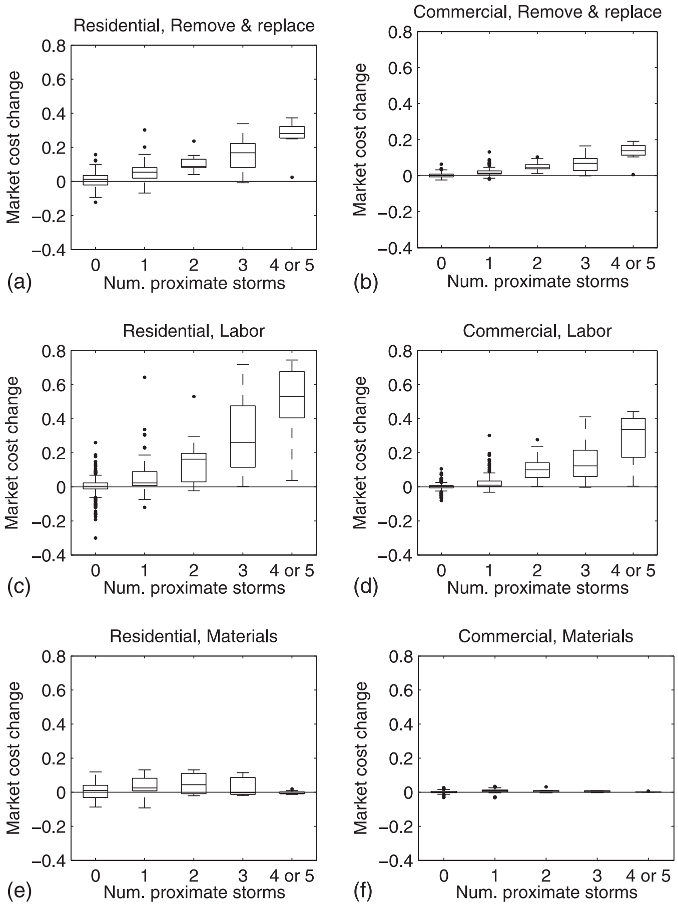

Fig. 3. Box-and-whisker plots of observed, relative, market cost change from July to January versus number of proximate tropical storms

confidence bands across all years. These observations support grouping the data by both region and year. The analogous figures for the commercial R&R and the residential and commercial labor component data are similar to Fig. 4. The figures for the material component cost changes, as suggested in Figs. 2(e and f), are uninteresting: the data scatter about roughly horizontal lines, which differ primarily in their cost-change-intercept value from year to year, with minor differences between geographic regions.

Fig. 4—as well as the analogous figures for the other sets of repair cost changes not shown—suggests that the year has an important influence on relative cost changes. In many years, specifically all years except 2004, 2005, and 2008, the cost changes have a relatively small variation about a mean, which is different from year to year, and the cost changes when there is a proximate storm are not different than the cost changes when there is no such storm. In 2004, 2005, and 2008, the cost changes when there is a proximate storm are distinct from those without a storm, and the slopes and cost-change-intercept values of the linear models can be different across these 3 years. There are differences from one region to another, justifying this grouping, but these differences are less obvious than those from one year to another.

Quantitative Models

This section proposes a series of multilevel models that formalize the authors' conjectures about the structure of the cost-change data. Based on the observations in the Data Exploration section, at the city level, the authors hypothesize that the wind speed of a proximate storm, the number of proximate storms, and cost changes in the first half of the year may predict the cost change in the last half of the year. The authors also suspect that the coefficient of each explanatory variable might vary annually, but to reduce the number of model parameters, models in which coefficients of interaction terms vary by year are not considered. For each of the three regions, the authors propose a full model structure to account for these conjectures

$$\Delta_c = \alpha_y + \beta_y w_c + \gamma_y n_c + \zeta w_c n_c + \eta_y \Delta_{1c} + \theta_y \Delta_{2c} + \kappa \Delta_{1c}\Delta_{2c} + \varepsilon_y \qquad (1)$$

where, for a given region in year y, $\alpha_y \sim \mathcal{N}(\mu_\alpha, \sigma_\alpha^2)$; $\beta_y \sim \mathcal{N}(\mu_\beta, \sigma_\beta^2)$; $\gamma_y \sim \mathcal{N}(\mu_\gamma, \sigma_\gamma^2)$; $\eta_y \sim \mathcal{N}(\mu_\eta, \sigma_\eta^2)$; $\theta_y \sim \mathcal{N}(\mu_\theta, \sigma_\theta^2)$; and α_y, β_y, γ_y, η_y, and θ_y are independently distributed; $\varepsilon_y \sim \mathcal{N}(0, \sigma_y^2)$ and represents the residual, or unexplained, variation within year y; at city c, Δ_c = relative cost change from July to the following January for a set of repairs; w_c = gradient wind speed in km/h; n_c = number of proximate storms; Δ_{1c} and Δ_{2c} = relative cost changes in the first and second quarters, respectively; and μ_α, μ_β, μ_γ, μ_η, μ_θ, σ_α^2, σ_β^2, σ_γ^2, σ_η^2, σ_θ^2, ζ, κ, and σ_y^2 = model parameters.

Each proposed model based on Eq. (1) includes a subset of the explanatory variables and has at least one year-dependent coefficient. The cost-change-intercept term and each first-order term may or may not be included in the model, and if included, the coefficient may or may not vary with year. Interaction terms may or may not be included in the model, but again, their coefficients are assumed constant across the years. These constraints on the proposed models result in 844 possible models for the data in each region.

To compare the proposed models, the authors estimate the parameter values and calculate Akaike's information criterion (AIC) (Akaike 1973). The AIC estimates how closely each model approximates reality as characterized by the available data set. Models with smaller AIC values more closely represent the data than models with larger AIC values. The authors use the *R: A Language and Environment for Statistical Computing* to calculate (1) the AIC value using the maximum-likelihood parameter estimates, and (2) the restricted maximum-likelihood parameter estimates for each proposed model. (Four of the models for commercial material component cost changes in Florida do not converge; these models are disregarded.) The difference, denoted Δ_{AIC}, is then found between each model's AIC value and the minimum AIC value among the proposed models. As a guideline, models with an AIC difference of 2 or less have substantial empirical support; that is, these models are not notably different from the model with the smallest AIC value, given the available data (Burnham and Anderson 2002, Section 2.6). Finally, the weight for model k is calculated as

$$\mathrm{weight}_k = \frac{\exp\left(-\frac{1}{2}\Delta_{\mathrm{AIC}k}\right)}{\sum_{m=1}^{M}\exp\left(-\frac{1}{2}\Delta_{\mathrm{AIC}m}\right)}$$

(Burnham and Anderson 2002, p. 75). The model weight can be interpreted as the probability that the model is best among those proposed and given the available data; the model weight is not the probability that the model is the best possible representation of reality. These calculations are repeated for each of the six sets of repair costs for the Gulf states, Florida, and the Atlantic states separately.

Table 1 shows the results of these calculations. Only six of the 18 data sets have a single model with substantial support. Three of these six models have weights near 1, and the remaining three have weights

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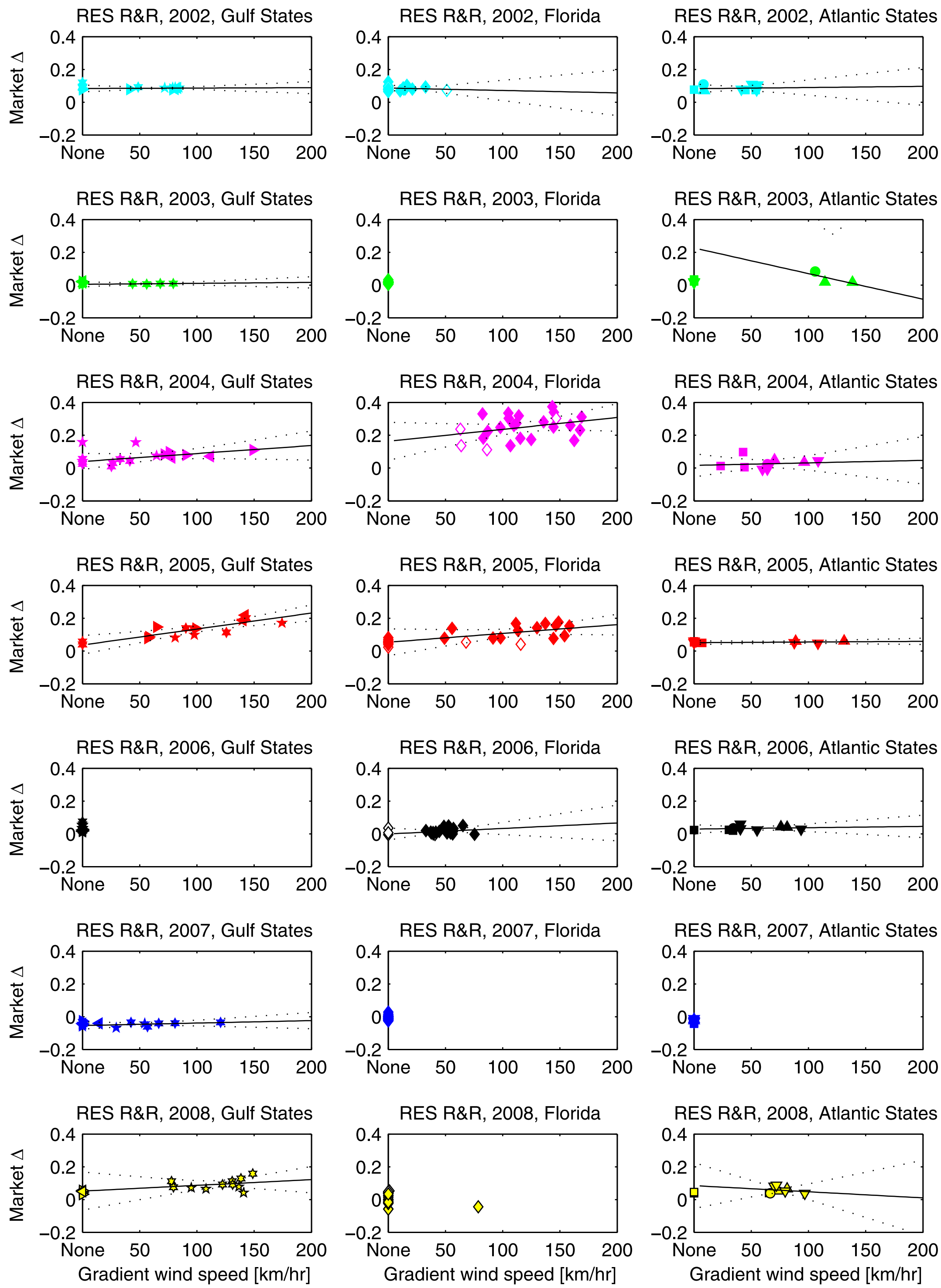

Fig. 4. (Color) Observed, market cost change versus wind speed, by geographic region and year, for residential R&R costs (solid line represents the mean of a simple linear regression given at least one proximate storm; dotted lines indicate 95% confidence bands for the mean cost change given wind speed; open symbols represent cities in northern Florida)

near or below 0.5. Thus, only the models for the commercial cost changes in Florida with the smallest AIC values are notably better than the other proposed models for the data sets. Table 2 lists the estimated parameter values for these three models. One of the remaining 12 data sets has three models with substantial support. However, the sum of the weights for these models is only 0.25, which suggests that additional data should be collected or additional knowledge applied to reduce the number of candidate models and select the best one.

The three models for commercial cost changes in Florida are now compared against their respective data sets to check for systematic deviations of the models' expected values from the observed data. If each model had a single level, the model's expected cost changes would first be calculated from the observed values of the explanatory variables, and then these predictions would be compared to the observed cost changes in a residual plot. Each of these residuals is deterministic in a single-level regression model. However, in a

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Table 1. Proposed Models and Their AIC Values for Relative Cost Changes from July to January by Region in the Southeastern United States

Region	Set of repairs	Multilevel model	Log-likelihood	AIC	Δ_{AIC}	Weight
GS	RES R&R	$\alpha_y + \beta w_c + \gamma n_c + \zeta w_c n_c + \theta\Delta_{2c} + \varepsilon_y$	144.6	−265.2	0.00	0.550
FL	RES R&R	$\alpha_y + \zeta w_c n_c + \eta\Delta_{1c} + \kappa\Delta_{1c}\Delta_{2c} + \varepsilon_y$	137.7	−255.5	0.00	0.110
FL	RES R&R	(Five additional models have substantial support)				
AS	RES R&R	$\alpha_y + \eta\Delta_{1c} + \theta\Delta_{2c} + \varepsilon_y$	116.2	−212.4	0.00	0.078
AS	RES R&R	(Six additional models have substantial support)				
GS	RES LAB	$\alpha + \beta_y w_c + \gamma n_c + \zeta w_c n_c + \theta\Delta_{2c} + \varepsilon_y$	105.3	−186.5	0.00	0.470
FL	RES LAB	$\alpha_y + \gamma n_c + \varepsilon_y$	75.2	−134.4	0.00	0.044
FL	RES LAB	(14 additional models have substantial support)				
AS	RES LAB	$\beta w_c + \gamma n_c + \eta\Delta_{1c} + \theta_y\Delta_{2c} + \kappa\Delta_{1c}\Delta_{2c} + \varepsilon_y$	89.6	−155.2	0.00	0.249
GS	RES MAT	$\alpha_y + \gamma n_c + \theta_y\Delta_{2c} + \varepsilon_y$	178.1	−332.3	0.00	0.192
GS	RES MAT	(Four additional models have substantial support)				
FL	RES MAT	$\alpha_y + \eta\Delta_{1c} + \theta\Delta_{2c} + \kappa\Delta_{1c}\Delta_{2c} + \varepsilon_y$	290.6	−561.3	0.00	0.275
FL	RES MAT	(Three additional models have substantial support)				
AS	RES MAT	$\beta w_c + \gamma n_c + \zeta w_c n_c + \eta_y\Delta_{1c} + \theta_y\Delta_{2c} + \kappa\Delta_{1c}\Delta_{2c} + \varepsilon_y$	171.0	−312.0	0.00	0.133
AS	RES MAT	$\beta w_c + \gamma n_c + \eta_y\Delta_{1c} + \theta_y\Delta_{2c} + \kappa\Delta_{1c}\Delta_{2c} + \varepsilon_y$	169.3	−310.5	1.45	0.064
AS	RES MAT	$\eta_y\Delta_{1c} + \theta_y\Delta_{2c} + \kappa\Delta_{1c}\Delta_{2c} + \varepsilon_y$	167.1	−310.1	1.85	0.053
GS	COM R&R	$\alpha_y + \zeta w_c n_c + \varepsilon_y$	180.5	−343.0	0.00	0.189
GS	COM R&R	(Four additional models have substantial support)				
FL	COM R&R	$\alpha + \beta_y w_c + \gamma_y n_c + n_y\Delta_{1c} + \theta\Delta_{2c} + \varepsilon_y$	302.5	−573.1	0.00	1.000
AS	COM R&R	$\alpha_y + \theta\Delta_{2c} + \varepsilon_y$	170.2	−322.4	0.00	0.044
AS	COM R&R	(12 additional models have substantial support)				
GS	COM LAB	$\alpha_y + \gamma n_c + \zeta w_c n_c + \theta\Delta_{2c} + \varepsilon_y$	125.4	−228.8	0.00	0.162
GS	COM LAB	(Five additional models have substantial support)				
FL	COM LAB	$\beta_y w_c + \gamma n_c + \theta_y\Delta_{2c} + \kappa\Delta_{1c}\Delta_{2c} + \varepsilon_y$	237.6	−451.3	0.00	0.986
AS	COM LAB	$\gamma_y n_c + \zeta w_c n_c + \varepsilon_y$	129.8	−241.6	0.00	0.023
AS	COM LAB	(19 additional models have substantial support)				
GS	COM MAT	$\alpha_y + \theta\Delta_{2c} + \varepsilon_y$	300.7	−583.3	0.00	0.240
GS	COM MAT	(Five additional models have substantial support)				
FL	COM MAT	$\alpha_y + \theta\Delta_{2c} + \kappa\Delta_{1c}\Delta_{2c} + \varepsilon_y$	687.1	−1356.1	0.00	0.962
AS	COM MAT	$\gamma_y n_c + \eta\Delta_{1c} + \theta_y\Delta_{2c} + \varepsilon_y$	236.4	−448.8	0.00	0.139
AS	COM MAT	(Three additional models have substantial support)				

Note: For brevity, only those models with substantial support are listed; if there are more than three such models, the model with the smallest AIC value and a count of the remaining models are shown instead. GS = Gulf states; FL = Florida; AS = Atlantic states.

Table 2. Estimated Parameter Values and Standard Error (SE) for Best Models of Market Cost Change from July to January for Repairs to Commercial Properties in Florida

Parameter	Associated explanatory variable	FL COM R&R	FL COM LAB	FL COM MAT
$\widehat{\mu_\alpha}$	(Cost-change intercept)	0.00649 (0.00625)	N/A	$2.45 \cdot 10^{-4}$ $(1.26 \cdot 10^{-7})$
σ_α	(Cost-change intercept)	N/A	N/A	0.0139
$\widehat{\mu_\beta}$	Wind speed	$-8.20 \cdot 10^{-6}$ $(1.40 \cdot 10^{-4})$	$2.47 \cdot 10^{-4}$ $(4.23 \cdot 10^{-4})$	N/A
$\sigma\beta$	Wind speed	$3.05 \cdot 10^{-4}$	$9.40 \cdot 10^{-4}$	N/A
$\widehat{\mu_\gamma}$	Number of proximate storms	0.0136 (0.00605)	0.0153 (0.00227)	N/A
σ_γ	Number of proximate storms	0.00396	N/A	N/A
$\widehat{\mu_\eta}$	Cost change in Q1	−0.410 (0.268)	N/A	N/A
σ_η	Cost change in Q1	0.459	N/A	N/A
$\widehat{\mu_\theta}$	Cost change in Q2	0.399 (0.115)	0.841 (0.636)	-0.654 $(3.00 \cdot 10^{-13})$
$\sigma\theta$	Cost change in Q2	N/A	1.40	N/A
$\hat{\kappa}$	Cross-term: cost changes in Q1 and Q2	N/A	6.30 (8.15)	5.84 $(3.29 \cdot 10^{-11})$
σ_y^2	(Residual variation in year y)	$\ln\mathcal{N}(-13.4, 95.6)$	$\ln\mathcal{N}(-10.3, 57.6)$	$\ln\mathcal{N}(-32.3, 1.52 \cdot 10^3)$

Note: As shown in Table 1, these best models do not include all terms in Eq. (1); the best models have parameters denoted as year dependent in Eq. (1), but the estimated parameter values are independent of year. N/A = the corresponding parameters are not in the best model for the data set.

multilevel model, the expected value of the response variable at a data point is stochastic because it depends on the values of parameters defined to be stochastic. Thus, an analysis of the multilevel models analogous to a standard residual plot must be used (Gelman and Hill 2007, Section 24.1). Because the values of the stochastic model parameters for a specific year cannot be anticipated, the authors sample from their distributions to define one realization of the model. This model is used to calculate its expected cost changes from the observed data points. Then, five statistics of the expected cost changes are calculated: the minimum and maximum values and the quartiles. The authors repeat this process 1,000 times, resulting in: 1,000 realizations of the multilevel model; 1,000 sets of expected

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cost changes from applying the model realizations to the single observed data set; and thus 1,000 values for each of the five statistics of the expected cost changes.

Fig. 5 shows the distributions of these statistics for the 1,000 sets of expected cost changes and overlays the statistics from the observed data set. A regression model is consistent with the observed data when the observed statistic value is near the central value of the corresponding distribution. For the R&R and labor component models, the observed minimum, first quartile, and median cost changes are near the center of their corresponding distributions from the model replications [Figs. 5(a–c) and (f–h)]. The observed third quartile and maximum cost changes are, respectively, 1.9 and 2.6 times larger (R&R) and 2.1 and 2.6 times larger (LAB) than the central values of their corresponding distributions [Figs. 5(d), (e), (i), and (j)]. These observations indicate that the models are consistent with the observed data when the expected cost changes are small or moderate [that is, cost changes less than roughly 0.038 (R&R) and 0.074 (LAB)]. For larger expected cost changes, the models systematically underpredict the observed data. For the material component model [Figs. 5(k–o)], only the observed minimum cost change is near the center of the distribution of minima from the sets of expected cost changes. For material cost changes larger than roughly -0.0047, the model underpredicts the observed data. The observed third quartile and maximum material cost changes are 4.7 and 7.4 times larger than the central values of the corresponding distributions.

Despite the observation in the Data Exploration section that some variability in the cost change data might be explained by the geographic region, the authors attempt to model the data without grouping by region. In other words, the authors propose the same series of models but now apply them to data grouped by year alone. The resulting models are applicable to any city in the southeastern United States. Table 3 summarizes the model comparisons. Only the data sets for commercial, R&R, and labor component cost changes can be modeled with a single model having substantial empirical support. The remaining data sets can be modeled by three or four models with substantial support. Note, however, that the total weight for the models with substantial support for each data set is between 0.56 and 0.76, and the primary difference between the candidate models is how to include the explanatory variables for wind speed and number of proximate storms. Thus, no one model or weighted average of the models with substantial support seems to have enough evidence at this point to recommend its use. Either the cost change data must be grouped by region, or the available data, knowledge of the underlying economic conditions, or both, are insufficient to distinguish one or a few best models.

Discussion

The data used in this study are the best available to the authors, but they are not ideal. The Atlantic hurricane season is officially from June 1 to November 30, but most hurricanes happen in August,

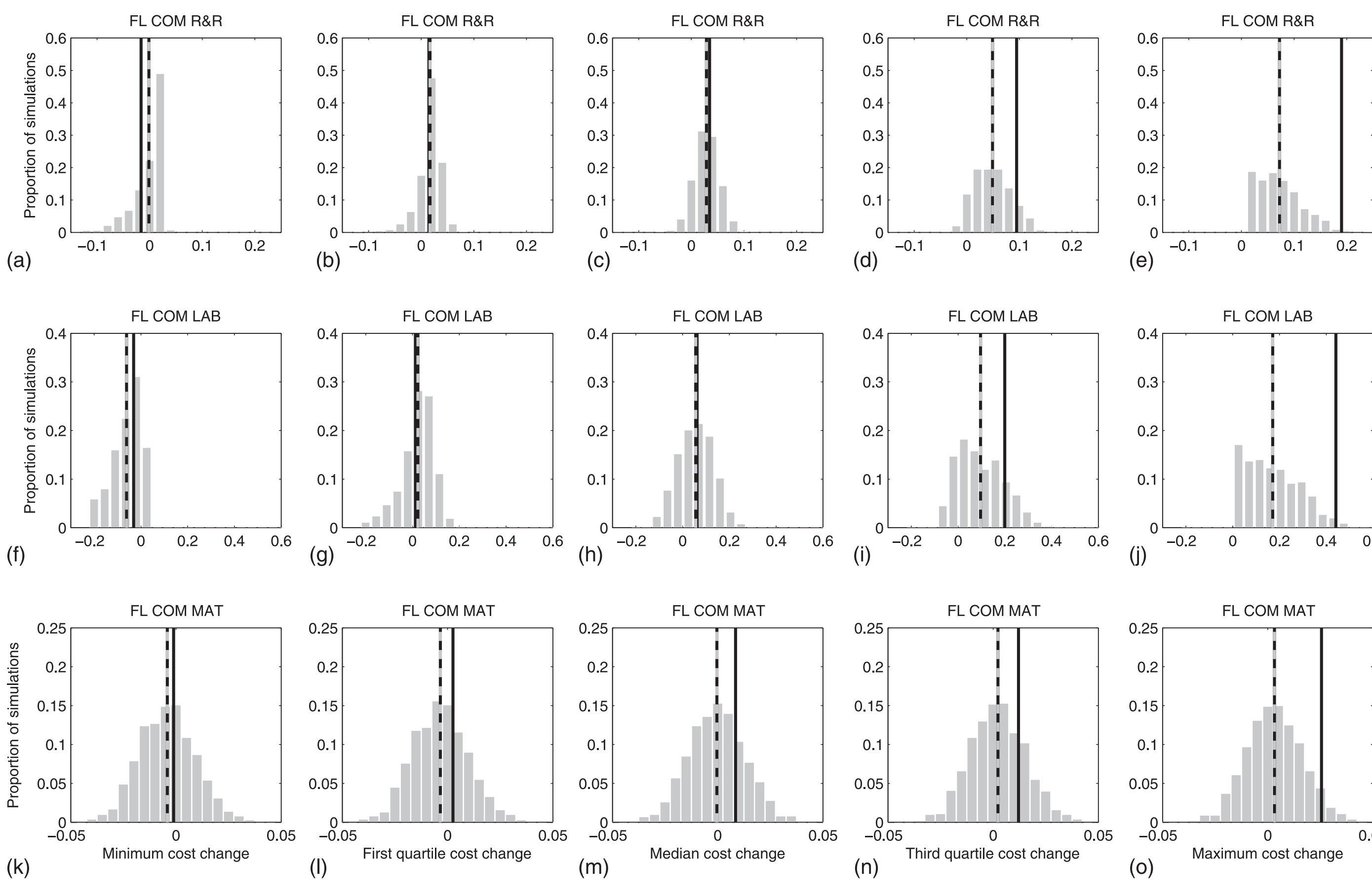

Fig. 5. Predictive checks of the three models for commercial, relative cost changes in Florida [parameter values of each model are sampled 1,000 times and expected cost changes are found given the observed data for each model replication; each column compares a statistic of the observed data sets (black lines) to the statistic of the expected cost changes from the model replications (gray distributions); a model is consistent with the observed data when the observed statistic is near the central value of the corresponding distribution (dashed line)]

Table 3. Proposed Models and Their AIC Values for Relative Cost Changes from July to January for Any City

Set of repairs	Multilevel model				Log-likelihood	AIC	Δ_{AIC}	Weight
RES R&R	α_y	$+\beta w_c + \gamma n_c + \zeta w_c n_c$	$+\theta\Delta_{2c}$	$+\varepsilon_y$	333.3	−640.7	0.00	0.379
RES R&R	α_y	$+\beta_y w_c + \gamma n_c + \zeta w_c n_c$	$+\theta\Delta_{2c}$	$+\varepsilon_y$	334.9	−639.7	0.94	0.236
RES R&R	α	$+\beta w_c + \gamma_y n_c + \zeta w_c n_c$	$+\theta\Delta_{2c}$	$+\varepsilon_y$	332.4	−638.8	1.92	0.145
RES LAB	α	$+\gamma_y n_c + \zeta w_c n_c$	$+\theta\Delta_{2c}$	$+\varepsilon_y$	195.0	−365.9	0.00	0.209
RES LAB	α_y	$+\beta_y w_c + \zeta w_c n_c$	$+\theta\Delta_{2c}$	$+\varepsilon_y$	196.9	−365.8	0.18	0.191
RES LAB	α	$+\beta w_c + \gamma_y n_c + \zeta w_c n_c$	$+\theta\Delta_{2c}$	$+\varepsilon_y$	195.7	−365.4	0.54	0.159
RES MAT	α_y		$+\theta_y\Delta_{2c}$	$+\varepsilon_y$	525.5	−1027.0	0.00	0.321
RES MAT	α_y	$+\beta w_c$	$+\theta_y\Delta_{2c}$	$+\varepsilon_y$	525.8	−1025.6	1.39	0.160
RES MAT	α_y	$+\zeta w_c n_c$	$+\theta_y\Delta_{2c}$	$+\varepsilon_y$	525.6	−1025.2	1.75	0.134
RES MAT	α_y	$+\gamma n_c$	$+\theta_y\Delta_{2c}$	$+\varepsilon_y$	525.6	−1025.1	1.84	0.128
COM R&R	α	$+\beta_y w_c + \gamma n_c + \zeta w_c n_c$	$+\theta_y\Delta_{2c}$	$+\varepsilon_y$	487.7	−945.4	0.00	0.635
COM LAB	α_y	$+\beta_y w_c + \zeta w_c n_c$	$+\theta_y\Delta_{2c}$	$+\varepsilon_y$	325.0	−616.0	0.00	0.624
COM MAT	α_y		$+\theta_y\Delta_{2c}$	$+\varepsilon_y$	827.9	−1631.7	0.00	0.276
COM MAT	α_y	$+\gamma n_c$	$+\theta_y\Delta_{2c}$	$+\varepsilon_y$	828.5	−1631.0	0.71	0.193
COM MAT	α_y	$+\zeta w_c n_c$	$+\theta_y\Delta_{2c}$	$+\varepsilon_y$	828.4	−1630.8	0.92	0.174
COM MAT	α_y	$+\beta w_c$	$+\theta_y\Delta_{2c}$	$+\varepsilon_y$	828.0	−1630.0	1.71	0.117

Note: As in Table 1, only those models with substantial empirical support are listed.

September, and October. A large tropical storm could affect a city at any time between reports of cost data in July and the following January. Thus, the data used in this study indicate both economic conditions independent of the weather and those caused by a tropical storm. For example, there may be a shortage of construction labor in the months before a tropical storm affects a city, but the effects of the shortage cannot be resolved from those of the storm. Also, although cost data for nine Atlantic hurricane seasons are available for this study, only seven seasons had landfalling hurricanes on the mainland United States. These issues presumably explain some of the variance in the models presented in this paper.

The way the authors calculate wind speed at a city contributes to the uncertainty in these models. The gradient wind speed at each city is calculated from observations of a storm system via the Holland Wind Profile (Holland 1980), rather than from surface observations made at each city. Data on observed wind speeds at a city would likely reduce some of the variance in these models. Furthermore, there may be a better way to define a proximate storm. This study uses a radius of 200 km from a city's center, but a smaller or larger radius might reduce the error variance in each model.

In the southeastern United States, the most extreme relative cost changes occur only when there is a large proximate storm (that is, a tropical storm within 200 km of a city with a gradient wind speed of at least 40 km/h inferred from the storm system using the Holland Wind Profile). There can be cost changes of 20% or more in the absence of such a storm, but there are only a few such observations. There are many more observations of large relative cost changes when there is a large proximate storm than when there is not, and intuitively, the authors expect large cost changes after such storms. Thus, the authors presume that large proximate storms cause large cost changes. More intense tropical storms and a greater number of storms affecting a city generally cause higher relative cost changes. The exception is the cost change of the material component, which does not appear to depend on wind speed or the number of proximate storms.

The data suggest how cost changes during Atlantic hurricane seasons might be minimized. For example, a property owner or insurer might make an agreement with a reconstruction contractor that specifies labor and material costs before a hurricane season. Because the data in this study show that tropical storms affect labor costs, but not material costs, the provisions limiting labor cost changes would be more important than those limiting material cost changes. The material cost changes may not significantly differ if the agreement is made or not. However, the labor cost changes under the agreement may be much less than those in the absence of the agreement. Under this scheme, both parties would benefit: in the event that a hurricane damages the property, the contractor would have guaranteed work, and the property owner or insurer would have a guaranteed cost for repairs.

Modeling demand surge is a multivariate problem with an imprecise response variable and unknown explanatory variables. The authors select a part of the demand-surge phenomenon, precisely define a response variable, and compare models with different sets of explanatory variables. The available data suggest that peak wind speed, the number of tropical storms affecting a city, the year, and the city's geographic region may contribute to how repair costs change after large tropical storms. These variables are presumably proxies for more fundamental contributors to cost changes. Peak wind speed and the number of storms are likely proxies for the amount of property damage and thus demand for repair materials and labor. The year may be a proxy for underlying economic conditions affecting demand for construction labor and materials before the hurricane season. The geographic region may represent local- or state-level governmental regulations regarding the movement of labor and materials after a natural disaster. The use of different, additional, or more refined explanatory variables may improve these models. Despite their limitations, the models provide insight into one aspect believed to be the largest contributor to demand surge.

Among the 18 data sets for repair-cost changes in the southeastern United States, the authors recommend models for only three: total repair cost changes and the labor and material component cost changes for commercial properties in Florida. These three models were the only ones with substantial empirical support and a model weight near 1, or, in other words, these models were distinctly better than the other models proposed for each data set. Although the authors find the best model for each data set among the 844 considered, the commercial cost change models for Florida are not ideal. Fig. 6 shows the distributions of expected cost changes using the three models evaluated for two sets of values of the explanatory variables. Note the large uncertainty in the expected cost changes, which results from the large uncertainty in parameter values from year to year. Within a given year, the cost changes in Florida can be modeled with little uncertainty (as suggested by Fig. 4), but the parameter values for the year are not predicted by the models. The year-to-year uncertainty might be reduced by introducing a group-level variable, such as the number of tropical storms making landfall

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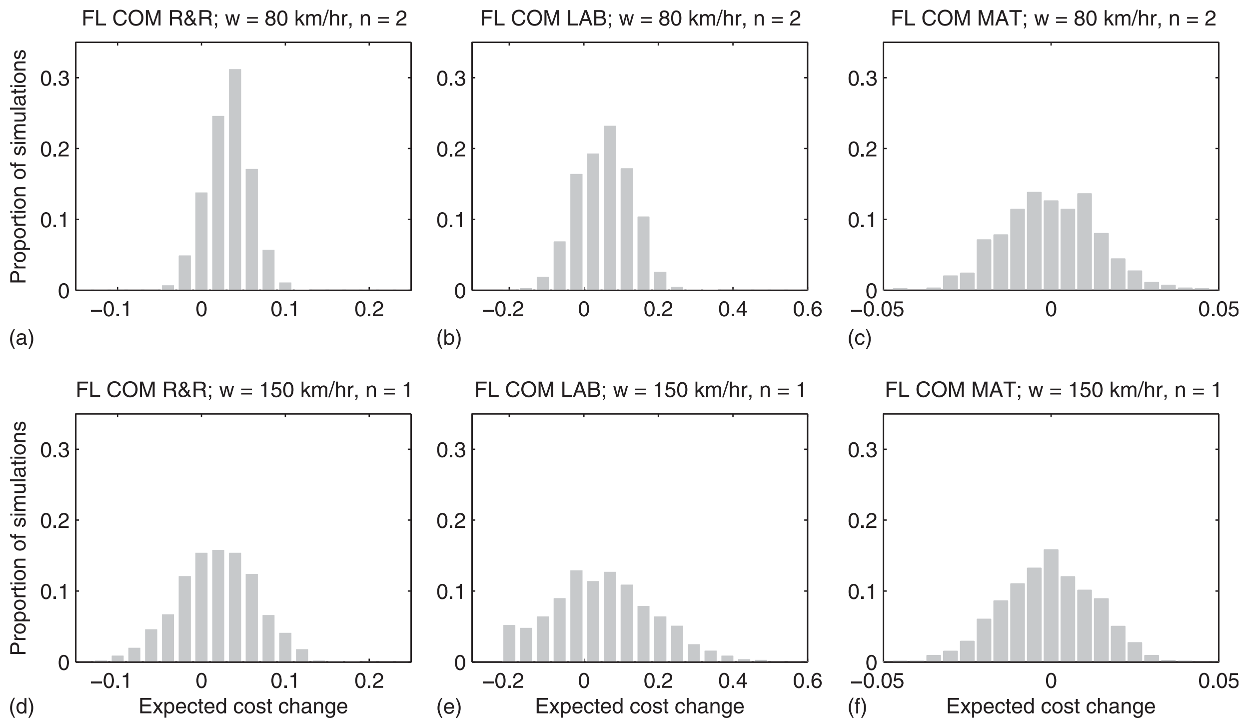

Fig. 6. Distributions of expected cost changes from 1,000 model replications evaluated at two sets of explanatory variable values: (a–c) models evaluated at a peak wind speed of 80 km/h in two proximate storms and relative cost changes in the first two quarters at their median values; (d–f) models evaluated for a single proximate storm with peak wind speed of 150 km/h and relative cost changes in the first two quarters also at their median values

in a given year or the demand for new construction in the first half of the year. Also, there are systematic biases in the R&R and labor component models' expected relative cost changes at the third quartile and maximum observed cost changes. The material component model has biases at all quartiles and the maximum observed cost changes. These biases suggest that the distributions of expected relative cost changes from the models should be shifted or more skewed to the right. Additional models should be proposed and evaluated to reduce the uncertainty and correct the biases.

If a model from this study is used to predict a future cost change, the authors recommend generating many replications of the parameter values and evaluating each replicated model at the peak wind speed, number of proximate storms, and relative cost changes in the first half of the years that are of interest. However, as shown in Fig. 5, the models underpredict large cost changes. For the R&R and labor component models, the predicted cost change can be taken from the center of the resulting distribution of predicted cost changes when the peak wind speed is less than 70 km/h. When the peak wind speed is increasingly greater than 70 km/h, the predicted cost change should be taken increasingly to the right of the distribution's center. For the material component model, the predicted cost change can be taken from the center of the distribution of expected cost changes when Δ_1 is zero or larger and Δ_2 is greater than 0.001. For increasingly larger values of Δ_1 and Δ_2, the predicted cost change should be taken increasingly to the right of the center. These guidelines are roughly midway between the values of the explanatory variables corresponding to the median and third-quartile observed cost changes in the respective data sets.

Although the authors do not find robust models for most data sets, the models' rankings are suggestive of the structures that might underlie the data. Models for the R&R and labor component cost changes with the lowest AIC values consistently include explanatory variables for peak wind speed, number of proximate storms, or both, as well as relative cost changes in the second quarter or an interaction of the first and second quarters. The explanatory variables in the top models for the material component cost changes are generally limited to relative cost changes in the first half of the year. This suggests that the R&R and labor cost changes are sensitive to severe tropical storms and the underlying economy, but the material component responds to economic pressures independent of any tropical storm affecting a city.

The authors develop models for relative cost changes when there is at least one tropical storm near a city in the southeastern United States; the models do not predict cost changes in the absence of a proximate storm. The authors anticipate that the models would be used most often to predict cost changes in future Atlantic hurricane seasons as opposed to cost changes at cities not studied in the years 2002–2008. Predictions of future cost changes from these models are valid if the underlying economic processes resulting in repair costs are stationary over many years and if the variability in the data from these seven seasons is representative of the variability in future hurricane seasons.

Conclusions

For cities in the southeastern United States during an Atlantic hurricane season, relative changes in the labor component of repair costs depend on the intensity and number of tropical storms affecting a city. Material component cost changes, however, are independent of these two explanatory variables. In the last half of a calendar year, changes in labor and material components of cost, as well as the total repair cost changes, depend on cost changes in the first half of the year. Labor cost changes drive the total cost changes, and thus a better understanding of the labor market during hurricane seasons

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should provide greater insight into heightened repair costs after large tropical storms.

Variability from year to year dominates the variability in relative cost changes when a tropical storm affects a city. Depending on the year, the same single storm or series of storms can result in systematically different cost changes. The variability in cost changes at cities near the Gulf of Mexico versus cities in Florida versus cities near the Atlantic Ocean is much smaller in comparison with the annual variability. Relative cost changes within a given geographic region and year show even less variability. The models proposed in this paper might be greatly improved by the addition of a year-level explanatory variable that predicts, for a given year, the values of the parameters that vary annually.

Of 18 data sets (for six sets of repair costs in the three geographic regions), only three have one model that is clearly superior to the other models considered: total repair cost and the labor and material components for commercial properties in Florida. Each of these models is distinct from the others considered for the data set. The models' predictions are consistent with the observed data for small to moderate cost changes, but the predictions underestimate the observations at larger cost changes. In the future, the models should be improved to correct this bias, which might be accomplished by including the year-level explanatory variable previously mentioned.

For the remaining 15 data sets (for residential properties in Florida and for residential and commercial properties in cities near the Atlantic and Gulf coasts), the authors do not find robust models. Either the available data are insufficient to distinguish the underlying structure of the data, or the underlying structure is more complex than the models tried or requires different explanatory variables than the ones used. Additional data, a better understanding of labor and material markets during Atlantic hurricane seasons, or both, might allow the authors to develop sound models for these data sets.

The regression models developed in this study do not model demand surge. The models predict cost changes for a set of repair line items. The purpose of these models is to test assumptions about the underlying drivers of demand surge, specifically increases in labor wages and material prices. As described in Olsen and Porter (2010), the authors expect that many factors not considered in this study could explain demand surge equally well as, or better than, changes in labor wages and material prices.

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