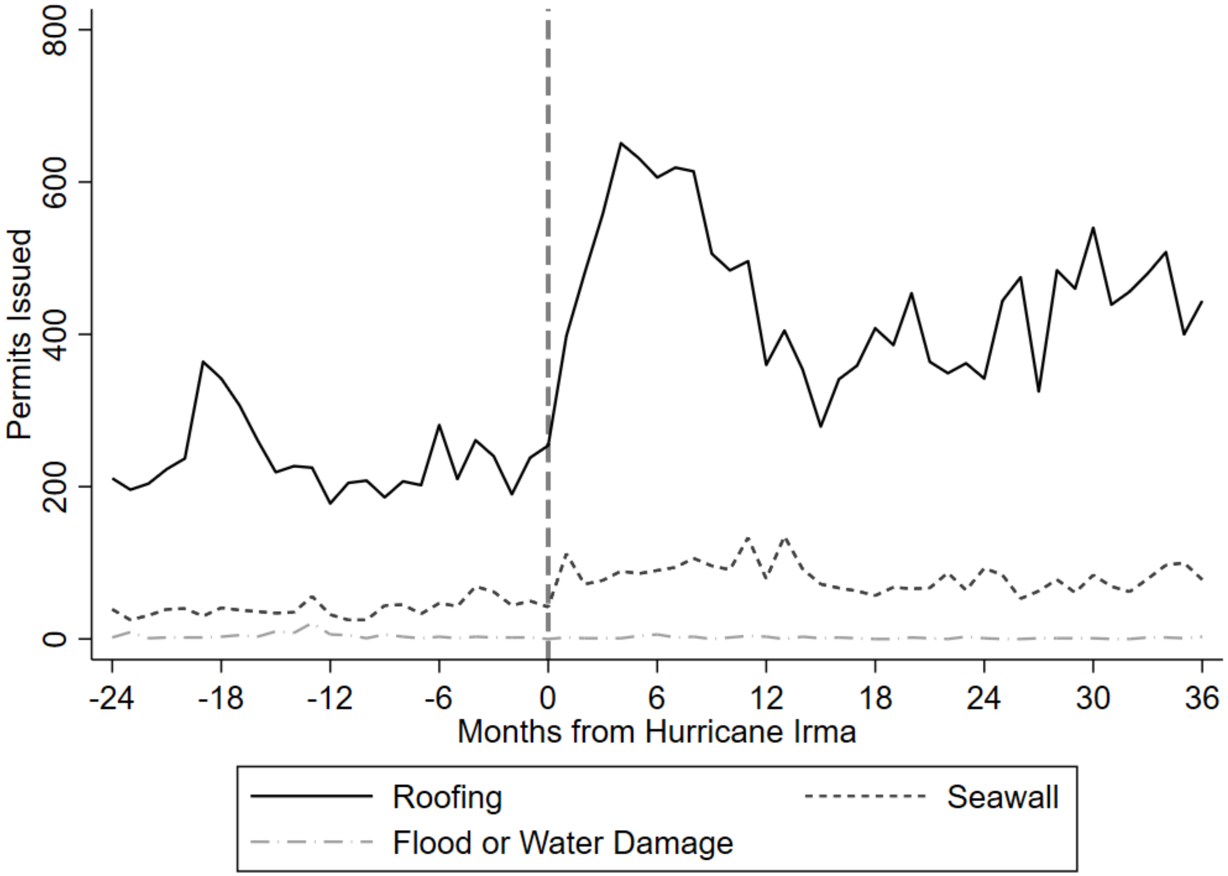
Online Appendix: Are Building Codes an Effective Adaptation to Wind Risk? Evidence from Remotely Detected Blue Tarps

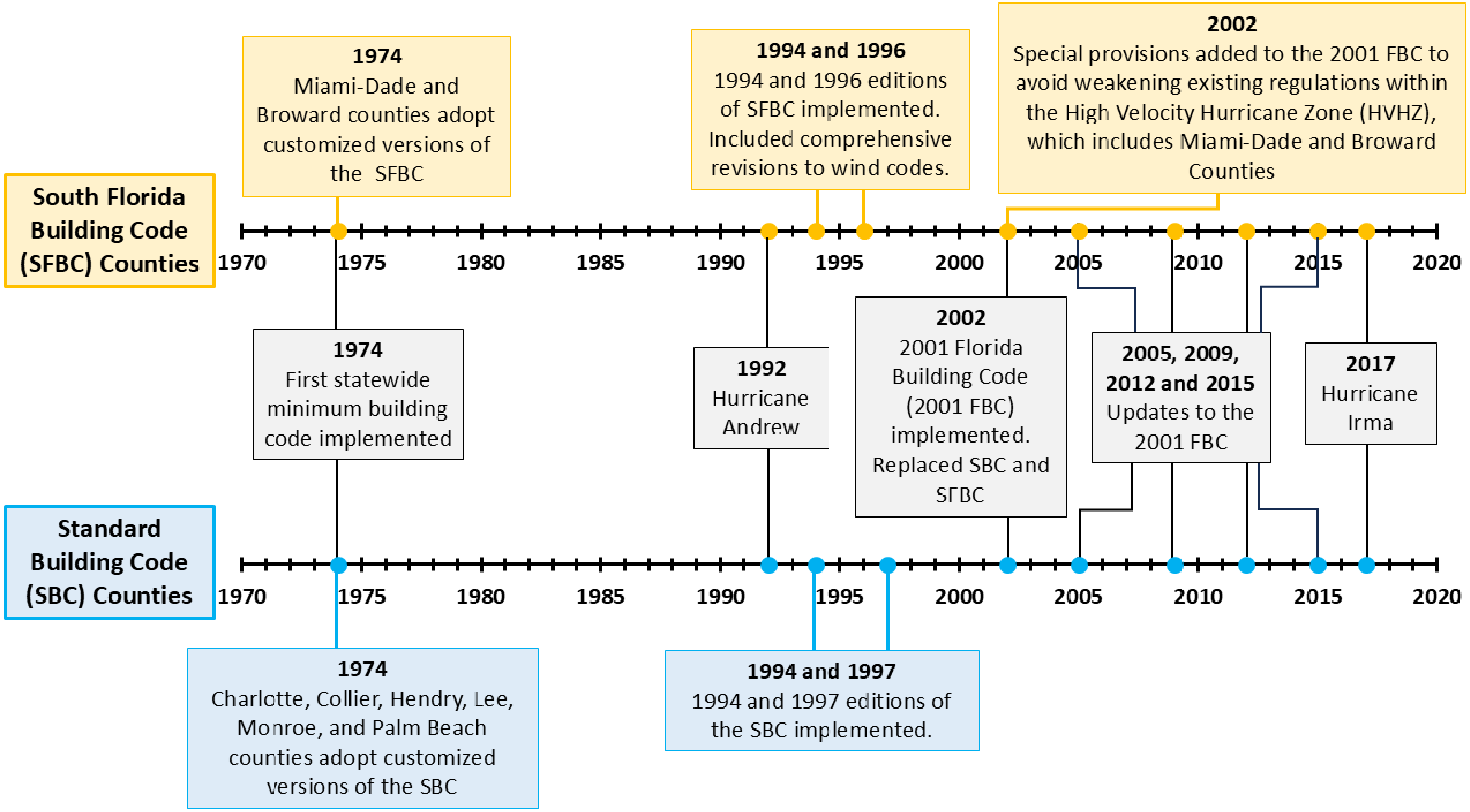
David Wolf and Kenji Takeuchi

Appendix A: Additional Tables and Figures

Appendix Figure A1 – Permits Issued in Lee County by Type and Time from Hurricane Irma



Appendix Figure A2 – Two Timelines Depicting the Evolution of Building Codes in Florida



Appendix Figure A3 – Aerial Drone Image vs Predicted Blue Tarp Locations

(A)

(B)

Figure notes: An aerial drone image taken in Lee County in January of 2017 is shown in Panel (A), while predictions of where wind damage occurred based on Object-Based Image Analysis (OBIA) (red highlight) is provided in Panel (B). The basemap image was supplied by the Lee County Board of County Commissioners.

Appendix Figure A4 – Building Codes' Impact on the Share of Homes with Wind Damage with Controls

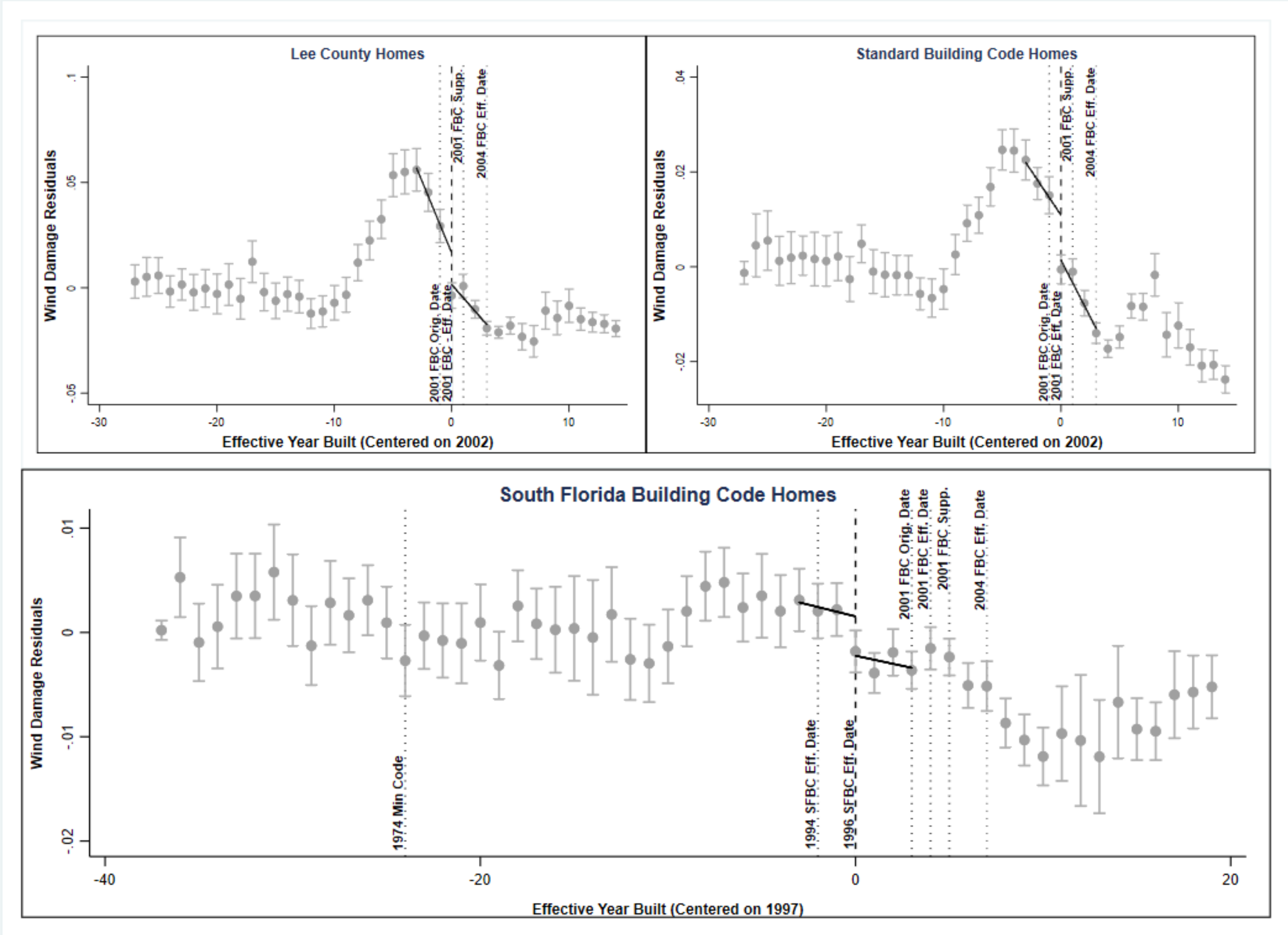


Figure notes: The outcome variable – wind damage (0/1) – is first regressed on a set of housing attributes and census block group fixed effects. Average residual values are then plotted alongside their 95% confidence intervals. Finally, three-year trend lines before and after the 2001 Florida Building Code (top) and 1996 South Florida Building Code (bottom) are plotted as black lines. Homes built before 1975 (1960) are binned into the 1975 (1960) year-bin when plotting the top (bottom) graphs. Eff. Date = Effective Date, Orig. Date = Original Date, and Supp. = Supplement.

Appendix Figure A5 – Roof Replacements, Roof Construction Year and Wind Damage

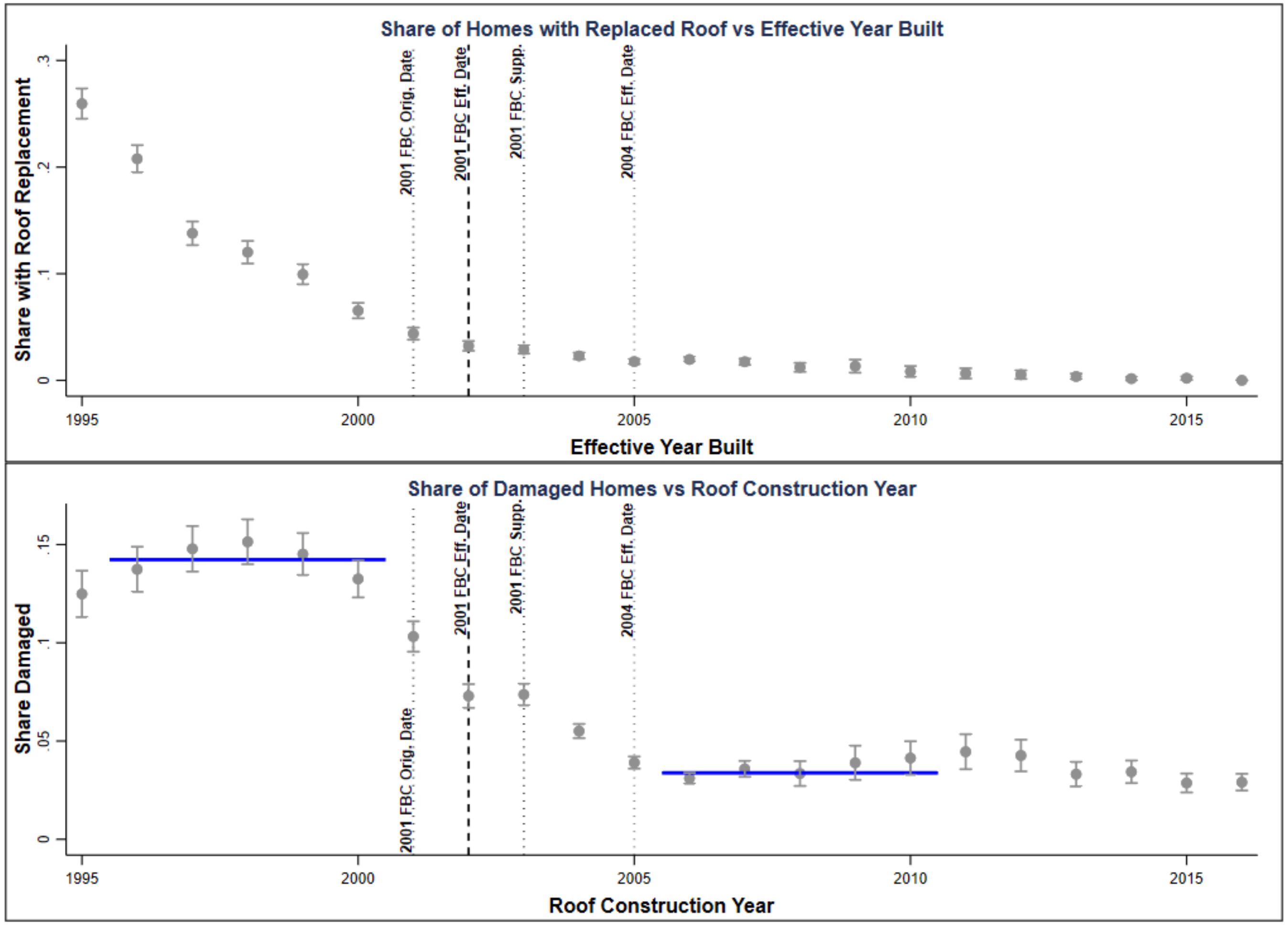


Figure notes: Share of homes in Lee County with new or retrofitted roofs prior to Hurricane Irma is plotted against the effective construction year of the home in the top panel. Share of wind damaged homes is plotted against roof construction year in the bottom panel. Data on roof construction year prior to 1995 is incomplete. 95% confidence intervals are shown. Blue lines show 5-year averages. Eff. Date = Effective Date, Orig. Date = Original Date, and Supp. = Supplement.

Appendix Figure A6 – Building Codes' Impact on Wind Damage Severity

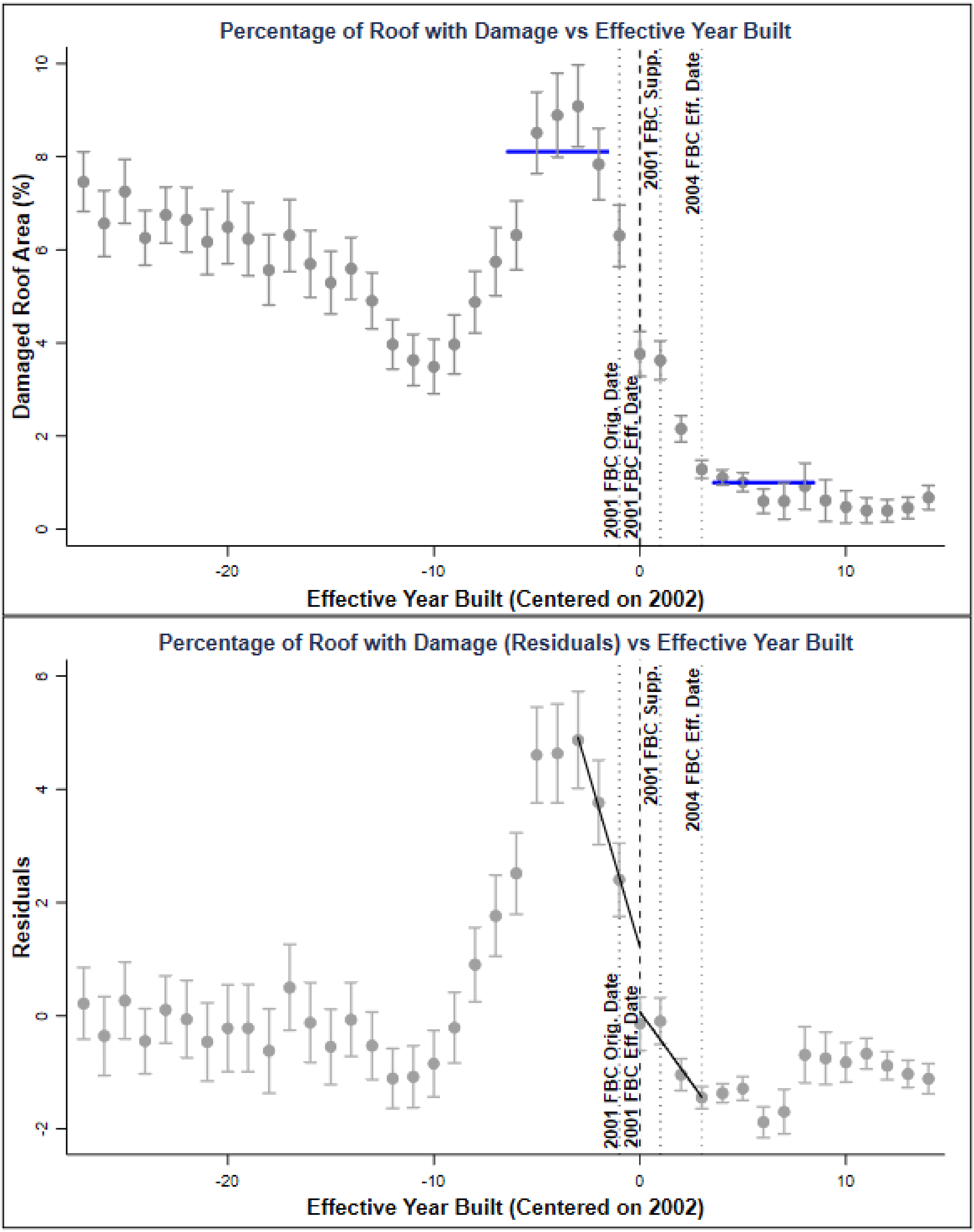


Figure notes: Percentage of roof with wind damage is plotted against effective construction year on the top, while the bottom figure plots the same two variables, after controlling for housing and locational controls and census block group fixed effects. Damaged and undamaged homes are included in each plot. 95% confidence intervals are shown for each construction year bin, along with the bin's average value. Blue lines show 5-year averages. Eff. Date = Effective Date, Orig. Date = Original Date, and Supp. = Supplement.

Appendix Figure A7 – Did Risk Preferences Update after Hurricane Irma?

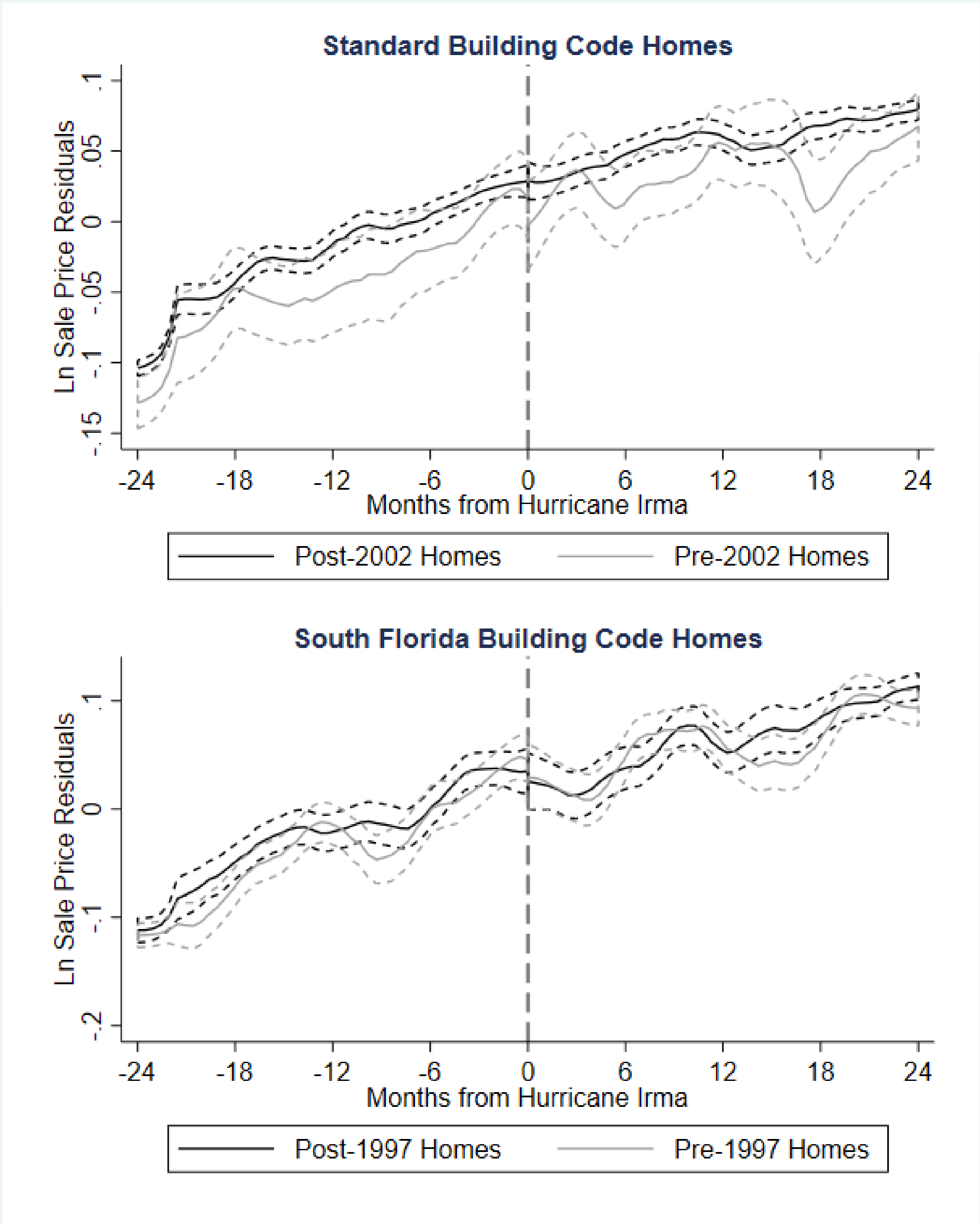


Figure notes: 95% confidence intervals are plotted as dashed lines. The sample is restricted to homes built within 3 years of the 2001 FBC (top) and within 3 years of the 1996 SFBC (bottom). Post-2002 (Post-1997) includes homes built within that year. The natural log of housing price is first regressed on housing and locational controls as well as census block group fixed effects. Residuals are then plotted across time using four local polynomial estimators that apply Epanechnikov kernels, local mean smoothing, and a 1-month bandwidth. The end points are binned so that -24 (+24) is a bin for transactions that occurred -32 months to -24 months (+24 month to +27 months) from the hurricane.

Appendix Figure A8 – Did Hurricane Irma Change What Type of Homes Were Sold?

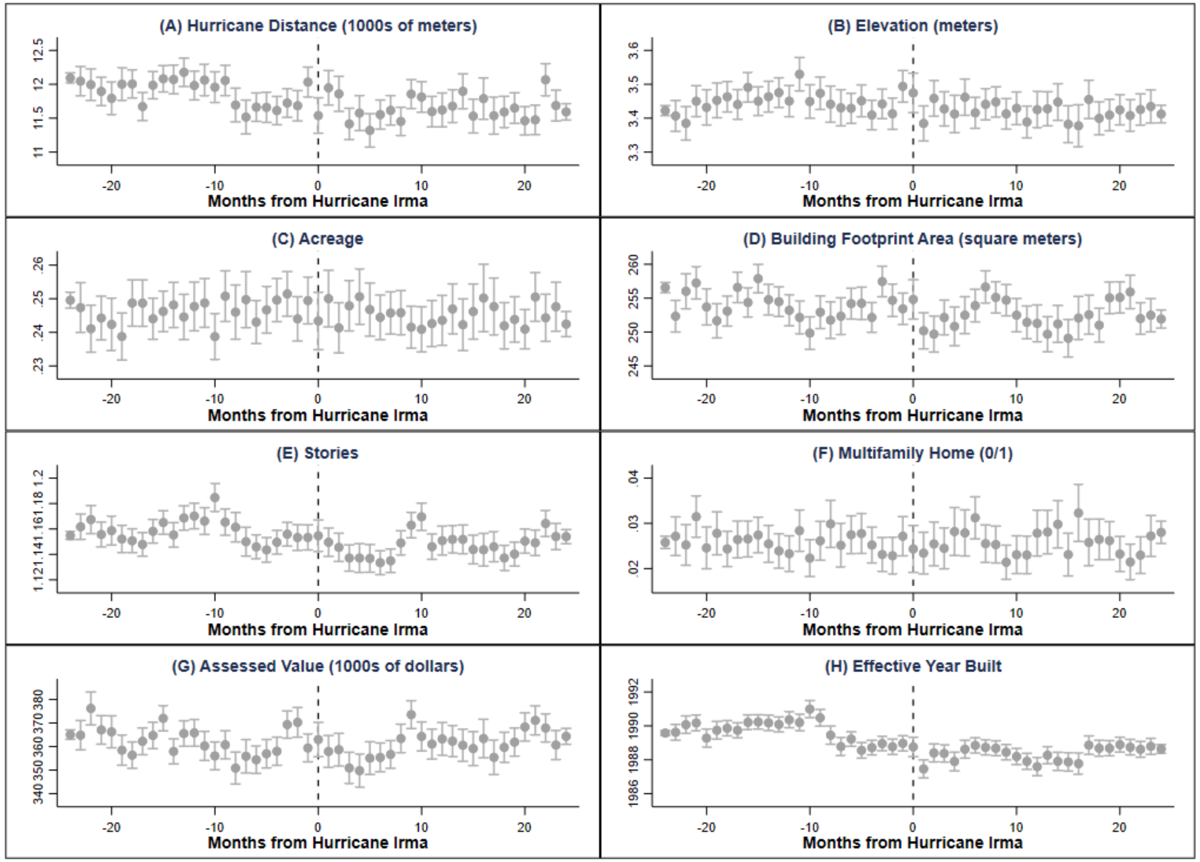


Figure notes: Housing and locational attributes from transacted homes are plotted across time, with average attribute values and their corresponding 95% confidence intervals reported at each sale month bin. The end points are binned so that -24 (+24) is a bin for transactions that occurred -32 months to -24 months (+24 month to +27 months) from the hurricane.

Appendix Figure A9 – Did Hurricane Irma Change What Type of Damaged Homes Were Sold?

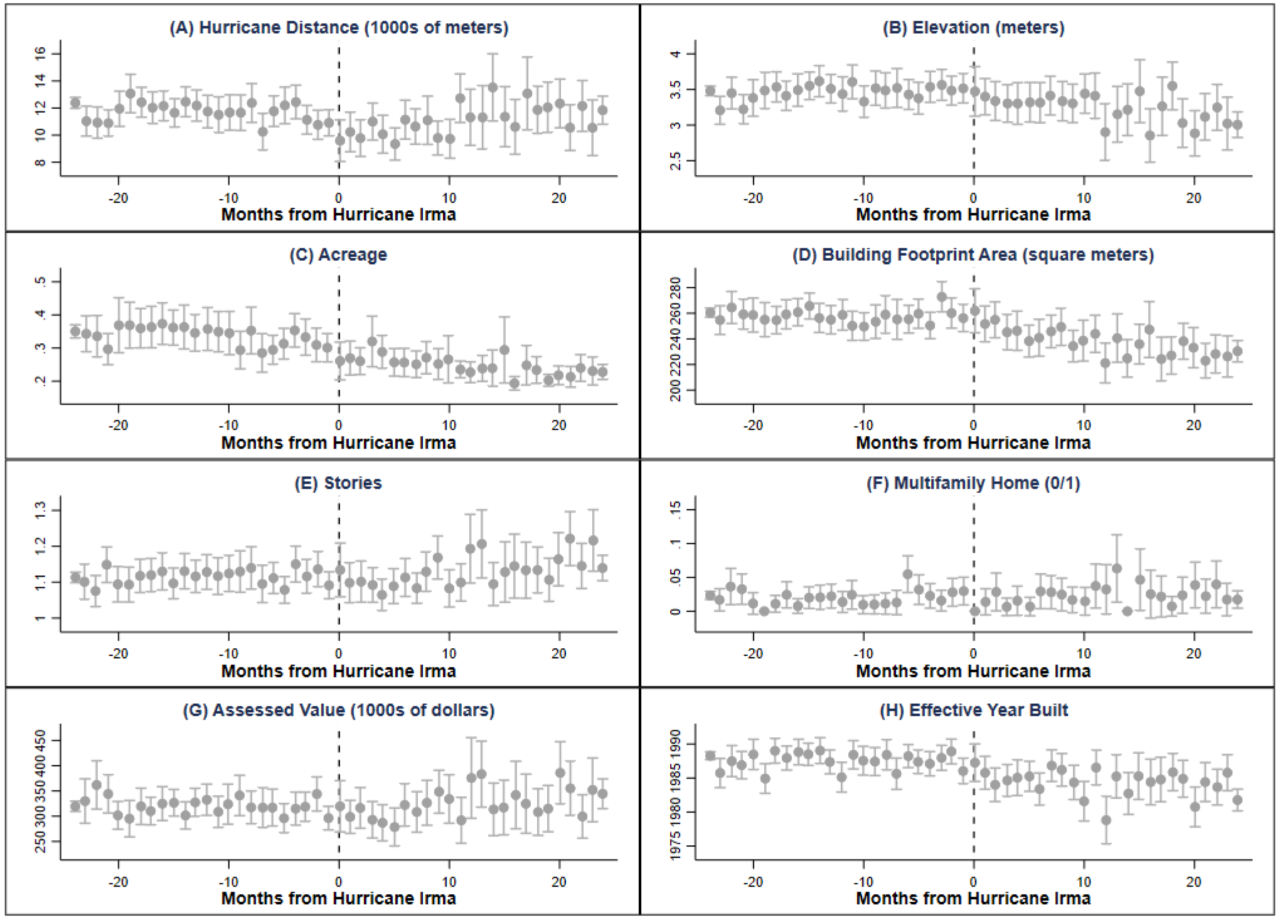


Figure notes: Housing and locational attributes from transacted homes are plotted across time, with average attribute values and their corresponding 95% confidence intervals reported at each sale month bin. Only transacted homes damaged or soon-to-be damaged by Hurricane Irma are taken into account. The end points are binned so that -24 (+24) is a bin for transactions that occurred -32 months to -24 months (+24 month to +27 months) from the hurricane.

Appendix Table A1 – Variable Description, Data Construction and Functional Form

Variables	Description	Source	Functional Form: Housing Dataset	Functional Form: Transaction Dataset	Functional Form: Sale Probability Dataset
Dependent Variables					
Sale Price (1000s of 2015 USD)	Sale price measured in 1000s of 2015 United States Dollars	CAO	-	NL	-
Transacted (0/1)	Indicator if house was sold during a given a quarter	CAO	-	-	DV
Wind Dmg Area (m^2)	Roof damage area measured in squared meters. Only available in Lee County.	CAO	NL	NL	NL
Wind Dmg (0/1)	Indicator for roof damage. Equal to one if blue tarp is detected within satellite or aerial drone imagery (latter only available for Lee County). Additionally, homes that received a roofing permit within one year of Hurricane Irma are also classified as damaged.	LCGIS/CMPO/ GEE	DV	DV	DV
Independent Variables					
Sale Year	Year of sale	CAO	-	DV	DV
Sale Month	Month of sale	CAO	-	DV	DV
Square Feet	Size of home measured in square feet	CAO	NL	NL	NL
Acres	Parcel lot size measured in acres	CAO	NL	NL	NL
Baths	Number of bathrooms	CAO	LIN	LIN	LIN
Assessed Value (1000s of USD)	Auditor assessed value of home measured in United States Dollars	CAO	NL	-	NL
Effective Year Built[a]	Effective year built at time of sale (transaction/sale probability dataset) or during 2017 (housing dataset)	CAO/CMPO	VARIOUS	-	-
Age	Age of home at time of sale	CAO	-	NL	NL
Pool (0/1)[b]	Indicator if home has a pool	CAO	-	-	-
Stories[b]	Number of stories	CAO	-	-	-
Garage (0/1)	Indicator if home has a garage	CAO	DV	DV	DV
Multifamily (0/1)	Indicator if home is a multifamily home (e.g., duplex, triplex, townhouse)	CAO	DV	DV	DV
Building Footprint Vertices[c]	Number of vertices in building footprint. Used as a proxy for roof shape.	LCGIS/MBF	NL	NL	NL
Building Footprint Area (m^2)[c]	Building footprint area measured in squared meters. Used as a proxy for roof area.	LCGIS/MBF	NL	NL	NL
Hurricane Distance (kms)	Distance to nearest point along Hurricane Irma's path measured in kilometers	NOAA	NL	NL	NL
Hurricane East (0/1)	Indicator if home is located east of Hurricane Irma's path	NOAA	DV	DV	DV
Ocean Distance (kms)	Distance to Atlantic Ocean measured in kilometers	USGS	NL	NL	NL
Elevation (meters)	Elevation of home from sea level measured in meters	USGS	NL	NL	NL
Building Density (%)	Proportion of land within a 100-meter radius of home that is covered by a building	LCGIS/MBF	LIN	LIN	LIN

Notes: CAO = County Appraiser Offices, CMPO = County and Municipality Permitting Offices, LCGIS = Lee County GIS Department, GEE = Google Earth Engine, NOAA = National Oceanic and Atmospheric Administration, MBF = Microsoft Building Footprint, USGS = United States Geological Survey, NL = Natural Log Transformed, DV = Dummy Variable (0/1), LIN = Linear. [a]In Dade and Monroe counties, the construction year was used instead of the effective year built due to the latter's imprecision, with values frequently rounded to benchmark years (e.g., 1990, 2000, 2010, etc.). [b]Data not available across entire study area. [c]For homes in Lee County, we used building footprint shapefiles maintained by the county rather than those created by Microsoft, as the county's shapefiles were generally more detailed. "-" entry indicates variable wasn't used as either a dependent or independent variable in specification. The final three columns indicate which functional form was used for each independent and dependent variable.

Appendix Table A2 – Summary Statistics for Lee County and Standard Building Code Homes

Lee County	Full Sample (N=47,224)		Pre-2001 Florida Building Code (N=13,328)		Post-2001 Florida Building Code (N=33,896)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Dependent Variables						
Wind Dmg (0/1)	0.064	0.245	0.108	0.310	0.047	0.212
Wind Damage Area (m^2)[a]	1.190	11.365	2.090	15.887	0.853	9.091
Independent Variables						
Square Feet	1,931.084	526.923	1,906.982	538.411	1,940.561	522.040
Acres	0.253	0.189	0.269	0.227	0.247	0.172
Baths	2.262	0.529	2.205	0.479	2.285	0.546
Assessed Value (1000s of USD)	192.013	112.809	206.211	122.460	186.430	108.274
Effective Year Built	2003	1.957	2000	0.811	2004	1.090
Garage (0/1)	0.965	0.185	0.952	0.213	0.970	0.172
Multifamily (0/1)	0.058	0.233	0.034	0.180	0.067	0.250
Building Footprint Vertices	15.212	4.472	15.548	4.751	15.080	4.350
Building Footprint Area (m^2)	289.071	91.721	297.584	92.255	285.724	91.295
Hurricane Distance (kms)	18.477	10.890	18.441	10.227	18.491	11.139
Hurricane East (0/1)	0.062	0.241	0.037	0.189	0.072	0.258
Ocean Distance (kms)	13.169	8.759	12.002	8.294	13.628	8.893
Elevation (meters)	4.208	1.931	3.957	1.889	4.307	1.939
Building Density (%)	0.142	0.064	0.153	0.056	0.138	0.066

Standard Building Code Counties	Full Sample (N=126,362)		Pre-2001 Florida Building Code (N=46,603)		Post-2001 Florida Building Code (N=79,759)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Dependent Variable						
Wind Dmg (0/1)	0.050	0.218	0.068	0.251	0.040	0.195
Independent Variables						
Square Feet	2,033.808	589.699	2,024.879	594.363	2,039.025	586.898
Acres	0.307	0.372	0.326	0.395	0.296	0.358
Baths	2.332	0.571	2.318	0.559	2.341	0.577
Assessed Value (1000s of USD)	303.660	218.493	324.413	232.224	291.534	209.106
Effective Year Built	2002	2.005	2000	0.773	2004	1.120
Garage (0/1)	0.877	0.329	0.865	0.341	0.883	0.321
Multifamily (0/1)	0.027	0.161	0.016	0.124	0.033	0.179
Building Footprint Vertices	9.531	5.378	8.858	5.188	9.924	5.448
Building Footprint Area (m^2)	287.376	86.495	287.559	87.328	287.270	86.005
Hurricane Distance (kms)	83.450	66.610	94.124	66.171	77.213	66.073
Hurricane East (0/1)	0.528	0.499	0.595	0.491	0.490	0.500
Ocean Distance (kms)	11.888	8.836	11.077	8.331	12.363	9.085
Elevation (meters)	4.662	1.680	4.579	1.631	4.710	1.706
Building Density (%)	0.158	0.072	0.163	0.069	0.155	0.074

Notes: The unit of observation is a house. Summary statistics are reported for houses with an effective year built between 1999 and 2005. [a]Data not available for all observations (non-missing N = 45,592)

Appendix Table A3 – Summary Statistics for South Florida Building Code Homes

South Florida Building Code Counties	Full Sample (N=56,705)		Pre-1996 South Florida Building Code (N=26,478)		Post-1996 South Florida Building Code (N=30,227)	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Dependent Variables						
Wind Dmg (0/1)	0.012	0.111	0.018	0.131	0.008	0.089
Independent Variables						
Square Feet	2313.648	741.439	2273.077	709.606	2349.186	766.490
Acres	0.181	0.111	0.181	0.112	0.180	0.109
Baths	2.392	0.601	2.331	0.555	2.445	0.634
Assessed Value (1000s of USD)	483.706	239.061	468.482	217.653	497.042	255.609
Effective Year Built	1997	2.000	1995	0.805	1998	1.159
Garage (0/1)	0.897	0.304	0.896	0.305	0.898	0.302
Multifamily (0/1)	0.010	0.100	0.007	0.082	0.013	0.114
Building Footprint Vertices	5.604	1.746	5.616	1.760	5.594	1.734
Building Footprint Area (m^2)	247.645	89.500	246.245	91.956	248.871	87.276
Hurricane Distance (kms)	136.308	8.757	136.509	8.480	136.133	8.989
Ocean Distance (kms)	18.088	7.595	18.319	7.334	17.886	7.812
Elevation (meters)	2.272	0.911	2.303	0.916	2.244	0.905
Building Density (%)	0.217	0.063	0.216	0.063	0.218	0.064

Notes: The unit of observation is a house. Summary statistics are reported for houses with an effective year built between 1994 and 2000. All South Florida Building Code homes are located east of Hurricane Irma's track (i.e., Hurricane East (0/1) = 1).

Appendix Table A4 – The Impact of Post-2002 Building Codes

Dep. Variable: Wind Damage (0/1)	2004 Florida Building Code[a] Model (1)	Model (2)
SBC * Eff. Year Built ≥ 2005	**-0.016***** **(0.003)**	- -
SBC * Eff. Year Built (2005 - 2006)	- -	**-0.015***** **(0.002)**
SBC * Eff. Year Built (2007 - 2008)	- -	**-0.016***** **(0.003)**
Eff. Year Built ≥ 2005	-0.003** (0.001)	-0.003** (0.001)
Eff. Year Built Window	[2002 - 2008]	[2002 - 2008]
Mean of Dep. Variable	0.028	0.028
R^2	0.084	0.084
Observations	170,469	170,469

Dep. Variable: Wind Damage (0/1)	2007 Florida Building Code[a] Model (3)	Model (4)
SBC * Eff. Year Built ≥ 2009	**-0.003** **(0.003)**	- -
SBC * Eff. Year Built (2009 - 2010)	- -	**-0.001** **(0.003)**
SBC * Eff. Year Built (2011 - 2012)	- -	**-0.006** **(0.004)**
Eff. Year Built ≥ 2008	0.000 (0.002)	0.000 (0.002)
Eff. Year Built Window	[2006 - 2012]	[2006 - 2012]
Mean of Dep. Variable	0.021	0.021
R^2	0.094	0.094
Observations	86,714	86,714

Dep. Variable: Wind Damage (0/1)	2010 Florida Building Code[a] Model (5)	Model (6)
SBC * Eff. Year Built ≥ 2012	**-0.003** **(0.003)**	- -
SBC * Eff. Year Built (2012 - 2013)	- -	**-0.001** **(0.003)**
SBC * Eff. Year Built (2014 - 2015)	- -	**-0.005*** **(0.003)**
Eff. Year Built ≥ 2012	0.001 (0.002)	0.001 (0.002)
Eff. Year Built Window	[2009 - 2015]	[2009 - 2015]
Mean of Dep. Variable	0.015	0.015
R^2	0.155	0.155
Observations	41,920	41,920

Notes: *, **, *** denotes significance at the 10%, 5%, and 1% level respectively. Eff. Year Built stands for the effective construction year of a home. SBC is equal to one when a home is within a Standard Building Code County. Rows 1 - 3 report results from the interaction between two dummy variables, while row 4 is a non-interacted dummy variable. [a]The 2004, 2007, and 2010 versions of the Florida Building Code went into effect in 2005, 2009 and 2012, respectively. Robust standard errors are clustered at the census block group level. Each regression includes census block group fixed effects, and housing and locational controls (see Appendix Table A1).

Appendix Table A5 – The Impact of Florida's 2001 Building Code on Wind Damage Severity

Dep. Variable: Wind Damage Area (m^2)	Model (1)	Model (2)	Model (3)	Model (4)
Eff. Year Built ≥ 2002	**-0.270*** **	**-0.377** **	**-0.452*** **	**-0.392*** **
	(0.072)	**(0.131)**	**(0.037)**	**(0.095)**
Area	Lee County	Lee County	Lee County	Lee County
Eff. Year Built Window	[1999 - 2005]	[1999 - 2005]	[1996 - 2008]	[1996 - 2008]
Running Variable Func. Form	Linear	Linear	Linear	Linear
Roofing Permit and Satellite Observations	Included	Excluded	Included	Excluded
Chi-squared (χ^2)	500.288	294.528	808.347	528.082
Observations	47,224	44,566	81,649	77,650

Notes: *, **, *** denotes significance at the 10%, 5%, and 1% level respectively. Eff. Year Built stands for the effective construction year of a home. Row 1 reports estimates from a dummy variable. Robust standard errors are clustered at the census block group level. Each regression includes census block group fixed effects, housing and locational controls (see Appendix Table A1), and allows the slope of the running variable to vary across the regression discontinuity cutoff. Reported coefficients are first estimated using a conditional Poisson estimator and then transformed into proportional effects using the transformation exp(β) - 1. Significance levels from the untransformed Poisson coefficients are reported. See Chen and Roth (2024) for more details. Columns 1 and 3 consider homes with roofing permits issued after Hurricane Irma or identified as having blue tarps via satellite imagery to have 100% roof damage, whereas columns 2 and 4 exclude these observations from the regression.

Appendix Table A6 – Summary Statistics for Homes Sold pre- and post-Hurricane Irma

Lee County	Full Sample (N=69,624)		Pre-Hurricane Irma (N=42,690)		Post-Hurricane Irma (N=26,934)	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Dependent Variable						
Sale Price (1000s of 2015 USD)	220.610	123.706	225.473	131.410	212.903	109.962
Independent Variables						
Wind Dmg (0/1)	0.030	0.171	0.033	0.178	0.025	0.158
Wind Dmg Area (m^2)	1.050	9.907	1.085	9.730	0.994	10.181
Sale Year	2017	1.429	2016	0.776	2018	0.648
Sale Month	6.364	3.318	6.069	3.218	6.832	3.419
Square Feet	1791.381	557.805	1804.288	558.794	1770.924	555.631
Acres	0.251	0.195	0.249	0.189	0.254	0.203
Baths	2.202	0.558	2.210	0.562	2.189	0.551
Age	22.836	15.194	21.131	15.489	25.537	14.305
Garage (0/1)	0.871	0.336	0.876	0.329	0.862	0.345
Multifamily (0/1)	0.063	0.243	0.061	0.239	0.066	0.249
Building Footprint Vertices	14.601	4.465	14.580	4.455	14.635	4.480
Building Footprint Area (m^2)	269.901	94.572	271.103	94.551	267.995	94.574
Hurricane Distance (kms)	17.495	10.368	17.341	10.387	17.739	10.333
Hurricane East (0/1)	0.098	0.297	0.099	0.298	0.096	0.295
Ocean Distance (kms)	14.654	9.592	14.775	9.563	14.462	9.635
Elevation (meters)	4.133	2.005	4.180	2.011	4.059	1.993
Building Density (%)	0.145	0.064	0.145	0.064	0.145	0.065

All Counties	Full Sample (N=306,344)		Pre-Hurricane Irma (N=181,336)		Post-Hurricane Irma (N=125,008)	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Dependent Variable						
Sale Price (1000s of 2015 USD)	283.469	157.346	283.440	165.249	283.512	145.119
Independent Variables						
Wind Dmg (0/1)	0.037	0.189	0.044	0.205	0.027	0.162
Sale Year	2017	1.419	2016	0.784	2018	0.655
Sale Month	6.471	3.278	6.152	3.162	6.932	3.388
Square Feet	1916.391	680.529	1924.280	679.090	1904.948	682.451
Acres	0.246	0.260	0.247	0.265	0.245	0.252
Baths	2.203	0.655	2.209	0.658	2.193	0.651
Age	33.186	18.823	31.492	19.016	35.642	18.263
Garage (0/1)	0.699	0.459	0.704	0.456	0.691	0.462
Multifamily (0/1)	0.026	0.159	0.026	0.159	0.026	0.159
Building Footprint Vertices	8.002	4.524	8.083	4.570	7.886	4.453
Building Footprint Area (m^2)	253.909	88.513	254.807	88.315	252.605	88.783
Hurricane Distance (kms)	100.843	61.530	98.944	62.044	103.597	60.672
Hurricane East (0/1)	0.681	0.466	0.669	0.470	0.697	0.459
Ocean Distance (kms)	11.821	8.319	11.944	8.393	11.641	8.207
Elevation (meters)	3.433	1.740	3.442	1.746	3.421	1.730
Building Density (%)	0.173	0.066	0.173	0.066	0.174	0.065

Notes: The unit of observation is a housing sale.

Appendix Table A7 – Repeat Sales and Repaired Homes

Dep Variable: Ln Sale Price	Model (1)	Model (2)	Model (3)	Model (4)
Post6*Wind Dmg (0/1)	**-0.067***	**-0.217****	**-**	**-0.077*****
	(0.035)	**(0.088)**	**-**	**(0.013)**
PostBeyond6*Wind Dmg (0/1)	**0.017**	**0.019**	**0.021**	**-0.003**
	(0.021)	**(0.042)**	**(0.042)**	**(0.008)**
Post6*High Wind Dmg (0/1)	**-**	**-**	**-0.336****	**-**
	-	**-**	**(0.152)**	**-**
Post6*Low Wind Dmg (0/1)	**-**	**-**	**-0.141**	**-**
	-	**-**	**(0.103)**	**-**
Post6*Repair (0/1)	-	-	-	0.129***
	-	-	-	(0.020)
PostBeyond6*Repair (0/1)	-	-	-	0.040***
	-	-	-	(0.009)
Area	All Counties	Lee County	Lee County	All Counties
Property Fixed Effects	Yes	Yes	Yes	No
Time Fixed Effects	Year x Month	Year x Month	Year x Month	Year x Month
R^2	0.913	0.908	0.908	0.802
Observations	89,674	22,063	22,063	308,944

Notes: *, **, *** denotes significance at the 10%, 5%, and 1% level respectively. Wind Dmg is equal to one if the house experienced wind damage from Hurricane Irma. Post is equal to one when the housing transaction occurs after Hurricane Irma. Post6 and PostBeyond6 divide Post into two periods: within 6 months of Irma and after 6 months. High and Low Wind Dmg divides damaged homes sold within 6 months of Irma into two groups based on if a home had above- (High Wind Dmg = 1) or below-average (Low Wind Dmg = 1) wind damage severity. Repair is an indicator equal to one if home was repaired before being sold. Robust standard errors are clustered at the census block group level. Each regression includes census block group by year fixed effects. Additional housing and locational controls (see Appendix Table A1) are included in model 4, while models 1 - 3 only include the age of the home as an additional control.

Appendix Table A8 – The Price Premium for Updated Building Codes before Hurricane Irma

	Standard Building Code Homes			
Dep. Variable: Ln Sale Price	Model (1)	Model (2)	Model (3)	Model (4)
Eff. Year Built ≥ 2002	**0.035*** **	**0.017*** **	**0.017*** **	**-**
	(0.009)	**(0.006)**	**(0.006)**	**-**
Eff. Year Built ≥ 1992	**-**	**-**	**-**	**0.031*** **
	-	**-**	**-**	**(0.005)**
Year Built Sample Window	[1999 - 2005]	[1999 - 2005]	[1999 - 2005]	[1989 - 1995]
Spatial Fixed Effects	Block Group	Block Group	Block Group x Year	Block Group x Year
Time Fixed Effects	Year x Month	Year x Month	Year x Month	Year x Month
Housing and Locational Controls[a]	No	Yes	Yes	Yes
R^2	0.644	0.793	0.808	0.819
Observations	24,792	24,792	24,792	16,040

	South Florida Building Code Homes			
Dep. Variable: Ln Sale Price	Model (5)	Model (6)	Model (7)	Model (8)
Eff. Year Built ≥ 1997	**0.034** **	**0.020*** **	**0.020** **	**-**
	(0.014)	**(0.007)**	**(0.008)**	**-**
Eff. Year Built ≥ 1987	**-**	**-**	**-**	**0.006**
	-	**-**	**-**	**(0.008)**
Year Built Sample Window	[1994 - 2000]	[1994 - 2000]	[1994 - 2000]	[1984 - 1990]
Spatial Fixed Effects	Block Group	Block Group	Block Group x Year	Block Group x Year
Time Fixed Effects	Year x Month	Year x Month	Year x Month	Year x Month
Housing and Locational Controls[a]	No	Yes	Yes	Yes
R^2	0.567	0.675	0.694	0.764
Observations	10,356	10,356	10,356	6,865

Notes: *, **, *** denotes significance at the 10%, 5%, and 1% level respectively. Eff. Year Built stands for the effective construction year of a home. Rows 1 and 2 reports estimates from a dummy variable. All transactions occurred between January of 2015 and August of 2017. [a]The age of a home is not included as a control (see Appendix Table 1 for a full list of controls) to avoid multicollinearity issues with the variable of interest, though its inclusion does not substantially change our findings. Robust standard errors are clustered at the census block group level.

Appendix Table A9 – House by Quarter Summary Statistics

Lee County	Full Sample (N=1,095,525)		Pre-Hurricane Irma (N=574,871)		Post-Hurricane Irma (N=520,654)	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Dependent Variable						
Transacted (0/1)	0.057	0.232	0.063	0.243	0.051	0.220
Independent Variables						
Wind Dmg (0/1)	0.032	0.176	0.034	0.180	0.030	0.171
Wind Dmg Area (m^2)	1.126	10.278	1.196	10.578	1.049	9.935
Square Feet	1766.513	553.494	1766.450	553.370	1766.583	553.632
Acres	0.256	0.204	0.256	0.203	0.256	0.204
Baths	2.176	0.545	2.176	0.545	2.176	0.545
Assessed Value (1000s of USD)	175.910	105.522	175.890	105.493	175.931	105.555
Age	24.764	14.139	23.557	14.087	26.097	14.076
Garage (0/1)	0.860	0.347	0.860	0.347	0.860	0.347
Multifamily (0/1)	0.062	0.242	0.062	0.242	0.063	0.242
Building Footprint Vertices	14.711	4.568	14.711	4.566	14.710	4.570
Building Footprint Area (m^2)	268.381	93.733	268.421	93.724	268.336	93.743
Hurricane Distance (kms)	17.811	10.319	17.824	10.316	17.797	10.322
Hurricane East (0/1)	0.097	0.296	0.097	0.296	0.097	0.296
Ocean Distance (kms)	14.456	9.663	14.450	9.658	14.463	9.669
Elevation (meters)	4.034	1.979	4.032	1.979	4.036	1.980
Building Density (%)	0.144	0.064	0.144	0.064	0.144	0.064

All Counties	Full Sample (N=5,151,938)		Pre-Hurricane Irma (N=2,724,062)		Post-Hurricane Irma (N=2,427,876)	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Dependent Variable						
Transacted (0/1)	0.056	0.231	0.061	0.239	0.052	0.222
Independent Variables						
Wind Dmg (0/1)	0.038	0.191	0.047	0.211	0.028	0.164
Square Feet	1912.517	679.022	1911.466	678.101	1913.696	680.051
Acres	0.249	0.263	0.250	0.269	0.247	0.258
Baths	2.190	0.644	2.190	0.643	2.190	0.645
Assessed Value (1000s of USD)	362.818	228.684	362.295	228.525	363.405	228.860
Age	34.204	17.905	32.962	17.833	35.597	17.883
Garage (0/1)	0.699	0.459	0.698	0.459	0.700	0.458
Multifamily (0/1)	0.026	0.158	0.025	0.158	0.026	0.158
Building Footprint Vertices	7.916	4.484	7.923	4.486	7.908	4.482
Building Footprint Area (m^2)	254.469	88.321	254.677	88.336	254.237	88.305
Hurricane Distance (kms)	103.044	60.739	102.567	60.912	103.579	60.539
Hurricane East (0/1)	0.695	0.460	0.692	0.462	0.698	0.459
Ocean Distance (kms)	11.735	8.361	11.727	8.348	11.744	8.375
Elevation (meters)	3.412	1.723	3.414	1.721	3.409	1.725
Building Density (%)	0.174	0.066	0.173	0.066	0.174	0.066

Notes: The unit of observation is house by quarter.

Appendix B: Object-Based Image Analysis

In this appendix, we provide more specifics regarding how object-based image analysis (OBIA) is applied to aerial drone imagery to identify blue tarp locations in Lee County Florida, Florida. We then outline how OBIA is adapted for use with satellite imagery, which is needed to expand the study area outside of Lee County where aerial drone imagery in unavailable. Finally, we discuss some limitations of using satellite imagery as a substitute for drone images, while also mentioning and addressing other misclassification concerns.

B.1 Implementation of Object-Based Image Analysis

As discussed in Subsection II.B, the OBIA process begins by overlaying county building footprint shapefiles onto aerial drone imagery taken in Lee County, and retaining only the areas where the two overlap. The resulting image is then segmented into thousands of discrete objects through a process known as segmentation. Pixels with similar colors that are also physically close are more likely to be grouped into the same segment, while pixels with contrasting colors and/or that are physically far apart are more likely to be categorized into separate segments. Each segment, in turn, represents a distinct object in the image. In the context of our study, this means each segment corresponds to a roof or a portion of a roof, since the image only contains imagery of buildings. Various software options are available for picture segmentation. In our study, we use ArcGIS's Segment Mean Shift add-on, part of the Image Analyst Toolbox. This tool allows users to adjust the relative importance of spatial proximity versus sharing similar spectral (color) characteristics in determining segment membership. We tested several different weighting schemes and found, through visual inspection, that the default settings produced the best segmentation.

Zonal color statistics were then extracted using ArcGIS's Zonal Statistics geoprocessing toolkit. This included finding the average red, green, and blue (RGB) pixel value from each segment as well as the standard deviation of each color. 6,429 segments were then manually labeled as having a blue tarp or not through visual inspection. Increasing or decreasing this number by a few hundred observations (i.e., 500 ~ 1000) did not have a substantial impact on our analysis. After collecting this data, we then trained a model using the TrainVectorClassifier function from the open-source Orfeo

ToolBox (https://www.orfeo-toolbox.org/).[1] Effectively, this model predicts which segment has a blue tarp and which does not based on the segment's color characteristics. Finally, we applied this model to all of the segments identified within the Lee County aerial drone imagery to identify which homes did and did not have wind damage following Hurricane Irma.

To validate the performance of the OBIA approach, we also report its confusion matrix in Appendix Table B1 using the sample of manually identified observations. In the table, a value of Blue Tarp = 0 indicates the absence of a blue tarp – either in reality (columns) or based on prediction (rows) – while Blue Tarp = 1 denotes the opposite. In general, the OBIA process is highly accurate, though it is more accurate in predicting non-blue tarp locations. When the segment actually has a blue tarp in it, OBIA correctly predicts this about 99.1% (≈ 6.61%/[6.61% + 0.06%]) of the time. Alternatively, when there is no blue tarp, OBIA correctly predicts this 99.9% (≈ 93.3%/[93.3% + 0.03%]) of the time.

In Appendix Table B2, we perform a similar analysis, except our sample of manually identified observations is first randomly split into a larger and smaller subsample using a 80-20 split. Dividing in a different manner does not produce markedly different results. We then train a predictive model using only data from the larger subsample and evaluate OBIA's ability to make accurate out of sample predictions by applying the trained model to the smaller subsample. Appendix Table B2 reports OBIA's accuracy in making out-of-sample predictions, in other words, while Appendix Table B1 reports in-sample accuracy. Regardless of which metric is used, we find the OBIA method is effective in pinpointing blue tarp locations.

B.2 Adapting Object-Based Image Analysis for use with Satellite Imagery

Lee County is somewhat unique in offering free, high-resolution aerial drone imagery each year. In many areas, such data is unavailable, difficult to access or costly to obtain. In this section, we demonstrate how satellite imagery from Google Earth Engine (GEE 2025) can serve as an alternative to aerial drone imagery for detecting blue tarp locations in Broward, Collier, Miami-Dade, Monroe,

[1] The TrainVectorClassifier function was developed specifically for remote-sensing applications and has been applied extensively for object classification purposes. We opted for the SVM classifier, which employs machine learning, based on its well-established reputation within the remote-sensing literature (Ma et al. 2017; Costa et al. 2023).

and Palm Beach counties. We outline modifications made to the OBIA process to accommodate this data and conclude with a discussion of some of the advantages of using satellite imagery as a substitute for drone-based imagery.

GEE (https://earthengine.google.com/) is an online platform that provides access to historical satellite imagery, allowing users to analyze and process geospatial data at scale. For our study, we downloaded monthly composite satellite images spanning the entire study area from the Harmonized Sentinel-2 (HS2) image collection. HS2 imagery is captured at a significantly lower resolution than the aerial drone imagery, with each pixel corresponding to an area of 10 meters by 10 meters. In comparison, the spatial resolution of the aerial drone imagery is 10 centimeters by 10 centimeters.[2]

Similar to the process outlined in Subsection II.B, we began by isolating portions of the HS2 imagery that correspond to a building, using Microsoft building footprint shapefiles (https://github.com/microsoft/USBuildingFootprints). However, due to the coarse resolution – each pixel covering approximately 100 square meters – it was not possible to segment rooftops into smaller components. Most roofs contained fewer than 10 pixels, while in contrast, the drone imagery provided roughly 100 times more pixels per rooftop. This limitation meant that our satellite-based analysis could only identify whether a roof had a blue tarp. We could not, in other words, also measure the size of each tarp like we did with the aerial drone imagery. Despite this, we followed a similar procedure as before when conducting OBIA: extracting color statistics for each rooftop from HS2 images taken in January 2018, visually inspecting several thousand rooftops to identify their condition,[3] using this labeled dataset to train a classification model, and then applying this

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[2] Aerial drone imagery also does not suffer from problems related to cloud interference, as drones are usually flown beneath the cloud line. To reduce the impact of cloud interference in the satellite imagery, we make two adjustments. First, we apply the Cloud Score+ quality assessment tool to mask out clouds within each raw satellite image. Since HS2 satellite images are typically available every five days for a given location, clouds often appear due to changes in weather conditions. Second, after applying Cloud Score+ to each image, we combine them into monthly composites. This method ensures a clearer, more consistent representation of roof conditions while minimizing noise from interference.

[3] The dataset used to train the aerial drone imagery-based OBIA model (N=6,429) contains many of the same observations that are within the satellite training dataset (N=7,623). Some of the observations within the former had to be dropped when conducting satellite-based OBIA, however, as the rooftop was clearly visible within the aerial drone imagery but not so in the satellite image due to shadows and cloud cover. In addition, we increased the sample size by about 1,200 when transitioning to the satellite imagery to help offset the loss in resolution. All of the manually-identified locations – for both datasets – are in Lee County, since we identified the "true" status of each roof

classification model on satellite imagery to map blue tarp locations across the entire study area.

Thus far, we have largely followed the same procedure described in Subsection II.B of the main text and Appendix Subsection B.1, without fully utilizing the benefits of satellite imagery. One key advantage of satellite imagery is its higher frequency of capture, with composite images available 12 times per year. In comparison, the aerial drone imagery is only able once per year. We utilize this extra information in two ways. First, we apply our satellite-based OBIA model to monthly composite images taken between Hurricane Irma and when the aerial drone imagery was taken. This gives us a much longer timeframe to detect blue tarps and reduces the chances of missing a tarp that was put up and taken down before January 2018. Our blue tarp indicator is equal to one, in other words, if a home is observed to have a blue tarp at any point between September 2017 and January of the following year.[4]

Second, satellite images taken just before Hurricane Irma can help identify cases of anticipatory tarping, where homeowners place blue tarps on vulnerable areas of their roof in anticipation of the upcoming storm. Failing to account for anticipatory tarping could introduce bias, as blue tarps observed after Hurricane Irma may be an indication of defensive behavior as opposed to a signal of wind damage. To address this, we apply OBIA to a composite of satellite images captured within one month before Hurricane Irma and then filter out homes with pre-existing blue tarps. We discuss this in more detail in Appendix C.

B.3 Limitations with Satellite Imagery

One drawback of relying solely on satellite-based OBIA is the increased risk of misclassification resulting from its lower resolution. This becomes more evident when comparing a satellite image to a drone photograph; both of which are taken at the same location and around the same time (January 2018), as shown in Appendix Figure B1. The red letters show the location of four blue-tarped houses.

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using the aerial drone imagery.

[4] Satellite images taken in September of 2017 but prior to Hurricane Irma are excluded from this analysis. In Lee County, a home is assumed to have sustained damage if a blue tarp is observed in either the satellite (September 2017 to January 2018) or aerial drone imagery (January 2018). For all other counties, however, we rely solely on satellite imagery to identify blue tarp locations. Additionally, we found very few cases where a blue tarp appeared after January 2018, but was not present before that time. Using Lee County as an example, approximately 0.1% of homes were detected to have a tarp for the first time in February 2018.

Houses A – C are completely tarped cover, while house D is only partially tarped over. From visual inspection, it is clear that the satellite imagery is better suited to identify completely tarped over houses (A – C) relative to partially tarped over homes (D).

We investigate this matter further by relating the OBIA predictions generated from the satellite imagery (rows) to those produced from the aerial drone photographs (columns) in Appendix Table B3. Similar to in Appendix Subsection B.1, Blue Tarp = 1 indicates the presence of a blue tarp based on prediction, while Blue Tarp = 0 suggests the opposite. Unlike before, however, Appendix Table B3 reports statistics for all of Lee County instead of focusing only on the subsample of homes where rooftop conditions are manually verified.

Treating the aerial drone predictions as the truth – given the strong performance metrics in Appendix Tables B1 and B2 – we see in the first column a high degree of consistency between both approaches. In locations where there is no tarp, satellite-based OBIA correctly predicts this 98.6% (≈ 95.26%/[95.26% + 1.39%]) of the time. While 1.38% of observations are classified as having a tarp via satellite imagery when the drone imagery shows otherwise (lower left cell), many of these may not be true misclassifications. If a tarp had been installed and later removed before the drone images were captured, the satellite-based predictions would still correctly identify these homes as having experienced wind damage, whereas the drone-based predictions would not.

The level of agreement between both approaches declines when examining locations with blue tarps (columns 2–5 of Appendix Table B3). Overall, satellite-based OBIA tends to underdetect homes with wind damage, particularly when the tarps are smaller. For instance, among tarps falling between the 25th and 50th percentiles in terms of size (column 3), the satellite-based OBIA correctly identified their presence 5.95% of the time (≈ 0.05%/[0.79% + 0.05%]). In contrast, accuracy improves significantly for the largest tarps – those above the 75th percentile – with correct predictions occurring 80.95% of the time (≈ 0.68%/[0.68% + 0.16%]).

These results suggest that while satellite imagery offers valuable temporal coverage, making it useful for identifying wind damage not visible in infrequently captured drone images, it is not a perfect substitute. The lower resolution increases the likelihood of missing damaged homes, especially those with small or partially visible tarps. Within the context of our study, this suggests that estimates derived from data outside of Lee County are likely to be biased towards zero as many partially tarped homes will be misclassified as having no damage at all.

B.4 Other Misidentification Concerns

Another limitation is that homeowners with a damaged roof may have used a different colored tarp (e.g., black) that OBIA would not detect regardless of which imagery type is used, or homeowners may not have installed a tarp at all despite having damage. We alleviate both of these concerns by supplementing our OBIA predictions with information gathered from roofing permits. Specifically, homes that applied for a roofing permit within one year of the hurricane are also considered as having roof damage, as it took approximately one year for the number of roofing permits to stabilize after Hurricane Irma (Appendix Figure A1). Increasing or decreasing the length of this cutoff does not substantially alter our findings.[5]

A second concern with the OBIA approach is the possibility of misclassifying all blue objects (e.g., pools, blue roofs, etc.) as hurricane tarps. This misclassification could lead to an overestimation of blue tarps. To address this, we apply our trained models to aerial drone and satellite images taken approximately 9 months before Hurricane Irma in January of 2017. Segments identified as blue tarps in 2017 are removed from the 2018 images, as these segments are likely misclassified (and may continue to be misclassified in the 2018 images) given that no major hurricanes affected the study area in 2015 or 2016.

[5] Another concern are households who experience roof damaged but did not use a tarp or apply for a roofing permit. These households will be incorrectly classified as part of the control group in our analysis, suggesting our coefficients should be interpreted as lower bound estimates.

References

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Appendix Table B1 – In-Sample Confusion Matrix

		Actual Values	
		Blue Tarp = 0	**Blue Tarp = 1**
Predicted Values	**Blue Tarp = 0**	**93.30%**	**0.06%**
	Blue Tarp = 1	**0.03%**	**6.61%**

Table notes: The above table reports the percentage of observations that were correctly (top left and bottom right) or incorrectly (top right and bottom left) classified as having a blue tarp or not, based on in-sample predictions from object-based image analysis (OBIA). The OBIA model was trained using the full training dataset – comprising observations with rooftop conditions verified through visual inspection and then evaluated using this same dataset. The reported statistics reflect the model's performance within this sample.

Appendix Table B2 – Out-of-Sample Confusion Matrix

		Actual Values	
		Blue Tarp = 0	Blue Tarp = 1
Predicted Values	Blue Tarp = 0	**93.31%**	**0.08%**
	Blue Tarp = 1	**0.08%**	**6.53%**

Table notes: The above table reports the percentage of observations that were correctly (top left and bottom right) or incorrectly (top right and bottom left) classified as having a blue tarp, based on out-of-sample predictions from object-based image analysis (OBIA). The OBIA model was trained on 80% of the original training dataset – comprising observations with rooftop conditions verified through visual inspection – and evaluated on the remaining 20%. The reported statistics reflect the model's performance on the holdout sample.

Appendix Table B3 – Satellite Versus Aerial Drone Image Predictions

		Aerial Drone Imagery				
		Blue Tarp = 0	Blue Tarp = 1 & Tarp Size < 25th Pctile	Blue Tarp = 1 & Tarp Size: 25th - 50th Pctile	Blue Tarp = 1 & Tarp Size: 50th - 75th Pctile	Blue Tarp = 1 & Tarp Size > 75th Pctile
Satellite Imagery	Blue Tarp = 0	95.26%	0.81%	0.79%	0.69%	0.16%
	Blue Tarp = 1	1.39%	0.02%	0.05%	0.15%	0.68%

Table notes: Predictions from object-based image analysis using satellite imagery (rows) and aerial drone imagery (columns) are reported for all homes in Lee County, Florida. Blue tarp locations predicted via drone imagery (columns 2 - 5) are broken down into four groups based on tarp size, with the size of the tarp increasing from left to right. Both approaches show a high level of agreement when there is likely no tarp (column 1) or when the house has a large tarp (column 5).

Appendix Figure B1 – Aerial Drone Versus Satellite Imagery

(A) **(B)**

Figure notes: Best viewed in color. Panel A shows a satellite composite image of a neighborhood in Lee County from January 2018, while Panel B shows a drone image of the same area and time. Red labels A through D indicate four locations with blue-tarped houses. Houses A through C are fully covered with tarps, whereas House D is only partially tarped. The left basemap image was supplied by European Union/ESA/Copernicus (2018), Harmonized Sentinel-2 MSI: MultiSpectral Instrument, and was downloaded from Google Earth Engine. The right basemap was supplied the Lee County Board of County Commissioners.

Appendix C: Robustness Checks, Alternative Explanations and Falsification Tests

In this appendix, we present robustness checks to our primary regression discontinuity analysis. We begin by presenting results from a local randomization estimator, which, in some circumstances, is better suited for regression discontinuity analysis than a more traditional estimator. We then explore and test alternative explanations for the observed discontinuous jumps in Figure 3, followed by a series of falsification tests.

C.1 Local Randomization

Local randomization is an alternative approach taken within the regression discontinuity design (RDD) literature and is particularly useful when the running variable takes on relatively few discrete values (Cattaneo et al., 2024). Instead of relying on the usual continuity assumption in potential outcomes at the cutoff, local randomization assumes that treatment is randomly assigned within a "neighborhood" around the cutoff. We re-estimate our results using this method, applying one-, two-, and three-year bandwidths while also testing different kernel weighting functions (Appendix Table C1). These estimates are qualitatively similar to those reported in Table 1.

C.2 Alternative Explanations

It is possible that the discontinuous jumps at 1997 and 2002 are due to factors unrelated to the 1996 South Florida Building Code (SFBC) and the 2001 Florida Building Code (FBC). For example, properties just left of the threshold might have been constructed in more wind-prone areas compared to those just right. If this were the case, then wind damage shares would drop at the construction years 1997 and 2002 even had there been no updating of standards. In the following subsection, we test several alternative explanations for our estimated effects, including the scenario above.

Hurricane wind damage is more likely if a home is in a hurricane's direct path or if it is located in a large open area where the wind is unobstructed. While homeowners typically have little control over the storm's path, they may consider their wind exposure when deciding where to live and how old of a house to live in. If this is the case, then homeowners may choose to live in high-speed wind areas only if they can hedge their risk by living in a newer, sturdier home. However, this would bias our estimated effects, as moving across the 1996 SFBC or 2001 FBC threshold would reflect not only a change in building standards but also a change in locational risk. Properties right of the threshold, in other words, could be located in riskier areas relative to properties left of the threshold.

We indirectly test this possibility by replacing the dependent variable in equation (1) with three control variables that describe a property's locational risk: distance to the nearest point along Hurricane Irma's path, elevation, and parcel lot acreage. The regression discontinuity plots from each analysis are shown in panel (A), (B), and (C) in Appendix Figure C1 (FBC homes centered on the effective construction year 2002) and Appendix Figure C2 (SFBC homes centered on the effective construction year 1997). Overall, we do not observe discontinuities in the locational variables, indicating that properties just above the threshold are not likely situated in riskier areas.

A similar concern arises when examining how homes are constructed. Taller and wider homes may be more vulnerable to wind damage. This, along with the incentive to offset the higher cost of compliance through design changes, could incentivize home builders to construct shorter homes or homes with smaller roofs following the implementation of the 2001 FBC or the 1996 SFBC. Similarly, owners of high-end homes may be more motivated to adopt wind-proofing technology if their property includes more vulnerable features such as large glass windows, oversized garage doors, or an enclosed pool. Additionally, multi-family homes may have different wind protection measures compared to single-family homes due to differences in management and ownership structures. In any of these cases, crossing the 1997 or 2002 threshold would not only coincide with a shift in building standards but also a change in physical features that factor into wind risk. This could introduce bias into our model. However, panels D – G in Appendix Figure C1 and C2 do not provide evidence supporting any of these concerns.

Another issue is the potential misidentification of blue tarps in satellite and drone imagery. A clear example of this would be residential pools, which could be mistaken for a blue tarp. If the likelihood of building a pool changed significantly due to the 1996 SFBC or the 2001 FBC – keeping in mind that these building codes affected not just roofs but various other components of a house – and our wind damage measure is correlated with pools, this could introduce bias. However, panel (H) in Appendix Figure C1 and C2 suggests that pool construction is not meaningfully correlated with either the 1996 SFBC or the 2001 FBC.

Additionally, homeowners with a leaky or aging roof may attempt to fortify their home before an upcoming storm by tarping their roof. If anticipatory tarping is more likely in older homes and if some of these tarps were detected in object-based image analysis (OBIA), then the effects of the 1996 SFBC and 2001 FBC would be overstated. Houses built just before the policy change would appear more damaged than houses built afterwards, when in reality the difference could be less pronounced or even the same.

We test this possibility by first collecting satellite images taken one month prior to Hurricane Irma (08/10/2017 – 09/10/2017). This should be a sufficient timespan to capture anticipatory tarping as Hurricane Irma was first spotted on August 30th, 2017. We then predict the number of anticipatory tarping cases using OBIA. Finally, we re-estimate equation (1) using anticipatory tarping as a dependent variable. The regression discontinuity plots for FBC and SFBC homes are shown in Appendix Figure C3. Looking at the figures, there does not appear to be evidence of a relationship between building codes and anticipatory tarping behavior. In general, the number of anticipatory tarping cases is also small (approximately 0.7% of homes). Since the actual damage status of these homes is unknown, we exclude them from our primary empirical analysis.

C.3 Falsification Tests

Some FBC homeowners may have taken note of some the conditions outlined in the 1996 SFBC and voluntarily adopted similar wind-protection standards (e.g., hurricane straps), despite not being required to do so until 2002. To test this hypothesis, we re-center the effective construction year variable around 1997 and then re-estimate equation (1) using only FBC homes. We do not find evidence of homeowners proactively acting in such a manner (top-left panel of Appendix Figure C4).

Survivor bias may be another confounding factor. Specifically, properties that withstood powerful hurricanes in the past may have unobservable features that afford them extra protection compared to newer properties. To test this, we re-estimate equation (1) with two major modifications. First, we use the year the home was built as the running variable as opposed to the effective construction year. Second, the cutoff is centered around 1993, which is approximately three months after the arrival of Hurricane Andrew. If survivor bias does exist, we would expect homes that survived Hurricane Andrew (left of the cutoff) to have substantially lower wind damage probabilities during Hurricane Irma relative to homes built immediately after Hurricane Andrew (right of the cutoff). Within the top-right panel of Appendix Figure C4, we do not see evidence supporting this.

When we identified blue tarps in the aftermath of Irma in 2017 using OBIA, we also used the same model to predict blue tarp locations in 2016. This was done to eliminate potential confounders, such as a house having a blue roof (see Appendix B for more details). Although we drop these observations from our primary analysis, we can still use them to conduct a falsification test. Specifically, we should not expect to see a discontinuous break in the share of homes detected to have a blue tarp or roof in 2016 at the 2001 FBC or 1996 SFBC threshold. If there is a break, then the discontinuities observed in the 2017 data could be related to something other than building standards. We do not find this to be the case in the lower half of Appendix Figure C4, though.

References

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Appendix Table C1 – Local Randomization

Standard Building Code (SBC) Homes

Dep. Variable: Wind Dmg (0/1)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Eff. Year Built ≥ 2002	**-0.020***	**-0.021***	**-0.028***	**-0.020***	**-0.021***
Eff. Year Built Sample Window	[2001 - 2003]	[2000 - 2004]	[1999 - 2005]	[1999 - 2005]	[1999 - 2005]
Kernel Function	Uniform	Uniform	Uniform	Triangular	Epanechnikov
Mean of Dep. Variable	0.051	0.052	0.050	0.050	0.050
Observations	51,505	89,413	126,362	126,362	126,362

South Florida Building Code (SFBC) Homes

Dep. Variable: Wind Dmg (0/1)	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)
Eff. Year Built ≥ 1997	**-0.007***	**-0.008***	**-0.010***	**-0.007***	**-0.008***
Eff. Year Built Sample Window	[1996 - 1998]	[1995 - 1999]	[1994 - 2000]	[1994 - 2000]	[1994 - 2000]
Kernel Function	Uniform	Uniform	Uniform	Triangular	Epanechnikov
Mean of Dep. Variable	0.011	0.012	0.012	0.012	0.012
Observations	24,075	40,115	56,705	56,705	56,705

Notes: *, **, *** denotes significance at the 10%, 5%, and 1% level respectively. Eff. Year Built stands for the effective construction year of a home. The first row of each panel reports estimates from a dummy variable. Local randomization is employed using Stata's rdrandinf command. Finite sample p-values are reported.

Appendix Figure C1 – Alternative Explanations (Standard Building Code Homes)

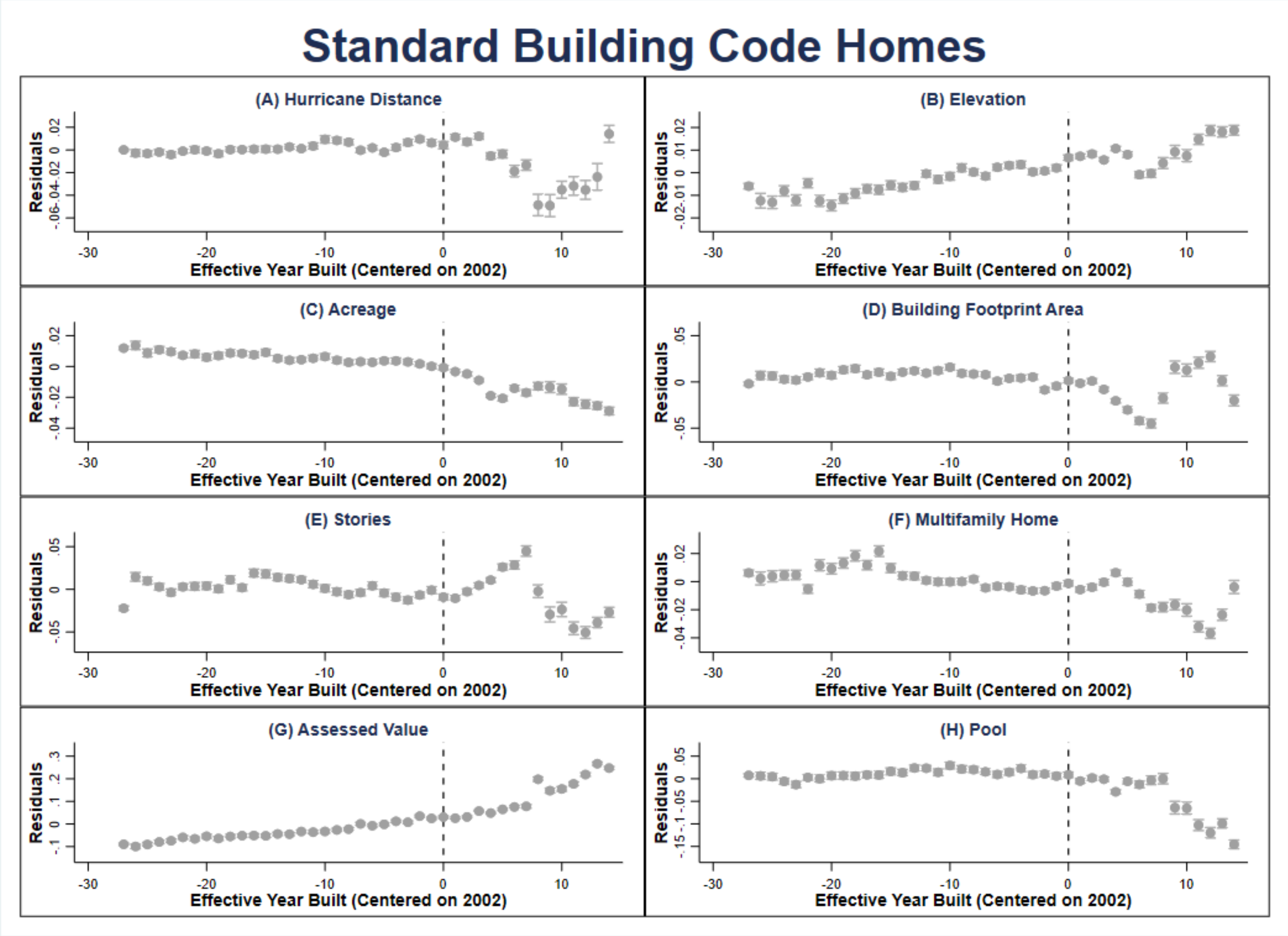

Figure notes: The outcome variable from each regression (listed at the top) is first regressed on a set of housing attributes, excluding itself, and census block group fixed effects. Average residuals for each construction year bin are then plotted (grey markers) alongside their 95% confidence intervals (grey brackets). Homes built before and during 1975 are binned into the same year bin for clarity.

Appendix Figure C2 – Alternative Explanations (South Florida Building Code Homes)

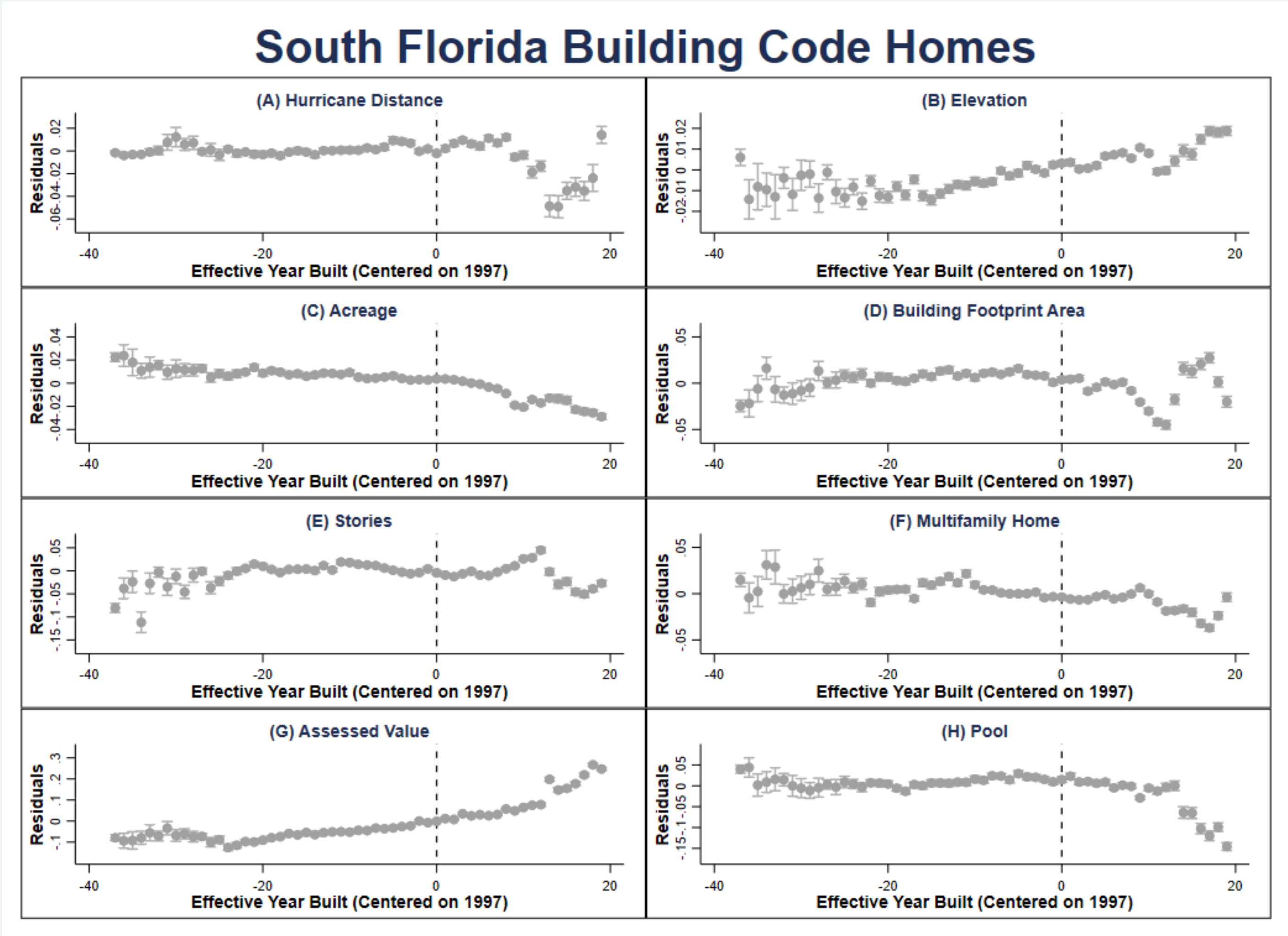

Figure notes: The outcome variable from each regression (listed at the top) is first regressed on a set of housing attributes, excluding itself, and census block group fixed effects. Average residuals for each construction year bin are then plotted (grey markers) alongside their 95% confidence intervals (grey brackets). Homes built before and during 1960 are binned into the same year bin for clarity.

Appendix Figure C3 – Anticipatory Tarping

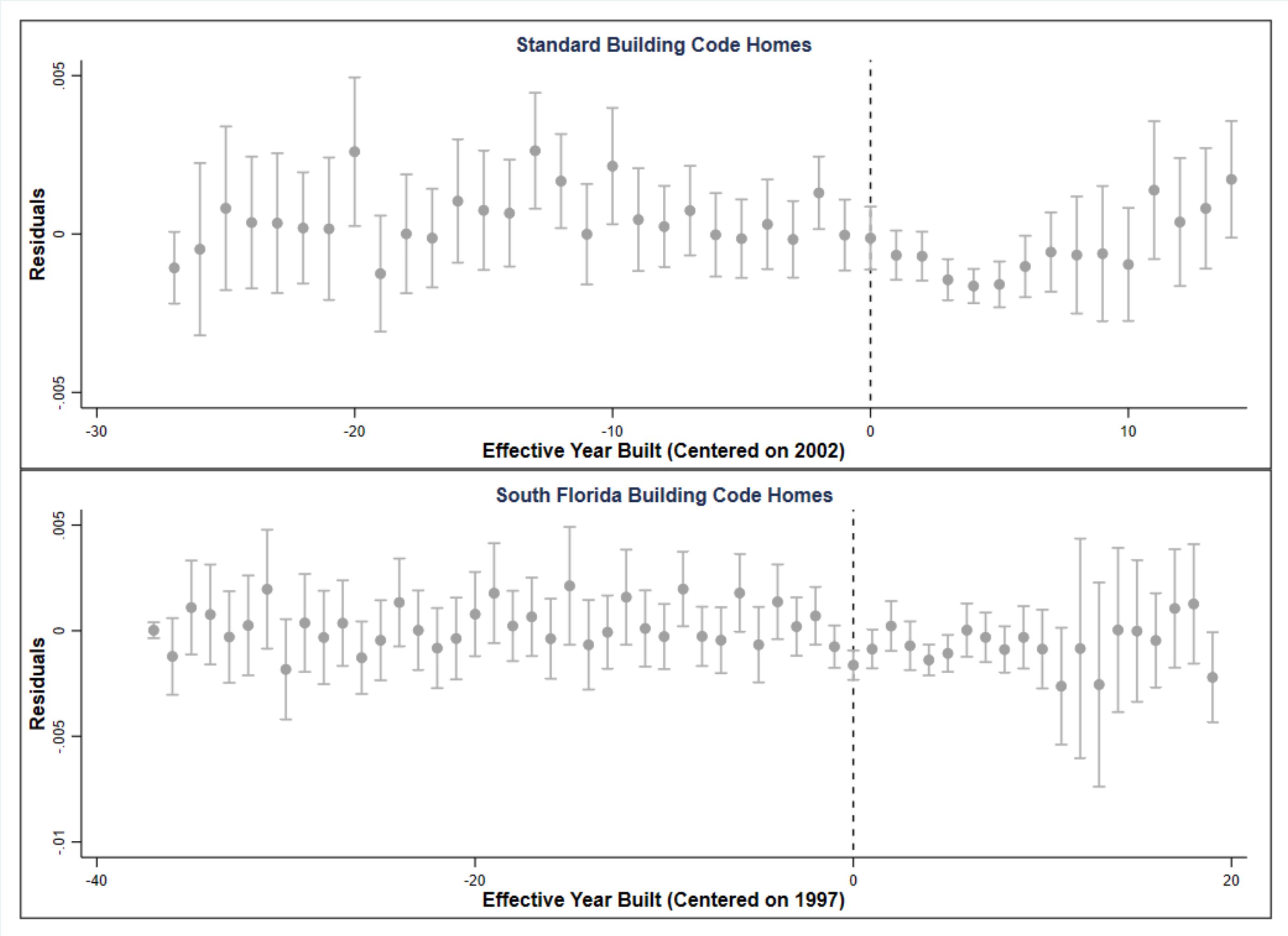

Figure notes: A binary variable indicating whether a home engaged in anticipatory tarping one month prior to Hurricane Irma is first regressed on a set of housing attributes and census block group fixed effects. Average residuals for each construction year bin are then plotted (grey markers) alongside their 95% confidence intervals (grey brackets). Homes built before and during 1975 (1960) are binned into the same year bin for clarity within the top (bottom) panel.

Appendix Figure C4 – Proactive Behavior, Survivor Bias and Falsification Tests

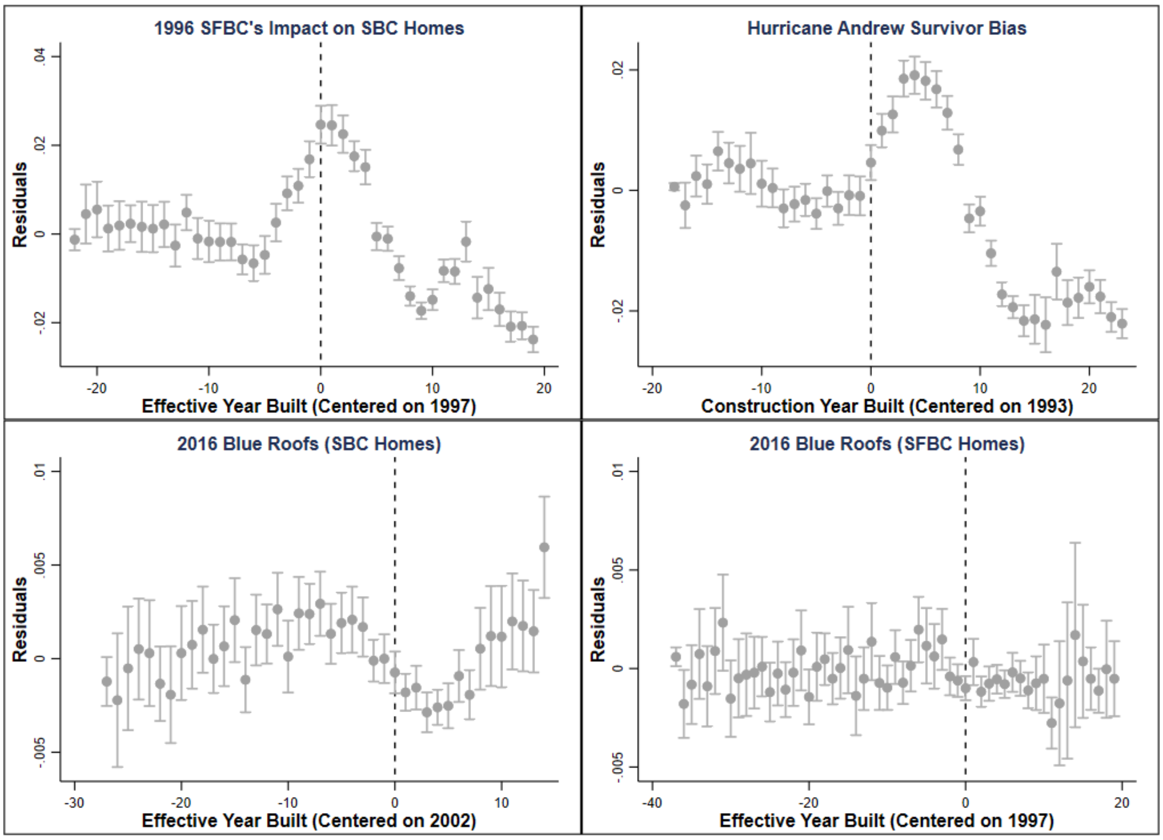

Figure notes: The top-left panel tests for the possibility that SBC (Standard Building Code) homeowners pro-actively adopted standards outlined within the 1996 SFBC (South Florida Building Code) when the SFBC was first enacted. The top-right panel examines whether homes built before and that withstood Hurricane Andrew in August of 1992 were also more resilient to Hurricane Irma nearly 25 years later. Finally, an indicator of whether a blue roof is detected in 2016 imagery is first regressed on a set of housing attributes and census block group fixed effects. Average residuals for each construction year bin are then plotted (grey markers) alongside their 95% confidence intervals (grey brackets) within the bottom panels. Homes built before and during 1975 (1960) are binned into the same year bin for clarity within the bottom left (right) panel.