Reducing the Cost of *Ex Post* Bailouts with *Ex Ante* Regulation: Evidence From Building Codes

Tatyana Deryugina*

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March 13, 2013

Abstract

The government acting as an insurer of last resort can cause moral hazard if agents respond by taking on more risk or reducing private insurance coverage, thinking they will be bailed out. Theoretically, *ex ante* measures can ameliorate this problem, but it is not known how effective actual policies are in reducing *ex post* government spending. Using instrumental variables and detailed building codes data, I show that stricter building codes reduce the amount of money spent by the federal government following a hurricane. Specifically, I find that raising the required wind speed a building must withstand by 1 mile per hour decreases the amount of money subsequently spent by the federal government by $2.2\% - 4\%$ or $\$14,000 - \$25,600$ per affected zip code during a hurricane. I also show that this decrease is entirely driven by reduced aid to homeowners as opposed to renters.

1 Introduction

This paper examines whether *ex ante* regulation reduces *ex post* public spending. It is well-established in the theoretical literature that the possibility of government bailouts can lead to inefficiently high risk-taking in settings ranging from banking to disaster assistance (e.g., Kaplow, 1991; Hellmann et al., 2000; Raschky and Weck-Hannemann, 2007; Farhi and Tirole, 2012). While *ex ante* risk regulation has the potential to reduce such moral hazard in theory, the extent to which

*deryugin@illinois.edu. I thank Jeff Brown, Don Fullerton, Nolan Miller, and Julian Reif for helpful feedback. I thank Mickey Ferri for help with the wind load data. Homer Li and Rachel Shen provided excellent research assistance.

actual regulations do so is not known. I shed light on this question by estimating the effect of building codes on federal disaster aid following a hurricane, providing what is, to my knowledge, the first empirical evidence pertaining to whether stricter building codes are effective at reducing *ex post* federal aid spending.

A particular concern with *ex ante* risk regulation is that it is often an endogenous response to risk-taking. For example, the higher capital requirements established by the Basel Accords were motivated by what regulators viewed as excessive risk-taking by banks. The advantage of my setting is that I am able to identify a plausibly exogenous source of variation in building code strength. Specifically, I instrument for building code strictness using physical measures of hurricane risk, which I construct with historic hurricane records. I show that historic wind speeds are highly correlated with building code strictness but are unlikely to be correlated with unobserved determinants of federal aid. Although historic hurricane risk is also correlated with actual wind speeds experienced during the study period, there is still substantial residual variation in the latter. In other words, there are areas with historically high (low) hurricane risk that experience low (high) wind speeds. This variation allows me to identify the effect of building codes on aid separately from the effect of actual wind speeds.

I estimate the relationship between building code strictness, as measured by the "wind load," and federal disaster aid in the aftermath of four hurricanes that hit Florida in 2004. I find that increasing the wind speed that a building must withstand by 1 mile per hour reduces federal disaster spending in a given zip code by an estimated $2.2\% - 4\%$ or $\$14,000 - \$25,600$. The estimated reduction per housing unit is about \$5.5 per hurricane. The spending reduction is entirely driven by a reduction in aid given to homeowners; transfers to renters are unaffected by building codes. To the extent that federal spending is proportional to damages, this finding also implies that building codes reduce damages, which are often very hard to measure. Unfortunately, data on damages and the costs of complying with the building codes are not systematically collected; thus, I cannot provide a full welfare analysis of building codes. However, a back of the envelope calculation suggests that, in order for stricter building codes to be cost-effective, damage reductions would have to be substantial and/or the costs of sturdier buildings would have to be implausibly small.

A key contribution of this paper is to highlight a previously ignored justification for mandatory building codes: moral hazard. A type of moral hazard that has been dubbed "charity hazard" arises when individuals expose themselves to excessive risk because they expect to be bailed out by the government. In the case of building codes, individuals may underinvest in protection against hazards because they expect some of the losses to be covered by the government. The first-best policy may be for the government to credibly commit to *not* bailing out individuals after their home is destroyed or to mandate private insurance coverage. I develop a simple model to show that building codes are a good alternative or complement in cases in which the government cannot credibly commit to not bailing out victims of a natural disaster, where individuals are myopic or underestimate the probability of a disaster, or where insurance mandates are infeasible or not easily enforced.

Despite the theoretical conclusion that building codes reduce damages and federal aid spending, there are several reasons why building codes may not lead to lower disaster aid spending in practice. First, if a building code is poorly designed or not enforced, it may not reduce damages. Second, the aid process has been shown to be heavily influenced by politics (Downton and Pielke, 2001; Garrett and Sobel, 2003). In particular, Garrett and Sobel (2003) estimate that as much as half of all disaster aid is politically motivated. In the extreme case, actual damages may matter little for aid spending. Third, households may respond to stricter building codes by reducing insurance coverage. In this case, the total amount of damages eligible for federal aid, which covers only uninsured losses, may increase even if total damages fall. Thus, whether building codes are effective at reducing *ex post* aid is ultimately an empirical question.

In addition to addressing the broad question of the effect of *ex ante* regulation on *ex post* government spending, considering the effectiveness of building codes is important in its own right. Extreme weather events represent a large and growing source of negative economic shocks. Larger population densities, ecosystem alteration, and movements of the population to hazardous areas are causing real damages from natural disasters to rise (Board on Natural Disasters, 1999). In 2005 dollars, insured losses have exceeded \$10 billion per year worldwide every year since 1987, reaching \$49 billion in 2004 (Kunreuther and Michel-Kerjan, 2007).[1] Damages are likely to continue growing as climate change is expected to increase the number and intensity of extreme events (e.g., Meehl et al., 2007; Schneider et al., 2007). Munich Re, a company specializing in disasters, estimates that worldwide damages will exceed \$300 billion a year by 2050, a 750 percent increase in real terms (Freeman et al., 2003).

Correspondingly, government spending on natural disaster relief is also on the rise. In the 1980s, US disaster aid averaged \$730 million per year (2009 dollars). In the 1990s and 2000s, that figure climbed to \$3.5 billion and \$9.2 billion per year, respectively. Between 1957 and 2009, US federal disaster aid increased by 8% annually, on average.[2] Furthermore, as Deryugina (2012) points out, this figure is certainly an underestimate because it does not reflect increased government spending via other transfer programs, such as unemployment insurance and Medicaid, caused by natural disasters. Both the trends in damages and in government aid spending highlight the importance of finding effective policy solutions.

To my knowledge, no study has considered the effect of building codes on disaster relief spend-

[1]Uninsured losses are difficult to estimate, but a reasonable rule of thumb is that they are about as large as the insured losses in developed countries and about ten times larger in developing ones.

[2]Author calculations based on data from `http://www.peripresdecusa.org/mainframe.htm`, accessed January 15, 2013.

ing, and only two studies have examined the relationship between newer building codes and damages (Fronstin and Holtmann, 1994; Dehring and Halek, 2013). However, these studies cannot quantify the strength of the newer building codes. As a result, their viability as a basis for drawing policy conclusions is extremely limited.

The rest of the paper is organized as follows. Section 2 outlines a simple conceptual framework to illustrate the potential interaction of building codes and federal disaster aid. Section 3 describes hurricanes, the history of building codes in Florida, and the data used for analysis. Section 4 outlines the empirical framework. Section 5 presents the results, and Section 6 concludes.

2 Conceptual Framework

I begin by outlining a simple conceptual framework that demonstrates the interaction between *ex post* disaster transfers from the government and *ex ante* mitigation efforts chosen by households. I then discuss how the government can counteract the moral hazard that arises when it cannot credibly commit to not providing *ex post* aid.

The simple model presented below is adapted from Kaplow (1991), who shows that the presence of government aid reduces incentives to mitigate and insure damages.[3] Intuitively, this circumstance arises because households take into account the effect of mitigation on the reductions in their *own* costs following a disaster, rather than the social cost, some of which is borne by the government. This situation can thus be viewed as one where the household's behavior imposes a negative externality on society because the household does not consider the full social cost when making its mitigation decisions.

Unlike Kaplow, I assume that mitigation measures reduce the *damage* caused by a natural hazard rather than its probability, and I allow *ex post* government transfers to depend on the level of damages rather than holding them fixed. Because I am not considering the optimal amount of federal aid, I also ignore taxation. However, in characterizing the solution when *ex post* aid is present as suboptimal, I am implicitly assuming that government transfers are socially costly.

Let m be the amount of money spent on *ex ante* mitigation by a household. The probability that a natural disaster occurs over the relevant time period is π. If the disaster occurs, damages are given by the function $D(m)$, where $D(m) > 0$, $D'(m) < 0$, and $D''(m) > 0$ for all m. I assume that the household has access to actuarially fair insurance, so the premium paid is equal to the expected payout. The household pays a premium equal to πI, where I is the amount of insurance purchased.

The household's pre-disaster wealth is w_0. The household's (concave) utility function is given by $U(w)$. I denote utility in the state with and without the disaster by U_d and U_0, respectively. I

[3] Kelly and Kleffner (2003) show that reduced incentives to mitigate also arise in a setting with a monopolistic insurer.

begin with the case of no government aid. The optimal level of mitigation, m^*, is the solution to the following equation:

$$\begin{aligned} max_{m,I}\pi U(w_0 - D(m) - m + I - \pi I) + (1-\pi)U(w_0 - m - \pi I) &= \\ max_{m,I}\pi U_d + (1-\pi)U_0 & \end{aligned}$$

Taking the first-order condition with respect to I gives:

$$\pi(1-\pi)U_l' + (1-\pi)(-\pi)U_0' = 0$$

It is clear that the household will choose to have equal marginal utility, and thus wealth, in each state of the world.

The first-order condition with respect to m is a slightly more complicated expression:

$$\pi U_l'(-D'(m) - 1) + (1-\pi)U_0'(-1) = 0$$

Recognizing that $U_0' = U_l'$ at the optimum, the optimal level of mitigation, m^*, is given by:

$$D'(m^*) = \frac{\pi - 1}{\pi} - 1$$

When aid is present, the government gives a transfer to the affected household when a disaster occurs. The transfer is a fraction of damages, αD, where $0 < \alpha < 1$.[4] When the household expects that some of the damages will be compensated by the government, its problem becomes:

$$max_{m,I}\pi U(w_0 - D(m) - m + \alpha D(m) + I - \pi I) + (1-\pi)U(w_0 - m - \pi I)$$

The household's solution to this problem will not correspond to the previous solution of m^*. Mechanically, this occurs because of the extra term $\alpha D(m)$ in the case where *ex post* aid is given. Intuitively, only $1-\alpha$ of total damages matters to the household now, reducing the incentive to mitigate damages.

It is easy to show that, when deciding how much insurance to purchase, the household will again equalize marginal utility and thus wealth in each state of the world. However, this will not necessarily translate to the same amount of insurance as in the first case because of the presence of government transfers and possible changes in mitigation expenditure.

[4]In practice, the government does not compensate for damages that are covered by insurance. However, incorporating this into the model would make it too cumbersome for the purposes of this paper. Not compensating for insured losses in this model would only strengthen the result, by providing an additional incentives to reduce insurance coverage.

From the household's point of view, the optimal amount of mitigation when *ex post* transfers are present, denoted by m^T, is given by:

$$D'(m^T) = \frac{\frac{\pi-1}{\pi} - 1}{1-\alpha}$$

Because $\frac{\pi-1}{\pi} - 1 < 0$ and $1-\alpha > 0$, $\frac{\frac{\pi-1}{\pi}-1}{1-\alpha} < \frac{\pi-1}{\pi} - 1$. Recall that the slope of $D(m)$ is assumed to be strictly increasing in m. Thus, $m^T < m^*$. In other words, in the case with government transfers, the household spends too little on mitigating damages. Intuitively, this is because the introduction of government transfers raises wealth and lowers marginal utility in the state of the world in which the disaster occurs. Because the household wants to smooth consumption, it responds by reducing mitigation spending, which raises the wealth in the state of the world in which the disaster does not occur. Subsequently, damages caused by the disaster will be higher, as will the federal expenditure on *ex post* aid.

Although this model focuses on mitigation expenditure, it is broadly applicable to any situation in which agents make decisions about risk exposure and where risk reduction is costly. As in this case, the presence of *ex post* government aid, assumed to be available for free to the agent, will lead her to reduce expenditure on risk reduction.

In this simple model, the government can reach the no-aid solution simply by mandating a level of mitigation expenditure that is equal to or greater than m^*. More realistically, the government can mandate protection measures that correspond to the desired level of mitigation expenditure, as in the case of building codes. In addition to decreasing the amount of damages sustained during a disaster, such a policy has the added benefit of lowering *ex post* government spending on aid, thus reducing the total cost of public funds and the total social cost.[5] However, with heterogeneity in risk preferences or in other dimensions, a simple floor on mitigation expenditure will not result in the first-best outcome. Nevertheless, establishing such a floor can improve on a situation in which the household is free to choose any mitigation expenditure it desires.

The government can also reach the first-best outcome in this model by mandating that all households purchase full insurance. Because the government does not in practice compensate for damages that are covered by insurance, this would completely eliminate *ex post* transfers and, assuming the insurance is actuarially fair, achieve the socially optimal level of mitigation. Other problems with this solution might include adverse selection and administrative costs.

Comparing mandating insurance with instituting building codes in a more realistic model is beyond the scope of this paper. However, some relevant considerations are worth discussing here. First, enforcing building codes may be cheaper than enforcing insurance requirements, as the for-

[5] Although total social costs would also be lowered by this mandate in the model, in practice social costs may be higher if compliance costs are high.

mer need to be checked once and provide protection for the entire duration of the structure's life, while the latter need to be checked continuously.[6] Second, as with health insurance, political constraints may prevent implementing an insurance mandate. The penalty for not having insurance needs to be high enough for most households to choose to insure; otherwise, moral hazard will continue to be a problem, as some households conclude that it is more beneficial to pay the penalty. However, implementing the optimal penalty level may also be politically difficult.

The model presented above also assumes that insurance is actuarially fair. In practice, homeowner insurance loads are among the highest in any insurance markets (of the Insurance Commissioner", 2004; Hunter, 2012). In this case, mandating full insurance might not be efficient. Finally, evidence suggests that homeowners are myopic and underestimate disaster risk. This leads them both to underinsure and to underinvest in protective measures (Kunreuther, 2000). In general, people seem to undervalue preventative measures: Healy and Malhotra (2009) provide evidence that voters reward politicians for *ex post* but not *ex ante* spending and estimate that an additional $1 spent on preparedness reduces expected future damages by about $15. As a result, homeowners may not choose the first-best level of mitigation even when forced to buy full insurance. Kunreuther (1996) suggests that a hybrid model of insurance and building codes may optimal for overcoming the issues related to disaster preparedness.

3 Background and Data

3.1 Hurricanes and Federal Disaster Aid

Hurricanes that affect the United States form in the Atlantic Ocean. Warm humid air over the ocean creates storms known as "tropical disturbances." If circulating winds develop, the disturbances become tropical cyclones. Prevailing winds and currents move cyclones across the ocean, where they gain or lose strength based on atmospheric and surface conditions. When a cyclone encounters cold water or land, it loses strength and gradually dissipates. Sometimes a circular area with low internal wind speeds, called the "eye," develops in the system's center. Although the entire storm system can span a few hundred miles, the perimeter of the eye (the "eyewall") is where the strongest winds are found. Wind intensity declines quickly further from the eyewall (or the center of the storm, if there is no eye). The outer parts of the hurricane are called "spiral bands." These are characterized by heavy rains but typically do not have hurricane-force winds.

Atlantic hurricanes are classified by maximum 1-minute sustained wind speeds using the Saffir-Simpson Hurricane Scale. A storm is considered a hurricane if maximum 1-minute sustained wind speeds exceed 74 miles per hour. Category 3 and higher hurricanes have wind speeds greater than

[6] Requiring individuals to provide proof of insurance when filing taxes may lower these costs.

111 mph and are called "major hurricanes." Category 1 and 2 hurricanes are "minor hurricanes," characterized by maximum wind speeds of $74 - 110$ mph. A tropical storm is a cyclone with wind speeds of $39 - 73$ miles per hour. Cyclones with lower wind speeds are called "tropical depressions." Hurricanes that make landfall cause widespread wind and flood damage: Physical damages from hurricanes in the US have averaged \$4.4 billion per landfalling hurricane (in 2008 dollars) or \$7.4 billion per year between 1970 and 2005 and \$2.2 billion per hurricane or \$3.7 billion per year if 2005 is excluded.[7]

I focus on four hurricanes and one tropical storm that hit Florida in 2004: Hurricanes Charley, Frances, Ivan, and Jeanne, and Tropical Storm Bonnie. It was an exceptional year in that four major hurricanes struck Florida. Charley, Ivan, and Frances were among the most destructive hurricanes in recent years, trailing only Hurricane Andrew in 1992. In the US, they caused \$14 billion, \$13 billion, and \$9 billion in estimated damages, respectively (all in 2004 dollars). Hurricane Jeanne was estimated to have caused about \$6.9 billion in damages. Tropical Storm Bonnie made landfall only a day before Hurricane Charley, making it hard to estimate its damages separately. They were likely relatively small, as Bonnie was much weaker than a hurricane. However, the subsequent disaster declaration combines Charley and Bonnie; therefore, I use wind data from both storms.

Federal disaster aid is made available to a county if the state's governor requests it and provides evidence that the state cannot cope with the disaster on its own. The final decision about whether to declare a major disaster is made by the US president. In practice, few such requests are denied. Once such a request is approved, federal money can be used to repair public structures, clean up debris, and make grants and loans to individuals and businesses. The Federal Emergency Management Agency (FEMA) also provides personnel, legal help, counseling, and special unemployment insurance for people who become unemployed as a result of the disaster. All four hurricanes that hit Florida in 2004 were declared major disasters.

3.2 Building Codes

Broadly, a building code is a set of requirements that a building must meet, with clauses ranging from ensuring structural integrity to fire protection measures. In addition to the benefit of building codes I identify in Section 2, there are two other generally accepted justifications for mandatory building codes. The first is that people do not take into account how building construction affects neighbors. For example, a household may choose to forego hurricane roof straps because it do not take into account the possibility that a blown-off roof damages their neighbor's house. Building codes can thus be seen as a tool for resolving negative externalities. The second reason for mandating building codes is that it may be very costly for individuals to assess the quality

[7] Author calculations using data from Nordhaus (2006).

of a building. In this case, despite their inflexibility, building codes are the best solution given information acquisition costs.

Building codes in the United States are not regulated at the federal level. While most states now follow a single building code, some leave it up to individual counties and cities. Most states with a single building code use the provisions of the International Building Code (IBC) and International Residential Code (IRC), developed by the International Code Council (ICC) and updated every three years. These codes are complex sets of requirements that are functions of local attributes, including exposure to natural hazards. The hurricane-related provisions in the IBC and IRC are developed by the American Society of Civil Engineers (ASCE) and are included in a broader set of guidelines called "Minimum Design Loads for Buildings and Other Structures" (or ASCE 7).

Quantifying the strictness of the ASCE's hurricane provisions would be a daunting task. Luckily, ASCE 7 provides maps of wind speeds that a building in a given area should be able to withstand ("wind loads"). The wind loads translate into specific design features, including the type of glass used for windows (to withstand wind-borne debris), whether a building needs to have roof trusses or hurricane straps installed, and the type of roofing material that can be used (to lower the roof's risk of being torn off by wind). The wind loads also govern requirements for vent coverings, storm shutters, and doors. Because quantifying all components of the building code is not feasible, I rely on wind loads as a proxy for the strictness of a building code. In addition to simplifying the statistical analysis, using the wind load as a measure of the strength of the building code also makes it more straightforward to interpret the findings and draw policy conclusions from them.[8]

I focus on the relationship between building codes and federal disaster spending in Florida. Prior to 2001, Florida did not have a uniform building code. In 2001, it adopted a slightly modified version of the ICC codes and has continued to use the updated versions of the codes since then. In addition to adopting the ICC building codes, Florida adopted the wind maps published in ASCE 7. Although ASCE 7 is updated periodically, the wind maps remained unchanged from 1995 to 2010.[9]

New building codes typically apply to new buildings only. Older buildings must update to comply with a more recent building code only if they undergo significant renovations. However, it is also likely that ASCE 7 wind loads are to some extent correlated with building codes that were in place prior to the adoption of ICC codes in 2001. Thus, my estimates are likely to capture more than just the short-run effects of stricter building codes.

[8]For example, Dehring and Halek (2013) estimate hurricane damage to houses built before and after a building code change. However, because they cannot quantify the strength of building codes, their ability to draw general policy conclusions is limited.

[9]The 1997 and 2003 IBC codes use ASCE 7-98, the 2006 IBC uses ASCE 7-05, and the 2009 IBC uses ASCE 7-10. The wind loads and wind speed boundaries are identical for ASCE 7-05, ASCE 7-02, ASCE 7-98, and ASCE 7-95.

3.3 Data

Data on wind loads come from the Applied Technology Council, which provides them for ASCE 7-10, ASCE 7-05, and ASCE 7-93, published in 2010, 2005, and 1993, respectively. The versions of ASCE 7 published in 1995 and 1998 specify the same wind loads as ASCE 7-05. Data were manually downloaded for every 0.01 degrees latitude and longitude to provide a comprehensive wind load map.[10] I then map the wind load points into zip code boundaries using zip code maps from the 2000 Census.[11] Finally, I average the wind load within a zip code to create a zip-level measure of building code strictness.

Data on actual wind speeds come from the National Oceanic and Atmospheric Administration's (NOAA) H*Wind dataset, which provides detailed wind speed grids for recent hurricanes in six-hour intervals. For each hurricane, H*Wind contains a set of vectors that can be used to calculate wind speed magnitudes and direction for multiple points on a grid around the storm center. I use data for the four hurricanes and one tropical storm that hit Florida in 2004: Hurricanes Charley, Frances, Ivan, and Jeanne, and Tropical Storm Bonnie.[12] I compute the wind speed corresponding to each vector location and map that location into zip code boundaries using the 2000 Census zip code maps. For each hurricane, I then compute the average wind speed in a zip code to arrive at a zip-level measure of hurricane strength.

Data on federal disaster aid come from FEMA through a Freedom Of Information Act request. I obtain aid information for disaster declarations associated with each of the hurricanes above.[13] The final dataset consists of the total amount of aid given to individuals by zip code and disaster declaration, as well as by ownership status (renter or owner). The total amount of individual aid given as part of these four declarations is slightly over $1 billion. About two-thirds of that amount was given to owners and one-third was given to renters. The total amount given to public assistance for the four declarations totalled about $2.5 billion.[14]

Finally, I use the historic Best Tracks (HURDAT) dataset, also from NOAA, to calculate a zip code's hurricane history to use as an instrument for the wind load.[15] The data are less detailed than those provided by H*Wind: they contain only the location of the storm center and the wind speed, also in six-hour intervals. The spatial extent of the storm is thus not observable. However, unlike H*Wind, which covers only recent hurricanes, Best Tracks data are provided for each North

[10] Retrieved from `http://www.atcouncil.org/windspeed/` in August 2012.

[11] Available from `http://www.census.gov/geo/www/cob/z52000.html`, accessed August 2012.

[12] The H*Wind datasets are available from `http://www.aoml.noaa.gov/hrd/data_sub/wind2004.html`, accessed August 2012.

[13] Specifically, I request data for disaster declarations 1539 (Charley and Bonnie), 1545 (Frances), 1551 (Ivan), and 1561 (Jeanne).

[14] Public assistance data are available only at the county level; therefore, I do not use them in my analysis.

[15] Available from `http://www.ncdc.noaa.gov/oa/ibtracs/index.php?name=wmo-data`. Accessed August 2012.

Atlantic hurricane and tropical storm since 1851. To calculate which zip codes were affected by a particular storm, I assume that its path is linear between consecutive storm locations. I also assume that the storm spans all zip codes within 5 kilometers of the path center. I then calculate the maximum historic wind speed and other hurricane-related metrics for each zip code to create instrumental variables for the wind load. I defer detailed discussion of instrument creation to Section 4.2.

Table 1 presents summary statistics for the zip codes in my sample. The wind load averages 118 miles per hour (mph) and ranges from 99 mph to 150 mph. The actual wind speeds average 48 mph and range from 3 mph to 120 mph. The historic maximum wind speed averages 78 mph with a standard deviation of 7. Taken together, these summary statistics indicate that the zip codes in my sample are exposed to hurricanes relatively frequently.

Individual assistance across the four hurricanes averages about $\$640,000$ per zip code with a standard deviation of \$1.3 million. Homeowners in an average affected zip code receive about $\$410,000$, while renters receive slightly over half of that amount or $\$240,000$. It is not immediately clear whether this difference occurs because fewer renters than homeowners apply for aid or because renters qualify for less aid, although the latter factor almost certainly plays a role.

Because of the skewness of the individual assistance variable, I use its log for regression analysis. I create two related measures: the log of the individual assistance amount and the log of the individual assistance amount plus 1. The latter measure avoids dropping zeros. Because only 39 observations (out of $1,761$) do not receive any assistance, the choice of transformation does not substantially affect my estimates when examining total assistance for both owners and renters. However, because renters are less likely to receive assistance than owners are, the specific transformation matters more when I consider renters and owners separately.

Figure 1 shows a map of the wind loads for Florida zip codes. Lighter areas represent higher wind loads. In general, areas that are closer to the coast generally have higher wind loads; by itself, however, proximity to the coast does not predict the wind load. The highest wind loads are found in the south of Florida, where hurricane exposure is greatest and storms tend to be the strongest. All parts of Florida are considered to be at some risk for hurricanes; thus, the lowest wind load in the state is 99 mph.

4 Empirical Framework

4.1 OLS

What happens to federal disaster spending at locations with a higher wind load, all else equal, including the actual wind speed of the hurricane? I begin to answer this question with a simple regression of federal disaster aid on the wind load:

$$Log(aid_{zh}) = \beta WL_z + \sum_{i=2}^{10} \lambda_i 1[WS_{zh} = i] + \sum_{i=2}^{10} \theta_i 1[D_z = i] + \rho Age_z + \alpha_h + \varepsilon_{zh}$$

where z indexes zip codes and h indexes hurricanes. The dependent variable is $Log(aid_{zh})$, the log of federal dollars given to individuals in zip code z for hurricane h, and WL_z is the wind load for zip code z. Variable $1[WS_{zh} = i]$ is an indicator equal to 1 if the zip code's actual wind speed during hurricane h is in the i^{th} decile (relative to other zip codes in the sample).[16] Similarly, $1[D_z = i]$ is an indicator equal to 1 if the zip code's distance to the coastline is in the i^{th} decile. The variable Age_z is the median age of the housing stock in the zip code. Finally, α_h is a set of four disaster declaration fixed effects, corresponding to each of the four hurricanes.

The coefficient of interest is β, which shows the relationship between the wind load and federal aid, holding constant the actual wind speed.[17] Because some zip codes are affected by more than one hurricane in 2004, all standard errors in this and subsequent specifications are clustered at the zip code level.

The above specification assumes that changes in federal aid are linear in the wind load. I also allow for non-linearities in the relationship:

$$\begin{aligned} Log(aid_{zh}) \quad = \quad & \beta_2 1[WL_z = 2] + \beta_3 1[WL_z = 3] + \beta_4 1[WL_z = 4] + \beta_5 1[WL_z = 5] \\ & + \sum_{i=2}^{10} \lambda_i 1[WS_{zh} = i] + \sum_{i=2}^{10} \theta_i 1[D_z = i] + \rho Age_z + \alpha_h + \varepsilon_{zh} \end{aligned}$$

where $1[WL_z = i]$ is an indicator equal to 1 if the zip code's wind load quintile is i.

One seemingly important variable left out of the specifications above is housing prices. Its omission could affect the analysis in two ways. First, homes that are closer to the coast are more expensive, more prone to experiencing high wind speeds, and are located in zip codes with higher wind loads. Not accounting for housing prices in this case might lead to a spurious relationship between disaster aid and wind loads. I address this concern by flexibly controlling for the distance from the zip code to the coastline in the above specifications, and I show that including these controls does not substantially affect my results.

Second, because of stricter building code requirements, homes in zip codes with higher wind loads are also more expensive to build and may sell at a higher price for that reason. While

[16] My results are very robust to controlling for a fifth polynomial of wind speeds instead of wind speed deciles.

[17] Ideally, I would also exploit intertemporal variation in building code strength. Unfortunately, wind loads did not change during my sample period: the first significant change since 1995 occurs in 2010, in ASCE 7-10. The effect of these changes is important to analyze in the future, but it is too soon to detect their impact at this point.

stricter building codes may reduce the *fraction* of the home value destroyed by the hurricane, it is theoretically possible that they raise the *total* amount of damages. If the amount of federal aid is proportional to the total level of damages, stricter building codes could actually increase federal spending. In this case, more expensive housing is a direct consequence of stricter building codes. Controlling for housing prices would then make building codes appear to be more beneficial for reducing federal spending than they really are. Because I want to capture the full effect of building codes on federal disaster spending, I do not include housing prices in my preferred specification. However, I show that my results are robust to controlling for housing prices (using 2000 Census data).

4.2 2SLS

If OLS estimates are to appropriately reflect the causal effect of building codes on federal aid, there must be no unobservables that covary with the wind load and affect federal aid at the zip code level. This assumption is potentially problematic, as areas with higher wind loads may also sustain higher damages for a given wind speed, for example because they are also located in flood-prone areas. In general, if the ASCE bases its wind loads on damage determinants other than wind speed, an endogeneity problem can arise, in which case the OLS estimates will be biased. ASCE determines appropriate wind loads through modeling the risk of a range of wind speeds, using historic records and simulations. Because it is a national organization, it is not likely to use hard-to-observe local attributes in establishing the wind loads. Flood-related provisions in building codes are treated separately from those related to high wind exposure, and thus flood risk is unlikely to affect the wind load of a given location.

A larger concern is that the ASCE wind loads may be based on hurricanes that are relatively recent and could have directly affected the building stock in a particular zip code. For example, it is likely that 1992's hurricane Andrew was used in determining the appropriate wind loads for nearby areas. In addition, Hurricane Andrew destroyed a lot of housing. Thus, areas affected by Hurricane Andrew are likely to have higher wind loads *and* newer housing stock. OLS estimates would then conflate the effect of stricter building codes with the effect of newer housing stock (which could lead to lower or higher aid *ex post*).

I address the endogeneity concerns outlined above by instrumenting for wind loads with historic wind speeds and number of storms in the area, variables that reflect a zip code's hurricane risk but that should not reflect other unobserved determinants of damage. The variation I exploit in the paper is that some areas with low wind loads/hurricane risk happened to experience high wind speeds during the 2004 hurricanes, while some areas with high wind loads/hurricane risk happened to experience low wind speeds at that time, due to the random nature of hurricanes. To minimize the probability of picking up the effect of a newer housing stock as a result of more recent hurricanes, I do not use data from storms that occurred after 1950 and I omit a zip code's own hurricane record from the construction of the instruments. I also control for the median age of the housing stock directly, using 2000 Census data. The necessary and sufficient identification assumption is that the historic hurricane record of a zip code's neighbors is uncorrelated with unobserved determinants of damages and/or federal aid.

To construct the instruments, I first calculate the maximum and average wind speeds each zip code is exposed to between 1851 and 1950. I also compute the number of tropical depressions, tropical storms, and Category 1-4 hurricanes for each zip code over the same time period.[18] To minimize endogeneity concerns, I only use the hurricane experience of nearby zip codes in constructing the risk measure. Specifically, for each zip code, I compute the weighted maximum and average wind speeds of all zip codes within 500 miles, using $\frac{1}{distance+1}$ as the weight.[19] I also compute the weighted total numbers of each storm type using the same procedure. To allow the wind load to vary flexibly with the maximum wind speed measure, I transform the latter into quintile indicators.

The first stage of the IV analysis is given by:

$$WL_z = \sum_{i=2}^{5} \delta_i 1[WH_z = i] + \sum_{i=1}^{4} \sigma_i NumCati_z + \sigma_5 NumTS_z + \sigma_6 NumTD_z$$

$$+ \sum_{i=2}^{10} \lambda_i 1[WS_{zh} = i] + \sum_{i=2}^{10} \theta_i 1[D_z = i] + \rho Age_z + \alpha_h + \upsilon_{zh}$$

where $1[WH_z = i]$ is an indicator equal to 1 if the zip code's historic maximum wind speed is in the i^{th} quintile (relative to other zip codes in the sample). The variable $NumCati_z$ is the total number of category i hurricanes between 1851 and 1950 (calculated across the zip code's neighbors). $NumTS_z$ and $NumTD_z$ represent the weighted total number of tropical storms and tropical depressions, respectively.

The second stage of the IV analysis is given by:

$$Log(aid_{zh}) = \beta \widehat{WL_z} + \sum_{i=2}^{10} \lambda_i 1[WS_{zh} = i] + \sum_{i=2}^{10} \theta_i 1[D_z = i] + \rho Age_z + \alpha_h + \varepsilon_{zh}$$

where $\widehat{WL_z}$ is the predicted wind load from the first stage.

Of course, the maximum wind speed and number of storm variables described above are not

[18] See Section 3.1 for definitions of storm types and hurricane categories.
[19] This may include zip codes outside Florida.

the only possible valid instruments. My results are robust to a large number of variations in the instrument set, including omitting the number of Category $1-4$ hurricanes, tropical storms, and tropical depressions from the IV analysis. In addition, using the *average* instead of the maximum historic wind speeds to instrument for the wind load does not affect my results.

A question important for interpretation is whether the instruments are picking up the effect of building codes or simply of hurricane risk. In other words, it may be that the building codes are weakly binding binding: individuals are making choices about what kinds of homes to build based on the historic hurricane risk in the area in the exact same way as the designers of the building codes. This would affect the mechanism through which hurricane risk affects building patterns, but not the policy conclusions. As long as there is variation in the sturdiness of the buildings created by the historic hurricane risk, policy conclusions about the effect of strenthening building codes on federal aid spending can be drawn.

5 Results

I now present and discuss the results of the analysis described above. In addition to examining the wind loads in levels, I replicate my estimates with the log of the wind load as a robustness check.

I begin with the first-stage estimates, shown in Table 2. Because many of the instruments are highly correlated, some of the coefficient signs are counterintuitive. The strongest consistent predictors of wind loads are the number of hurricanes in each category. The first-stage F-statistics range from 184 to 199, indicating that in combination the instruments are extremely strong. This is not surprising, as the ASCE 7 wind loads should be determined primarily by an area's historic hurricane record. Using only historic wind quintiles does not change the strength of the instruments or the second-stage conclusions. But because wind speed loads are likely functions of several moments of historic wind speeds, I use the more comprehensive set of instruments in my preferred estimates.[20]

In Table 3, I show the OLS estimates of the effect of building codes on federal spending. Panel A shows the relationship between building codes and the log of total aid amount, while Panel B uses the log of total aid amount plus one as the dependent variable, which adds 23 observations that did not receive any federal aid. All of the estimates are highly significant and robust across the different specifications. The OLS estimate in Column 1 implies that increasing the wind load by 1 mph reduces the amount of federal aid by $3.4\% - 4.8\%$. Adding controls for housing prices lowers the estimate somewhat to $2.4\% - 3.5\%$. The point estimates for the housing values are consistently negative, suggesting that some of the building code effects are captured by the housing price variable. At the mean amount of federal disaster aid ($\$640,000$), the preferred specification

[20] A full set of results is available from the author upon request.

(Column 1) corresponds to an estimated spending reduction of $\$21,800 - \$30,700$ per zip code and hurricane.

The log-log specifications in Columns 3 and 4 show that a 1% increase in the wind load is associated with a 3.1-4.3% decrease in federal aid, holding 2004 wind speeds constant. The estimates in Panel B are again slightly larger, suggesting a reduction of $4.3\% - 5.9\%$. Because the mean wind load is about 120, these estimates are close to the OLS at the mean level of federal aid. The preferred specification, which does not control for housing prices, implies that a 1% increase in the wind load leads to a reduction in spending of about $\$19,900 - \$27,500$ per zip code and hurricane.

Table 4 shows the 2SLS estimates for the effect of building codes on federal spending. The estimates are smaller than the correponding OLS ones: most of the OLS point estimates in Panel A fall slightly out of the 95% confidence interval for the corresponding 2SLS estimates. The downward bias of the OLS estimates suggests that the wind load is negatively correlated with unobservable determinants of damage/aid and that instrumenting is necessary. The 2SLS estimates confirm that stricter building codes reduce the amount of money spent by the federal government on disaster aid. Specifically, a 1 mph increase in the wind load reduces federal aid by $1.1 - 2.2\%$, while a one percent increase in the wind load reduces it by $1.3 - 2.7\%$. Again, the semi-log and log-log estimates are very similar. The dollar amounts corresponding to the linear and log specifications without housing price controls in Panel A are $\$14,000$ and $\$17,300$, respectively.

I also estimate the reduction in aid per housing unit, using 2000 Census data to establish the number of housing units. Table 5 shows the OLS estimates, and Table 6 shows the 2SLS estimates. As before, the OLS estimates are slightly larger in absolute value. The 2SLS estimates show that increasing the wind load of a zip code decreases the amount spent per housing unit by $2.4\% - 4.1\%$ when zip codes receiving no aid are excluded (Panel A) and by $4.0\% - 5.9\%$ when they are included (Panel B). Relative to the mean aid level of \$133, a 4.1% reduction corresponds to \$5.5 per housing unit.

Table 7 shows the nonlinear effect of building codes, estimating the average reduction in spending for the following four wind load categories: $106 - 112$ mph, $112 - 121$ mph, $121 - 129$ mph, and $129 - 150$ mph. Columns 1 and 2 show the OLS estimates, which indicate some nonlinearities: Wind loads of $106 - 112$ do not provide more protection than wind loads of $99 - 106$, while wind loads of $112 - 121$ and $121 - 129$ are substantially more effective. However, wind loads of $129 - 150$ do not appear to reduce federal spending more than wind loads of $121 - 129$ and may actually lead to more spending: in Column 2, the coefficient on the $129 - 150$ mph wind load differs from the coefficient on $121 - 129$ mph wind load at the 10% level. **CHECK - still true?** The corresponding coefficients in Column 1 are not statistically different from each other.

The statistical difference in Column 2 could occur for several reasons. For one, the extra building requirements for higher wind loads in this range may not reduce physical destruction to a significant degree. However, if these requirements cost substantially more to implement, they could actually *increase* monetary damages, resulting in more federal aid. In addition, people may respond to stricter building codes by reducing insurance coverage. If this reduction is nonlinear, we may see an increase in federal aid for some ranges of the wind load, even if monetary damages are not higher.

Table 8 shows nonlinear 2SLS estimates. Unfortunately, even with many instruments, the first stage is not strong enough in this case (all of the F-statistics are below 3), so I cannot draw reliable conclusions from this set of results.

Tables 9 and 10 show the OLS and 2SLS estimates for renters, respectively. Although some of the OLS estimates suggest that building codes slightly reduce the amount of aid given to renters, the 2SLS estimates do not support this finding and are in some cases positive. Overall, stricter building codes do not appear to lead to a significantly higher amount of aid given to renters. This makes sense in the context of disaster aid, as renters are never compensated for damages to their dwellings. However, they do in some cases qualify for temporary living assistance. This suggests that building codes reduce damages, but not necessarily the probability that a structure or a neighborhood is temporarily uninhabitable. Alternatively, it could be that rental homes and apartments are less likely to have been built to code by 2004 or that building codes are less effective for multi-family buildings.

Finally, Tables 11 and 12 show the OLS and 2SLS estimates for owners, respectively. Both sets of estimates show that stricter building codes have a large negative effect on federal spending for owner assistance. A 1 mph higher wind load reduces federal aid to owners by $3.2\% - 4.2\%$ according to the OLS results and by $2.2\% - 3.2\%$ according to the 2SLS results. The estimates using the log of the wind load instead of the level are very similar at the mean wind load. As before, including zip codes that receive no aid in the analysis (Panel B) raises the estimated effect of building codes.

It is important to keep in mind that the level of observation is zip code by hurricane. Thus, the figures above correspond to amounts expected to be saved in a relatively small geographic area. A back-of-the envelope calculation can provide a more informative estimate. Overall, $1,616$ zip codes received some disaster aid during the 2004 hurricane season, implying that the total savings from 1 mph increases in building code strictness were around \$22.6 million in that year. Of course, not all of these zip codes were equally affected by the hurricanes. Assuming that the savings would be realized only in zip codes that experienced above-median wind speeds would halve the savings estimate to about \$11.3 million.

The year 2004 was also unusual in that four hurricanes made landfall in Florida. The average Florida zip code in my sample experienced only 1.5 hurricanes that were Category 1 or higher between 1851 and 1950, although a few experience as many as 20.[21] In this case, which is certainly a lower bound, my estimates would imply that increasing the strictness of all building codes by 1 mph would result in savings of about \$34 million over 100 years.

The benefits of stricter building codes are almost certainly heterogeneous across zip codes, with benefits being highest for zip codes in which hurricanes are frequent. This will be reflected in future estimates of the benefits of building codes. In addition, damage reductions should also be taken into account. Finally, these estimated reductions must be weighed against the cost of making all the homes in a zip code comply with a stricter building code.

6 Conclusion

I estimate the effect of an *ex ante* government policy on *ex post* aid. I find that stricter building codes in Florida led to a substantial reduction in federal disaster spending in the exceptional 2004 hurricane season. Specifically, a 1 mile per hour increase in the wind load for a zip code reduced federal disaster aid by an estimated $\$14,000$. All of the decrease can be attributed to lower aid for homeowners: the amount of aid given to renters is not affected.

The policy implications of this analysis are applicable only to the case in which the government's main concern is reducing *ex post* aid. I observe neither the costs of the stricter building codes nor the amount by which they reduce damages. Thus, I cannot carry out a complete cost-benefit analysis. However, the estimated reduction of \$5.5 per housing unit per hurricane suggests that in order for building code improvements to be cost-effective, damage reductions have to be substantial and/or the costs of making a building sturdier have to be very low. It is unlikely that the latter is true, but there is unfortunately little empirical evidence available on damage reductions.

In addition, my estimates are for only one hurricane season. Because housing is durable, the long-run spending reductions from stricter building codes are larger. Finally, it is almost certain that many buildings in the affected zip codes did not conform to the ICC's building codes as of 2004, as Florida adopted them only in 2001. Because I compare spending reductions *across* zip codes, my analysis should be valid as long as stricter building codes do not result in relatively less construction in areas with higher wind loads. If stricter building codes depress construction activity more in higher wind load areas, my results are likely an underestimate of the potential for stricter building codes to reduce federal disaster aid. However, they are a valid estimate of the outcome of stricter building codes, because any changes in construction are a direct consequence of the building codes.

Because building codes are set at the state level, I do not claim that the stricter building codes were implemented in order to reduce federal disaster aid. It is possible that the state government

[21] This count is significantly larger if I also include tropical storms. To be conservative, however, I exclude them.

was concerned about its own expenditure on disaster aid, which is not observable to me. Alternatively, the reductions in *ex post* disaster aid may be an unintended consequence of stricter building codes. In either case, my research suggests that it is important to incorporate such reductions into future policy considerations.

An important omission from the analysis is the interaction between building codes and insurance. As shown in previous studies, insurance and self-insurance may be substitutes (Ehrlich and Becker, 1972). In other words, people may have responded to the stricter building codes by reducing their insurance coverage. In my setting, any such reduction was not enough to offset the damage-reducing effect of building codes (otherwise aid spending would have remained unchanged or increased). However, this represents an important area for future research.

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Figure 1: Florida Wind Loads

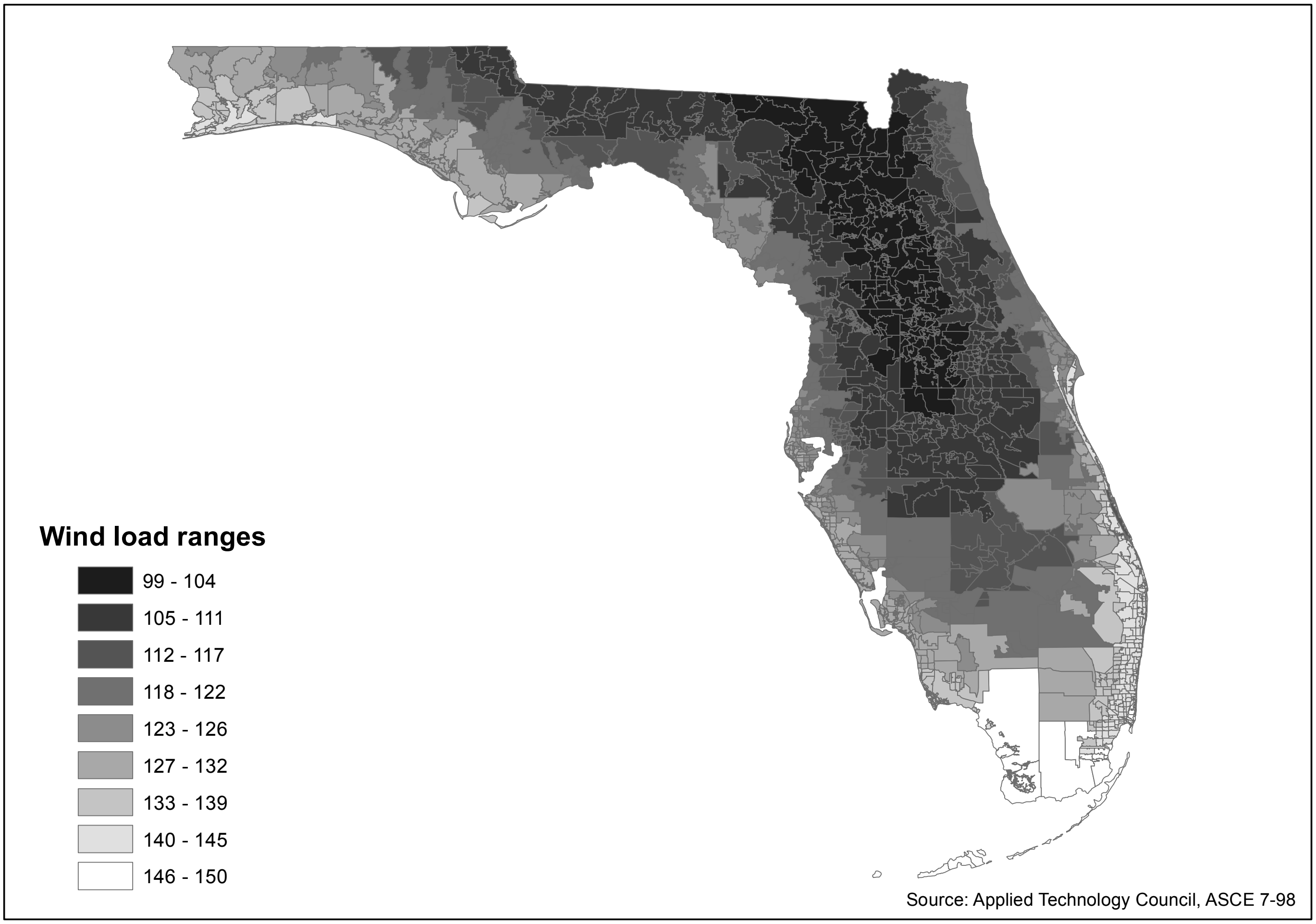

Table 1: Summary statistics

	(1) Mean	(2) Std. Dev.	(3) Min	(4) Max	(5) Obs
Wind load (ASCE 7-05, mph)	117.9	12.8	99.2	150	1,637
Observed wind speed (mph)	48.3	17.5	2.9	120	1,639
Max historic wind speed (mph)	77.5	6.6	66.3	96	1,608
Individual Assistance (IA), all (dollars)	640,506	1,306,666	0	17,326,102	1,639
IA per housing unit, all (dollars)	133.2	475.0	0	14,480	1,639
IA, owners (dollars)	414,123	815,719	0	11,762,763	1,624
IA, renters (dollars)	242,628	576,492	0	7,429,017	1,538
Log IA, all	12.0	1.9	2.8	17	1,616
Log (IA + 1), all	11.8	2.4	0	17	1,639
Log (IA per housing unit), all	3.4	2.0	-6	10	1,616

Unit of observation is zip code by hurricane. The data contain 795 unique zip codes. The number of zip code by hurricane observations for each variable is given in Column 5.

Table 2: First stage regressions

	(1)	(2)	(3)	(4)	(5)	(6)
		Wind load			Log wind load	
2nd quint. of hist. wind speeds = 1	-2.61***	-2.61***	-2.86***	-0.02***	-0.02***	-0.03***
	(0.58)	(0.58)	(0.57)	(0.00)	(0.00)	(0.00)
3rd quint. of hist. wind speeds = 1	-3.05***	-3.05***	-3.27***	-0.03***	-0.03***	-0.03***
	(0.70)	(0.70)	(0.70)	(0.01)	(0.01)	(0.01)
4th quint. of hist. wind speeds = 1	-0.70	-0.70	-0.75	-0.01	-0.01	-0.01
	(0.77)	(0.77)	(0.75)	(0.01)	(0.01)	(0.01)
5th quint. of hist. wind speeds = 1	5.80***	5.80***	5.62***	0.04***	0.04***	0.04***
	(1.78)	(1.78)	(1.75)	(0.01)	(0.01)	(0.01)
Num. tropical depressions	-8.04***	-8.04***	-7.16***	-0.07***	-0.07***	-0.06***
	(1.47)	(1.47)	(1.43)	(0.01)	(0.01)	(0.01)
Num. tropical storms	-0.96**	-0.96**	-0.99**	-0.01**	-0.01**	-0.01**
	(0.45)	(0.45)	(0.42)	(0.00)	(0.00)	(0.00)
Num. Cat. 1 hurricanes	4.46***	4.46***	4.13***	0.04***	0.04***	0.04***
	(1.66)	(1.66)	(1.60)	(0.01)	(0.01)	(0.01)
Num. Cat. 2 hurricanes	-8.40***	-8.40***	-7.74***	-0.07***	-0.07***	-0.07***
	(1.86)	(1.86)	(1.83)	(0.02)	(0.02)	(0.01)
Num. Cat. 3 hurricanes	35.79***	35.79***	35.15***	0.30***	0.30***	0.30***
	(4.86)	(4.86)	(4.82)	(0.04)	(0.04)	(0.04)
Num. Cat. 4 hurricanes	14.64**	14.64**	15.10**	0.09*	0.09*	0.09**
	(6.04)	(6.04)	(5.95)	(0.05)	(0.05)	(0.05)
First-stage partial F	199.03	199.03	195.55	187.62	187.62	183.97
Observations	1,601	1,601	1,601	1,601	1,601	1,601
R-squared	0.90	0.90	0.90	0.90	0.90	0.90
Housing Price	No	No	Yes	No	No	Yes
Housing Age	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors (clustered by zip code) in parentheses. Significance levels: *10 percent, ** 5 percent, *** 1 percent. All specifications include declaration fixed effects, distance from the coast bins, and flexible controls for actual wind speeds.

Table 3: The effect of building codes on federal spending, OLS

	(1)	(2)	(3)	(4)
		Panel A: Log of total aid		
Wind load	-0.034***	-0.024***		
	(0.005)	(0.005)		
Log of wind load			-4.329***	-3.118***
			(0.652)	(0.665)
Median year built	-0.038***	-0.022***	-0.038***	-0.022***
	(0.007)	(0.007)	(0.007)	(0.007)
Log of median housing value		-0.884***		-0.879***
		(0.143)		(0.142)
Observations	1,608	1,608	1,608	1,608
R-squared	0.435	0.460	0.436	0.461
		Panel B: Log of (total aid + 1)		
Wind load	-0.048***	-0.035***		
	(0.008)	(0.008)		
Log of wind load			-5.926***	-4.347***
			(0.930)	(0.916)
Median year built	-0.033***	-0.013*	-0.033***	-0.013
	(0.008)	(0.008)	(0.008)	(0.008)
Log of median housing value		-1.091***		-1.095***
		(0.194)		(0.194)
Observations	1,631	1,631	1,631	1,631
R-squared	0.380	0.406	0.380	0.406

Standard errors (clustered by zip code) in parentheses. Significance levels: *10 percent, ** 5 percent, *** 1 percent. All specifications include declaration fixed effects, distance from the coast bins, and flexible controls for the actual wind speed.

Table 4: The effect of building codes on federal spending, 2SLS

	(1)	(2)	(3)	(4)
		Panel A: Log of total aid		
Wind load	-0.022***	-0.011*		
	(0.006)	(0.006)		
Log of wind load			-2.679***	-1.349*
			(0.759)	(0.799)
Median year built	-0.038***	-0.020***	-0.038***	-0.020***
	(0.007)	(0.007)	(0.007)	(0.007)
Log of median housing value		-0.976***		-0.976***
		(0.150)		(0.150)
Observations	1,579	1,579	1,579	1,579
R-squared	0.432	0.458	0.433	0.459
First-stage partial F	198.069	194.712	188.079	184.139
		Panel B: Log of (total aid + 1)		
Wind load	-0.040***	-0.027***		
	(0.009)	(0.009)		
Log of wind load			-4.888***	-3.286***
			(1.132)	(1.147)
Median year built	-0.034***	-0.013	-0.034***	-0.013
	(0.008)	(0.008)	(0.008)	(0.008)
Log of median housing value		-1.130***		-1.132***
		(0.201)		(0.200)
Observations	1,601	1,601	1,601	1,601
R-squared	0.380	0.405	0.380	0.405
First-stage partial F	199.030	195.549	187.616	183.968

Standard errors (clustered by zip code) in parentheses. Significance levels: *10 percent, ** 5 percent, *** 1 percent. All specifications include declaration fixed effects, distance from the coast bins, and flexible controls for the actual wind speed. The instruments for wind load are quintiles of spatially weighted maximum wind speed and the number of tropical depressions, tropical storms, and Category 1-4 hurricanes for the time period 1851-1950.

Table 5: The effect of building codes on federal spending, OLS

	(1)	(2)	(3)	(4)
	Panel A: Log of aid per housing unit			
Wind load	-0.051***	-0.036***		
	(0.005)	(0.005)		
Log of wind load			-6.350***	-4.488***
			(0.645)	(0.626)
Median year built	-0.037***	-0.012**	-0.036***	-0.012**
	(0.006)	(0.006)	(0.006)	(0.006)
Log of median housing value		-1.353***		-1.351***
		(0.144)		(0.144)
Observations	1,608	1,608	1,608	1,608
R-squared	0.492	0.549	0.493	0.550
	Panel B: Log of (aid per housing unit + 1)			
Wind load	-0.066***	-0.047***		
	(0.008)	(0.007)		
Log of wind load			-8.048***	-5.812***
			(0.923)	(0.895)
Median year built	-0.031***	-0.003	-0.031***	-0.003
	(0.007)	(0.007)	(0.007)	(0.007)
Log of median housing value		-1.544***		-1.551***
		(0.185)		(0.185)
Observations	1,631	1,631	1,631	1,631
R-squared	0.424	0.474	0.423	0.474

Standard errors (clustered by zip code) in parentheses. Significance levels: *10 percent, ** 5 percent, *** 1 percent. All specifications include declaration fixed effects, distance from the coast bins, and flexible controls for the actual wind speed.

Table 6: The effect of building codes on federal spending per housing unit, 2SLS

	(1)	(2)	(3)	(4)
		Panel A: Log of aid per housing unit		
Wind load	-0.041***	-0.024***		
	(0.006)	(0.006)		
Log of wind load			-5.045***	-2.994***
			(0.743)	(0.737)
Median year built	-0.038***	-0.011*	-0.038***	-0.011*
	(0.006)	(0.006)	(0.006)	(0.006)
Log of median housing value		-1.474***		-1.476***
		(0.144)		(0.143)
Observations	1,579	1,579	1,579	1,579
R-squared	0.492	0.554	0.493	0.555
First-stage partial F	198.069	194.712	188.079	184.139
		Panel B: Log of (aid per housing unit + 1)		
Wind load	-0.059***	-0.040***		
	(0.009)	(0.009)		
Log of wind load			-7.283***	-4.963***
			(1.139)	(1.124)
Median year built	-0.034***	-0.004	-0.033***	-0.003
	(0.007)	(0.007)	(0.007)	(0.007)
Log of median housing value		-1.610***		-1.615***
		(0.183)		(0.182)
Observations	1,601	1,601	1,601	1,601
R-squared	0.426	0.478	0.425	0.478
First-stage partial F	199.030	195.549	187.616	183.968

Standard errors (clustered by zip code) in parentheses. Significance levels: *10 percent, ** 5 percent, *** 1 percent. All specifications include declaration fixed effects, distance from the coast bins, and flexible controls for the actual wind speed. The instruments for wind load are quintiles of spatially weighted maximum wind speed and the number of tropical depressions, tropical storms, and Category 1-4 hurricanes for the time period 1851-1950.

Table 7: The nonlinear effects of building codes, OLS

	(1)	(2)	(3)	(4)
	Log of total aid		Log of (total aid + 1)	
Wind load = 106-112	-0.101	0.002	0.083	0.210
	(0.153)	(0.151)	(0.173)	(0.175)
Wind load = 112-121	-0.596***	-0.563***	-0.387*	-0.339
	(0.175)	(0.179)	(0.213)	(0.223)
Wind load = 121-129	-1.236***	-1.130***	-1.057***	-0.919***
	(0.211)	(0.206)	(0.248)	(0.248)
Wind load = 129-150	-1.382***	-1.003***	-1.661***	-1.191***
	(0.203)	(0.210)	(0.273)	(0.273)
Median year built	-0.036***	-0.019***	-0.030***	-0.009
	(0.007)	(0.007)	(0.008)	(0.008)
Log of median housing value		-0.944***		-1.119***
		(0.142)		(0.194)
Observations	1,608	1,608	1,631	1,631
R-squared	0.447	0.474	0.387	0.413

Standard errors (clustered by zip code) in parentheses. Significance levels: *10 percent, ** 5 percent, *** 1 percent. All specifications include declaration fixed effects, distance from the coast bins, and flexible controls for the actual wind speed. Omitted category is wind load of 99-106.

Table 8: The nonlinear effect of building codes on federal spending, 2SLS

	(1)	(2)	(3)	(4)
	Log of total aid		Log of (total aid + 1)	
Wind load = 106-112	-1.896	-1.076	-1.366	-0.312
	(1.444)	(1.393)	(1.696)	(1.633)
Wind load = 112-121	0.545	0.346	1.827	1.638
	(1.073)	(0.932)	(1.295)	(1.158)
Wind load = 121-129	-0.231	-0.036	0.321	0.576
	(0.735)	(0.657)	(0.845)	(0.762)
Wind load = 129-150	-1.028	-0.575	-0.932	-0.360
	(0.766)	(0.724)	(0.895)	(0.846)
Median year built	-0.046***	-0.028**	-0.039***	-0.017
	(0.011)	(0.012)	(0.013)	(0.014)
Log of median housing value		-0.803***		-0.900***
		(0.201)		(0.254)
Observations	1,579	1,579	1,601	1,601
R-squared	0.232	0.371	0.197	0.322
First-stage partial F	2.076	1.631	2.092	1.639

Standard errors (clustered by zip code) in parentheses. Significance levels: *10 percent, ** 5 percent, *** 1 percent. All specifications include declaration fixed effects, distance from the coast bins, and flexible controls for the actual wind speed. The instruments for wind load are quintiles of spatially weighted maximum wind speed and the number of tropical depressions, tropical storms, and Category 1-4 hurricanes for the time period 1851-1950.

Table 9: The effect of building codes on federal spending, renters, OLS

	(1)	(2)	(3)	(4)
		Panel A: Log of aid to renters		
Wind load	-0.003	0.004		
	(0.006)	(0.006)		
Log of wind load			-0.513	0.329
			(0.787)	(0.806)
Median year built	-0.059***	-0.048***	-0.059***	-0.048***
	(0.008)	(0.009)	(0.008)	(0.009)
Log of median housing value		-0.650***		-0.643***
		(0.152)		(0.152)
Observations	1,470	1,470	1,470	1,470
R-squared	0.370	0.382	0.370	0.381
		Panel B: Log of (aid to renters + 1)		
Wind load	-0.018**	-0.006		
	(0.009)	(0.009)		
Log of wind load			-2.234**	-0.810
			(1.048)	(1.081)
Median year built	-0.079***	-0.061***	-0.079***	-0.061***
	(0.011)	(0.011)	(0.011)	(0.011)
Log of median housing value		-1.074***		-1.069***
		(0.232)		(0.231)
Observations	1,532	1,532	1,532	1,532
R-squared	0.316	0.332	0.316	0.332

Standard errors (clustered by zip code) in parentheses. Significance levels: *10 percent, ** 5 percent, *** 1 percent. All specifications include declaration fixed effects, distance from the coast bins, and flexible controls for the actual wind speed.

Table 10: The effect of building codes on federal spending, renters, 2SLS

	(1)	(2)	(3)	(4)
		Panel A: Log of aid to renters		
Wind load	0.009	0.016**		
	(0.007)	(0.007)		
Log of wind load			1.202	2.156**
			(0.885)	(0.916)
Median year built	-0.058***	-0.046***	-0.058***	-0.046***
	(0.008)	(0.009)	(0.008)	(0.009)
Log of median housing value		-0.731***		-0.736***
		(0.158)		(0.159)
Observations	1,445	1,445	1,445	1,445
R-squared	0.371	0.382	0.370	0.381
First-stage partial F	197.983	191.030	188.681	182.546
		Panel B: Log of (aid to renters + 1)		
Wind load	0.003	0.016		
	(0.010)	(0.010)		
Log of wind load			0.498	2.137*
			(1.220)	(1.289)
Median year built	-0.078***	-0.057***	-0.078***	-0.057***
	(0.011)	(0.011)	(0.011)	(0.011)
Log of median housing value		-1.231***		-1.235***
		(0.242)		(0.242)
Observations	1,505	1,505	1,505	1,505
R-squared	0.313	0.329	0.312	0.329
First-stage partial F	197.203	192.428	187.928	183.510

Standard errors (clustered by zip code) in parentheses. Significance levels: *10 percent, ** 5 percent, *** 1 percent. All specifications include declaration fixed effects, distance from the coast bins, and flexible controls for the actual wind speed. The instruments for wind load are quintiles of spatially weighted maximum wind speed and the number of tropical depressions, tropical storms, and Category 1-4 hurricanes for the time period 1851-1950.

Table 11: The effect of building codes on federal spending, owners, OLS

	(1)	(2)	(3)	(4)
		Panel A: Log of aid to owners		
Wind load	-0.042***	-0.032***		
	(0.005)	(0.005)		
Log of wind load			-5.303***	-4.093***
			(0.602)	(0.613)
Median year built	-0.024***	-0.009	-0.024***	-0.009
	(0.006)	(0.006)	(0.006)	(0.006)
Log of median housing value		-0.856***		-0.852***
		(0.138)		(0.138)
Observations	1,593	1,593	1,593	1,593
R-squared	0.452	0.477	0.454	0.479
		Panel B: Log of (aid to owners + 1)		
Wind load	-0.057***	-0.044***		
	(0.007)	(0.007)		
Log of wind load			-6.992***	-5.494***
			(0.855)	(0.861)
Median year built	-0.026***	-0.007	-0.026***	-0.007
	(0.007)	(0.007)	(0.007)	(0.007)
Log of median housing value		-1.026***		-1.030***
		(0.191)		(0.190)
Observations	1,616	1,616	1,616	1,616
R-squared	0.388	0.412	0.388	0.413

Standard errors (clustered by zip code) in parentheses. Significance levels: *10 percent, ** 5 percent, *** 1 percent. All specifications include declaration fixed effects, distance from the coast bins, and flexible controls for the actual wind speed.

Table 12: The effect of building codes on federal spending, owners, 2SLS

	(1)	(2)	(3)	(4)
	Panel A: Log of aid to owners			
Wind load	-0.032***	-0.022***		
	(0.006)	(0.006)		
Log of wind load			-4.067***	-2.762***
			(0.718)	(0.752)
Median year built	-0.025***	-0.008	-0.025***	-0.008
	(0.006)	(0.006)	(0.006)	(0.006)
Log of median housing value		-0.931***		-0.929***
		(0.144)		(0.144)
Observations	1,566	1,566	1,566	1,566
R-squared	0.452	0.479	0.454	0.480
First-stage partial F	202.334	204.452	191.283	191.680
	Panel B: Log of (aid to owners + 1)			
Wind load	-0.046***	-0.034***		
	(0.008)	(0.008)		
Log of wind load			-5.751***	-4.202***
			(0.972)	(1.010)
Median year built	-0.027***	-0.007	-0.027***	-0.007
	(0.007)	(0.007)	(0.007)	(0.007)
Log of median housing value		-1.077***		-1.077***
		(0.198)		(0.197)
Observations	1,588	1,588	1,588	1,588
R-squared	0.389	0.412	0.389	0.413
First-stage partial F	198.591	198.979	187.053	186.106

Standard errors (clustered by zip code) in parentheses. Significance levels: *10 percent, ** 5 percent, *** 1 percent. All specifications include declaration fixed effects, distance from the coast bins, and flexible controls for the actual wind speed. The instruments for wind load are quintiles of spatially weighted maximum wind speed and the number of tropical depressions, tropical storms, and Category 1-4 hurricanes for the time period 1851-1950.