Reducing the Cost of Ex-post Bailouts with Ex-ante Regulation: Evidence From Building Codes

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Abstract

The government often serves as the insurer of last resort in contexts ranging from natural disasters to macroeconomic crises. However, this can cause moral hazard if agents respond by taking on more risk or reducing insurance coverage because they know they will be bailed out. Ex-ante measures can theoretically 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 spent by the federal government by 2.6% or $\$16,600$ per affected zip code during a hurricane. I also show that this decrease is entirely driven by aid given to homeowners as opposed to renters. These findings underscore the importance of comprehensively analyzing the costs and benefits of policies where ex-ante moral hazard is a concern.

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;

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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 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 for 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. The advantage of my setting is that I am able to identify a plausibly exogenous source of variation in building code strength. I then 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 zip code by an estimated 2.6% or $\$16,600$. This 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.

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 commit to not bail 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 where the government cannot credibly commit to not bail 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 the building code is poorly designed or not enforced, it may not reduce damages. In addition, the aid process has been shown to be heavily affected 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. Finally, households may respond to stricter building codes by reducing insurance coverage. In this case, the total amount of damages eligible for federal aid, which only covers 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 gov-

ernment spending, considering the effectiveness of building codes is important in its own right. Extreme weather events are a large and growing source of negative economic shocks. Larger population densities, ecosystem alteration, and population movements to hazardous areas are causing real damages from natural disasters to rise (Board on Natural Disasters, 1999). In 2005 dollars, world insured losses have exceeded $10 billion per year 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 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 the fact that natural disasters lead to increased government spending in other transfer programs, such as unemployment insurance and Medicaid. Both the trends in damages and in government aid spending highlight the importance of finding effective policy solutions.

To my knowledge, however, only two studies have looked at the relationship between newer building codes and damages (Fronstin and Holtmann, 1994; Dehring and Halek, 2013), and none has considered the effect of building codes on disaster relief spending. Moreover, these studies cannot quantify the strength of the newer building codes. As a result, their ability to draw policy conclusions are 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 outlinining 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

[1] Uninsured losses are difficult to estimate, but a 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 using data from http://www.peripresdecusa.org/mainframe.htm, accessed January 15, 2013.

credibly commit to not give ex-post aid.

The simple model below is adapted from Kaplow (1991), who shows that the presence of government aid reduces the incentives to mitigate and insure damages. Intuitively, this arises because individuals take into account the effect of mitigation on the reductions in their *own* cost from a disaster, rather than the social cost, some of which is borne by the government.[3] Unlike Kaplow, I assume that mitigation measures reduce the damage of the 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 labeling the solution when ex-post aid is present 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 the individual has access to actuarially fair insurance and pays a premium equal to πI, where I is the amount of insurance purchased.

In the event that a disaster occurs, the government gives a transfer to the affected household. The transfer is a fraction of damages, αD, where $1 > \alpha > 0$.[4] 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 begin with the case of no government aid. The first-best level of mitigation solves:

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

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:

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

[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 have the additional effect of reducing incentives to insure.

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

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 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 solution to this problem will not correspond to the socially optimal solution m^* because the household does not take into account the costs of public funds that the government incurs in providing the transfers.

It is easy to show that, when deciding how much insurance to purchase, the household will again equalize marginal utility/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.

From the household's point of view, the optimal amount of mitigation when there is ex-post aid, 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, when there are government transfers, the household spends too little on mitigating damages. Intuitively, this is because the introduction of government transfers raises the wealth and lowers the marginal utility in the state of the world where 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 where the disaster does not occur. Subsequently, damages from the disaster will be higher, as will be the federal expenditure on ex-post aid.

Although this model focuses on mitigation expenditure, it is broadly applicable to any situation where agents make decisions about risk exposure and 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 first-best simply by mandating a level of mitigation expenditure 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. However, if there is heterogeneity in risk preferences or other dimensions, a simple floor on mitigation expenditure will not result in the first-best outcome. Nevertheless, it can be an improvement over the situation in which the household is free to choose any mitigation expenditure it desires.

Another way the government can reach the first-best outcome in this model is by mandating that all households purchase full insurance. Because the government does not in practice compensate for damages that are covered by insurance, this completely eliminates ex-post transfers and, assuming the insurance is actuarially fair, leads to the socially optimal level of mitigation.

A comparison of mandating insurance and 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 former need to be checked once, while the latter need to be checked continuously.[5] Second, as with health insurance, there may be political constraints to implementing an insurance mandate. The penalty for not having insurance needs to be high such that most households 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, implemeting the optimal penalty level may be difficult politically.

The model above also assumes that insurance is actuarially fair. In practice, homeowners insurance loads are among the highest seen in insurance markets (of the Insurance Commissioner", 2004; Hunter, 2012). In this case, mandating full insurance might not be efficient. Finally, there is evidence that homeowners are myopic and underestimate disaster risk. This leads them to both underinsure and 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 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 be best to overcome the issues present in disaster preparedness.

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

3 Background and Data

3.1 Hurricanes and Federal Disaster Aid

Because my empirical strategy is to estimate the impact of building codes on federal aid in the aftermath of several Florida hurricanes, it is instructive to provide some background on hurricanes in general.

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 disturbance becomes a tropical cyclone. Prevailing winds and currents move the cyclone across the ocean, where it gains and loses strength based on the favorability of 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 as one moves away 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 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 it to land cause widespread wind and flood damage: Physical damages from hurricanes in the US have averaged $4.4 billion per hurricane (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.[6]

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 some of the most destructive hurricanes at that time, trailing only Hurricane Andrew in 1992. In the US, they caused $14, $13, and $9 billion in estimated damages, respectively (all in 2004 dollars). Hurricane Jeanne was estimated to cause about $6.9 billion in damages. Tropical Storm Bonnie made landfall only a day before Hurricane Charley, making it hard to separately estimate its damages. They were likely

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

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 handle the disaster on its own. The final decision about whether to declare a major disaster is made by the US President. In practice, few requests are denied. Once the 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 unemployed due to 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, ranging from clauses 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 the construction of their building affects their neighbors. For example, residents may choose levels of fire resistance that are lower than socially optimal because they do no internalize the possibility that their neighbor's house also catches fire. Building codes can thus be seen as a tool to resolve a negative externality. The second reason for mandating building codes is that it may be very costly for individuals to assess the quality 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 ASCE's hurricane provisions would be a daunting tasks. Luckily, ASCE 7 provides maps of wind speeds that a building in that 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 risk of

the roof being torn off by wind). The wind loads also govern requirements for vent coverings, storm shutters, and doors. Because quantifying each component of the building code is not feasible, I rely on the wind loads as a proxy for the strictness of the building code.

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. Along with the adoption of the ICC building codes, Florida adopted the wind maps published by the ASCE 7. Although the ASCE 7 is also updated periodically, the wind maps have remained unchanged from 1995 to 2010.[7]

New building codes typically apply to new buildings only. Older buildings must update to the current building code only if they undergo significant renovations. However, it is also likely that the ASCE 7 wind loads are to some extent correlated with building codes 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.

3.3 Data

As mentioned above, attempting to take into account all the wind-related features of a building code would render a statistical analysis intractable. Therefore, I focus on one easily quantifiable feature of the Florida building code: the wind speed that a building in a particular location must be able to withstand or "wind load". 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]

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 have 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.[9] I then map the wind load points into zip code boundaries using zip code maps from the 2000 Census.[10] Finally, I average the wind load within a zip code to create a zip-level measure of building code strictness.

[7]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.

[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 are limited.

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

[10]Available from http://www.census.gov/geo/www/cob/z52000.html#shp, accessed August 2012.

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.[11] I compute the wind speed corresponding to each vector location and map that location into zip code boundaries using the 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.[12] 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.[13]

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.[14] The data are less detailed than 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 only covers recent hurricanes, Best Tracks data are provided for each North 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 the detailed discussion of instrument creation until 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

[11] The H*Wind datasets are available from http://www.aoml.noaa.gov/hrd/data$_sub/wind2004.html, accessedAugust2012$.

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

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

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

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 is 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 - log of the individual assistance amount and log of the individual assistance amount plus 1. The latter measure avoids dropping zeros. Because there are only 39 observations (out of 1,761) that do not receive any assistance, which transformation I use does not significantly affect my estimates when looking at total assistance for both owners and renters. However, because renters are less likely to receive assistance than owners, 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. Areas that are closer to the coast have in general higher wind loads; However, this by itself 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 if the wind load in an area is increased, holding constant 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:

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

where z indexes zip codes and h indexed hurricanes. $Log(aid_{zh})$ is the logged amount of federal dollars given to individuals in zip code z for hurricane h, and WL_z is the wind load for zip code z. $1[WS_{zh} = i]$ 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). 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. Finally, α_h is a set of declaration/hurricane fixed effects. The coefficient of interest is β, which shows the relationship between the wind load and federal aid, holding constant the actual wind speed.[15] Because some zip

[15] Ideally, I would also exploit intertemporal variation in building code strength. Unfortunately, there were no changes to wind loads during my sample period: the first significant change since 1995 occurs in the 2010 version of the ASCE, ASCE 7-10. The effect of these changes is important to analyze in the future, but it is likely too early to

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:

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

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. Their 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 and 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 probably sell at a higher price for that reason. While 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 a 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 analysis.

4.2 IV

In order for the OLS estimates to reflect the causal effect of building codes on federal aid, it must be true that there are no unobservables that covary with the wind load and affect federal aid at the zip code level. Areas with higher wind loads may also sustain higher damages for a given wind speed, for example because they are also located in a flood-prone area. In general, if the ASCE bases its wind loads on damage determinants other than wind speed, there will be an endogeneity problem, and the OLS estimates will be biased. ASCE determines appropriate wind loads through

detect their impact at this point.

modeling the risk of different 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 are covered separately from the wind loads and thus flood risk is unlikely to be affecting the wind load of a 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 the 1992 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* a newer housing stock. OLS estimates would then conflate the effect of a newer housing stock (which could lead to lower or higher aid ex-post) with the effect of stricter building codes.

I address the endogeneity concerns outlined above by instrumenting for wind loads with historic wind speeds and number of storms, variables that reflect a zip code's hurricane risk but that should not reflect other determinants of damage. To avoid 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.

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.[16] Then, to create a smooth estimate of risk, I also incorporate the hurricane experience of nearby zip codes. 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.[17] I include the zip code's own hurricane experience in this average with a distance value of 0 (and thus a weight of 1). 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 instrumental variables regression is given by:

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

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

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). $NumCati_z$ is the total number of category

[16] See Section 3.1 for definitions of storm types and hurricane categories.

[17] This may include zip codes outside Florida.

i hurricanes between 1851 and 1950 (calculated across the zip code and its neighbors). $NumTS_z$ and $NumTD_z$ represent the weighted total number of tropical storms and tropical depressions, respectively.

The second stage of the instrumental variables regression is given by:

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

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

Of course, the maximum wind speed and number of storm variables described above are not the only possible valid instruments. My results are robust to a large number of variations in the set of instruments, 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.

5 Results

I now present and discuss the results of the analysis described above. In addition to looking at 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 of correlation between many of the instruments, 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 210 to 230, indicating that the instruments are extremely strong. This is not surprising, as the ASCE 7 wind loads should mostly be determined by an area's historic hurricane record. Using only historic wind quintiles does not change the strength of the instrument 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 as my preferred estimate.[18]

Panels A and B of Table 3 show the OLS and IV estimates of the linear effect of building codes on federal spending, respectively. The OLS estimate in Column 1 implies that increasing the wind load by 1 mph reduces the amount spent on federal aid by 3.2%. Adding controls for distance to the coast (my preferred specification) results in a statistically identical estimate of 3.5%. At the mean amount of federal disaster aid ($\$640,000$), this corresponds to an estimated reduction of $\$22,400$ per zip code and hurricane.

The log-log specifications in Columns 3 and 4 show that a one percent increase in the wind load is associated with a 3.8-4.5% decrease in federal aid, holding 2004 wind speeds constant. Because

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

the mean wind load is about 120, these estimates are very close to the OLS at the mean level of federal aid. The preferred specification, which includes controls for distance to the coast, implies that a one percent increase in the wind load leads to a reduction in spending of about $\$28,800$ per zip code and hurricane.

The IV estimates in Panel B of Table 3 are slightly smaller, but 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 $2.4-2.6\%$, while a one percent increase in the wind load reduces it by $2.9-3.2\%$. Again, the level and log estimates are very similar. The dollar amounts corresponding to the linear and log specifications with coastal distance fixed effects are $\$16,600$ and $\$20,500$, respectively.

Table 4 estimates the nonlinear effect of building codes. 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: The two estimates in Column 2 are different from each other at the 10% level, while those in Column 1 are not statistically different. The difference could occur for several reasons. For one, the extra building requirements for higher wind loads in this range may not reduce physical destruction much. 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. Columns 3 and 4 of Table 4 show the nonlinear IV estimates. Unfortunately, even with many instruments, the first stage is not strong enough in this case, so I cannot draw reliable conclusions from this set of results.

Finally, Table 5 shows OLS and IV estimates from Table 3 broken down by whether the aid was given to renters versus owners. Although the OLS estimates suggest that building codes reduce the amount of aid given to renters slightly, the IV estimates contradict this finding (Panel A). Overall, stricter building codes do not appear to lead to a significant change in the amount of aid given to renters. This makes sense in the context of disaster aid, as renters are never compensated for damages done to their dwelling. 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 homes for rent and apartments were less likely to be built up to code by this time or that building codes are less effective for multi-family homes.

Panel B shows the corresponding point estimates for owners. In this case, stricter building codes have a large negative effect on federal spending for owner assistance. A 1 mph increase in

the wind load reduces federal aid to owners by $4.3 - 5.7\%$ according to the OLS results and by 3.7-4.9% according to the IV results. The corresponding dollar amounts are $\$27,500 - \$36,500$ and $\$23,700 - \$31,400$, respectively. The estimates using the log of the wind load are very similar at the mean wind load.

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, there are $1,616$ zip codes that received some disaster aid during the 2004 hurricane season, implying that the total savings from a 1 mile per hour increase in building code strictness were around $27 million in that year. Of course, not all 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 $27 million.

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.[19] 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 $20 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 $\$16,600$. All of the decrease can be attributed to lower aid for homeowners: There is no change in the amount of aid given to renters.

Policy implications of this analysis are only applicable to the case where the government's main concern is reducing ex-post aid. I do not observe the costs of the stricter building codes or by how much they reduce damages. Thus, I cannot carry out a complete cost-benefit analysis. In addition, my estimates are only for 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

[19] This count is significantly larger if I also include tropical storms. However, to be conservative, I exclude them.

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* different zip codes, my analysis should be valid as long as stricter building codes do not result in less construction. If stricter building codes depress construction activity, 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 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 interaction omitted from the analysis is that between building codes and insurance. As shown by previous researchers, 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 should be an important area for future research.

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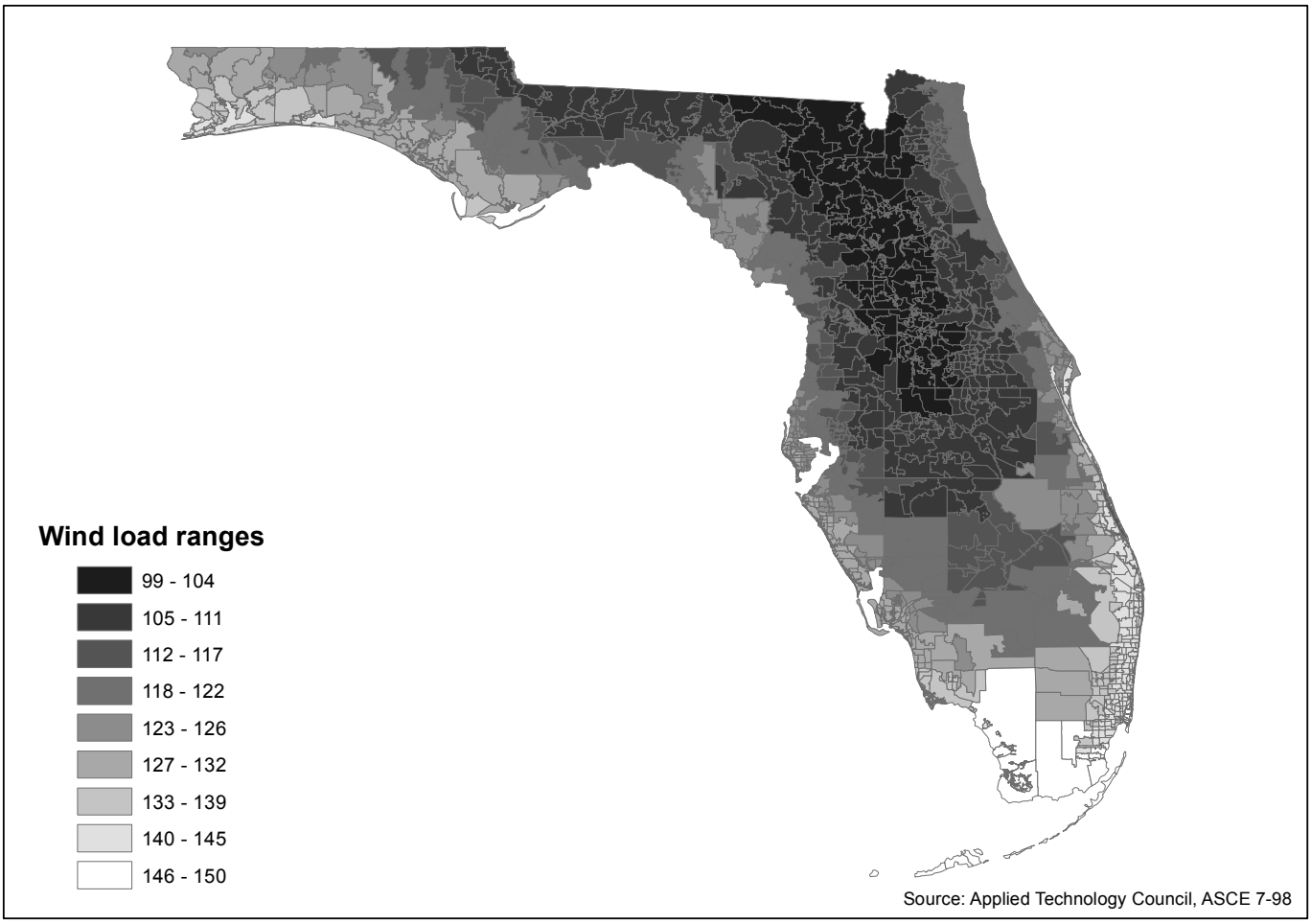
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Figure 1: Florida Wind Loads



Tables

Table 1: Summary Statistics

	Mean	Std. dev.	Min	Max	Obs
Panel A: wind loads and speeds					
Wind load (ASCE 7-05, mph)	118	13	99	150	1,637
Observed wind speed (mph)	48	18	3	120	1,639
Max historic wind speed (mph)	78	7	66	96	1,608
Panel B: Federal aid					
Individual Assistance - All ($)	640,506	1,306,666	0	17,300,000	1,639
Individual Assistance - Owners ($)	414,123	815,719	0	11,800,000	1,624
Individual Assistance - Renters ($)	242,628	576,492	0	7,429,017	1,538
Log Individual Assistance - All	11.99	1.95	2.83	16.67	1,616
Log (Individual Assistance + 1) - All	11.82	2.39	0	16.67	1,639

Unit of observation is zip code by hurricane. The data contain 795 unique zip codes.

Table 2: First stage regressions

	(1)	(2)	(3)	(4)
	Wind load		Log wind load	
Second quintile of historic wind speeds = 1	-4.931***	-4.931***	-0.026***	-0.026***
	(0.803)	(0.803)	(0.005)	(0.005)
Third quintile of historic wind speeds = 1	-6.002***	-6.002***	-0.019***	-0.019***
	(0.870)	(0.870)	(0.006)	(0.006)
Fourth quintile of historic wind speeds = 1	-7.372***	-7.372***	0.002	0.002
	(1.012)	(1.012)	(0.006)	(0.006)
Fifth quintile of historic wind speeds = 1	0.611	0.611	0.067***	0.067***
	(1.885)	(1.885)	(0.012)	(0.012)
Number of tropical depressions	15.999***	15.999***	0.02	0.02
	(2.249)	(2.249)	(0.013)	(0.013)
Number of tropical storms	-14.385***	-14.385***	-0.050***	-0.050***
	(2.472)	(2.472)	(0.012)	(0.012)
Number of Category 1 hurricanes	30.107***	30.107***	0.203***	0.203***
	(5.997)	(5.997)	(0.030)	(0.030)
Number of Category 2 hurricanes	17.638***	17.638***	0.102***	0.102***
	(6.040)	(6.040)	(0.038)	(0.038)
Number of Category 3 hurricanes	-21.497***	-21.497***	-0.067***	-0.067***
	(1.470)	(1.470)	(0.010)	(0.010)
Number of Category 4 hurricanes	0.493	0.493	-0.002	-0.002
	(0.526)	(0.526)	(0.003)	(0.003)
Distance to coast bins	N	Y	N	Y
Observations	1,607	1,607	1,607	1,607
R-squared	0.77	0.77	0.90	0.90
First stage F-stat	229.42	229.42	210.10	210.10

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

Table 3: The effect of building codes on federal spending

	(1)	(2)	(3)	(4)
	Panel A: OLS			
Wind load	-0.032***	-0.035***		
	(0.004)	(0.006)		
Log wind load			-3.859***	-4.511***
			(0.512)	(0.682)
Distance to coast bins	N	Y	N	Y
Observations	1,614	1,614	1,614	1,614
R-squared	0.40	0.41	0.41	0.41
	Panel B: IV			
Wind load	-0.024***	-0.026***		
	(0.005)	(0.007)		
Log wind load			-2.871***	-3.243***
			(0.604)	(0.822)
Distance to coast bins	N	Y	N	Y
Observations	1,585	1,585	1,585	1,585
R-squared	0.40	0.41	0.40	0.41
First stage F-stat	214.11	202.07	209.92	200.63

Dependent variable is log of federal disaster aid given to individuals. Standard errors (clustered by zip code) in parentheses. Significance levels: *10 percent, ** 5 percent, *** 1 percent. All specifications include declaration fixed effects 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 4: Non-linear effects of building codes

	(1)	(2)	(3)	(4)
	OLS		IV	
[Wind load = 106-112]	0.026	-0.112	0.890	0.448
	(0.134)	(0.147)	(0.923)	(0.903)
[Wind load = 112-121]	-0.466***	-0.762***	0.769	0.302
	(0.152)	(0.191)	(0.522)	(0.747)
[Wind load = 121-129]	-1.219***	-1.642***	-0.373	-0.519
	(0.173)	(0.220)	(0.420)	(0.586)
[Wind load = 129-150]	-0.941***	-1.336***	-0.297	-0.550
	(0.165)	(0.214)	(0.445)	(0.584)
Distance to coast bins	N	Y	N	Y
Observations	1,614	1,614	1,585	1,585
R-squared	0.42	0.44	0.38	0.42
First stage F-stat			2.19	2.09

Dependent variable is log of federal disaster aid given to individuals. Standard errors (clustered by zip code) in parentheses. Significance levels: *10 percent, ** 5 percent, *** 1 percent. All specifications include declaration fixed effects and flexible controls for the actual wind speed. Omitted category is wind load of 99-106.

Table 5: Renters versus owners

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS				IV			
	Log ($)	Log ($+1)	Log ($)	Log ($+1)	Log ($)	Log ($+1)	Log ($)	Log ($+1)
	Panel A: Renters							
Wind load	-0.004	-0.018**			0.004	-0.001		
	(0.007)	(0.009)			(0.008)	(0.010)		
Log wind load			-0.647	-2.381**			0.554	-0.061
			(0.840)	(1.084)			(0.952)	(1.238)
Distance to coast bins	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,475	1,537	1,475	1,537	1,450	1,510	1,450	1,510
R-squared	0.32	0.27	0.32	0.27	0.33	0.27	0.32	0.27
First stage F-stat					214.06	214.08	211.15	211.08
	Panel B: Owners							
Wind load	-0.043***	-0.057***			-0.037***	-0.049***		
	(0.005)	(0.007)			(0.006)	(0.008)		
Log wind load			-5.467***	-7.127***			-4.602***	-6.092***
			(0.623)	(0.859)			(0.783)	(0.988)
Distance to coast bins	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,599	1,622	1,599	1,622	1,572	1,594	1,572	1,594
R-squared	0.44	0.38	0.44	0.38	0.44	0.38	0.44	0.38
First stage F-stat					202.15	208.28	201.99	207.59

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