Wind Code Effectiveness and Externalities: Evidence from Hurricane Michael

Laura Bakkensen* Logan Blair †

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Abstract

In 2001 Florida adopted the first statewide wind specific building code in the US, mandating technologies like storm shutters and roof straps. Aggregate insurance loss data suggests that the code led to reduced damages in subsequent hurricanes. Whether benefits are wholly internalized by the individual homeowner, or spill over to adjacent properties through reduced airborne debris however remains an open question reserved for individual level observation. This paper applies high resolution areal imagery of Bay County, FL acquired two months after Hurricane Michael to detect individual residential temporary roof covers—a proxy for damage made additionally reliable through the USACE "Blue Roof" program providing free tarps to damages homes. Exploiting plausibly exogenous changes in wind-related building qualities, we find that homes built just after the wind code went into effect were less likely to require temporary roof protection than those built just before, but that being surrounded by homes built to code further reduced the emergence of a tarp. Results suggest that welfare gains from wind strengthening investments are in part derived from the the collective nature of public policy interventions.

*Laura Bakkensen is an associate professor of economics in the School of Government and Public Policy at the University of Arizona (laurabakkensen@arizona.edu).

†Logan Blair is a PhD candidate in School of Government and Public Policy at the University of Arizona (blairlo@arizona.edu).

1 Introduction

Southeastern coastal US counties are projected to encounter a hurricane with winds greater than 74mph every 5-16 years (NOAA, 2018), and an average loss of $10,089 per home (Simmons et al., 2018). Pushed by the extraordinary loss during Hurricane Andrew, Florida implemented the first and only statewide wind code in the US in 2001. The code ensures wind construction strength based on geographic location, and led to broad reductions in hurricane damage on the peninsula in 2004 and 2005 (Done et al., 2018). Despite losses likely within the lifespan of any home, and early success in Florida, Minimum building standards and enforcement remains unpopular with many home builders and political agents in other high risk areas (Simmons et al., 2020, Healy and Malhotra, 2009). Studies investigating the effects of building code policy often focus attention on the individual, when their legitimizing public value may rest on spill overs across property. This study helps fill that gap by considering the role of wind building codes externalities following Hurricane Michael.

Studies investigating the effects of wind code policy to date utilize insurance data aggregated to zip code or larger, or small-n surveys. In both cases they have a limited ability to casually identify impacts. Aggregate data also prohibits partitioning benefits of individual building strength, from any that are derived from the construction of neighboring homes. This study overcomes previous data limitations by generating a novel dataset classifying tarp (tarpaulin) coverings in areal images taken 2-3 months after Hurricane Michael as a proxy for roof damage. This approach exploits the recent US Army Corp of Engineers (USACE) "Operation Blue Roof" which install tarps free of charge for any damaged residential roof that qualifies after a storm.

We employ a regression discontinuity design (RDD) that identifies the returns of wind-specific investments on housing damage in Bay County following the Hurricane. Our analysis relies on plausibly exogenous change in wind-specific construction across a code implementation threshold in 2001, while confirming that other observable factors remain functionally smooth across the same time period. In a fixed effects model, we search for externalities by including the count of buildings under code within 100 and 500 feet of a home controlling for other observable factors constant like wind speed, house age, height, taxable value, and other neighborhood characteristics. Initial results show that homes constructed just after the FBC reduced the probability of damages by 2 to 14% compared to those built just prior during hurricane Michael. We also find significant evidence that the number of homes under code nearby lead to lower damages during a hurricane. Together, findings suggest that wind specific building strength matters, but that ignoring spatial dependencies could understate the importance of public administration and enforcement of wind code policy.

The remainder of the chapter is organized as follows. Section 2 presents theoretical arguments for building codes as a corrective policy in the face of underinvestment and spillover. We discuss previous research on code effectiveness and research gaps in Section 3. Section 4 describe data collection followed by Section 5 discusses the paper's empirical strategy, and Section 6 present preliminary results. We conclude with a brief discussion of issues and implications. Appendix A contains auxiliary regression results, and Appendix B steps through the remote sensing techniques used to measure covered roof damage in areal images.

2 Two Building Code Effects

Building codes have been in use in the United States for over 100 years (Dehring, 2006b). Discussed by Dumm et al. 2011 and (Dehring, 2006a,b), the imposition and enforcement of residential building codes are justified for two primary reasons: to correct for individual homeowner-homebuyer information asymmetries including behavioral factors and insurance market inefficiencies, and to correct for externalities that threaten adjacent property. In this way, wind codes aimed at preventing hurricane related damage should draw their justification through both individual and externality mechanisms, and that a focus on individual effects only might under-emphasize the importance of collective action.

2.1 Individual Effects

According to NOAA, southeastern coastal US counties expect a hurricane with winds greater than 74mph every 5-16 years depending on location (NOAA, 2018). With hurricanes likely during the lifespan of any home, we would further expect private individuals in the southeast to protect their assets though wind strengthened construction. This however does not appear to be occurring, or to the level at which is necessary to protect against major residential losses from storms like Hurricane Andrew (Fronstin and Holtmann, 1994),Sandy (Kunz et al., 2013), and Katrina (King, 2013). While climate change and building cost are commonly cited and important to consider, key theories of information asymmetries, behavioral biases, and moral hazard play an important role in individual underinvestment. In addition, there is mounting evidence that exceptional hurricanes like Andrew are exacerbated by climatic change (Emanuel, 2005, Knutson et al., 2010), and that today's storms might not be fully capitalized into construction behavior in years past.

While climate change is an important part of the story, billion-dollar residential property loss has been a growing and documented problem in the southeast US since the turn of the 20th century (Pielke and Landsea, 1998). Climate change helps explain the rise in the consequences of underinvestment, but only partially explains underinvestment itself that stems from information asymmetries and risk perception. That is, homebuyers may be unaware of the property risk associated with extreme weather (Pope, 2008, Fronstin and Holtmann, 1994), may not possess the technical expertise to assess the structural integrity of their home (Dehring, 2006b), or if so, might not know if additional investment will withstand future storms (Neumayer et al., 2014, Bubeck et al., 2013).

Even when full information is made available, individuals in laboratory settings tend to misinterpret the cognitively complex probability of extreme events, myopically discount the future benefits of mitigation, and procrastinate when mitigating low-probability, high consequence events (Meyer, 2006). Surveys confirm that individuals who correctly estimate the probability of their homes being affected by Hurricane Isaac and Sandy, expressed little concern over damage, and only 25% of the 593 respondents took protective measures against the storms (Meyer et al., 2014), and that underinvestment becomes larger as the individual's expectation of extreme events declines (Neumayer et al., 2014).

Actors may logically forgo protection if the cost of construction is higher than expected mitigated losses, however this calculus should typically encourage investment in coastal counties. Examining aggregated insurance data from Florida, the average individual claims ranged from $10,800 in the case of Hurricane Irma, to $65,890 after Michael (Schmidt, 2020) and $10,089 across all hurricane losses from 2001 to 2010 (Simmons et al., 2018). In comparison, the cost of wind strengthening a wooden home to withstand Irma's maximum winds of 130 mph and associated flying debris range from a 2.57% to 3.93% increase in the average price of a comparable home without wind protection, or $5,499 to $8,410 for the median Florida home.[1] [2] Likewise, building to withstand 150 mph winds and associated debris seen during hurricane Michael ranges from a 3.33% to 4.94% increase in the price of construction or $7,062 to $10,571. Lesser designs, built to withstand 100-120 mph winds can add as little as $0.23 per sq. foot, or a 0.51% price increase over comparable homes (Applied Research Associates Inc, 2002). A thin but growing benefit cost literature finds that building to higher wind standards would be cost effective in many other coastal states outside of Florida like Alabama, Georgia, Mississippi, and Louisiana among others (Simmons et al., 2020).

Insurance can serve as an efficient tool in shaping mitigating behavior in theory. However, an insurance market does not necessarily reduce individual damages unless premiums are conditional on physical protection. In practice, research suggests that reductions in premiums do not fully reflect individual investment because of transaction costs associated with private home inspection, program design, and administration (Kunreuther, 1996, Fronstin and Holtmann, 1994, Neumayer et al., 2014). Some argue that insurance encourages riskier structures to be built by guarding against the financial losses of extreme weather—— presenting a classical moral hazard (Fronstin and Holtmann, 1994, Neumayer et al., 2014). When inexpensive transportation and improved weather forecasting are available, individuals might rely on evacuation over costly structural improvements knowing that losses will be covered and that risks to their life are increasingly low (Sadowski and Sutter, 2005). Moral hazard might also extend to individual expectations of federal aid, or "social insurance", as a substitute for planning and property protection (Davlasheridze and Miao, 2019, Raschky and Weck-Hannemann, 2007).

Standardized, strictly enforced, wind building codes based on best science should in theory remedy underinvestment brought on by information asymmetries, behavioral biases, and moral hazard by ensuring investment that would not have occurred otherwise. The premise of this paper is that if any of the aforementioned conditions lead individuals to underinvest in wind protections, we would expect to find significant differences between wind damage to homes under code and homes built in an unrestricted market after a hurricane event. However, if private individuals already adapt to sustain hurricane winds, codes designed to

[1] Based on 2013-2017 American Community survey median Florida home value

[2] Price ranges listed include impact coverings such as storm shutters as the most cost-effective means to mitigate debris risk. Impact glass as an alternative option to shutters, can more than double costs.

withstand similar wind speeds should have no meaningful effect.

2.2 Spillover Effects

An individual's decision to invest in wind protection may not be felt in isolation, rather their investments could spill over to neighboring individuals. This is made possible through what Silva, Kruse, and Wang (De Silva et al., 2008) call the "debris effect". Much like the role that airborne particles play in transmitting disease, physical surveys commonly suggest that windborne debris from adjacent properties compound wind damage (Coch, 2015, Ginger et al., 2007). Through simulations and controlled settings, the engineering literature is also very clear that hurricane damage is co-determined by wind strength and associated flying debris from adjacent structures(Lin and Vanmarcke, 2010). However, it is unlikely that individuals take these effects into account when building or purchasing their homes.

Take for example a home near the coast in southeastern US. Homes surrounding it, built to withstand high winds, might serve as an effective barrier from wind and airborne debris (regardless of the construction quality of the individual home under consideration). Alternatively, poorly constructed homes nearby would make for ineffective barriers, and could fall or break apart and cause damage. Under this classic scenario, strong neighboring homes provide a (free) benefit to others. This condition also means that if, based on individual preferences neighbors do not invest in wind hardening, but would have were they able to receive compensation for residual benefits provided to others, the decision to not invest is socially suboptimal and the additive benefits from protecting capital is left on the table.[3]

Some argue that formal policy to correct the welfare loss described above is not necessary if transaction costs of negotiating are very low (zero), and property rights—in the form of benefits to others from improvement—are perfectly known. In the current example a market solution would however require negotiating with some unknown number of neighbors about building stronger homes under a perfect understanding of how and to what degree their investment brings benefit to others. Since both conditions are nearly impossible to satisfy, a common policy solution imposes collective investment within the area whose property values are spatially dependent through some institution, agreement, or building code. If policy is implemented such that the marginal benefit gained from collective action remains higher than the marginal cost of the policy, social welfare increases under most scenarios.[4] Typical examples of successful policy targeting spillover include neighborhood associations and zoning laws, but broad wind code administration and enforcement are likely to have analogous welfare affects (Dehring, 2006a).

[3] There may also be concerns over free riding by extracting benefits from others, but deliberately avoid payment or investment themselves. While a theoretical possibility, it seems unlikely that individuals would have the information necessary to weigh their own risk tolerance relative to the structural investments made to adjacent properties.

[4] A full discussion on the theoretical costs to code implementation and enforcement are outside the scope of this paper. A good overview of code costs can be found in (Listokin and Hattis, 2005)

3 Literature

Only a handful of observational papers have attempted to link building code adoption to hurricane damages, in part because very few local governments have imposed codes, and granular loss data is difficult to obtain. Fronstin and Holtman (1994) identified that the slow degradation in building standards likely translated to lower building quality and in turn higher damage in newer south Florida subdivisions after Hurricane Andrew. In a widely cited series of papers, Simmons, Czajkowski and Done 2018, and Done, Simmons and Czajkowski (2018) find up to 68% reductions in damages for homes built under the FBC compared to their pre-FBC counterparts during the 2004 to 2005 hurricane season.

Smaller-n (typically $<$1000 observations) ground surveys such as those found from the Structural Extreme Event Reconnaissance Network (StEER) employ UAV's ground survey techniques, and vehicle mounted cameras to document incredibly detailed damage. Prevatt and Roueche (2019) descriptively analyzed Hurricane Michael StEER data and found that in almost all wind speeds and damage types (eg. roof, siding, etc.) post-FBC homes displayed less damage than those built prior to the code, and observed very few roof failures in homes under code compared to 1-in-5 failures with non-FBC homes. In a similar analysis, Gurley and Masters (Gurley and Masters, 2011) collected 126 surveys asking residents subjected to Hurricanes Ivan, Frances, Jeanne, and/or Charley in the 2004 season to indicate housing and roof damage estimates. Sorting into pre- and post- FBC requirement, the authors found that 15 percent of homes built under the FBC indicated greater than 5 percent roof damage while 51 percent of those built from 1991-2001 reported greater than 5 percent damage. An extensive engineering literature has also described wind debris damage dynamics and the importance of building strength through simulated data, and laboratory experiments (see (Minor, 1994)).

The observational studies above contributed heavily to the creation and justification of Florida's modern-day wind policy, but all were necessarily estimated using development, census tract, or zip code level data. If any omitted variables are correlated with included variables and impact damages within groups, bias could threaten valid inference. (Simmons et al., 2018) employed a discontinuity-like process to search for the optimal way to include housing age in their regressions, but their zip code-decade loss data did not allow for a full RD design. On the other side of the spectrum, engineering literature using simulated data, and sterile laboratory experiments have limited external validity (see (Minor, 1994)). In the way of externalities, Silva, Kruse, and Wang (2008) searched for and found that tornado losses in Oklahoma were spatially correlated. Similar effects have been hypothesized about the hurricane environment and that building codes might attenuate these effects but have yet to be empirically tested (Dehring, 2006a).

4 Data

To test for individual and spillover affects of wind protections we turn to Bay County, Florida where on October 10th, 2018 Hurricane Michael made landfall as the first Category 5 hurricane to strike the US since Hurricane Andrew in 1992. The size of Bay County also affords this study a good deal variation in wind exposure, damage and building code takeup.

4.1 Physical Attributes

Building footprints were provided by the Bay county GIS department, and sorted for single family property by spatial intersections with assessor's data. Building footprints provide the general size and position of a home, while assessors data contain relevant structural characteristics like year built, heated area, taxable value, number of stories, and number of bathrooms and bedrooms. The full dataset of all buildings and building types contains 115,175 observations total, 69,431 of which are single family properties. 5,497 observations were dropped because they did not report an assessed value or were valued +/- $1m/$50k. 8,373 properties were dropped because there was no building structure on the parcel designated as single family or the building footprint was dramatically misaligned with building structures.[5] An additional 5,059 properties were dropped if larger than 10,000 square feet or missing information on the year built, ground elevation, the number of bedrooms/bathrooms or stories. After cleaning, the analyzed dataset comprised of 50,502 single family homes.

4.2 Building Code Treatment

Since 2001 the Florida State Building Code (FBC) has required new construction to incorporate wind strengthening measures such as hurricane straps and approved shingles designed to maintain roof integrity under extreme wind loads. In addition to wind protection, some homes were also subject to wind debris requirements that called for impact resistant materials such as storm shutters and impact resistant glass and doors. In Bay County, all homes constructed after 2001 were required to adhere to the wind strengthening. Homes constructed farther than 1 mile from the coast received exemptions from wind debris requirements (until 2006 when the exemption was lifted), while homes within 1 mile of the coast were required to follow wind resistance and wind debris requirements. It is also important to note that construction within 100 feet from the coast were subject to the Coastal Construction Control Line (CCCL), and those located within 1500 feet from the coast adhered to the Coastal Building Zone (CBZ), both of which were in place well prior to 2001 and may confound the construction quality counterfactual (Yazdani and Kadnar, 1993).

We also split the full sample into 2 additional subsamples. The first contains all homes built inland farther than 1 mile from the coast. The second sample contains homes built less than 1 mile but greater than 1500 feet from the coast. In this way, we include homes

[5] Damage data, discussed further below, is contingent on building footprint vectors aligning with the home itself in an image. Footprint vectors in this analysis were either hand drawn by Bay County, collected from open street maps project, or Microsoft's footprint project—all of which are subject to human, or model error.

subjected to strengthening and debris requirements but omit those that might fall under confounding historical building restrictions for beachside homes. Omitting homes within 1500 feet also avoids systematic differences in construction on account of their coastal proximity compared to the broader population. Observations in both the split and the full dataset are considered treated if built after 2001 or in the baseline otherwise. We also assign the total the number of buildings within a 100 and 500 foot buffer that were built after 2001, and the number of buildings within a 100 and 500-foot buffer.

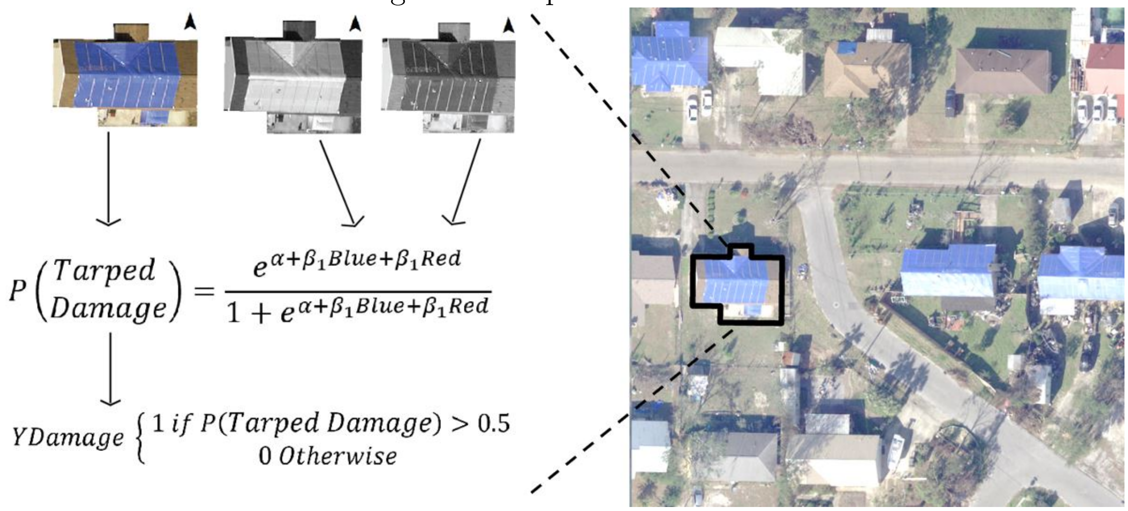
4.3 Covered Damages

This paper employs an original dataset describing the existence of tarpaulin nylon ("tarp") coverings emerging 60-90 days after Hurricane Michael made landfall in Bay County as an indicator of housing damage. The presence of emergency roof covering provides a reasonable proxy for housing damage for several reasons. During a wind event, roofs often receive a large bulk of the damage. Repairs can take time, and depending on insurance claim processing, cleanup efforts, contractor availability, and building supplies, a homeowner typically waits months, or in some cases years, for full restoration. In the interim, homeowners are incentivized to waterproof their roofs with tarps to avoid additional rain damage to drywall, electrical and flooring. Aside from roof specific damage, tarp coverings may also indicate envelope and internal damage as a result of airborne debris strikes. That is because once air from outside enters a home, upward pressure on its roof can double, resulting in a higher chance of failure (Applied Research Associates Inc., 2002).

Exploiting tarp cover as a proxy for damages is made additionally reliable through the "Operation Blue Roof" program. Started by USACE in 2004, and fully in effect during the Hurricane Michael recovery, the blue roof program allows the Army Corp to install tarps free of charge for any damaged residential roof so long as properties had less than 50% structural damage and inhabitable after covering. Priority is given to single family homes with shingle roofs, but mobile homes and other roof types are considered on a case by case basis. While individuals may choose to cover their roofs on their own, the Blue Roof Program helps insure that covered damages used in this analysis are not based on access, financial, or physical limitations.

Tarp identification was made possible using high resolution areal imagery provided by request from Bay County's GIS department. The data is comprised of several hundred orthorectified images collected via aircraft in January of 2019 with a spatial (pixel) resolution of 3 inches for the entire 1,033 square mile county. To convert the images into useful physical quantities we first clip them by known building footprints to generate a set of pixels known to exist as roof cover before the storm. We cluster the select pixels based on k-means sampling and model the probability that each cluster is a tarp, based on variation in brightness of the cluster's 4 bands—–red, green, blue, and near infrared (NIR). For example, if a cluster reflects strongly in blue, and low in red, it is likely to be a tarp. For the purposes of this paper, we recover a binary indicator 1 if the predicted probability of a parcels containing tarp is > 0.5 and 0 otherwise (Figure 1). A deeper discussion of the remote sensing techniques explored to classify the Bay County imagery can be found in Appendix B.

Figure 1: Tarp Classification



4.4 Hurricane Michael Wind Exposure

Spatially explicit wind intensity data was taken from proprietary Hwind data purchased from Risk Management Services (RMS) and intersected with Bay County building footprints in ArcGIS. Hwind represents the sustained maximum sustained 1-minute wind speed experienced at 10 meters above ground level as modeled from weather station readings and other meteorological data. Hwind (hereafter referred to as wind speed) is a gridded product providing a spatial resolution of 6km and is heavily cited in engineering and meteorological studies.[6] The maximum 1-minute sustained wind in the data ranges from 75-150 miles per hour within the Bay County study area with mean of 114 miles per hour (see Table 1).

5 Empirical Strategy

We apply two empirical approaches. The first is a regression discontinuity design (RDD), which under the assumptions discussed below recover the causal impact of building code treatment on the probability of roof damage. However, because code density around a home is not strictly determined by an observable threshold in the data—-that is, being built after 2001 is necessary, but not sufficient condition for treated neighbors—We propose a probit model that estimates the spillover effects of nearby coded homes on the probability of damage, after carefully controlling for other factors that determine damage and spatial autocorrelation among observations.

[6] See for descriptions of Hwind Data products, and for a list of peer reviewed papers utilizing HWind.

Table 1: Tarp Classification

	Full Sample		Inland Sample		Coastal Sample	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
1 min. Max Wind Speed (mph)	114	14	119	9	96	12
Building Density (# within 500ft)	60	35.	51	26	75	32
Building Area (square ft.)	2,375	1,066	2,443	1,090	2,242	857
Taxable Building Value ($2019)	95,786	84,411	88,739	71,838	116,404	69,758
Bathrooms	2.02	0.66	2.00	0.64	2.09	0.56
Bedrooms	2.96	0.70	3.02	0.67	2.86	0.65
Stories	1.19	0.45	1.13	0.37	1.21	0.44
N	50,502		39,204		5,164	
Homes w/Covered Damages	35%		39%		18%	

5.1 Estimating Individual Effects

An RDD design here seeks the causal effects of building codes on housing damage by establishing a counterfactual from untreated homes just prior to implementation. As discussed above, the Florida Building Code was administered using strict implementation rules, or cutoff year c_i. In this analysis c_i refers to homes constructed in or after 2001. The identifying assumption is that, besides treatment, all other damage-determining qualities about a home vary smoothly across c_i. Meeting this assumption is theoretically tenable since c_i was selected by a punctuated and random political process while housing qualities change slowly over time and space. Expanding from the basic RD design (Jacob et al., 2012, Imbens and Lemieux, 2008), We estimate the following model for home i constructed in year r:

$$Y_i Damage = \beta_0 Code_i + \beta_1 Code_i \times (r_i - c_i) + \beta_2 (1 - Code_i) \times (r_i - c_i) + \delta X' + \epsilon_i \qquad (1)$$

Recall that dependent variable, tarp covered damage takes on a 1 for any covered damage in home i in zip code j or 0 otherwise and estimate as a linear probably function. The estimator of interest is Code, an indicator that takes on a 1 if home i was constructed after the code threshold c_i, and 0 otherwise. We center construction year by threshold c_i so that discontinuity occurs when $(r_i - c_i) = 0$ and include separate trend terms β_1 and β_2 such that $\beta_1 = \beta_2$ if trends are identical above and below c_i. Unequal slopes are a reasonable functional addition, considering that the impacts of housing age on damage likely depends on housing quality enhanced by the code.

If treatment is determined exactly by construction year r, and all construction is forced to comply, the "sharp" discontinuity observed in equation 1 should recover the average causal effect of the building code on compliers. However, if individuals or contractors illegally avoid adopting the FBC (never takers), take up protection before the code (always takers), adopt it partially, build to the code incorrectly over some period, or even build riskier structures in protest (defiers), we would not expect treatment for all construction at c_i. Either of these circumstances would likely attenuate the expected negative affect of code on damage, therefor equation 1 remains conservative and policy relevant in the context of Bay County population and will be presented with this caveat.

We estimate the models above using both local linear and global parametric specification. The local linear approach limits the bandwidth observations just before and after the policy threshold where the effects of construction date on damage is likely linear. As bandwidth widen from the threshold, more observations offer additional precision, but tradeoff with potential bias if housing age is correlated with unobservables. We use a common cross validation technique to narrow the bandwidth to the point that linear mean square error (MSE) becomes less than a higher order polynomial for the same model on each side of the threshold. Depending on the sample (Coastal, inland, or full) this process suggests that 4 to 7 years is the optimal bandwidth size on either side of the threshold.[7] For this analysis we select a 6-year bandwidth for consistent comparison across samples, and because after 2006 there were additional policy changes that could theoretically confound results in a 7-year bandwidth. Results (not reported) generally held when bandwidths were doubled but were not significant when halved in size. We estimate the local regression using a triangle kernel that weights observations according to their distance from the policy threshold. The usual global parametric (OLS) approach includes every observation in their respective samples. We allow for different slopes on either side of the policy threshold and report effects without covariates, with all covariates, and with all covariates and zip code fixed effects.

5.2 Estimating Spillover Effects

The goal of this model is to estimate the spillover effects of building codes on single family housing damage, holding constant all other factors that determine damage. Provided this is the first paper of its kind related to wind code policy, we turn to the health economics literature for identification strategies. A particularly compelling specification comes from Edward, Miguel and Kremer (2004) who looked at the effects of deworming treatments in Kenya on the health outcomes of treated schools, as well as the spillover effects of the treatment status of nearby schools on their neighbors. Using school level health, outcomes took on a binary 1 when "any moderate-heavy infection" was found and 0 otherwise. In addition to the treatment status of individual schools, the authors include the number of treated schools within 3 and 6 km and the total number of schools within 3 and 6 km. In this way they recovered the independent effects of students treated nearby holding general transmission effects fixed.

Analogous to a bacterial infection in humans, hurricane damages likely "transmit" from home to home via airborne debris. The overall density of buildings may increase the chances of damage (infection) or second impact damage (reinfection). As with the effects of a drug, we would expect transmission to reduce as nearby homes are treated with stricter building codes. To test for these effects, We estimate a second equation (3):

[7] Standard selection in the rdrobust package in R following (Calonico et al., 2014)

$$Y_{ij} = \beta_0 + \beta_1 T_{ij} + \beta_2 W_{ij} + \beta_3 T_{ij} \times W_{ij} + \sum \gamma N_{bd}^T + \sum \delta N_{bd} + X_i' + \rho_j + u_{ij} \qquad (2)$$

Where Y_{ij} remains a binary indicator for covered damage of home i in zip code j and estimated probit. T_{ij} represents the building code treatment that home i is expected to take based on its construction date and geographic location. W_{ij} is the maximum 1 minute sustained windspeed experienced by home i. The interaction between code treatment and windspeed controls for any heterogeneous effects that tratemnt has on damages across a range of wind speeds. Alternatively interpreted, β_3 recovers the effects of windspeed on damage, depending on what treatment alternative home i is constructed under.

N_{bd}^T is the number of buildings b treated buildings within distance d, and N_{bd} is the total number of buildings b within distance d. In this study, d takes on a value of either 100 feet or 500 feet.[8] Subscript b is used instead of i to reflect the fact that all building structures (e.g. commercial, multifamily) are considered in this summation, not only single-family homes in the sample.[9] The effect of an additional nearby buildings being treated are captured by γ, controlling for any independent effects of housing density δ.

Since treatment T_{ij} varies by year built and distance from the coast they are likely correlated with construction characteristics also sensitive time and space. To the extent construction characteristics are correlated with damages, estimates will be bias in unknown ways. For example, homes built next to the coast contain large panel windows to improve view. If not properly reinforced, the unique window construction could increase the homes risk of wind damage. The same home might have additional protections or innate quality built in simply because of its location. We include a vector of individual property characteristics X_i' to control for differences in construction quality indicated by age of the home, number of stories, footprint size, building area, and taxable value.

Similarly, spatial autocorrelation can introduce bias when the features of one observation influence the features of other observations to take on similar characteristics (F. Dormann et al., 2007). This correlative relationship violates idiosyncratic error assumptions and may be apparent in this work through the size, style, and quality of a home directly affecting similar features of their neighbors. Kuminoff et al. (2010) argue that the use of spatial errors and spatial lag techniques used to purge models of omitted variable bias and autocorrelation have become "stylized facts" in housing models. Through a series of Monte Carlo replications, Kuminoff et al. (2010) find evidence that various levels of spatial fixed effects most efficiently control for bias. Following their convention, we include zip code level fixed effects ρ_j and individual errors u_{ij} clustered at the zip code level.

[8] The distance of 100 and 500 feet was selected to capture the effects of immediate neighbors in a typical suburban setting (100 feet), as well as a typical neighborhood block (500 feet).

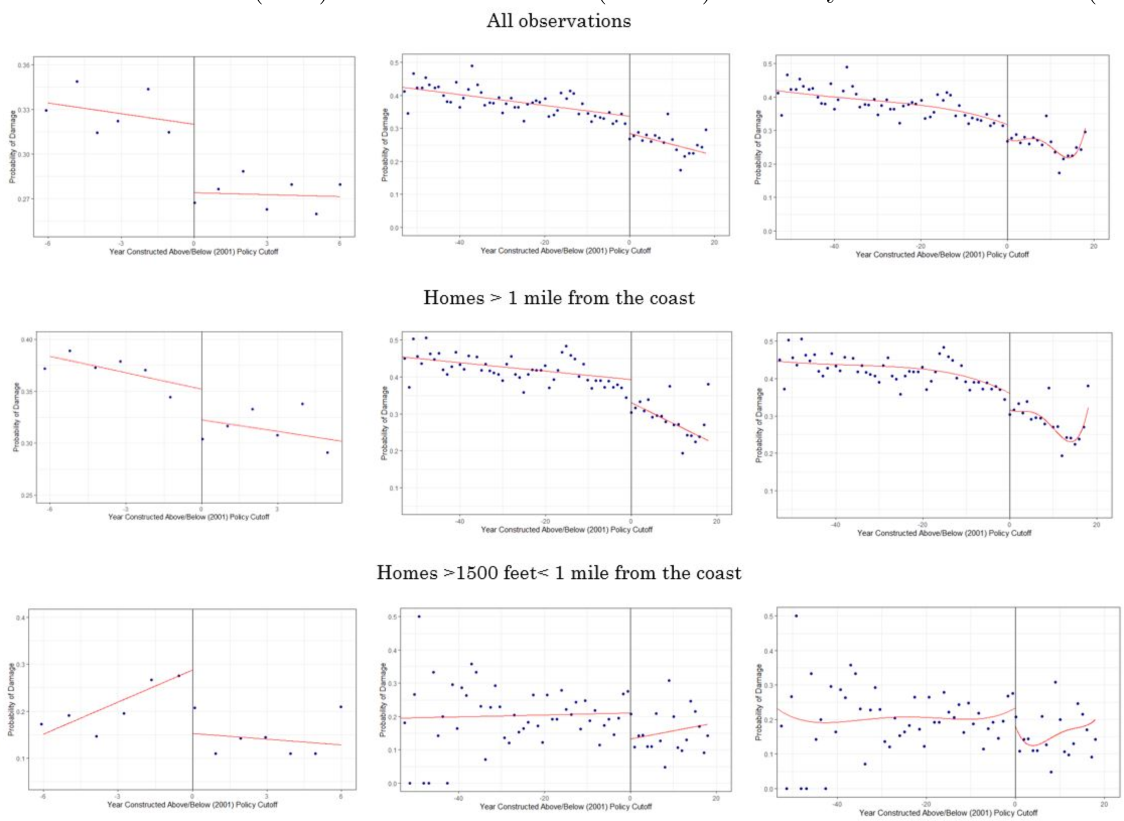
[9] The effects code regulation impacted commercial and multifamily structures as well. Therefore, while this is an examination of benefits to single family homes, externalities from all buildings are considered.

6 Results

6.1 Individual Estimates

Illustrated in Figure 2 all samples report a discontinuity in damages across the policy threshold. Estimates report a reduction in the predicted probability of roof damage ranging from 2.6 percent in the full sample under some parametric models (Table 2), to 13.9 percent in local linear models of coastal properties (Appendix A, Table 5). The local linear models estimated using all observations (Top left panel in Figure 2 and Figure 2), suggest a treatment effect of a 4.4 percent reduction in the probability of damage. All models are statistically significant except for the local linear model estimated from our inland sample.

Figure 2: Local Linear (Left) Linear Parametric (Middle) and Polynomial Functions (Right)



The internal validity of both global and local techniques rests on the crucial assumption covariates are functionally smooth across the policy threshold such that observation just prior offer a reliable counterfactual to those just after. Figure 3, Figure 4, and Figure 5 in Appendix A plot the average values of each covariate in full, inland and coastal samples respectively by construction year while a horizontal line marks the 2001 policy threshold as usual. In the full sample (Figure 3, Appendix A), homes built just after the threshold seem to experience slightly lower winds on average. However, this discontinuity is alleviated somewhat in more geographically specific samples described in Figure 4, and Figure 5. There is also a “kink” in housing density (number of homes within 500 ft of a home) in the full and coastal samples, and a general drop in density after the threshold for inland homes. Structural variables like area, bedrooms, and bathrooms appear to be in stable, upward sloping trends.

Table 2: Local Linear and OLS results (sharp design): Full Sample

	Dependent variable: *Roof Damage (Binary)*			
	(1)	(2)	(3)	(4)
	Local Linear	OLS	OLS	OLS
Construction ≥ 2001	-0.044***	-0.044***	-0.026***	-0.038***
	(0.021)	(0.009)	(0.009)	(0.010)
Construction < 2001*years from cutoff		-0.002***	-0.001***	-0.001***
		(0.0001)	(0.0001)	(0.0002)
Construction ≥ 2001*years from cutoff		-0.004***	-0.002*	-0.003***
		(0.001)	(0.001)	(0.001)
Observations	4,379	50,502	50,502	50,502
Main Controls		No	Yes	Yes
Zip Code FE		No	No	Yes
Mean of Dependent Variable:				
Note:				*p**p***p<0.01

6.2 Spillover Estimates

Model 1 in Table 3 provides baseline estimates on individual treatments only. Models 2 and 3 describe individual and externality effects of homes under code within 100 and 500 feet respectively. Models 1-3 include housing controls and zip code fixed effects. All coefficients are presented as the marginal effects on the probability of damage holding all other covariates at their means, along with standard errors in parenthesis. Windspeed is mean centered, and the main effects of the wind speed-policy interactions should be interpreted as the effects of treatment at mean wind exposure (114 mph in our data). Note that some coefficients have been scaled for interoperability indicated in parenthesis.

The effects if individual treatment without considering externalities (Table 3, Model 1) is negative and significantly different from zero. This suggest that when hurricane winds are at their mean, the probability of roof damage for a treated home is 7.3 percentage points lower than uncoded homes. The positive and significant sign on the interaction between windspeed and treatment suggests that the damage saving effects of treatment are reduced by 0.8 percentage points for every 10 miles per hour increase in sustained wind speed.

Following Model 2 and 3, the probability of damage significantly increases as the number the buildings within 100 and 500 feet of a home increase, but for every building treated within those bands, the estimated probability of damage is reduced by roughly the same amount or more. To conceptualize the impacts of externalities, consider a scenario in which

Table 3: Probit Model Results

	Dependent Variable: Covered Damage (Binary)		
	(1)	(2)	(3)
Winds Speed (per 10 mph)	0.010***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)
Built >2001	-0.073***	-0.049***	-0.053***
	(0.007)	(0.010)	(0.008)
Buildings under code within 100ft		-0.007***	
		(0.002)	
Buildings within 100ft		0.006***	
		(0.001)	
Buildings under code within 500ft (Per 10 buildings)			-0.009***
			(0.002)
Buildings within 500ft (Per 10 buildings)			0.004***
			(0.001)
Winds Speed × Built >2001	0.008**	0.008*	0.007*
	(0.004)	(0.004)	(0.004)
Constant	1.220***	1.349***	1.201***
	(0.318)	(0.319)	(0.318)
Observations	51,663	51,663	51,663
Mean of Dependent Variable	0.35	0.35	0.35
Zip Code FE.	Yes	Yes	Yes
Housing Variables	Yes	Yes	Yes
Akaike Inf. Crit.	61,929	61,896	61,888
Note:			*p**p***p<0.01

there are uncoded buildings nearby, compared to some proportion of those buildings are under code. The median number of buildings within 500 feet of a home in the data is 50. Holding all other factors at their mean, 50 untreated buildings within 500 feet increases the probability of damage by $5 \times 0.004 - 0 \times 0.009 = 2.0$ percentage points. If 10 out of the 50 buildings are treated (the mean in the data), the probability of damage from the same 50 homes is $5 \times 0.004 - 1 \times 0.009 = 1.1$ percentage points, or a marginal reduction in damage of 0.9 percentage points. Treating roughly half of the surrounding buildings would flip the positive effects of building density on damage altogether based on the model.

It is important to note that the effects of individual treatment status in Model 2 and 3 in Table 3 are noticeably smaller than estimates in Model 1 suggest without externalities. For example, Model 1 estimates that the impact of individual treatment status is 2.4 percentage points larger (more negative) that in Model 2. This finding suggests that the treatment status of a home is positively correlated with the treatment status of buildings nearby. A Pearson test confirms that the correlation between the individual treatment and treated buildings within 500 feet is 0.53. Since the probability of damage is negatively related to treated buildings nearby, and the treated buildings nearby is positively correlated with individual treatment, individual treatment effects in Model 1 are biased downward (more negative) when terms describing neighboring treatment is unobserved.

7 Discussion

This study contributes to the literature by recovering some of the first casual impacts of wind codes on roof damage during category 5 hurricane event, and the first large-n observational evidence of a long-standing theory that individual homes benefit from wind-resistant investment of their neighbors. This positive externality is likely achieved by reducing airborne missiles and debris that otherwise render individual building decisions less important. From a policy perspective, externalities found here suggest that the public administration and enforcement on building requirements may be just as important to the protection of individual property as any single individual's construction decisions. While wind codes in Bay County and other regions of Florida have decidedly imposed community wide code, other states, counties, and local governments concerned with individual liberties should be reminded of these welfare increasing effects.

From an empirical perspective, past and future research investigating the individual benefits of building code may be biased to the extent that homes built under code cluster together or are spatially correlated. Given that homes are often built in developments, this is very likely. Studies that find large individual benefits associated with building codes may be misattributing part of those benefits to individual construction when instead protections stem from the higher probability that nearby properties are also built under code and minimize airborne debris related damage.

Note that estimates have just as much to do with the quality of existing building counterfactual in Bay County prior to the FBC as it does with the code itself. That is, we might not expect the same results to emerge from a state or county with a stronger history of self imposed building quality prior to enforcement. While our RDD design offers a careful, magnified view of code treatment effects, the applicability of its results to other regions should be thought through carefully. Results only apply to similar hardening investments made to early 2000's style construction in the southeast coastal US. Without further investigation, result may not describe retrofit policies, nor for homes constructed in future decades with advanced materials and practices not tested here. It is also not clear if these results will hold as homes age and become re-exposed to wind hazards.

With respect to measuring damage, there are bound to be individuals who refuse or cannot cover their roofs, receive wind losses not indicated by roof damage, or manage to repair their roofs sooner than the imagery used in this analysis was acquired. As mentioned in the empirical section of this paper, its likely that tarp cover represents wide range of damage depending on personal preferences and unobserved constraints. Similarly, there is no reason to cover a structure that is completely destroyed or as good as destroyed. For these reasons this study is limited to estimating effects on the extensive margin from no covered damage, to some low-moderate levels of damage. It says nothing about treatment effects on the intensive margin, or preventing a complete loss.

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Appendix A. Regression Details

Table 4: Local Linear and OLS results (sharp design): Inland Sample

	Dependent variable: *Roof Damage (Binary)*			
	(1)	(2)	(3)	(4)
	Local Linear	OLS	OLS	OLS
Construction ≥ 2001	-0.026	-0.051***	-0.030***	-0.031***
	(0.025)	(0.011)	(0.011)	(0.011)
Construction < 2001*years from cutoff		-0.001***	-0.001***	-0.001***
		(0.0002)	(0.0002)	(0.0002)
Construction ≥ 2001*years from cutoff		-0.006***	-0.004***	-0.005***
		(0.001)	(0.001)	(0.001)
Observations	3,159	39,204	39,204	39,204
Main Controls		No	Yes	Yes
Zip Code FE		No	No	Yes
Mean of Dependent Variable:				
Note:				*p**p***p<0.01

Table 5: Local Linear and OLS results (sharp design): Coastal Sample

	Dependent variable: *Roof Damage (Binary)*			
	(1)	(2)	(3)	(4)
	Local Linear	OLS	OLS	OLS
Construction ≥ 2001	-0.139***	-0.096***	-0.113***	-0.094***
	(0.047)	(0.019)	(0.019)	(0.020)
Construction < 2001*years from cutoff		0.0003	0.0004	0.0005
		(0.001)	(0.001)	(0.001)
Construction ≥ 2001*years from cutoff		0.004**	0.006***	0.003*
		(0.002)	(0.002)	(0.002)
Observations	634	5,164	5,164	5,164
Main Controls		No	Yes	Yes
Zip Code FE		No	No	Yes
Mean of Dependent Variable:				
Note:				*p**p***p<0.01

Figure 3: Covariate function across policy threshold: Full Sample

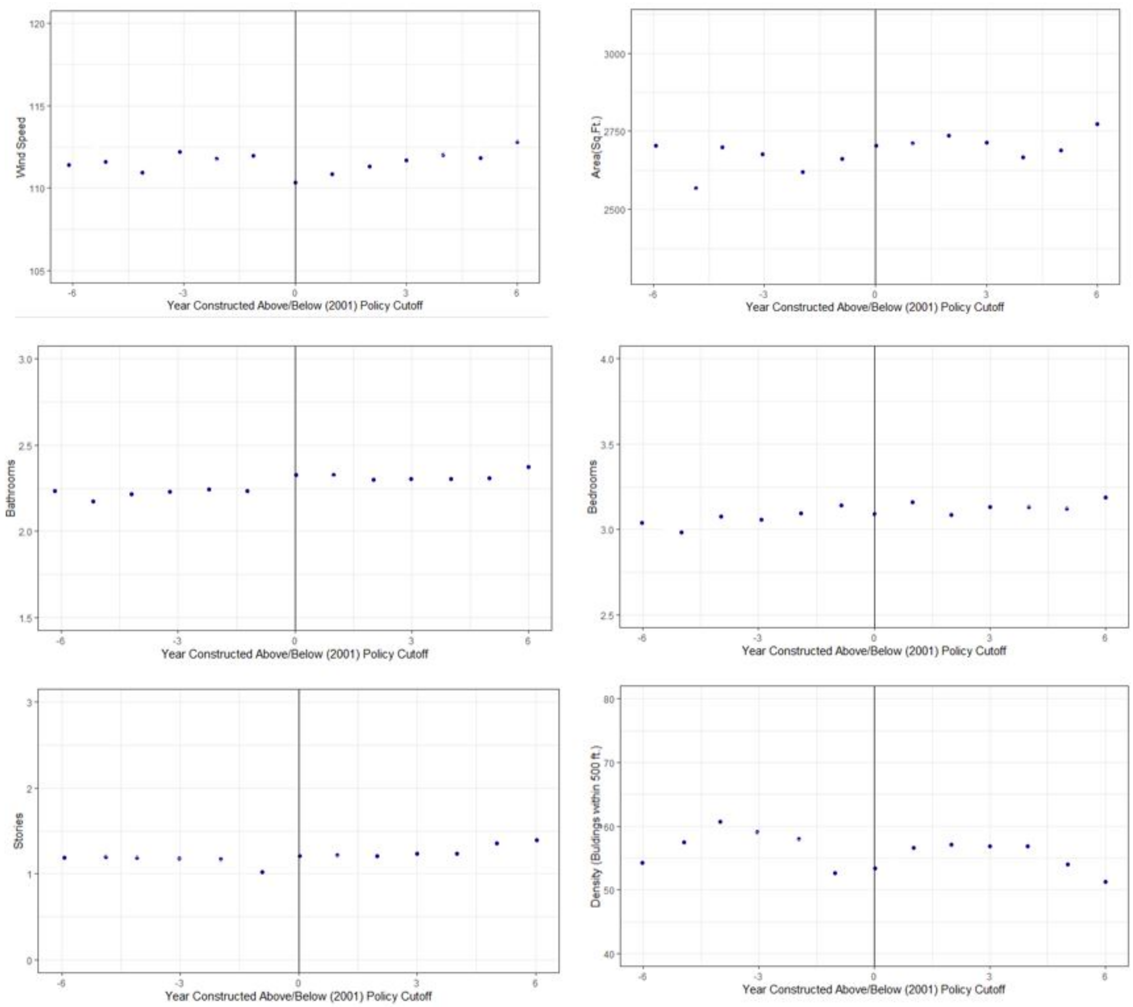


Figure 4: Covariate function across policy threshold: Inland Sample

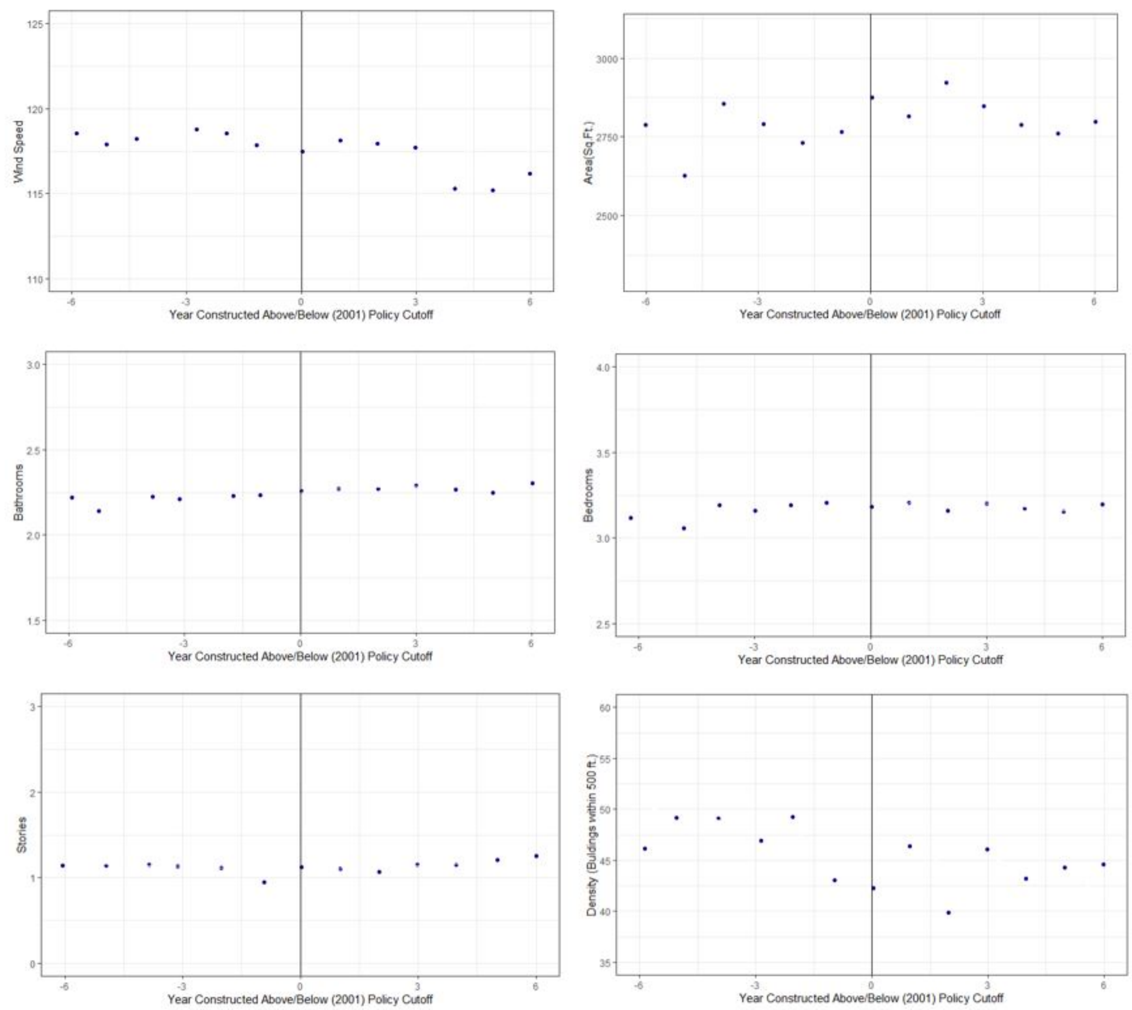


Figure 5: Covariate function across policy threshold: Coastal Sample

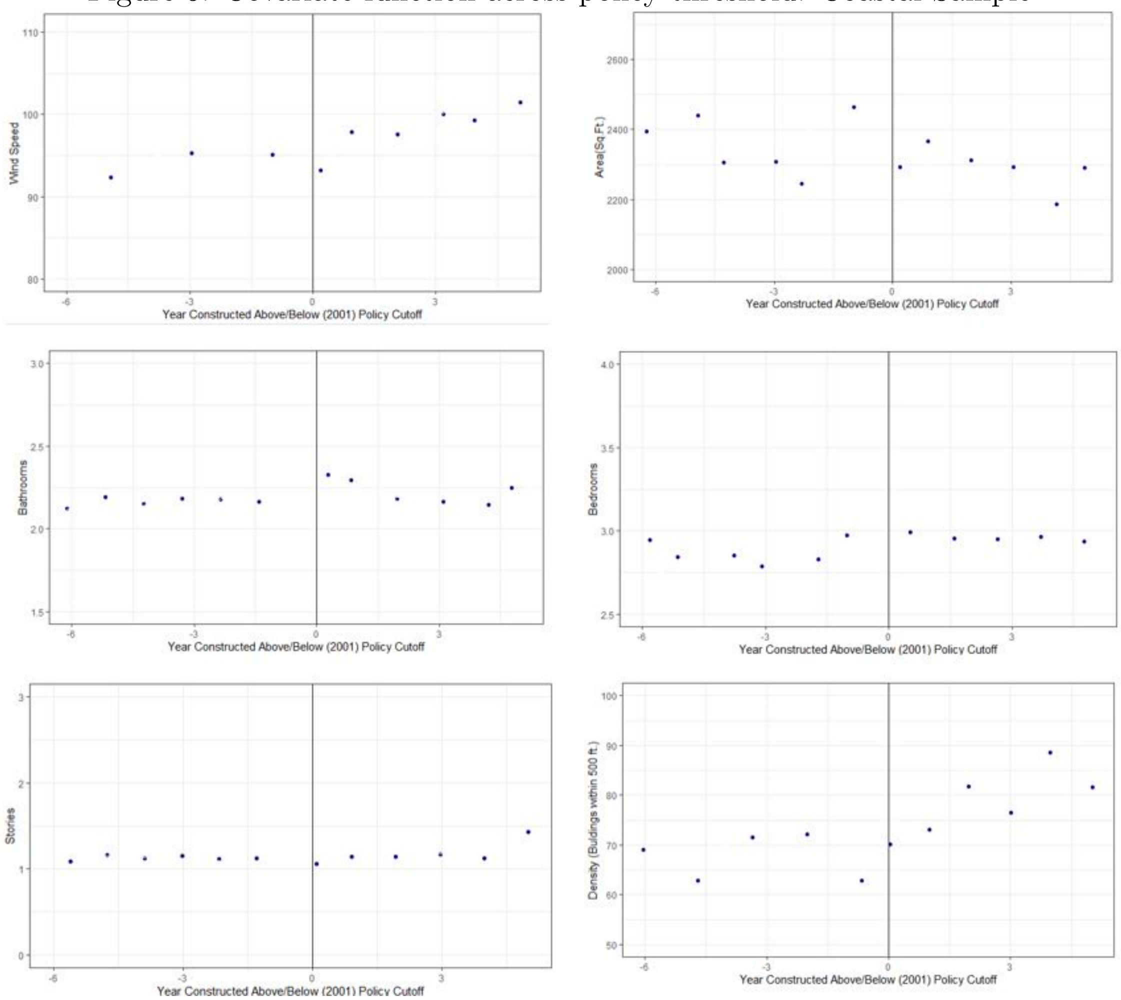


Table 6: Probit Model Control Variables

	Dependent Variable: Covered Damage (Binary)		
	(1)	(2)	(3)
Year Built	-0.001^{***}	-0.001^{***}	-0.001^{***}
	(0.000)	(0.000)	(0.000)
Taxable Building Value (per $10,000)	-0.004^{***}	-0.004^{***}	-0.004^{***}
	(0.000)	(0.000)	(0.000)
Building Area (per 100 sq.ft.)	-0.005^{***}	-0.005^{***}	-0.005^{***}
	(0.000)	(0.000)	(0.000)
Footprint Size (per 100 sq.ft.)	0.010^{***}	0.010^{***}	0.010^{***}
	(0.000)	(0.000)	(0.000)
Ground Elevation	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)
Bathrooms	0.019^{***}	0.019^{***}	0.018^{***}
	(0.005)	(0.005)	(0.005)
Bedrooms	-0.012^{***}	-0.012^{***}	-0.010^{**}
	(0.004)	(0.004)	(0.004)
Stories	0.107^{***}	0.106^{***}	0.101^{***}
	(0.006)	(0.006)	(0.006)
Observations	51,663	51,663	51,663
Zip Code FE.	Yes	Yes	Yes
Policy Variables	Yes	Yes	Yes
Akaike Inf. Crit.	61,929	61,908	61,896

Appendix B. Classification

Remotely sensed data, a simple picture, does not alone provide very meaningful quantitative information. In the current example, we might look at post-hurricane imagery and conclude that damage is present based on what we see. We might also successfully assess the percent damage to an individual home, or a few homes in our study manually. But, what about damage to every home in the image? As our study grows larger across space and/or time to include thousands, or millions of observations, the ability for one or multiple persons to generate accurate and consistent measures of damage to individual homes quickly diminishes.

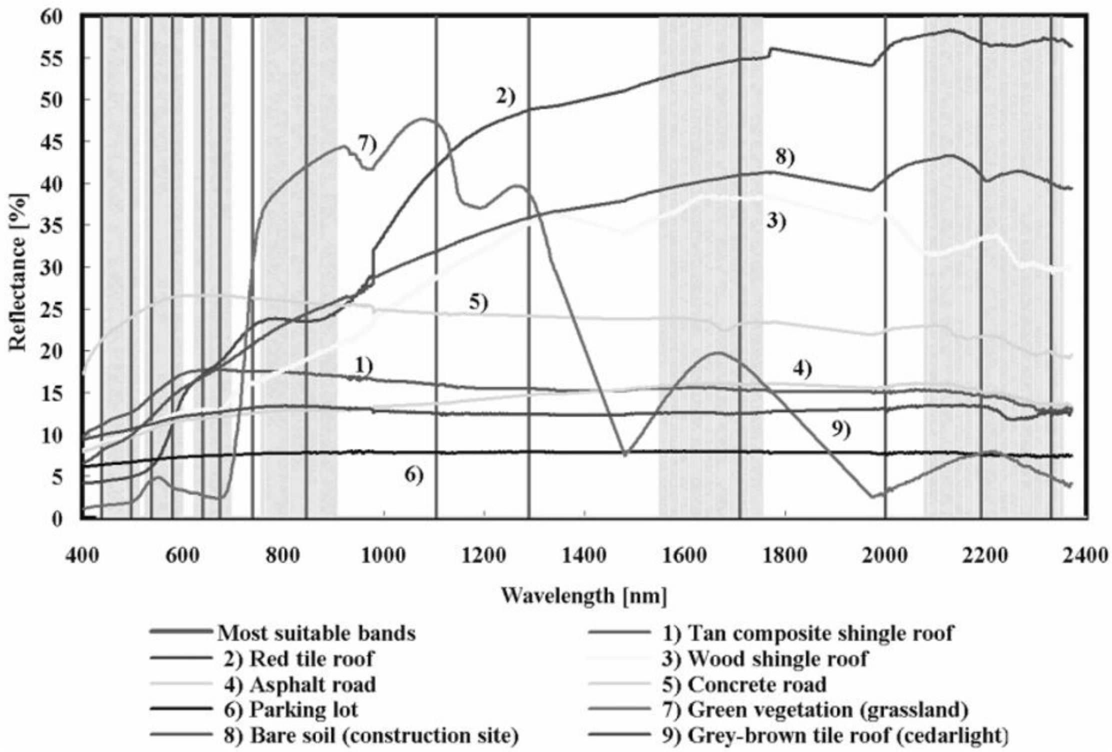
One common solution in physical and social sciences is to convert an image into interesting land cover categories. To accomplish this, we model the probability of what that object is based on variation in the intensity of n bands of light being reflected. For example, we might want to predict grass pixels in an image given red, green, and blue intensity as independent variables. Here we might model grass as:

$$Grass = Pr(Grass|Red, Green, Blue) \tag{3}$$

Where grass is either grass (1) or not grass (0), and red, green, and blue are given on a (0-100%) percent reflectance scale, or "digital number" representing the raw voltage reported at a sensor, commonly 0-255.

We might also exploit additional bands of light not visible to the human eye, but collected by modern sensors such as near infrared, ultraviolet etc. Akin to including additional right-hand-side variables to explain some social phenomenon, the more bands sensed, the more variables, and thus information we have to make a successful prediction. Spectral signatures of common lab tested materials are given in Figure 6. The horizontal axis is wavelength (in nanometers) of energy reflected from respective objects, and the reflectance across wavelengths on the vertical. While reflections across the spectrum are continuous, intensity/reflectance in images are averaged into discrete bands. From left to right, blue is represented by the first shaded area (400-500nm), green in the second (500-600nm), red in the third (600-700nm) and near infrared (NIR) as the fourth band (800-900nm).

Figure 6: Spectral Characteristics of Common Urban Land Covers



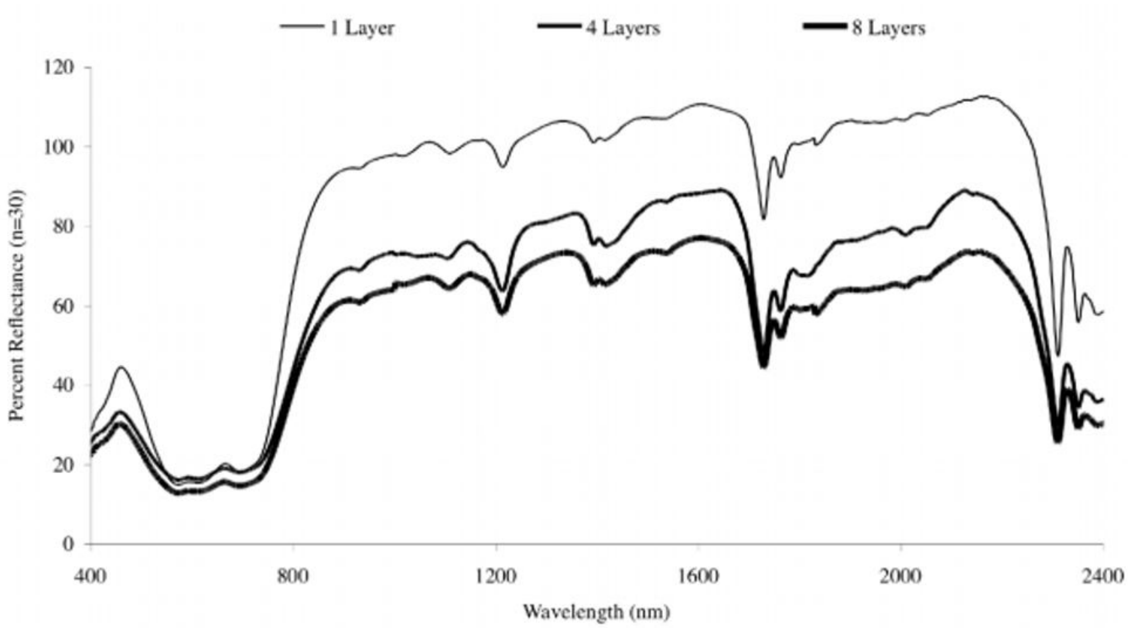
As we might expect, grass (line 7 in Figure 6) reflects strongly in the green band, and poorly in blue and red. Also note grass has an extremely strong reflectance in the NIR band relative to other land cover types in the figure. This heterogeneity makes grass quite predictable or identifiable in land cover classification studies, especially with an urban backdrop represented by the remaining signatures in the figure. Unfortunately, remaining urban land covers in Figure 6 are much more spectrally homogeneous. In the current study, and others like it focused on urban damage, identifying an undamaged roof vs. damaged roof characterized by an unpredictable mix of building materials, wood, dirt etc. is challenging in theory and in practice.

Sensing Tarp Cover

After a major hurricane, such as Michael, major repairs depend on the speed of insurance claim settlements, the local labor market, and other factors. Accordingly, it typically takes months, and in extreme cases years, for damaged roofs to be repaired. To mitigate leaks in the interim, homeowners commonly cover roof damage by polyethylene tarpaulin "tarps". As damage increases, large, purpose-built tarps bought locally or provided by government relief services protect the underlying home from additional water damage.

This study targets the presence of tarps roughly 8-12 weeks after Hurricane Michael as a proxy for roof damage for two reasons. First, physical damage leading to leaking roofs might be present at a scale impossible to detect using imagery collected immediately after the event. However, homeowners are likely to apply tarps on isolated sections of roof, however small, to prevent leaks. Second, tarps provide a great deal of spectral heterogeneity with respect to roofing and other urban materials. In Figure 7 tarps in a laboratory setting reflect strongly in the blue spectrum, and interestingly, in NIR. Also note that the overall reflectance% of the tarp in all bands is higher than most other urban covers in Figure 7, as it is simply a brighter material.

Figure 7: Spectral Characteristics of Polyethylene Tarpaulin "Tarps"



We do not assume tarps are blue a priori, but given that is a differentiating feature of most tarps, this is likely to be built into the model implicitly without more sophisticated methods. Based on lab generated signatures above it is also intuitive that if an object reflects in blue, but also strongly in green and red, the object might be concrete, tared roof or paved driveway on the fringe of an image. At the least, we might be less sure it is a tarp. Thus the impact of blue light intensity in an image object on the probability of it being tarp cover depends on the reflectance levels of other bands.

We acquired high resolution areal imagery from Bay County, Florida's GIS division. The data were collected via aircraft January 2019 with a spatial (pixel) resolution of 3 inches for the entire 1,033 square mile county.[10] The imagery includes 4 bands—or variables—red, green, blue, and NIR (see Figure 8) . The reflection, or intensity scale in each band pixel is given in digital numbers (DN) ranging from 0 to 255. Note the darker (lower reflection) tarp cover found in red (Image 1) and green (Image 2) bands, but brighter (high reflectance) in blue (Image 3) and NIR (Image 4). [11]

[10]The entirety of the dataset is roughly 1.5 TB and over 200 individual images.

[11]DN's are raw readings of voltage at the sensor, and do no not account for different sensor angles, atmospheric distortion, and irradiance (energy from the sun at some time /month). Some studies convert DN to a unitless reflectance values for consistency and comparison with other images and times. However, flight times and viewing angles per image are unknown to make these corrections. Further, minimum levels of atmospheric distortions are present across aerial sensors opposed to satellites

Figure 8: Individual Band Reflections (RGBN)

Image 1. Reflection Intensity in Red

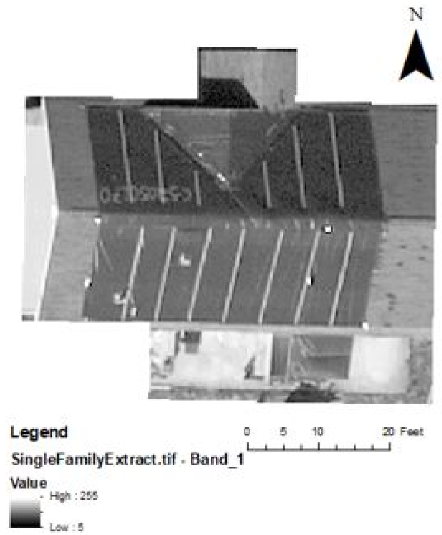


Image 2 Reflection Intensity in Green

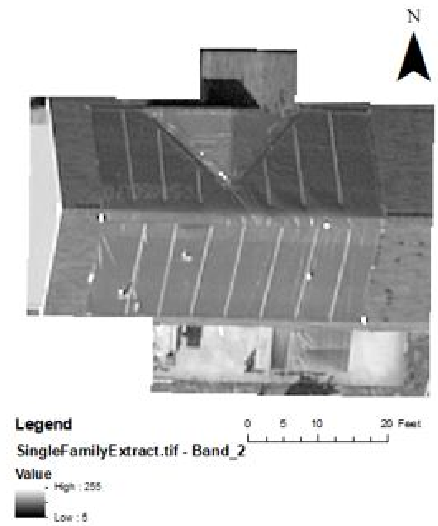


Image 3. Reflection Intensity in Blue

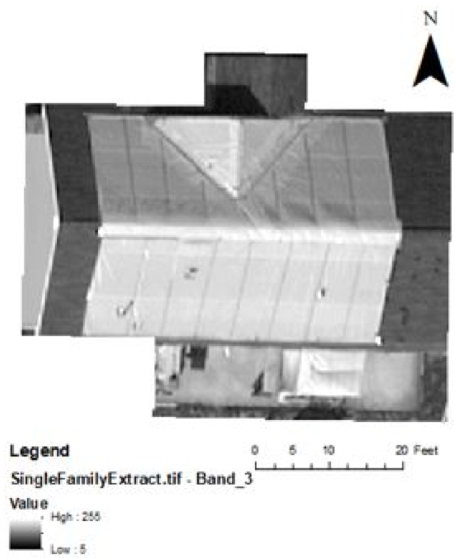
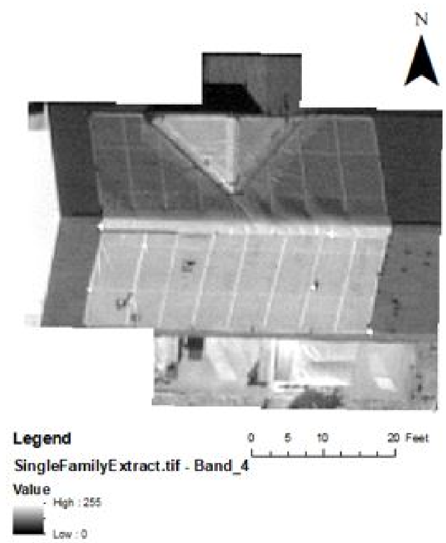
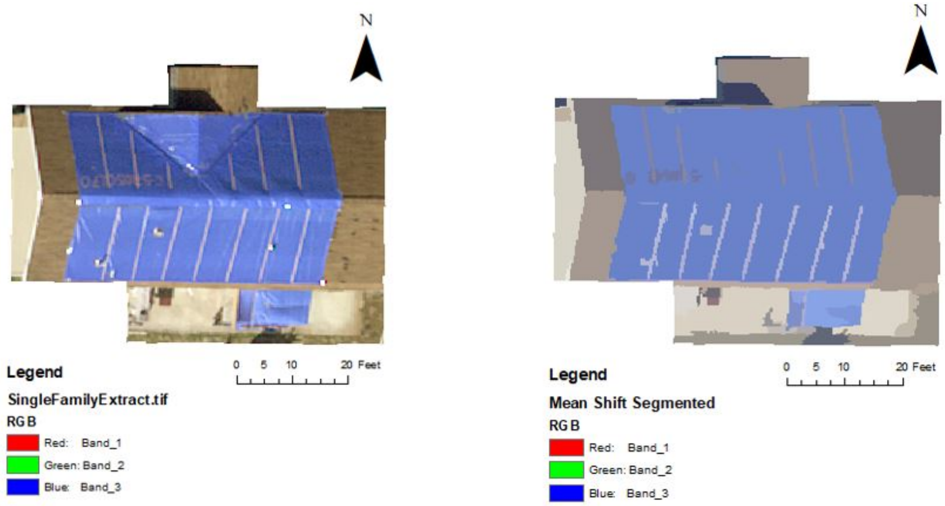


Image 4. Reflection Intensity in Near Infrared



A critical component to image classification is the selection and processing of training data. That is, for a sample of observations with n right-hand side hand variables discussed above we must manually assign a "success" for the existence of some dependent land cover variables, in this case tarp, roof, shadow, or other, and a "failure" if not. We randomly select 100 parcels to capture land cover heterogeneity across the image that might occur from different building materials, shadows, sun exposure etc. Random selection also minimizes the possibility of spatially correlated observations within the training set. Individual pixels in high resolution imagery do not represent individual observations and are likely to have highly correlated errors with their neighbors leading to model bias and overfitting. That is, the land cover of a 3-inch pixel is likely to be correlated with land cover adjacent pixels. To create feasibly independent observations, we aggregate individual pixels into "objects", based on a mean shift algorithm that seeks to minimize the variance in in the data given some number of arbitrary clusters. Visually represented in Figure 9, each new object takes on the mean of all pixels in that cluster. Our unit of analysis for the classification is now the object, which across all training objects have a mean of 547 pixels.

Figure 9: Aggregating Pixels into Objects Using Mean Shift Algorithm



We manually assign one of 4 possible land cover categories to each object found in 100 randomly selected building footprints to produce a training set of 434 observations. 170 observations are identified as roof, 149 as tarp, 24 as shadows, and 89 "other" which include anything on the fringe of a poorly drawn footprint such as patio, grass, a car etc. (Table 7

Table 7: Training Data Summary Statistics

	N	Mean	St. Dev.	Min	Max
Land Cover	432				
Roof	170				
Tarp	149				
Shadow	24				
Other	89				
Image Bands					
Red	432	135.7	46.3	42.5	254.6
Green	432	143.9	43.3	46.5	254.7
Blue	432	167.8	46.2	83.5	254.8
NIR	432	131.1	58.9	28.6	254.1

There are many model choices for classifying image objects. Current research is pushing the bounds of machine learning, artificial neural nets, and other various vector support machines—many of which may be unnecessarily complex, or beyond the scope of our needs. That said, estimating land cover using simple OLS would lead to bias and nonsensical results as the dependent variable is categorically split into 4 different types of land cover with no peculiarly meaningful order. This section proceeds by estimating a logistic regression models to address binary versions of the dependent variable. In this way, we constrains the probability of some land cover between 0 and 1 given as the inverse of log odds:

$$P(LandCover) = \frac{\exp(\alpha + \beta X')}{1 + \exp(\alpha + \beta X')} \tag{4}$$

Where X' is a vector containing Red, Green, Blue and/or NIR reflections and Land Cover predicted via maximum likelihood. In theory, we only need to be concerned with predicting the existence of a tarp or not to the extent that building footprints are accurate, and our assumptions about tarping damage hold. Any other remaining area in the imagery is assumed to be undamaged roof, shadow, or some other undetermined land cover. Following this we consider a logit model where:

$$Landcover(Tarp) = \begin{cases} 1, \text{if Tarp} \\ 0, \text{Roof, Shadow, Other} \end{cases} \tag{5}$$

Despite having four available bands, their values tend to be colinar since each represent discrete averages taken from the full electromagnetic spectrum. This means that two bands close together along the spectrum, such as blue and green, are likely to share more variance than those that are further apart. Based on a simple covariance matrix (Table 8), all bands in our training data are highly collinear, but blue-red, and NIR-red show lower correlations than other pairs. Since it is impossible to add a third or fourth variable without introducing correlation between variable above 0.6, I seek a simple model, likely with one or two variables.

Table 8: Covariance Matrix of Independent variable choices

	Green	Blue	Red	NIR
Green	1			
Blue	0.75	1		
Red	0.97	0.59	1	
NIR	0.67	0.76	0.56	1

Remote sensing literature commonly employs two or more bands to generate a single index such as the normalized difference vegetation index (NDVI), the normalized difference water index (NDWI), and many others to exploit variation in multiple bands, and avoid collinearity issues. The NDVI for example is simply:

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{6}$$

Where objects that reflect strongly in the NIR and poorly in red, like vegetation——and it just so happens, tarps——the NDVI produces high value which are conveniently scaled between -1 and 1. We also consider a slight variant of the NDVI, which we'll call the Normalized Difference Tarp index (NDTI), that exploits variation between blue and red in a similar way:

$$NDTI = \frac{Blue - Red}{Blue + Red} \tag{7}$$

We tested 5 potential models based on theory and analysis discussed to this point. Each model predicts the probability of tarp cover. Model 1 in Table 9 provides results with all covariates for comparison. Model two contains red and blue as covariates, model three red and NIR, model four NDVI only, and fifth NDTI only. All coefficients are in log odds.

Table 9: Regression Coefficients

	Dependent variable: Log Odds of Tarp				
	RGBN (1)	RB (2)	RN (3)	NDVI (4)	NDTI (5)
Red	0.138**	-0.102***	-0.061***		
	(0.065)	(0.011)	(0.006)		
Green	-0.353***				
	(0.102)				
Blue	0.230***	0.118***			
	(0.054)	(0.014)			
NIR	0.012		0.043***		
	(0.014)		(0.004)		
NDVI				12.435***	
				(1.143)	
NDTI					22.990***
					(2.094)
Constant	-8.781***	-7.575***	1.182**	-0.827***	-4.243***
	(2.175)	(1.213)	(0.493)	(0.163)	(0.436)
Observations	432	432	432	432	432
Note:					*p**p***p<0.01

Table 9 confirms that our estimators are statistically significant, except for NIR in the all covariate model. The direction of effects is also what we might expect when detecting tarp cover. Model 2 and 3 reveals that an increase in blue and NIR reflectance increases the log odds of tarp cover, and that an increase in red decreases the log odds of tarp cover. Similarly, the log odds of tarp cover increase as the NDVI and NDTI increase. Model 1 gives confusing and counter intuitive results, most likely a symptom of multicollinearity discussed above.

To help choose a correct model, Table 10 gives three measures of fit. McFadden R2 calculates one minus the ratio of log likelihoods of a model with no predictors over one with predictors. The higher the McFadden R2 value, the more variation the model explains relative to a simple average probability of success (theta with no predictors). The Akaike Information Criterion (AIC) is a similar measure of fit, but penalizes the model as additional

Table 10: Fit Statistics Predicting Tarp Cover

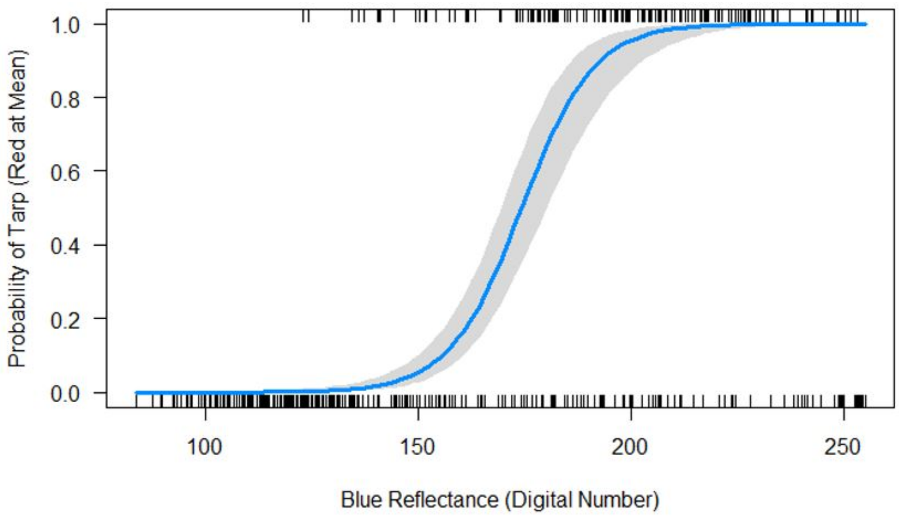
	Models				
Fit Statistics	RGBN (1)	RB (2)	RN (3)	NDVI (4)	NDTI (5)
McFadden R2	0.86	0.82	0.49	0.47	0.66
AIC	86.1	103.4	287.7	293.8	189.2
All Correct Predicted	97.9%	98.4%	88.7%	87.5%	93.5%
Tarp Correctly Predicted	94.6%	95.3%	90.1%	83.8%	93.3%
Other Correctly Predicted	99.7%	100%	85.9%	89.4%	93.6%
All Predicted Above Null	32.3%	32.8%	23.2%	21.9%	27.9%

parameters are included. Unlike McFadden R2, a smaller AIC is preferred over a large one. Finally, the percentage of correctly predicted (PCP) observations is given for each model, as well as the difference between PCP with a model and PCP with null model, which is 65.5

Model 1 (RGBN), with all variables, report the largest R2 and smallest AIC, but not by a huge margin over model 2 (RB) that includes only red and blue as covariates. Surprisingly, RB actually predicts more observations correctly than RGBN. Model 3 (RN) and model 4 NDVI turned out to be a relatively poor predictors most likely since both tarp and grass/trees respond strongly to those band combinations. Given this evidence, we select model 2 as "best" model, which despite having slightly lower R2 and higher AIC, predicted the most observations with only 2 variables. Additionally, the more parsimonious model 2 contains less multicollinearity (albeit not zero), than model one. Promising fit statistics from the NDTI overall might suggest its usefulness under different model specifications or in scenarios where tarps are not blue.

Transforming log odds to predicted probability, Figure 10 illustrates Model 2 along with 95% confidence intervals. When levels of red are held at their mean, the estimated probability of an object being a tarp when blue reflectance is 150 is only 2.6%. But, an increase in blue from 150 to 175, holding red at its mean, increases the probability that an object is a tarp by 32.1%. At levels of blue reflectance at 200, the probability of cover is 91.1% holding red refelctance of an object at its mean.

Figure 10: Probability of Tarp Cover Given Blue Reflectance (Red Reflectance at Mean)



Note that logit models are non-linear and non-additive such that the effects of a unit change in blue on the probability of tarp cover depend on the level of blue, as well as levels of red. To illustrate, solid blue line in Figure 11 represents the marginal effects of blue reflectance values on tarp probabilities holding red at it's mean as before. Darker dashed lines represent the same probabilities as red reflectance decreases from its mean, and lighter dashed lines as red reflectance increases from its mean. Predicted probabilities thus become higher faster when red reflectance is low but remain near zero for high levels of red. In fact, when reflectance levels of red are two standard deviations above the mean, there is no level of blue reflectance that yields a probability higher than 36%—far below any reasonable threshold for positive identification.

Figure 11: Probability of Tarp Cover Given Blue Reflectance, for Various Levels of Red)