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# The Impact of Hurricane Mitigation Features and Inspection Information on House Prices

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**Abstract** This paper examines the effect of hurricane mitigation features and their verification on the transaction prices of single-family homes. Some of these features are obvious to buyers and sellers (visible) and others are not easily observed (hidden). Prior research on the relationship between mitigation features and house prices has implicitly assumed the features are known and that buyers and sellers are equally informed. This paper contributes to the literature by examining the potentially different effects of the visible and hidden features, and the verification of each by professional inspection, on prices in an environment of incomplete and asymmetric buyer-seller information. Generally, findings are consistent with expectations – that visible mitigation features are positively correlated with price increases; that the effects of the visible and hidden features on price differ significantly; and that inspection information significantly increases the implicit price of hidden features. Interestingly, the inspection is found to also increase the implicit price of the set of visible features, suggesting the implicit

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prices of characteristics that are, or should be, visible to buyers and sellers may be affected by verification or disclosure.

**Keywords** House prices · Asymmetric information · Information disclosure

## Introduction

In negotiating the sale of a house the seller is typically perceived as holding a better set of property-specific information than the buyer, especially as it pertains to the structure itself. This information imbalance, or asymmetry, can place the buyer at a disadvantage. State and local governments have enacted disclosure laws associated with real property transactions as one way to mitigate these information asymmetries. The disclosures are intended to "level the field" by providing information that can materially affect the buyer/seller reservation prices and, ultimately, the transaction price negotiated.

In most cases, disclosures convey information to the buyer that is known (or could be known) by the seller that may negatively affect the value of the property (e.g., structural defects, the presence of contaminants such as asbestos, radon, or urea formaldehyde, or the property's proximity to airport noise, toxic waste, and other externalities). In contrast, sellers may seek to confirm or certify information that may positively affect the property's value (e.g., the historic status of the home and its neighborhood, its construction quality, or its energy consumption characteristics as indicated by an Energy Star rating or LEED certification).[1] Understanding the effect of new (i.e., verified) positive information on observed transaction prices and the implied buyer and seller reservation prices is of particular interest.

Specifically, this study examines the effects that hurricane mitigation features, and their verification by inspection, have on the transaction prices of single family homes in areas at risk in Florida. Some of the mitigation features are visible to buyers and sellers and others are hidden. While the visible mitigation features may be known by both parties, the hidden features are likely to be known only to the sellers, if at all. The information is not readily available in public databases such as the MLS, nor by disclosure.[2] Because of the concealed nature of some of the construction information, the study provides a unique setting to examine the impact of both visible and hidden feature information on prices, as well as the impact of the verification of this information by professional inspection. Thus, this paper contributes to the literature by examining the potentially different effects of the visible and hidden features on prices, and the availability of inspection information, in an environment where buyers and sellers may not be fully or equally informed.

[1] Energy Star is a government-labeling program initiated by the U.S. Environmental Protection Agency and the U.S. Department of Energy. LEED (Leadership in Energy and Environmental Design) is a rating system devised by the U.S. Green Building Council to evaluate the environmental performance of a building.

[2] The mitigation features, both hidden and visible, are contained in a proprietary database from Citizens Property Casualty Insurance Company. This is not public information for buyers of properties and not included in required sales disclosure forms. Examples of visible features include roof shape of the home and existence of hurricane shutters. Examples of hidden features include the method of roof attachment to the perimeter wall, method of the attachment of the shingles to the sheathing, and the presence of a secondary water barrier.

Merging the Miami-Dade County master property tax file with a dataset of insured properties from Citizens Property Insurance Corporation, we assemble a dataset that includes house prices, property characteristics, and hurricane mitigation features at the property level, along with other locational information, to examine whether the mitigation features are priced by the housing market in the Miami-Dade MSA. Initially, as a benchmark, we estimate several standard hedonic models that implicitly assume the buyer-seller information is symmetric. We consistently find the coefficient estimates on the set of visible and hidden mitigation features in the hedonic models are positive and statistically significant (e.g., estimates range from $\beta = 0.012$ to $\beta = 0.026$). Combined, the hidden and visible features are correlated with price increases ranging from 2.2% to 4.3%. However, we show that if information is not symmetric with respect to a positive amenity the standard hedonic coefficient estimates may be biased and may understate the actual price effect. In addition, it's not clear whether the price increase is due to the risk mitigating benefits of the features or the insurance premium discounts they represent.

Using a treatment effects model we relax (partially) the assumption of symmetric information by explicitly modeling the inspection decision and include this information (i.e., the verification of the visible and hidden mitigation features) in the second stage pricing model. In this model the estimated price effects of the visible and hidden features vary and increase significantly when verified by inspection. While the known visible features are correlated with a modest but statistically significant increase in prices ($\beta = 0.015$) and the hidden features with a modest price decrease ($\beta = -0.016$), verification of the features is positively correlated with a significant price increase. When the features are verified by inspection, sale prices are estimated to increase 4.2% to 10.4%. We suggest that the price increases from the inspection are most likely at the lower end of this range and that they appear to be due primarily to the capitalization of the insurance premium credits represented by the confirmed mitigation features.

This study is organized as follows. In the next section we briefly review the literature. "Florida's Hurricane Mitigation Incentive Program" section provides an overview of Florida's hurricane mitigation program. A model is presented in "Model" section. The data are described in "Data" section and the specification of the models estimated is discussed in "Specification of the Estimation Models" section. The results are reported in "Results" section, followed by a conclusion.

## Literature

Our work is broadly related to a large number of studies that have examined neighborhood- or property-specific characteristics that not are always easily observed, but can substantially affect the value of single-family homes. Examples include studies that examine the impact of environmental conditions such as flood zones (Pope 2008a), air quality (e.g., Nelson 1978 and Smith and Huang 1995), water quality (e.g., Leggett and Bockstael 2000, ground contamination (e.g., Case et al. 2006; Gayer et al. 2000; and Keil and McClain 1995), noise levels (e.g., Pope 2008b; Nelson 2004 and McMillen 2004); neighborhood conditions such as crime and education (e.g., Danielsen et al. 2014; Linden and Rockoff 2008; Clapp et al. 2008; Figlio and Lucas 2004; and Haurin and Brasington 1996); and property-specific features such as the presence of asbestos, lead, or radon (e.g., Smith and Desvousges 1990). A common thread among these studies is not only that they examine the effect of the feature on home values, but that they involve evaluating information that is often more available to the seller than to the buyer. Some of these conditions require disclosure of the information by the seller, if known, to the buyer when part of a sales transaction, but many do not. Hurricane mitigation features are not required to be disclosed to the buyer.

Studies by Brounen and Kok (2011) and Pope (2008a, b) are of particular interest. In a study of the European effort to adopt home energy labels, Brounen and Kok (2011) find that energy certificates provide additional transparency regarding the efficiency and performance of individual dwellings and that this information is capitalized into the price of the home. Interestingly, Pope (2008a, b) reports that use of disclosure forms to convey new information to the seller can influence transaction prices, even when the information may be viewed as widely available to buyers. He finds that the use of airport noise and flood zone disclosure forms are correlated with a reduction in transaction values of 2.9 and 4.0%, respectively. While related to each, our study is unique in that some of the hurricane storm mitigation features are visible to buyers while others may be hidden. In addition, the verification of the features (both visible and hidden) by professional inspection allows the homeowner to claim a credit on his or her homeowner's insurance premium.

## Storm Risk Mitigation

A number of papers focus on the decision to mitigate. Prior studies have examined incentives to mitigate related to risk aversion (e.g. Christoplos et al. (2001); Dionne and Eeckhoudt 1985); substitution effects between mitigation and insurance (e.g. Ehrlich and Becker 1972; Briys and Schlesinger 1990), the desire to protect their home and those living in it (e.g. Kleindorfer and Kunreuther 1999; Peacock (2003); and Kunreuther 2006. Carson et al. (2013) use a Florida-based sample to provide empirical tests of many of these incentives. Their paper focuses on the decision to mitigate homes as part of a state hurricane mitigation program. They look at both the decision to mitigate and the extent of mitigation.[3] It should be noted that while our study focuses on mitigation efforts designed to harden the home, studies such as Smith et al. (2006), consider the resident's response to disaster in terms of the decision to move, self-protect (mitigate) or insure in their study of Dade County residence responses to Hurricane Andrew. They find that low income and middle income households tend to move, but high income households, for whom self-protection and insurance are an option, tend to stay.

[3] In addition to hurricane mitigation, studies have also considered incentives related to mitigation related to tornados. For example, Miller et al. (2002) find that although consumers are willing to pay for tornado safe rooms, the "safety premium" they are willing to pay is less than the cost of producing them. This is consistent with, Simmons and Sutter (2007) who also report that consumers are willing to pay a partial premium for internal shelters. Simmons et al. (2002) are the only researchers who have examined the price effects of voluntary hurricane mitigation measures by homeowners. Using single-family home data for a single city located on the Gulf coast, they examined the effects of storm shutters and structural integrity on selling price. They find that the presence of storm shutters adds approximately 5 % to the selling price although they do not make any direct comparison between the sales price differential and the cost of the storm shutters.

### House Prices and Mitigation

Prior research has linked house prices to mitigation. The majority of this research has focused on the consumer buying response to changes in building codes for new home construction or homeowners' insurance premiums. Building codes and regulations appear to be observed information that are evaluated by land and home buyers. Dehring (2006), for example, examines the effect changes in coastal building regulations had on land prices for Florida's barrier islands. She reports that land values decreased in response to the regulatory measures (i.e., the cost of compliance outweighed the value of the safety benefits). In contrast, Dumm et al. (2011) examine the capitalization of the 2002 Florida Building Code in the house prices for the Miami and Jacksonville, Florida housing markets.[4] They find that houses in the windborne debris region (i.e., area of greatest wind risk) that were built under the new stricter building code (1994 for Miami and 2002 for Jacksonville) sold for approximately 10.4% and 4.5% more on average than those built under the older less strict code for Miami and Jacksonville, respectively. For areas with substantial risk exposure, consumers positively valued the stricter building code and were willing to pay a "safety premium." Nyce et al. (2014) measure the capitalization effect of increases in insurance premiums on housing prices in Miami-Dade County. Consistent with a study by Bin, Kruse and Landry (2008) that looks at flood hazards, they find that insurance premiums are a "risk signal" to consumers with increases in premiums adversely impacting house prices.

In summary, prior research suggests that hurricane mitigation features are priced by the market. However, research has not explored the extent to which hidden and visible mitigation features are priced separately, nor the value of verifying or certifying these features.

## Florida's Hurricane Mitigation Incentive Program

Since 2003, Florida Statutes have required that certain windstorm resistant features of a home, when verified by a licensed windstorm inspector, result in specified discounts to the hurricane portion of the policy premium. The discount depends on the modeled impact of a specific mitigation feature on loss damage relativities and is determined by the Florida Office of Insurance Regulation (OIR). Effective 2005, insurance companies must notify homeowners that windstorm mitigation discounts are available on their homeowners' insurance policies.[5]

The official windstorm inspection provides homeowners with a form prescribed by the OIR, the four-page Uniform Mitigation Verification Inspection Form (inspection form). The inspection form verifies existing features that reduce the expected loss costs in event of a hurricane, with the expected savings based on relativity studies submitted

[4] These working papers are available at www.stormrisk.org.

[5] Statutes and rules indicated, "Using a form prescribed by the Office of Insurance Regulation, the insurer shall clearly notify the applicant or policyholder of any personal lines residential insurance policy, at the time of the issuance of the policy and at each renewal, of the availability and the range of each premium discount, credit, other rate differential, or reduction in deductibles, and combinations of discounts, credits, rate differentials, or reduction in deductibles, for properties on which fixtures or construction techniques demonstrated to reduce the amount of loss in a windstorm can be or have been installed or implemented."

by Applied Research Associates to the OIR in 2002 and 2008.[6] The Florida Division of Emergency Management website recommends improvements that could be made to better protect the home against windstorm and provides an online calculator to estimate insurance credits available for each mitigation improvement, or feature.[7]

The inspection form focuses on protecting openings and strengthening roofs in the following categories: roof deck attachment, secondary water barrier, code-plus roof covering, bracing gable end walls, strengthening roof-to-wall connections, protecting or replacing window openings, and protecting or replacing doors. The inspection form provides the homeowner with verification of their features designed to provide a general indication of how well the home is expected to perform in the event of a hurricane. Neither the inspection forms nor information obtained from them are placed into a publicly accessible database. It is also important to note that the inspection forms (and thus the insurance credits that may result) are not transferable with the transfer of property. Insurers require that a new insured homeowner on a property get a new inspection even if there is a known existing inspection on the property. However, it is reasonable to suspect that sellers may convey this information, which is especially relevant in high risk areas, to potential buyers.

## Model

House values reflect the consumers' valuation of the characteristics of the structure and its location, including the mitigation of any perceived risks associated with hurricane damage. The level of risk is considered to be a qualitative characteristic of a differentiated good. Consumers can choose to mitigate risk through their choice of housing characteristics and location.

Following the standard hedonic price model, the market value of housing, P, is assumed to be described by the function,

$$\ln \mathrm{P} = \mathrm{b\,X} \tag{1}$$

where X is a vector of structural and locational characteristics (Brueckner 1983) and b is a vector of shadow prices corresponding to X.[8] The marginal price of each characteristic is determined as the partial derivative of the hedonic price function with respect to that particular characteristic (Rosen 1974). Each consumer chooses an optimal bundle of housing characteristics (h) and all other goods (g) to maximize their utility function,

$$\max \mathrm{U}\ (\mathrm{h}, \mathrm{g}), \textit{subject} \text{ to a } \textit{budget constraint}\ \mathrm{y} = \mathrm{P}, \mathrm{g} \tag{2}$$

Eq. (1) implicitly assumes that X is known and that buyers and sellers are fully informed. Although X is not directly traded, Rosen (1974) shows that b is still well defined and can be estimated without bias when buyers and sellers are partially, but equally, informed. If buyers and sellers are equally informed, the market value (P) is

[6] http://www.floir.com/sections/pandc/productreview/uniformmitigationform.aspx

[7] http://www.floridadisaster.org/Mitigation/RCMP/index.htm

[8] The individual property and time subscripts, i and t, have been suppressed in the model notation.

given by the tangencies along the bid and offer function [Fig. 1]. The bid and offer prices of heterogeneous buyers and sellers represent a distribution of possible price combinations. In a competitive market, trades are observed in the range of prices between buyers with the highest bid and sellers with the lowest offer, indicated as the maximum bid and minimum offer envelope in Fig. 1, and the market value (P) is set by the tangencies along the bid and offer functions at different levels of X.

If the information sets held by buyers and sellers regarding the property characteristics are asymmetric, the estimated shadow prices of characteristics may be biased (Pope 2008a). To highlight the potential bias, we adopt the bargaining model of Harding et al. 2003, and explicitly model the effect of the mitigation amenity as

$$\ln \mathrm{P} = \mathrm{b\,X} + \mathrm{c\,M} \tag{3}$$

where M is a vector of hurricane storm mitigation features and c is a vector of shadow prices corresponding to M. The mitigation features can be further parsed such that $M = (M_v + M_h)$, where $M_v$ is a vector of mitigation characteristics that are visible and $M_h$ is a vector of mitigation characteristics that are hidden. Relevant information regarding X and M may be made available to sellers and buyers by personal inspection, professional inspection or certification, regulatory procedures such as code enforcement or required disclosure, or via public information sources. Thus, X and M are subject to the information set, Φ, available at time t. Inserting the components of M and the information characteristic into Eq. (3) yields,

$$\ln \mathrm{P} = \left(\mathrm{b\,X} + \mathrm{c_v M_v} + \mathrm{c_h M_h}\right)\Big|\,\Phi \tag{4}$$

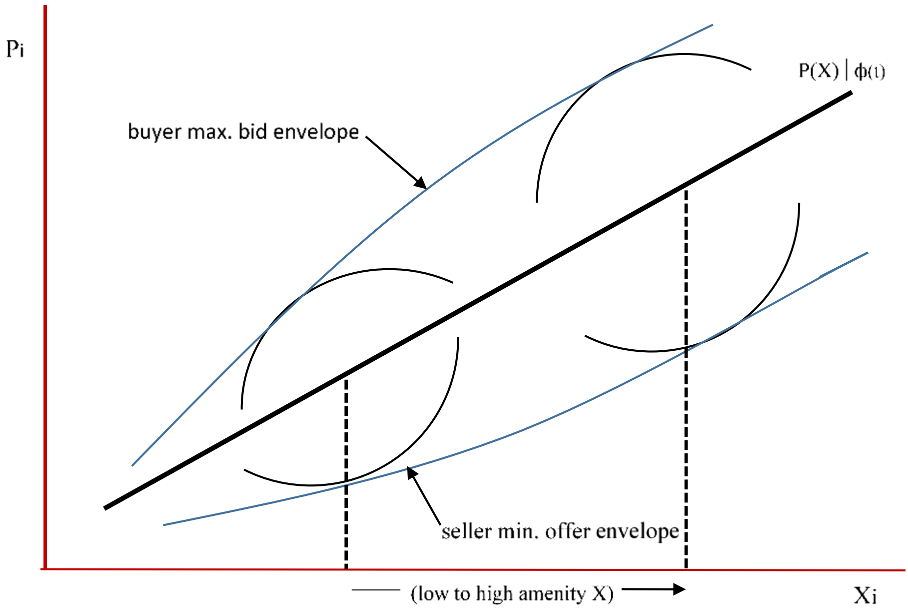


**Fig. 1** Characteristic prices with incomplete information but equally informed buyers and sellers

It may be reasonable to assume that buyers and sellers are equally informed regarding X and $M_v$; however, buyers and sellers may not be equally informed as to $M_h$, the hidden mitigation characteristics. If, for example, $M_h$ is known to the seller but not to the buyer, then the offer and bid prices will be disproportionately affected. If $M_h$ is a positive amenity, the seller's offer will increase as the level of $M_h$ increases, while the buyer's bid will not be affected (remains level). Alternatively, if the feature is known to the buyer, but not to the seller, bid prices will increase while offer prices remain level. Thus, the value of an amenity is biased toward zero whenever there is incomplete and asymmetric buyer–seller information of a positive characteristic. This effect is graphically represented in Fig. 2.[9]

In Fig. 2 we can see that if $M_h$ is observed by the seller but hidden from the buyer, the buyers' maximum bid envelope is compressed and the bid-offer envelope expands asymmetrically causing the hedonic estimates of $c_h$ to be biased. Seller offers increase as $M_h$ increases, while the distribution of buyer bids is disproportionately affected by incomplete information. This compresses the bid envelope and shifts the range of possible transactions prices downward. If $m_h$ is a positive amenity, $c_h$ is biased toward zero.[10] To mitigate the bias, new information may be conveyed to buyers by seller disclosure, market research, regulatory enforcement, or other mechanisms. The value of the new relevant information provided to sellers and buyers is positive, and reflects not only the value of the bias, but also the transaction frequency resulting from the decreased number of bid-offer pairs acceptable for transaction.

## Data

The data used for this study include information obtained from the Florida Department of Revenue's (DOR) property tax records, the Miami-Dade County municipal property tax records and the Citizens Property Insurance Corporation (Citizens). The sources contain both windstorm-inspected and uninspected single-family residential properties. The DOR data are compiled annually for each county in the state of Florida for auditing purposes under a statutory provision. The data include transaction information, if sold, on every property in the state and a limited set of property- and owner-specific characteristics. The DOR data for Miami-Dade County were merged with data obtained from the Miami-Dade County Property Appraiser which included additional property-specific characteristics (e.g., information on lot size, number bedrooms and bathrooms), yielding 368,907 single-family detached housing observations. The DOR and Miami-Dade County property records do not contain mitigation-related data.

Visible mitigation characteristics, hidden mitigation characteristics, and inspection data are obtained from Citizens, the largest property insurer in the state of Florida. They maintain policy level data including mitigation features and

[9] Pope (2008a) graphically shows the effect of asymmetric buyer and seller information for a disamenity.

[10] The shadow price estimated by the standard hedonic will be biased toward zero when there is incomplete and asymmetric buyer-seller information regarding a positive property characteristic. If the seller is informed but the buyer is not, the buyer's bid price will be diminished. Similarly, if the buyer is informed and the seller is not, the seller's offer price will be diminished. In both cases the transaction price, on average, will be less.

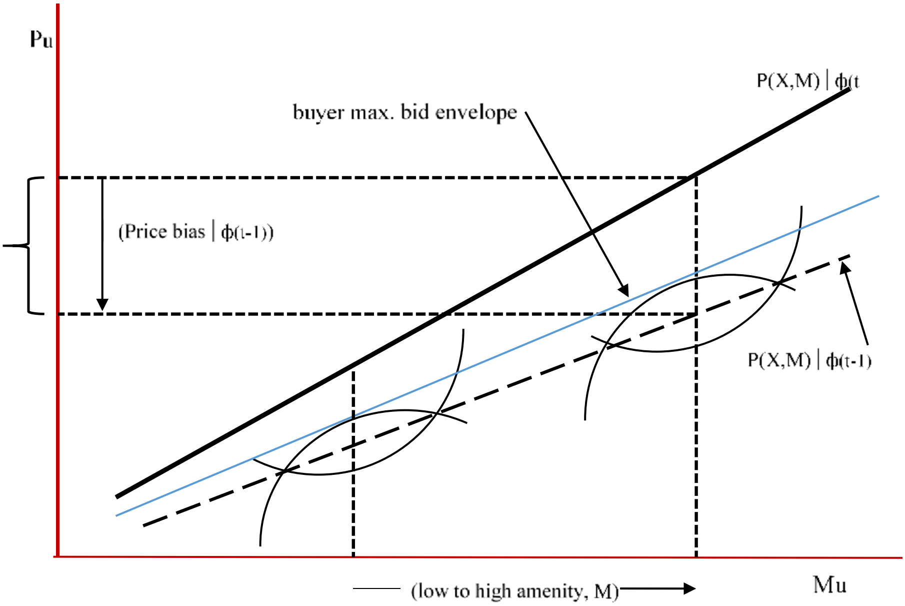


**Fig. 2** Characteristic Price Bias with Incomplete Information and Asymmetrically Informed Buyers and Sell

mitigation inspection dates for single-family attached and detached residences throughout the state of Florida, including multi-peril policies for 260,740 unique parcels in Miami-Dade. The reported mitigation features include visible features (e.g. roof shape, type of window shutters) and hidden features (e.g. roof to wall attachment method, roof sheathing nail pattern, secondary water barrier). In most cases, this information has been verified by professional windstorm inspection which is noted in the file. In other cases, the features are merely self-reported and not verified by a current inspection. Many insurers (including Citizens) require verification of the mitigation features by professional inspection before providing premium discounts, including those features that may be obvious for any new insurance policy issued or known for other reasons.

Merging the Citizens single-family detached housing records with the property data produced a dataset of 152,885 observations. Observations with transactions occurring during the study period (2007 to 2011) were identified. Transactions recorded as transfers of ownership, non-qualified sales (distressed and non-arm's length transactions) were omitted as well as new property sales (e.g., AGE < 1). This yielded a final data set of 28,487 observations. The variables and their definitions are reported in Table 1, with summary statistics in Table 2.

Table 2 indicates that of the 28,487 properties in the dataset, 27.05% (7705) received inspection reports (mitigation inspection) prior to sale of the property. Casual inspection of the data suggests that those homes receiving inspections sold, on average, at prices less than those that did not (i.e., \$315,250 to \$357,890). In addition, they were slightly larger and older, but located at similar distances from the coast. As could be expected, inspected properties were more likely to be owner-occupied (i.e., homesteaded), to have hurricane-rated shutters, and to have more hidden mitigation features (e.g., roof

**Table 1** Variable definitions

| Variable | Definition |
|---|---|
| SP | Transaction price ($000 s). |
| lnSP | Natural log of the transaction price, SP. |
| SQFT | Building conditioned square footage. |
| LOT | Land area square footage. |
| AGE | Effective actual age of the building (years). |
| BDRS | Number of bedrooms. |
| BTHS | Number of baths. |
| FLRS | Number of floors. |
| DTC | Distance to nearest coastline (miles). |
| HMSTD | Dummy variable = 1 if homestead exemption claimed, otherwise 0. |
| COND_A | Dummy variable = 1 if construction quality excellent, otherwise 0. |
| COND_B | Dummy variable = 1 if construction quality above average, otherwise 0. |
| COND_C | Dummy variable = 1 if construction quality below average, otherwise 0. |
| COND_D | Dummy variable = 1 if construction quality poor, otherwise 0. |
| FBC | Dummy variable = 1 if built after 1994 S.Fl bldg. code adopted, otherwise 0. |
| I_FLOOD | Dummy variable = 1 if in flood zone A, AH, or AE, otherwise 0. |
| C_FLOOD | Dummy variable = 1 if in flood zone VE, otherwise 0. |
| HRA | Dummy variable = 1 if in Citizen's coastal account zone, otherwise 0. |
| H_SHUT | Dummy variable = 1 if property has hurricane rated shutters, otherwise 0. |
| B_SHUT | Dummy variable = 1 if property has basic rated shutters, otherwise 0. |
| U_SHUT | Dummy variable = 1 if property has no or unknown shutters, otherwise 0. |
| H_ROOF | Dummy variable = 1 if property has a hip shaped roof, otherwise 0. |
| BARRIER | Dummy variable = 1 if roof has an underlayment water barrier, otherwise 0. |
| A_NAILS | Dummy variable = 1 if roof has 6d nails every 6–12 in., otherwise 0. |
| B_NAILS | Dummy variable = 1 if roof has 8d nails every 6–12 in., otherwise 0. |
| C_NAILS | Dummy variable = 1 if roof has 8d nails every 6 in., otherwise 0. |
| CLIPS | Dummy variable = 1 if metal clip attaches roof truss to wall, otherwise 0. |
| DWRAP | Dummy variable = 1 if double wrap attaches roof truss to wall, otherwise 0. |
| SWRAP | Dummy variable = 1 if single wrap attaches roof truss to wall, otherwise 0. |
| NWRAP | Dummy variable = 1 if no wrap/clip attaches roof truss to wall, otherwise 0. |
| W_CRED | Percentage credit from the OIR credit table for the property's mitigation features. |
| VISIBLE | Dummy variable = 1 if visible mitigation features present, otherwise 0. |
| HIDDEN | Dummy variable = 1 if hidden mitigation features present, otherwise 0. |
| P_INSP | Number of mitigation inspections performed in property's census area prior. |
| INSP | Dummy variable = 1 if mitigation inspection prior to sale, otherwise 0. |
| Q07:1 to Q11:4 | Dummy variable = 1 if sold in respective quarter 2007:1 to 2011:4, otherwise 0. |

This table provides a list of variable definitions. In addition, dummy variables are included for each of the census tracts in the Miami region

attachment methods). Still, with regard to the other characteristics, bedrooms, baths, floors, condition, and flood zone designation, they are very similar.

**Table 2** Descriptive statistics

| Panel A: Non-dichotomous variables | | | | |
|---|---|---|---|---|
| Var | Stat | ALL | INSP = 1 | INSP = 0 |
| | | 28,487 obs | 7705 obs | 20,782 obs |
| Structure and Location Characteristics | | | | |
| SP | Mean | 346.35 | 315.25 | 357.89 |
| (000 s) | Med | 255.00 | 225.00 | 270.00 |
| | Min | 28.00 | 33.00 | 28.00 |
| | Max | 4825.00 | 4750.00 | 4825.00 |
| | SD | 337.21 | 308.79 | 346.46 |
| SQFT | Mean | 2080.20 | 2120.09 | 2065.42 |
| | Med | 1900.00 | 1944.00 | 1880.00 |
| | Min | 1000.00 | 1001.00 | 1000.00 |
| | Max | 5000.00 | 4992.00 | 5000.00 |
| | SD | 767.92 | 758.80 | 770.77 |
| LOT | Mean | 9562.37 | 10,215.06 | 9320.38 |
| | Med | 7800.00 | 8056.00 | 7638.31 |
| | Min | 1242.00 | 1384.00 | 1242.00 |
| | Max | 204,732.00 | 127,195.20 | 204,732.00 |
| | SD | 7717.61 | 7681.00 | 7717.31 |
| AGE | Mean | 30.44 | 31.93 | 29.90 |
| | Med | 28.00 | 30.00 | 28.00 |
| | Min | 1.00 | 1.00 | 1.00 |
| | Max | 98.00 | 90.00 | 98.00 |
| | SD | 18.58 | 16.09 | 19.40 |
| DTC | Mean | 9.77 | 9.85 | 9.74 |
| | Med | 10.14 | 10.18 | 10.12 |
| | Min | 0.47 | 1.17 | 0.47 |
| | Max | 11.21 | 11.13 | 11.21 |
| | SD | 1.23 | 1.14 | 1.26 |
| BRDS | Mean | 3.32 | 3.33 | 3.31 |
| BTHS | Mean | 2.12 | 2.11 | 2.12 |
| FLRS | Mean | 1.17 | 1.15 | 1.18 |
| Mitigation-related variable | | | | |
| P_INSP | Mean | 94.1 | 217.4 | 48.3 |
| Annual insurance premiums | | | | |
| | Mean | 2782 | 2954 | 2718 |
| | Med | 2347 | 2507 | 2285 |
| | Min | 0 | 228 | 0 |
| | Max | 32,186 | 21,479 | 32,186 |
| | SD | 1760 | 1703 | 1776 |
| Panel B: Dichotomous variables | | | | |
| Var | Stat | ALL | INSP = 1 | INSP = 0 |
| | | 28,487 obs | 7705 obs | 20,782 obs |

**Table 2** (continued)

| | | | | |
|---|---|---|---|---|
| Structure and location characteristics | | | | |
| HSTD | (%) | 62.2 | 74.6 | 57.7 |
| COND_A | (%) | 9.6 | 8.3 | 10.1 |
| COND_B | (%) | 24.6 | 26.5 | 23.9 |
| COND_C | (%) | 59.2 | 59.9 | 59.0 |
| COND_D | (%) | 6.6 | 5.3 | 7.0 |
| FBC | (%) | 23.0 | 15.2 | 25.8 |
| I_FLOOD | (%) | 58.1 | 58.2 | 58.0 |
| C_FLOOD | (%) | 0.1 | 0.0 | 0.1 |
| HRA | (%) | 20.9 | 13.0 | 23.9 |
| Mitigation characteristics – opening protection | | | | |
| H_SHUT | (%) | 29.0 | 36.3 | 26.3 |
| B_SHUT | (%) | 1.7 | 2.5 | 1.4 |
| U_SHUT | (%) | 69.3 | 61.2 | 72.3 |
| Mitigation characteristics – roof, decking, and attachment | | | | |
| H_ROOF | (%) | 27.3 | 24.6 | 28.3 |
| BARRIER | (%) | 2.3 | 2.0 | 2.5 |
| A_NAILS | (%) | 31.1 | 6.1 | 40.3 |
| B_NAILS | (%) | 15.9 | 23.4 | 13.1 |
| C_NAILS | (%) | 43.8 | 68.4 | 34.7 |
| CLIPS | (%) | 11.7 | 21.7 | 8.0 |
| DWRAP | (%) | 1.6 | 1.4 | 1.7 |
| SWRAP | (%) | 39.0 | 58.2 | 32.0 |
| NWRAP | (%) | 47.5 | 18.6 | 58.3 |
| Other mitigation-related variables | | | | |
| VISIBLE | (%) | 47.2 | 50.8 | 45.9 |
| HIDDEN | (%) | 62.6 | 96.4 | 50.0 |
| INSPECT | (%) | 27.0 | 100.0 | 0.0 |
| WCRED | (%) | 46.3 | 59.9 | 41.3 |

This table provides descriptive statistics for the entire dataset (ALL), that contains 28,487 property transactions, the subset of transactions that were inspected for verification (INSP = 1), and the subset of transactions that were not inspected (INSP = 0). The variable definitions are reported in Table 1. Panel A reports mean, median (Med), minimum (Min), maximum (Max) and standard deviation (SD) for non-dichotomous variables. Panel B reports frequency (%) statistics for dichotomous variables. The transaction price (SP) is reported in \$1000 s. Distance to coast (DTC) is reported in miles

## Specification of the Estimation Models

A standard hedonic model is initially estimated using two specifications to provide benchmark results as described in "The Baseline Hedonic Model" and "An Alternative Specification" sections below. The benchmark results are estimated under the assumption that agents are equally informed. The standard hedonic model is then relaxed in "The Treatment Effects Model and Inspection Information" section to explicitly include the decision to obtain a professional inspection and verify the mitigation information available to agents regarding the visible and hidden mitigation characteristics. The modified model is estimated as a treatment effects model.

## The Baseline Hedonic Model

The standard hedonic is widely used in the literature to estimate the implicit marginal value of characteristics of the structure, such as size and condition, or the characteristics associated with its location, such as air quality, school quality, noise or the effect of crime.[11] Following this literature, we initially estimate Eq. (3) as

$$\ln P_{it} = a_0 + \beta_j X_{jit} + c_m M_{mit} + \delta_t D_{it} + e_{it} \tag{5}$$

where $P_{it}$ is the transaction price of property i at time t,; $\beta_j$ is a vector of j coefficients on the property- and location-specific characteristics, $X_{jit}$; c is a vector of m coefficients on the mitigation-specific characteristics, $M_{mit}$; $\delta_t$ are the coefficients on $D_{it}$ time dummies with values of 1 if the ith property sold in period t and 0 otherwise; and $e_{it}$ is the random error with mean, 0, and variance σ. The coefficients, $c_m$, yield an estimate of the marginal effect of the mitigation features on the composite price of the property, evaluated at its mean, assuming that agents are equally informed and that the model is well defined.

The property-specific control variables, X, include the square footage of the property's conditioned space (SQFT), the square footage of the lot (LOT), the property's effective age (AGE), the number of bedrooms (BDRS), the number of bathrooms (BTHS), and the number of floors (FLRS). The squared values of SQFT, LOT and AGE are included to allow for decreasing marginal effects of the respective variables. Dummy variables (COND_A, COND_B, COND_C and COND_D) are included to control for the construction quality categories identified by the Miami-Dade County property appraiser. FBC is included as a dummy variable equal to 1 if the property was constructed after 1994, otherwise 0. This is included to control for the higher construction standards put in place when Florida's residential building code was substantially strengthened to require hurricane-resistant features in South Florida. To capture maintenance, tax, and other factors that may be associated with owner-occupied properties and the homestead designation we include HMSTD, a dummy variable set equal to 1 for owner-occupied properties claiming a homestead exemption at the time sale, otherwise zero.

The relationship between the hurricane mitigation features and transaction prices is the focus of this study. To examine this we include in the model the individual mitigation-specific structural characteristics, M, that are identified in the home inspection and deemed to be important in mitigating loss or damage from a hurricane by the Florida Department of Emergency Management and the Residential Building Code. Some features are visible to the buyers and sellers and some are hidden. Visible features include the roof shape (e.g., hip roofs (H_ROOF)) and the use of shutters and their materials (e.g., hurricane shutters (H_SHUT), basic shutters (B_SHUT), no shutters (U_SHUT)). Features identified by the inspection but typically hidden to the buyer and

[11] See, for example, the literature cited in Section II, as well as reviews by Boyle and Kiel (2001) and Smith and Huang (1993).

seller that may be revealed through inspection include the manner of attachment of the roof sheathing to the roof rafters (e.g., roof nail type and spacing (A_NAILS, B_NAILS, C_NAILS); the manner of attachment of the roof rafters to the wall framing (e.g., metal clips (CLIPS); double wraps (D_WRAP); or single wraps (S_WRAP), and the inclusion of a secondary water barrier (BARRIER).

One challenge in estimating the separate effects of the individual features is that their overall use may not be independent. For example, in some cases, roof attachment methods and roof to wall framing are selected together for a complementary effect.[12] To address this, the factors are also specified as dummy variables, VISIBLE and HIDDEN. VISIBLE represents the presence of mitigation features easily observed by buyers and sellers, and are reasonably expected to be known. HIDDEN represents mitigation features that are difficult to verify by casual inspection and more likely to be revealed to the homeowner by professional inspection. This information may or may not be conveyed by the seller to potential buyers.[13] We expect VISIBLE to be positively correlated with lnSP. While HIDDEN is also expected to be positive correlated, we anticipate it will need to be identified by formal inspection to influence price.

To control for location-specific variation in house prices, we identify and include the flood zones, both inland flood and coastal flood zones (I_FLOOD and C_FLOOD, respectively), the property's distance from the coast (DTC), and whether it resides in Citizen's coastal account (HRA) area.[14] Testing the possible relationship of these variables did not show strong collinearities and all are included in the empirical models estimated. Census tract dummies are mapped to the data to control for other location- and neighborhood-specific characteristics that may be correlated to the sale price. The estimation strategy utilizes a fixed-effects model in space and time.

## An Alternative Specification

One limitation of the standard hedonic, as specified above, is the possible influence that omitted variables and collinearity among the included variables may have on the estimated coefficient of the explanatory variable of interest. If an independent variable is omitted that is correlated with both the dependent variable and one or more of the included right-hand-side variables, the estimated coefficient of the included explanatory variable will be biased. This, of course, is relevant here if omitted or included variables are correlated with the mitigation variables of interest. The direction of the bias depends on several factors. Positive covariance, for example, of an omitted variable with both the explanatory and dependent variables (i.e., the most likely case) will result in the estimated coefficient of the included variable of interest being overstated.

Because it is very possible that the mitigation variables of interest are correlated with other factors, omitted or included, we consider and evaluate an alternative specification.

[12] Mitigation features are not additive; several found in combination result in a different final insurance discount than the sum of the individual discounts.

[13] Because information indicating that a property is "hardened" and qualifies for insurance credits due to unobserved features may be important to buyers there is an incentive for this information to be conveyed by sellers. However, we do not know if verification of unobserved mitigation features by inspection was specifically conveyed to potential buyers when the property is sold.

[14] Citizens' coastal account was known as the high risk account until 2012. Dummies for wind zones were initially included as well, but are omitted here due to multicollinearity with the other location variables.

Following work by Clapp and Giacotto (1992) and others, this alternate approach replaces the property-specific variables with the local appraiser's estimate of value. Other research suggests that valuation expertise, involvement in the identification and weighting of sale information, and property inspection of the neighborhood by the appraiser may provide relevant information.[15] It is important to note that we are not advocating this as a generally preferred approach to the standard hedonic – it is not without its limitations. Nor are we suggesting that the appraiser is able to identify or include the hidden mitigation features in the assessed value. Rather, the method is offered here as an alternative specification to ease possible biases inherent in the explicit variable hedonic model. In addition, it provides better estimation properties for the treatment effects model presented in the next section.

To evaluate the appraiser's assessed value (AV), we first include it as an independent explanatory variable in the standard hedonic (5) above and assess its effect on the base model estimate. We then replace the property- and location-specific variables with the assessed value (AV) and estimate,

$$\mathrm{lnP_{it}} = \mathrm{a_0} + \beta_\mathrm{j} lnAV_\mathrm{jit} + \mathrm{c_m M_{mit}} + \delta_\mathrm{t} \mathrm{D_{it}} + \mathrm{e_{it}} \tag{6}$$

where $\mathrm{lnAV_{jit}}$ is the log natural of the appraiser's estimate of market value prior to any adjustments for assessment purposes and $\mathrm{M_{it}}$ and $\mathrm{D_{it}}$ defined as in (5), and compare the explanatory power of the two base models, the standard hedonic and the assessed value hedonic. Consistent with the standard hedonic, the AV specification (6) is estimated using a fixed-effects model in space and time.

## The Treatment Effects Model and Inspection Information

One assumption of the hedonic models above is that relevant information is equally available to all market participants. M is comprised of visible and hidden mitigation features. Because all mitigation characteristics may not be equally available to the seller and the buyer, as discussed earlier the estimated coefficients on these variables may be affected. Further, new information regarding M, may be verified by professional inspection for sellers and potentially conveyed to buyers. To examine the effect of this information on the coefficient estimates we modify the standard hedonic model to include the decision by home owners to have their property inspected. We expect this new information to be positively correlated with price and, potentially, to reduce the amenity price bias resulting from buyer-seller information asymmetries noted earlier in Fig. 2. Because the decision to obtain an inspection may be correlated with the mitigation features, as well as other characteristics of the house, Eq. (6) is estimated as a two-stage treatment effects model such that,

$$\mathrm{lnP_{it}} = \mathrm{a_0} + \beta_\mathrm{j} lnAV_\mathrm{jit} + \mathrm{c_m M_{mit}} + \delta_\mathrm{t} \mathrm{D_{it}} + \mathrm{e_{it}}, \tag{7a}$$

where $\mathrm{M_{it}}$ includes an inspection variable, INSP, such that

[15] See, for example, Holway and Burby (1990), Mooney and Eisgruber (2001), Malpezzi (2003), Fisher et al. (2007) and Gatzlaff and Holmes (2013) for additional applications and discussion.

$$INSP^*_{it} = a_0 + \gamma_k Z_{kit} + \delta_t D_{it} + u_{kt}, \tag{7b}$$

where INSP = 1 if INSP* > 0, and INSP = 0 otherwise; $\gamma_j$ is a vector of k coefficients on the owner- and property-specific characteristics, $Z_{jit}$, corrected with the inspection decision; $\delta_t$ are the coefficients on $D_{it}$ time dummies with values of 1 if the ith property sold in period t and 0 otherwise; and $u_{it}$ is the random error term.

INSP is included as a dummy variable defined as equal to 1 if the home was inspected, otherwise 0. The estimated coefficient on INSP in the second-stage estimate (7a) is designed to indicate if the inspection information is capitalized in the sale price of the home (lnSP). The value of the mitigation inspection form to buyers is related to the information it provides regarding the safety and/or insurance benefits of the home. The safety information provided is explicit since the inspection form itemizes features the home possesses that are known to reduce losses in the event of hurricanes and other wind events. The information regarding the insurance benefits of owning the home may be more implicit within the mitigation form than the safety information (e.g., no premium discount amounts or percentages are provided on the certificate itself), but the connection between the mitigation form and potentially large insurance discounts is well publicized by Florida insurers, state agencies and non-governmental public relations entities.[16]

The inspection variable, INSP, is modeled as a decision variable. The homeowner (seller) decides whether to obtain an inspection certificate. It is expected that known features are highly correlated with the decision to obtain an inspection. To the extent that the homeowner's decision to mitigate is influenced by the appeal of insurance premium reduction and neighborhood information, we also expect that the decision to obtain an inspection will be influenced by mitigation features visible to the homeowner and the potential information conveyed by neighbors that are obtaining inspections. The study hypothesis is that the presence of visible mitigation features (e.g., hip roof (H_ROOF) and the presence of hurricane shutters (H_SHUT)), will each be positively correlated with INSP. We control for other variables that can be expected to relate to the inspection decision as well, such as the distance to coast, the effective age of the home, the construction quality and size of the home. In work related to the decision to mitigate and the extent of mitigation, Carson et al. (2013) examined several factors, including reduction in insurance premiums and the reduced costs of mitigation achieved by gathering information from neighbors.[17] For this reason, we expect that the presence of other inspections in the neighborhood will increase the chance that a homeowner has an inspection because the homeowner heard of the positive

[16] For example, the Florida Department of Emergency Management posts estimated homeowners insurance discounts for specific home features through a pamphlet, "Make Mitigation Happen," that can be downloaded from its website at www.floridadisaster.org. Insurers are required by Florida Statute to inform policyholders of the 1802 Form and insurance discounts available for mitigation features present on their homes.

[17] Carson et al. (2013) specifically examined Florida homeowners in light of the MSFH program setting, lending added relevance to the study here. They also provide an extensive review of prior studies on the decision to mitigate.

benefits from neighbors. We include a variable related to the number of known inspections in the property's census track (P_INSP) as an instrument.[18]

## Results

### The Baseline Hedonic Model

The coefficient estimates for the baseline standard hedonic are reported in Table 3. Model 3.1 includes only the set of visible mitigation features (VISIBLE) in the model, along with the individual structural and locational characteristics. Model 3.2 adds the set of hidden mitigation features (HIDDEN) to the model. The individual mitigation characteristics are specified in Model 3.3.

Model 3.1 "explains" a substantial portion of the variation in the prices (adj-R2 = 0.898). As expected, the estimated coefficients for home size (SQFT), lot size (LOT) and quality of construction (COND_A is the omitted variable) are all highly significant and positively related to property price (lnSP). Evaluated at the mean, the marginal value per square foot is estimated to be \$173.18. The effective age (AGE) of the property is negatively related to price ($\beta = -0.004$). The square footage, age, and lot size variables all influence price at a decreasing rate, as indicated by estimated coefficients on SQFT2, AGE2 and LOT2. In general, the estimates of the coefficients (magnitudes and signs) on the structural variables are consistent with expectations.

As expected, homesteaded (HMSTD) properties are positively correlated with property price ($\beta = 0.012$) reflecting the capitalization of structural maintenance and neighborhood amenities associated with ownership. Interestingly, but consistent with expectations, the coefficient estimates on distance to the coast variable (lnDTC) and the HRA coastal areas, both statistically significant, are dominated by the coastal amenity effects over the storm risk effects. This is consistent with the coefficient estimates on C_FLOOD – the value-enhancing impact of the amenities associated with close proximity to coastal bodies of water dominate the storm risk effects. While not explicitly reported in the table, controls for census track and quarter of sale are included in the model. The set of structural and locational variables in Model 3.1 are included as controls in the Models 3.2 and 3.3 and remain relatively stable across the models.

Model 3.1 (Table 3) includes a variable for known mitigation features (VISIBLE). These characteristics, such as roof shape and the existence of hurricane shutters, are easily verified by both the seller and buyer. As expected, the aggregate effect of these factors as a group is positive and significantly related to sale price ($\beta = 0.024$). Model 3.2 adds the set of features that are costly to verify and likely to be only revealed through an inspection (HIDDEN). In this case, estimated coefficients on both the known (VISIBLE) and concealed (HIDDEN) features are positive and significantly related to price ($\beta = 0.017$ and $\beta = 0.026$, respectively). Each of the individual

[18] The number of known inspections is the sum of all inspections performed in a census tract prior to the date of inspection for each inspected property and is not related to the date of sale. This variable will vary for properties within the same census tract that sell in the same time period. As a robustness test, a previous inspection variable at the neighborhood code level (rather than the census tract) was also created and used, the results were unchanged. The number of known inspections variable is not highly correlated with our log sale price variable. The correlation is −0.058.

**Table 3** Standard Hedonic Model Estimates

| Dependent Variable = lnSP | | | | | | |
|---|---|---|---|---|---|---|
| | Model 3.1 | | Model 3.2 | | Model 3.3 | |
| Variable | coeff. | s.e. | coeff. | s.e. | coeff. | s.e. |
| SQFT | 0.0005*** | 0.00001 | 0.0005*** | 0.00001 | 0.0005*** | 0.00001 |
| SQFT2 | −3.93e-08*** | 1.95e-09 | −3.91e-08*** | 1.94e-09 | −3.93e-08*** | 1.94e-09 |
| LOT | 0.00002*** | 4.61e-07 | 0.00002*** | 4.61e-07 | 0.00002*** | 4.61e-07 |
| LOT2 | −7.05e-11*** | 4.13e-12 | −7.04e-11*** | 4.13e-12 | −7.03e-11*** | 4.13e-12 |
| AGE | −0.004*** | 0.0005 | −0.005*** | 0.0005 | −0.005*** | 0.0004 |
| AGE2 | 2.09e-06 | 5.95e-06 | 7.14e-06 | 5.98e-06 | 6.17e-06 | 6.02e-06 |
| BDRS | 0.005* | 0.003 | 0.005* | 0.003 | 0.005* | 0.003 |
| BTHS | 0.018*** | 0.003 | 0.018*** | 0.003 | 0.018*** | 0.003 |
| FLRS | −0.002 | 0.005 | −0.001 | 0.005 | −0.002 | 0.005 |
| COND_B | −0.124*** | 0.008 | −0.123*** | 0.008 | −0.123*** | 0.008 |
| COND_C | −0.173*** | 0.010 | −0.172*** | 0.010 | −0.172*** | 0.010 |
| COND_D | −0.301*** | 0.019 | −0.301*** | 0.019 | −0.301*** | 0.019 |
| FBC | 0.002 | 0.007 | 0.007 | 0.007 | 0.003 | 0.007 |
| HMSTD | 0.012*** | 0.003 | 0.008*** | 0.003 | 0.009*** | 0.003 |
| lnDTC | −0.084*** | 0.005 | −0.084*** | 0.005 | −0.084*** | 0.005 |
| I_FLOOD | 0.002 | 0.004 | 0.002 | 0.004 | 0.002 | 0.004 |
| C_FLOOD | 0.412*** | 0.065 | 0.413*** | 0.065 | 0.411*** | 0.065 |
| HRA | 0.019*** | 0.006 | 0.024*** | 0.006 | 0.023*** | 0.006 |
| VISIBLE | 0.024*** | 0.003 | 0.017*** | 0.003 | | |
| HIDDEN | | | 0.026*** | 0.003 | | |
| H_ROOF | | | | | 0.014*** | 0.004 |
| H_SHUT | | | | | 0.012*** | 0.003 |
| B_SHUT | | | | | 0.011 | 0.011 |
| BARRIER | | | | | 0.002 | 0.009 |
| B_NAILS | | | | | 0.019*** | 0.006 |
| C_NAILS | | | | | 0.029*** | 0.005 |
| SWRAP | | | | | −0.006 | 0.005 |
| DWRAP | | | | | −0.021* | 0.012 |
| CLIPS | | | | | 0.002 | 0.006 |
| Census Dum Incl. | Yes | | Yes | | Yes | |
| Time Dum Incl. | Yes | | Yes | | Yes | |
| Constant | 12.52*** | 0.236 | 12.52*** | 0.236 | 12.52*** | 0.236 |
| Obs. | 28,487 | | 28,487 | | 28,487 | |
| Adj.-$R^2$ | 0.898 | | 0.899 | | 0.899 | |

This table reports the estimates from the baseline hedonic model, Eq. (5). The variable definitions are listed in Table 1. The ***, **, * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. s.e denotes robust standard errors. Cluster based on properties that sold during the period mitigation features are specified in Model 3.3. Hip roof shape (H_ROOF) and hurricane shutters (H_SHUT) are positively correlated with the house sale price. Similarly, a more durable method of roof attachment (B_NAILS, C_NAILS) also has a positive impact on the sales price. Surprisingly, the coefficient estimates on the roof-to-wall attachments and the water barrier are not statistically significant. It is likely that the individual roof and wall attachment features are applied in combination and that the estimated coefficients are affected by substantial multi-collinearity among the individual mitigation features. Thus, we focus on the estimated coefficients of the grouped variables (VISIBLE and HIDDEN) in evaluating the models estimated going forward.

## The Baseline AV Hedonic

The results of the AV hedonic specification (6) are reported in Table 4 and compared to the standard hedonic estimates in Table 3.[19] In general, the explanatory power of Models 3.4, 3.5, and 3.6 is slightly stronger than the standard hedonic (e.g., adj-R2 = 0.908 vs adj-R2 = 0.899) and the coefficient estimates of the variables of interest, the hurricane mitigation characteristics, are very similar to those reported in Table 3. In all cases the coefficient estimates are within two standard deviations of each other, except for the coefficient on HIDDEN. The estimated coefficients on HIDDEN in the standard hedonic (Model 3.2) and the AV hedonic (Model 3.5) are 0.026 and 0.012, respectively. The coefficient estimate in 3.5 is consistent with the possibility that the explanatory variable HIDDEN in 3.2 is correlated with omitted characteristics resulting in its upward bias. Because of this, the stability of the other coefficients estimated, and the explanatory strength of the AV hedonic, Models 3.4 and 3.5 are used as the second-stage specification in the treatment effects models that follow.

## The Treatment Effects Model and the Impact of Inspection Information

We modify the standard hedonic model to include the decision by home owners to have their property inspected. We recognize that the insured's decision to obtain a mitigation inspection is likely related to the known mitigation features of the house. For this reason, we estimate a series of treatment effect models in which the presence of a mitigation inspection is instrumented to control for selection bias. The first-stage estimate of the treatment-effects model is reported in Table 5. The likelihood of inspection is positively correlated with larger, older, and higher-quality properties that are owner-occupied and located in neighborhoods where other homes have been recently inspected. It is interesting to note that the likelihood is not related to property's location relative to the coast. Because some of the mitigation features are hidden and their verification may carry with it new information, insurance premium reductions, and

[19] As discussed in "The Treatment Effects Model and Inspection Information" section, the assessed value variable was initially added to the standard hedonic model to examine its effect. Adding the assessed value variable to the standard hedonic explanatory variables increases the explanatory power of the base hedonic models from adj-R2 = 0.898 (or 0.899) to 0.912 in each model reported in Table 3. This supports the idea that additional information may be embedded in the assessed values and the omitted variable concerns. Because it violates the assumption of independence among the explanatory variables and potentially affects the coefficient estimates on the interacted variables of interest, including both the hedonic and the assessed value variables in the final model is not an option for the models estimated in Table 4.

**Table 4** Baseline assessed value (Av) model estimates

| Dependent variable = lnSP | | | | | | |
|---|---|---|---|---|---|---|
| | Model 3.4 | | Model 3.5 | | Model 3.6 | |
| Variable | coeff. | s.e. | coeff. | s.e. | coeff. | s.e. |
| lnAV | 0.805*** | 0.004 | 0.805*** | 0.004 | 0.803*** | 0.004 |
| Visible | 0.022*** | 0.003 | 0.019*** | 0.003 | | |
| Hidden | | | 0.012*** | 0.003 | | |
| H_ROOF | | | | | 0.021*** | 0.003 |
| H_SHUT | | | | | 0.012*** | 0.003 |
| B_SHUT | | | | | 0.004 | 0.010 |
| BARRIER | | | | | 0.002 | 0.009 |
| B_NAILS | | | | | 0.010** | 0.005 |
| C_NAILS | | | | | 0.014*** | 0.004 |
| SWRAP | | | | | −0.005 | 0.005 |
| DWRAP | | | | | −0.018* | 0.011 |
| CLIPS | | | | | 0.003 | 0.005 |
| Census Dum Incl. | Yes | | Yes | | Yes | |
| Time Dum Incl. | Yes | | Yes | | Yes | |
| Constant | 3.446*** | 0.226 | 2.744*** | 0.225 | 2.766*** | 0.225 |
| Obs. | 28,487 | | 28,487 | | 28,487 | |
| Adj.-$R^2$ | 0.908 | | 0.908 | | 0.908 | |

This table reports the estimates from the baseline hedonic AV model, Eq. (6). The variable definitions are listed in Table 1. The ***, **, * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. s.e denotes robust standard errors. Cluster based on properties that sold during the period

possible reductions in asymmetric information, we expect the inspection to be positively correlated with price.

The coefficient estimates for the second-stage of the treatment effects model are reported in Table 6. Model 4.1 adds the inspection variable (INSP) to the base model. The estimated coefficient on INSP is positive (β = 0.102) and statistically significant at a 1% level. Because the magnitude of the estimate is substantially larger than the combined effects of the visible and hidden mitigation features estimated in Models 3.5 and 3.6 (i.e., approximately 3.1% to 4.3%), it suggests that the inspection may convey new relevant information regarding the mitigation features, including the insurance premium credits that accompany the features, and that this information is priced by the market. This is examined further in Models 4.2 and 4.3.

Model 4.2 adds the explanatory variables VISIBLE and HIDDEN to the second stage of Model 4.1. This specification is identical to Model 3.5 except that it includes the INSP decision variable and is estimated as a two-stage treatment effects model. The estimated coefficient on INSP increases slightly from the estimate in 4.1 (β = 0.111 vs β = 0.102); however, the estimates are not statistically different. The estimated coefficient on the set of visible mitigation features is positive and nearly identical to the Model 3.5 hedonic estimate (β = 0.021 vs β = 0.019). Interestingly, the estimated

**Table 5** Treatment-effects model

| First stage estimate – Dep. Var. = INSP | | |
|---|---|---|
| | First Stage Model Est. | |
| Variable | coeff. | s.e. |
| SQFT | 0.0002*** | 0.00006 |
| SQFT2 | −1.90e-08 | 1.21e-08 |
| AGE | 0.009*** | 0.001 |
| COND_B | −0.097** | 0.041 |
| COND_C | −0.163*** | 0.040 |
| COND_D | −0.008 | 0.058 |
| HMSTD | 0.365*** | 0.021 |
| lnDTC | 0.002 | 0.011 |
| HRA | −0.391*** | 0.034 |
| H_ROOF | −0.013 | 0.023 |
| H_SHUT | 0.287*** | 0.021 |
| YEAR07 | −2.116*** | 0.057 |
| YEAR08 | −1.220*** | 0.047 |
| YEAR09 | −0.140*** | 0.027 |
| YEAR10 | −0.016 | 0.024 |
| P_INSP | 0.004*** | 0.0001 |
| Year Dummy Inc. | Yes | |
| Constant | −1.572*** | 0.146 |

This table reports the first stage estimates of the two-stage treatment effects model, Eq. (7b). The variable definitions are listed in Table 1. The ***, **, * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. s.e denotes robust standard errors. Cluster based on properties that sold during the period

coefficient on HIDDEN declines significantly from the base model estimate. In Model 4.2 the estimated coefficient is −0.016 compared to 0.012 in Model 3.5, the base model. Both estimates are statistically significant. The change is attributed to the inclusion and estimate of the decision variable, INSP, in Model 4.2.

To further evaluate the effects of the inspection, we interact the treatment-defined decision variable INSP with the set of mitigation variables, VISIBLE and HIDDEN, in Model 4.3. The estimated coefficient on VISIBLE features is 0.037 if verified by inspection (INSP = 1) versus 0.015 if not verified (INSP = 0). While unexpected, this result is consistent with that reported by others indicating that verified information may influence the shadow prices of known characteristics (e.g., Pope 2008b). As expected, the estimated coefficient on HIDDEN increases if inspected ($\beta = -0.016$ vs $\beta = 0.004$). Thus, verification of the VISIBLE and HIDDEN features by inspection is found to increase their effects on price by 2.2% and 2.0%, respectively. Evaluated together with the estimated coefficient on INSP ($\beta = 0.081$), the inspection (the treatment) of the mitigation features is estimated to increase the price of the properties examined by 10.4% (i.e., average treatment effect (ATE) = 0.104) with a standard error of 0.008. These estimates provide strong evidence that the inspection of the

**Table 6** Treatment-effects model

| Second stage estimates – Dep. Var. = lnSP | | | | | | |
|---|---|---|---|---|---|---|
| | Model 4.1 | | Model 4.2 | | Model 4.3 | |
| Variable | Coeff. | s.e. | Coeff. | s.e. | Coeff. | s.e. |
| lnAV | 0.808*** | 0.004 | 0.804*** | 0.004 | 0.804*** | 0.004 |
| INSP | 0.102*** | 0.007 | 0.111*** | 0.007 | 0.081*** | 0.015 |
| VISIBLE | | | 0.021*** | 0.003 | | |
| VISIBLE (INSP = 0) | | | | | 0.015*** | 0.003 |
| VISIBLE (INSP = 1) | | | | | 0.037*** | 0.005 |
| HIDDEN | | | −0.016*** | 0.003 | | |
| HIDDEN (INSP = 0) | | | | | −0.016*** | 0.003 |
| HIDDEN (INSP = 1) | | | | | 0.004 | 0.013 |
| Census Dum Incl. | Yes | | Yes | | Yes | |
| Time Dum Incl. | Yes | | Yes | | Yes | |
| Constant | 2.460*** | 0.055 | 2.512*** | 0.055 | 2.507*** | 0.055 |
| Obs. | 28,487 | | 28,487 | | 28,487 | |
| Wald chi2 | 286,322 | | 286,768 | | 286,908 | |
| Stage 1 Stats | | | | | | |
| Lambda | −0.029*** | 0.004 | −0.031*** | 0.005 | −0.032*** | 0.005 |
| Rho | −0.134 | | −0.145 | | −0.146 | |
| Sigma | 0.217 | | 0.217 | | 0.217 | |

This table reports the second stage estimates of the two-stage treatment effects model, Eq. (7a). The variable definitions are listed in Table 1. The ***, **, * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. s.e denotes robust standard errors. Cluster based on properties that sold during the period

visible and hidden features provides new relevant information that increases prices in a range bounded from 4.2% to 10.4%.[20]

It is important to note that the estimated coefficient on INSP represents the price effect correlated with the inspection that is uncorrelated with the interaction of INSP with VISIBLE or HIDDEN. This suggests that other information valued by the seller/buyer may be associated with the inspection (e.g., how best to mitigate), mitigation occurred after the inspection but prior to the sale, or that the inspection is correlated with other property or data characteristics unrelated to the mitigation characteristics of

[20] It should be noted that observed transaction prices of the homes sold during the period are used to evaluate the effect of the inspection. It is, of course, possible that the sample of sold homes is selective. Unfortunately, time-on-market data are not available that would allow us to control for this, nor are we able to estimate a selection correction model. Fisher et al. (2003) show that constant-liquidity values may be higher than observed transaction prices during periods of growth (high sale frequency periods) and lower than observed transaction prices in periods of low sale frequency. If the inspection increases the home's likelihood of sale then its constant-liquidity value, on average, may be greater than the price observed. This suggests that the estimated coefficient on INSP represents a lower-bound. The effect of sample selectively on the price estimate, if any, is likely quite small (Gatzlaff and Haurin 1998). Alternatively, the effect of INSP on the prices may be viewed as the variable liquidity price actually observed.

interest,[21] or some combination of these factors.[22] Thus, it is likely that the estimated coefficient on INSP is overstated and the effect of the inspection is closer to the lower bound of the 4.2% to 10.4% range.

### Capitalization of the Insurance Benefit

To gauge the overall magnitude of the capitalized benefit of the credits, the insurance premium credits (WCRED) are regressed on transaction prices. The estimated coefficients on WCRED, reported in Table 7, range from 0.055 to 0.064 across the two models. This indicates that a 100% insurance premium credit increases property values by approximately 5.5% to 6.4%.[23] In comparison, the information provided by the inspection (i.e., some combination of the risk mitigating and insurance credit information) is estimated to increase property values by 4.2% to 10.4%. Because the price effect of the inspection information is likely at the lower end of the range (closer to 4.2% than 10.4%), the increase from the inspection appears to be largely dominated by the capitalization of the insurance premium credits the features represent to the homeowner, rather than the risk mitigating benefits revealed.

## Conclusion

This study examines the effect that hurricane mitigation features, and their verification by inspection, have on the transaction prices of single-family homes in an area at risk in Florida. Past work using standard hedonic models has implicitly assumed that buyers and sellers are equally informed. Although some mitigation features may be visible to both buyers and sellers, others are concealed (hidden) by construction. The study contributes to the literature by examining the effects of the hidden and visible features, and the verification of each, in an environment of potentially incomplete and asymmetric buyer-seller information.

We examine a dataset that includes transaction information (i.e., price, structure, and location characteristics) on all detached single-family residential properties in Miami-Dade County merged with a dataset of properties insured by Citizens Property Insurance Corporation that identifies the mitigation characteristics and their verification by inspection. Using a treatment effects model, we relax (partially) the assumption of symmetric information by explicitly modeling the inspection decision and including

[21] For example, owners who maintain their property at higher levels may be more inclined to have their properties inspected. This could be partially captured by the estimated coefficient of INSP.

[22] To further examine the influence of other variables, unrelated to the mitigation, on the estimated coefficient of INSP we estimate the model using only the observations having no mitigation features. The estimated coefficient on INSP was positive and of similar magnitude. Although the number of observations tested is very small and the results limited, this provides some evidence that the inspection variable may be correlated with other unavailable (omitted) variables.

[23] It should be noted that the average premium discount is roughly estimated to be $1900 per year. If the discount is fully capitalized at 5.0% it translates to a price increase of $38,000, evaluated at the mean during the period examined. In comparison the capitalized benefit of the full credit estimated by regression and evaluated at the mean is approximately $20,000. This indicates that the discount is not fully capitalized. It's interesting to note that the average cost of the inspection is approximately $200 (e.g. 1% of the average benefit).

**Table 7** Regression of credit estimates on sale price

| Dependent Variable = lnSP | | | | |
|---|---|---|---|---|
| | Model 5.1 | | Model 5.2 | |
| Variable | coeff. | s.e. | coeff. | s.e. |
| lnAV | 0.803*** | 0.004 | | |
| SQFT | | | 0.0005*** | 0.00001 |
| SQFT2 | | | −3.88e-08*** | 1.94e-09 |
| LOT | | | 0.00002*** | 4.61e-07 |
| LOT2 | | | −7.05e-11*** | 4.13e-12 |
| AGE | | | −0.005*** | 0.0005 |
| AGE2 | | | 6.33e-06 | 5.95e-06 |
| BDRS | | | 0.005 | 0.003 |
| BTHS | | | 0.018*** | 0.003 |
| FLRS | | | −0.001 | 0.005 |
| COND_B | | | −0.123*** | 0.008 |
| COND_C | | | −0.173*** | 0.010 |
| COND_D | | | −0.300*** | 0.018 |
| FBC | | | 0.0001 | 0.007 |
| HMSTD | | | 0.008*** | 0.003 |
| lnDTC | | | −0.083*** | 0.005 |
| I_FLOOD | | | 0.002 | 0.004 |
| C_FLOOD | | | 0.416*** | 0.065 |
| HRA | | | 0.022*** | 0.006 |
| WCRED | 0.055*** | 0.005 | 0.064*** | 0.005 |
| Census D Included | Yes | | Yes | |
| Time D Included | Yes | | Yes | |
| Constant | 2.756*** | 0.225 | 12.51*** | 0.236 |
| Obs. | 28,487 | | 28,487 | |
| Adj.-$R^2$ | 0.909 | | 0.899 | |

This table reports OLS regression results. WCRED, the variable of interest, is the percentage insurance credit from the Office of Insurance Regulation's credit table for the property's mitigation features. The variable definitions are listed in Table 1. The ***, **, * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. s.e denotes robust standard errors. Cluster based on properties that sold during the period

this information (i.e., the verification of the visible and hidden mitigation features) in the second stage pricing model.

Consistent with expectations, we find that visible mitigation features are positively correlated with price increases; that the effects of the visible and hidden features on price differ significantly; and that inspection information significantly increases the implicit price of the hidden features. Interestingly, and surprisingly, the inspection is found to also increase the implicit price of the set of visible features. Consistent with previous work (Pope 2008a), this suggests the implicit prices of characteristics that are, or should be, known (visible) to buyers and sellers may be affected by verification or disclosure.

The overall effect of the verification of the mitigation features by inspection is estimated to increase the prices of the properties examined by 4.2% to 10.4%. Additional evidence that suggests that the price increases from the inspection are most likely at the lower end of this range. While the price effects of the inspection are due to a combination of the risk mitigating benefits of the features and the insurance premium credits they represent, they appear to be due primarily to the capitalization of the insurance premium credits represented by the mitigation features confirmed.

This study is limited to the housing market within one MSA, Miami-Dade, and for one peril type, windstorm. Additional work is needed to evaluate the impact of safety features on house prices in other geographic areas and for other perils. Still, while specific to storm mitigation characteristics and the property market, the results have broad implications regarding the use of both premium credits in mitigating risk and information disclosure in markets with asymmetrically informed agents.

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