

Omitted variable bias in wetland-flood regressions

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Abstract

We revisit a recent and influential study that reported flood protection values for all wetlands in the continental United States, which found that a 0.79% decline in wetland area over 2001–2016 increased nationwide insured flood damages by 23.6%. We show that this unusually large estimate is due to a few observations from one hurricane. We then provide evidence that several omitted flood-risk variables which predict these pivotal outliers—such as flood maps, elevation, and the path of a major hurricane—also predict treatment status in the authors’ research design.

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1 Introduction

Wetland ecosystems deliver diverse public goods, but their conservation often involves competing economic and environmental interests that can create controversy (U.S. Supreme Court, 2006). After more than a half-century of extensive federal, state, and local government regulation of the decisions of private landowners following the 1972 Clean Water Act, methods to value wetlands remain crucial to efficiently design conservation policy and assess an array of other government programs, such as the taxpayer-backed flood insurance programs (NFIP), public lands such as national forest and park designations, and the planning and permitting of various civil infrastructure projects.

To this debate, Taylor and Druckenmiller (2022) (hereafter, TD) contribute regression analyses finding large, positive flood protection externalities of upstream wetlands, a textbook example of a public good that dates to at least Samuelson (1976). They argue that their findings “represent the cost to US taxpayers of converting wetlands to other uses—and thus have policy implications for the highly subsidized NFIP as well as jurisdictional debates around wetland protection under . . . one of the most important federal regulations governing land use in the United States” (p. 1360). Beyond the academic economics community, the results have been cited by major advocacy groups (Woods, 2024; Gourevitch, 2024), legal scholars (Owen, 2024), and at least three federal agencies for official regulatory purposes (Army and EPA, 2022, pp. 86–87; OMB, 2024, p. 29).

These results would indeed have broad-ranging policy implications. The authors conclude that “the 331,000 hectares of wetlands lost over this period increased annual NFIP claims by more than \$600 million per year, which amounts to 23 percent of the average annual program-wide NFIP payouts between 2001 and 2016” (TD, p. 1356). The authors’ data indicate about 41.9 million hectares of the United States were wetlands in 2001, making their estimate equivalent to finding that the less than one percent (0.79%) decline in wetland area increased insured flood damages by 23.6%, or an elasticity of $0.236/0.0079 \approx 29.9$. This elasticity contrasts sharply with prior estimates, which find flood protection elasticities in the ranges of 0.60–0.86 (Brody *et al.*, 2015), 0.57–0.80 (Sun and Carson, 2020), and 0.20–0.46 (Aronoff and Rafey, 2026).

In this comment, we revisit TD’s calculations and their interpretation. Our concern is not that wetlands lack flood-protection value, but rather that the TD long-difference estimates may fail to account for some important underlying

differences in local flood risk and hurricane exposure correlated with both outcomes and treatment status. In their empirical work, these omissions (a) lead to numerical estimates that are highly sensitive to outliers and (b) raise concerns about the validity of the identifying assumptions necessary for the authors’ causal interpretation of their findings.

Our remarks involve three points. First, using TD data only, we show that the baseline TD coefficient is driven entirely by a few outlier zip codes; without these outliers, the estimate falls by more than an order of magnitude and becomes statistically indistinguishable from zero, as do their bottom-line estimates for policymakers. Second, using TD data only, we report state-level estimates, intended to obtain more policy-relevant estimates and to isolate the source of instability, which reveal that the outliers live in Texas and Louisiana. Third, we collect additional data on elevation, underlying flood risk, and the path of Hurricane Harvey—the second-costliest hurricane in U.S. history, which affected only Texas and Louisiana, and occurred in the authors’ post-period—to argue that omitted variable bias is a plausible explanation for the TD findings, rather than some unusually specific form of treatment-effect heterogeneity. Elevation, flood zone maps, and exposure to Hurricane Harvey all predict both costly flooding (the outcome) and local wetland change (the treatment).

2 Robustness using the TD data

We begin by reassessing the robustness of TD’s long-difference estimates using only the TD replication data and code. The concern is that the authors’ outcome data, realized claims, are highly dispersed across zip codes, so a small number of extreme flood-damage observations can have substantial influence on a linear specification.¹ If the coefficient estimates used to value nationwide wetlands depend heavily on these observations, then the national estimate may not be a stable basis for policy valuation.

¹The TD outcome data—zip-code-level changes in realized flood insurance claims, 2001–2016, calculated for each zip code by subtracting its 1999–2003 annual mean from its 2014–2018 mean—exhibit a large number of zeros (59.9%) and extreme dispersion (coefficient of variation of 16.7). The 99th, 99.9th, and 100th percentiles of zip-code-level changes in flood insurance claims are \$1.43 million, \$21.78 million, and \$112.98 million, respectively.

2.1 Long-difference estimates

We first replicate TD’s long-difference estimate from column (1) of their Table 1 (TD, p. 1348). We then look at two robustness specifications. First, we trim the outcome variable by dropping zip codes with claims growth below the 0.5th percentile or above the 99.5th percentile. Second, we drop zip codes with claims growth below the 1st percentile or above the 99th percentile.

These exercises do not impose a new structural model of flood damages, nor do they require changing the TD control set. Instead, they ask whether the published long-difference estimate is robust to removing the least and most extreme outcome observations.

Table 1 shows that the baseline estimate is not robust. We begin with columns (1)–(3), which use the TD replication data and vary only the treatment of extreme claims observations. Column (1) reproduces the negative TD coefficient on wetland change. The point estimate is -229.2 , implying that zip codes with greater wetland loss experienced larger increases in NFIP claims. However, once extreme claims observations are removed, the estimate falls sharply. With 0.5/99.5 percentile trimming, the coefficient falls to -14.4 . With 1/99 percentile trimming, it falls to -5.5 . Neither coefficient is statistically distinguishable from zero.

Note that, while dropping the outliers makes the headline coefficient statistically insignificant in (2) and (3), the overall fit of the model nearly doubles. After dropping the most extreme one percent of claims observations, for example, the R^2 approximately doubles from 0.057 to 0.112. This indicates that the imprecision in the wetland coefficient is not due to a specification that explains less of the outcome variation. On the contrary, removing extreme observations both improves model fit and eliminates the large negative estimate.

2.2 Average wetland values

The analysis above focuses on the primary coefficient in TD’s main table, but their policy recommendations are based on a more complicated specification that distinguishes between positive and negative net wetland changes and also upstream wetlands.

Table 2 shows that these more complicated research designs have no effect on the conclusion that everything is driven by the outliers. That is, the instability carries directly into the implied valuation exercise. In the original full sample, exactly as TD report, the spatial-lags model implies an average annual

wetland value of about \$1,897 per hectare (TD, p. 1350). Under the 0.5/99.5 percentile trimming rule, the corresponding value falls to \$406. Under the 1/99 percentile trimming rule, it falls to \$132. Excluding Texas and Louisiana—for reasons we discuss below—yields \$99. The same pattern holds for the difference-in-differences valuation and for the developed-area and undeveloped-area decompositions: the implied values are much smaller under the robustness samples than in the full sample.

These results indicate that TD’s average wetland value is not a stable national statistic. The estimate is highly sensitive to extreme claims observations, which can change implied wetland values by an order of magnitude. Appendix Table A2 reports additional winsorization exercises, which similarly show that the headline estimate is sensitive to the tails of the claims and wetland-change distributions. Together, these tests suggest that the empirical results in TD are highly sensitive to a small number of realized claims.

2.3 State-level analysis

Tables 1–2 establish that the results are wholly driven by 1% of the observations. A natural next step is to ask whether these observations are concentrated in certain states, given that an unusual aspect of the authors’ design is to include all wetlands in the continental United States, rather than study narrower geographic regions or storm events like most prior work.²

Table A1 runs the authors’ primary specification separately for each state. Note that this maintains all of the same identifying assumptions as the authors, who include state fixed effects in all specifications. The results vary widely. Only five of the forty-nine³ state-specific regression coefficients are statistically significant at the 10% level, and three of the five significant ones have the opposite sign of the authors’ reported finding: i.e., for those three states, a causal interpretation of the wetland-flood regression would lead one to conclude that greater wetlands lead to greater flood damage. Overall, of the 42 states with nonzero estimates, 22 have coefficients of the opposite sign (including Florida), whereas 20 are of the authors’ sign. This instability raises concerns with the TD research design beyond the scope of the discussion here, but suggests that more narrowly tailored study areas may be more fruitful for future work than the national scope

²For example, studies of the Gulf Coast (Brody *et al.*, 2015), Florida (Aronoff and Rafey, 2026), or Louisiana (Barbier, 2013), or analyses at the hurricane level (Sun and Carson, 2020).

³DC is included but Alaska and Hawaii are not.

of TD.

Of course, the state-level estimates must aggregate to the large and negative national coefficient in the pooled regression. Column (4) of Table A1 indicates a potential explanation. Two states in TD’s dataset have extreme outlier outcomes: Texas and Louisiana, which saw increases of 1.0 million and 1.2 million in claims per zip code per year, respectively. These increases are about four times as large as the state with the next-largest outcome (Florida, at 0.29 million) and more than ten times any state other than Florida and the Carolinas. These data are consistent with coastal states bearing most of the burden of flood risk in the United States, but raise concerns for a research design that pools all wetlands in the United States into a single regression.

One might wonder whether something interesting happened in Texas and Louisiana during the authors’ study period. The answer is Hurricane Harvey, the second-costliest hurricane in U.S. history (NOAA, 2018, 2024), which struck Texas and Louisiana in August 2017, midway through the authors’ post-period (2014–2018).

Columns (4) and (5) of Table 1 directly test the Harvey explanation for the authors’ main findings. Column (4) runs the original TD specification exactly as the authors do, except without zip codes in Texas and Louisiana. The estimate of the coefficient falls by nearly an order of magnitude (to -38.6 from -229.2), and, as in columns (2) and (3), ceases to be statistically distinguishable from zero. Column (5) leverages additional data that we discuss below on zip codes that were affected by Hurricane Harvey (242 out of 25,734 zip codes, or 0.94% of the observations). Note that because the authors run a long difference in levels, all time-invariant characteristics of zip codes will be differenced out in their regression, so controlling for whether a zip code is affected by Hurricane Harvey cannot change their coefficient estimate. Column (5) therefore interacts the treatment variable, the change in wetlands from 2001–2016, with an indicator for Harvey. The results are stark: only wetland changes in Harvey zip codes have a statistically significant flood-protection coefficient, and the coefficient is 80 times as large as the authors’ reported national coefficient ($18369.6/229.16 = 80.16059$).

3 Omitted variables and Hurricane Harvey

Section 2 showed that the TD estimate depends on a small number of zip codes in Texas and Louisiana. A natural question is whether this sensitivity exclusively

indicates treatment-effect heterogeneity—that wetlands in the zip codes exposed to Hurricane Harvey happen to be exceptionally valuable—or a distinct concern with omitted variable bias related to underlying flood risk that also correlates with treatment status.⁴

Figure 1, which maps the authors’ outcome variable for Texas and Louisiana zip codes, provides an illustration of the authors’ identification strategy and the omitted variable concern. The Taylor and Druckenmiller (2022) long-difference, state-fixed-effects design compares places with relatively little wetland disappearance, such as Amarillo in north Texas (an average of -10 ha per zip code of upstream wetland change from 2001–2016, according to the authors’ data), with zip codes with a lot of wetland disappearance, such as in Houston and Galveston in the Texas Gulf Coast (-211 and -161 ha/zip, respectively). As Figure 1 shows, these places did experience massive differences in flooding: average claims rose by \$8,017,430 and \$889,170 per zip code in Houston and Galveston, respectively, compared with only \$10,960 per zip code in Amarillo. The threat to exclusion is that the land in these places is wet (i.e., exposed to floods) for similar reasons that wetlands are present: the latter group consists of low-lying, humid subtropical grasslands, swamps, and forests (at 87.3 and 23.0 feet above sea level, resp.), whereas the former is high-elevation, semi-arid plateau (average elevation of 3,624 feet above sea level). But to interpret their estimates as causal, the authors’ identification strategy requires that residual wetland changes are randomly assigned across places like Amarillo, Houston, and Galveston.

To test this prediction more systematically, we now augment the original TD data with three new data sources on underlying flood risk and storm exposure, discussed in detail in Appendix A: (a) geocoded USGS storm monitors that measured the intensity of Hurricane Harvey (USGS, 2017); (b) street-level flood zone maps for each state from the FEMA (2023) National Flood Hazard Layer (NFHL); and (c) elevation measures from topographic data in Texas and Louisiana (Open-Elevation, 2026).

3.1 Omitted flood risks predict floods

We begin with the geography of realized flood claims (the outcome variable). Figure 1 maps zip-level NFIP claims growth in Texas and Louisiana, with the

⁴Each explanation raises distinct econometric questions about the study’s validity for US-wide wetland valuation, but the omitted-variable concern cannot be addressed with more flexible transformations of TD’s own dataset.

zip codes affected by Hurricane Harvey outlined in black. Not surprisingly—given the estimate in column (5) of Table 1, where interacting treatment with an indicator for Harvey shows the interaction drives the entire growth in claims—the map shows significant growth in flood claims in the path of Hurricane Harvey. In Texas, for example, we calculate that Harvey zip codes account for 81.2 percent of Texas claims growth from 1999–2003 to 2014–2018 in the TD data (Table 3).

Harvey’s devastation also correlates with the other determinants of flood risk that we match to the TD sample: elevation and flood zone designations (mapped in Appendix Figures A2–A4). Table 3 shows that Texas zip codes have mean elevation of 39 meters inside Harvey’s path, in contrast to the rest of the state, where elevation averages 335 meters. Likewise, FEMA designates 25.37 percent of land inside Harvey zip codes as flood zones, compared with 11.26 percent of the rest of the state. These calculations underscore that, within Texas, the zip codes affected by the hurricane differ systematically from other zip codes in the state in terms of underlying determinants of flood risk, a reason why the authors’ state fixed effects did not absorb the omitted Harvey variable.

Similar selection on underlying flood risk also occurs in Harvey’s path through Louisiana, where mean elevation is 13 meters inside Harvey and 33 meters outside. Harvey disproportionately struck flood-zone-designated areas in Louisiana: mean NFHL area is 44.32 percent inside Harvey zip codes, compared with 29.10 percent for the rest of Louisiana. This indicates that Harvey’s path—and, in particular, its large effects on the outcome variable in the TD research design—was not random across zip codes in the affected Gulf Coast states. Consistent with these findings and the earlier result in column (5) of Table 1 that interacted treatment with an indicator for Harvey and found that only the interaction term remained statistically significant, column (6) of Table 1 runs the interaction with the flood zone share variable; the wetland coefficient outside designated flood hazard zones is positive and statistically insignificant, and the interaction is negative but imprecise.

3.2 Omitted flood risks predict wetland change

The preceding evidence shows that claims growth is spatially concentrated in Harvey’s path, especially in Texas, and among lower-lying zip codes in existing flood zones. We next ask whether these omitted variables—Harvey exposure and pre-existing topographical and hydrological determinants of flood risk—are also

related to the authors’ definition of treatment status, local wetland change.

Table 4 provides a direct test of the omitted-variable concern. The dependent variable is TD’s measure of local wetland change. The estimates show that zip codes exposed to Harvey floods saw considerably larger, statistically significant, declines in wetland extent, with a coefficient of -18.8 hectares (relative to the mean of -0.69 across all zip codes). Likewise, zip codes with greater Harvey flooding (higher maximum high water height above ground) and more Harvey high-water-mark observations had significant, negative local wetland growth. An additional foot of Harvey flooding (column 2) predicts an additional -4.5 hectares of wetland change and an additional high-water-mark monitor predicts an additional -1.5 hectares of wetland change (column 3).

The same pattern appears within just the zip codes struck by Harvey. Columns (6)–(7) of Table 4 show that the share of a zip code’s area lying within flood zones is negatively associated with local wetland change, with the effect driven by Zone A (100-year floodplain exposure, more relevant for Harvey’s inland flooding), rather than Zone V (coastal storm-surge flood zone). Within the path of Harvey, lower-lying zip codes were also systematically more likely both to experience greater Hurricane Harvey flooding (Table A3, column 9) and to experience local wetland declines, with a one-meter decrease in elevation correlating with 0.29 hectares of additional wetland loss (Table 4, column 8). See also Figure A1, which shows the corresponding maps of wetland area in 2001 and 2016.

Taken together, zip codes more exposed to Harvey, more intensely affected by Harvey, or more exposed to pre-existing flood risk experienced systematically different wetland change. Appendix Tables A3–A6 further underscore the omitted variable concern. Appendix Tables A3 and A4 show that Harvey exposure, Harvey intensity, elevation, and NFHL exposure are strongly related to NFIP claims, while Appendix Tables A5 and A6 show that these same measures still predict wetland change for the Texas and Louisiana subsample and for an alternative definition of treatment status (wetland loss). Harvey did not strike a random subset of zip codes. It struck a particular geography: low-lying, flood-prone areas along the Gulf Coast and inland floodplain. These are precisely the types of places where wetlands are likely to be present, converted, regulated, restored, or otherwise changing over time. A long-difference regression that omits this geography risks attributing Harvey-related claims to wetland change.

4 Conclusion

Our above analysis indicates that the authors’ main estimates—intended to serve as a foundation for national wetlands policy⁵—depend entirely on a few extreme observations in just two states. Once outliers are removed, the estimated wetland effects fall by an order of magnitude and are no longer statistically distinguishable from zero. The implied wetland values with spillovers fall similarly.

In addition to driving the main results, the unprecedentedly devastating event experienced by Texas and Louisiana during the authors’ post-period correlates with variables that predict treatment status. Harvey exposure, flood zone maps, and elevation each independently predict unusually large local and upstream wetland changes (treatment status) as well as very costly flooding (outcomes), conditional, of course, on all of the authors’ controls. This omitted-variable structure threatens the causal interpretation of the TD long-difference design.

Our bottom line is not that wetlands have no flood-protection value, but rather that the methods in Taylor and Druckenmiller (2022) do not recover a relationship that is either robust or obviously causal. Future work on the empirical patterns of floods and wetlands—particularly work that proposes causal interpretations of these patterns—should consider more narrowly tailored research designs in settings that allow clearer separation between wetland change, realized disaster exposure, and underlying flood risk.

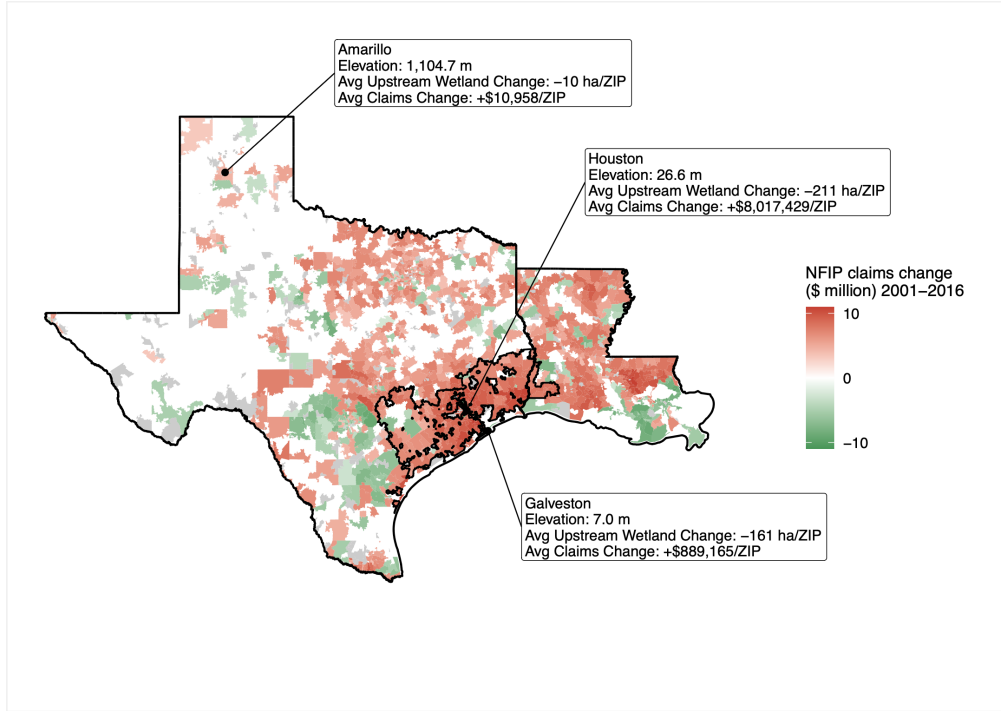
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⁵This is the authors’ stated motivation: “Addressing this lack of information is the core motivation for this paper: the EPA and Army Corps cite a lack of credible estimates of the value of wetlands to justify the exclusion of most wetland benefits under the 2020 NWPR rule” (TD, p. 1345).

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5 Figures and Tables



Zip-level change in NFIP claims, 2001–2016. Selected cities are labeled.

Figure 1: NFIP Claims Change in Texas and Louisiana

Notes: Selected city labels aggregate zip observations intersecting Census place boundaries and included in the TD sample: Amarillo (11 zips), Houston (106 zips), and Galveston (3 zips). Average claims change from 2001–2016 is the average TD outcome (change from 1999–2003 to the 2014–2018 five-year averages) calculated over all zip codes within each labeled city group. Black outline denotes zip codes struck by Hurricane Harvey. Elevations are reported in meters; the corresponding values in feet are 3,624 (Amarillo), 87 (Houston), and 23 (Galveston).

Table 1: Reassessing the Effect of Wetlands on Flood Damage

	<i>Dependent variable:</i>					
	Change in zip code-level NFIP claims (US\$)					NFHL
	All	99pct	98pct	No TX/LA	Harvey	
	(1)	(2)	(3)	(4)	(5)	(6)
Wetland change, 2001–2016	−229.158 (127.697)	−14.360 (15.143)	−5.529 (7.195)	−38.636 (29.409)	−50.665 (115.091)	63.123 (110.208)
Wetland change × Harvey zip code					−18,369.610 (6,830.679)	
Wetland change × NFHL share						−14.759 (9.925)
Observations	25,734	25,476	25,218	23,752	25,734	25,734
R ²	0.057	0.112	0.113	0.036	0.134	0.063
Adjusted R ²	0.055	0.110	0.111	0.034	0.132	0.061

Notes: The unit of observation is the zip code. Column (1) replicates the baseline TD long-difference specification. Columns (2)–(3) drop zip codes with claims growth below the 0.5th percentile or above the 99.5th percentile and below the 1st percentile or above the 99th percentile, respectively. Column (4) drops Texas and Louisiana. Columns (1)–(4) use only the TD replication data. Columns (5)–(6) add newly collected measures of Hurricane Harvey exposure and FEMA National Flood Hazard Layer (NFHL) exposure. All specifications include the baseline TD controls and fixed effects. Standard errors are clustered at the county level.

Table 2: Recalculating Average Wetland Value

	All	99pct	98pct	No TX/LA	Harvey	NFHL
Spillovers, spatial lags model (\$/ha/year)	1,897	406	132	99	1,487	1,646
Spillovers, DID	1,843	308	107	388	1,583	1,575
Spillovers, spatial lags model, developed areas only	7,978	1,455	553	937	3,473	6,202
Spillovers, DID, developed areas only	9,715	1,726	676	962	4,850	7,024
Spillovers, spatial lags model, undeveloped areas only	463	117	44	−20	529	166
Spillovers, DID, undeveloped areas only	403	62	25	206	914	307

Notes: This table reports implied average wetland values calculated using TD’s valuation formulas. Column (1) replicates TD’s baseline average-value calculations using the full TD sample. Columns (2)–(3) use the claims-trimmed samples that drop zip codes with claims growth below the 0.5th percentile or above the 99.5th percentile and below the 1st percentile or above the 99th percentile, respectively. Column (4) excludes Texas and Louisiana. Columns (1)–(4) use only the TD replication data. Columns (5)–(6) report the implied values from specifications that add newly collected Hurricane Harvey exposure and NFHL exposure measures.

Table 3: Claims, Wetlands, Elevation, and Flood Hazard Summary

	TX	LA	US Other
Panel A. NFIP claims			
Flood claims in 2001 (000s)	212,291.46	48,868.50	292,489.53
Flood claims in 2016 (000s)	1,781,586.77	556,405.27	777,321.35
Change in flood claims, 2001–2016 (000s)	1,569,295.31	507,536.77	484,831.82
Change in flood claims outside Harvey zips (000s)	295,093.24	502,406.72	484,831.82
Change in flood claims inside Harvey zips (000s)	1,274,202.07	5,130.05	—
Share of total change inside Harvey zips (%)	81.20	1.01	—
Panel B. Wetlands			
Wetland area in 2001 (ha)	2,209,963.10	2,973,916.45	34,543,246.66
Wetland area in 2016 (ha)	2,170,512.97	2,985,026.22	34,553,813.51
Net wetland change, 2001–2016 (ha)	−39,450.13	11,109.77	10,566.85
Net wetland change outside Harvey zips (ha)	−28,561.32	11,720.86	10,566.85
Net wetland change inside Harvey zips (ha)	−10,888.81	−611.09	—
Share of total wetland change inside Harvey zips (%)	27.60	−5.50	—
Panel C. Elevation			
Mean elevation (m)	291.23	32.30	—
Mean elevation outside Harvey zips (m)	335.29	32.81	—
Mean elevation inside Harvey zips (m)	39.10	13.00	—
Difference: inside minus outside (m)	−296.18	−19.81	—
Panel D. FEMA flood hazard			
Mean NFHL exposure (%)	13.38	29.50	9.53
Mean Zone A exposure (%)	12.76	27.45	9.26
Mean Zone V exposure (%)	0.62	2.05	0.27
Mean NFHL exposure outside Harvey zips (%)	11.26	29.10	9.53
Mean NFHL exposure inside Harvey zips (%)	25.37	44.32	—
Difference: inside minus outside (pp)	14.11	15.22	—

Notes: Claims and wetland measures are constructed from TD replication data. Elevation and NFHL exposure are newly merged zip-level measures. NFHL exposure is measured as the share of zip land area in FEMA flood hazard Zones A or V. Harvey zip codes are derived from zip codes included in the TD data. The US–Other column excludes Texas and Louisiana. Elevation is reported only for Texas and Louisiana. Appendix A contains additional details on the data sources not present in TD’s dataset.

Table 4: Harvey Exposure and Flood-Risk Geography Predict Wetland Change

	<i>Dependent variable: Local wetland change (ha)</i>							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Harvey indicator	-18.819 (7.680)							
Max Harvey flood height		-4.474 (1.541)		-3.097 (1.465)				
Harvey high-water marks count			-1.534 (0.758)		-0.601 (0.447)			
Flood zone share						-0.585 (0.390)		
Zone A share							-1.086 (0.427)	
Zone V share							0.483 (0.774)	
Elevation								0.290 (0.109)
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓
Full sample	✓	✓	✓					
Harvey zips only				✓	✓	✓	✓	✓
Mean dep. var. (ha)	-0.69	-0.69	-0.69	-47.52	-47.52	-47.52	-47.52	-47.52
Observations	25,734	25,734	25,734	242	242	242	242	242
R ²	0.057	0.058	0.057	0.396	0.391	0.401	0.421	0.398
Adjusted R ²	0.055	0.056	0.055	0.376	0.370	0.380	0.398	0.378

Notes: Dependent variable is local wetland change (hectares), 2001–2016, from TD. The table tests whether Hurricane Harvey exposure and underlying flood-risk geography predict wetland change, conditional on TD baseline controls. Standard errors are clustered at the county level. Harvey indicator is defined as 1 if the zip code is in the Harvey path (Appendix A) and 0 otherwise. Flood zone share is calculated as the sum of share of Zone A (100-year floodplain) and Zone V (coastal storm-surge zone) shares and are scaled to 0–100 (percentage points) rather than 0–1 for readability. Appendix Table A5 reports analogous TX/LA-only specifications, and Appendix A6 reports a wetland-loss version of the same exercise. Appendix A contains additional details and variable definitions.

Online Appendix – Supplementary Tables

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Table A1: State-by-State Baseline Wetland Coefficients

State	Wetland coefficient	Std. error	Observations	Mean claims change (\$000s)	R-squared
National	-229.16	(127.70)	25734	99.544	0.057
AL	-725.43	(521.35)	548	15.444	0.328
AR	17.13	(21.15)	469	15.868	0.074
AZ	11.46	(7.11)	296	7.038	0.275
CA	41.81	(38.27)	1298	8.407	0.046
CO	68.22	(70.41)	402	-0.062	0.131
CT	0.00	(0.00)	229	0.000	—
DC	13,403.82	(23,497.51)	8	9.256	0.671
DE	-368.40	(67.19)	52	-62.749	0.156
FL	256.96	(164.33)	787	287.635	0.028
GA	366.40	(716.59)	608	26.189	0.233
IA	-23.02	(24.26)	823	4.559	0.140
ID	-7.20	(7.36)	234	2.909	0.048
IL	13.24	(15.88)	1119	5.653	0.013
IN	110.18	(107.52)	646	6.081	0.023
KS	4.63	(8.57)	618	4.071	0.114
KY	-243.47	(215.28)	571	14.505	0.111
LA	-2.33	(387.15)	429	1183.069	0.217
MA	-0.00	(0.00)	411	0.000	—
MD	2,368.20	(2,463.67)	359	-68.588	0.059
ME	-0.00	(0.00)	379	0.000	—
MI	21.74	(30.75)	861	6.451	0.398
MN	-127.85	(81.57)	700	-1.983	0.411
MO	83.20	(247.38)	851	33.739	0.042
MS	5.61	(31.57)	359	2.587	0.071
MT	-0.31	(2.11)	282	1.049	0.122
NC	-7,494.97	(1,537.84)	690	150.593	0.072
ND	-1.06	(1.13)	203	-0.136	0.038
NE	-1.38	(1.32)	503	1.919	0.065
NH	-0.00	(0.00)	213	0.000	—
NJ	-0.00	(0.00)	388	0.000	—
NM	0.01	(0.93)	220	0.911	0.058
NV	55.08	(13.09)	117	4.390	0.285
NY	-6.58	(19.61)	1256	3.495	0.012
OH	-90.11	(129.09)	919	3.085	0.067
OK	37.61	(13.46)	565	9.728	0.085
OR	-0.76	(1.26)	349	0.498	0.040
PA	745.85	(268.52)	1189	-1.070	0.037
RI	-0.00	(0.00)	54	0.000	—
SC	-1,005.48	(691.26)	362	208.059	0.197
SD	0.92	(1.05)	312	0.585	0.287
TN	-40.18	(84.17)	559	-1.097	0.017
TX	-1,200.80	(816.68)	1553	1010.493	0.137
UT	-0.20	(0.50)	239	0.272	0.030
VA	896.90	(1,230.43)	721	-29.540	0.068
VT	0.00	(0.00)	228	0.000	—
WA	-197.69	(145.52)	486	4.814	0.138
WI	13.78	(24.66)	697	6.234	0.031
WV	-422.00	(519.77)	463	8.896	0.031
WY	4.80	(6.47)	109	2.269	0.119

Notes: Each row reports the coefficient on local wetland change from the baseline TD long-difference regression for each state. The dependent variable is TD's measure of the change in annual NFIP claims at the zip code level (from 1999–2003 to 2014–2018). All regressions include TD baseline controls and standard errors are clustered at the county level when possible and are reported in parentheses. Rows with undefined R^2 reflect states where the within-state regression has insufficient residual variation or too few usable observations after dropping missing values.

Table A2: Reassessing the Effect of Wetlands on Flood Damage (Winsorized)

	<i>Dependent variable:</i>						
	Change in zip code-level NFIP claims (US\$)						
	All (1)	Both (2)	Both (3)	Claims (4)	Claims (5)	Wetlands (6)	Wetlands (7)
Wetland change, 2001–2016	–229.16 (127.70)			–57.69 (37.47)	–25.55 (16.39)		
Wetland change, 2001–2016		–296.79 (107.87)				–992.64 (419.88)	
Wetland change, 2001–2016			–231.53 (68.26)				–1,687.93 (640.62)
Baseline controls	✓	✓	✓	✓	✓	✓	✓
Claims winsorized		0.5/99.5	1/99	0.5/99.5	1/99		
Wetland change winsorized		0.5/99.5	1/99			0.5/99.5	1/99
Full sample	✓	✓	✓	✓	✓	✓	✓
Mean dep. var. (US\$000s)	99.54	47.33	29.89	47.33	29.89	99.54	99.54
Observations	25,734	25,734	25,734	25,734	25,734	25,734	25,734
R ²	0.057	0.147	0.177	0.145	0.175	0.058	0.059
Adjusted R ²	0.055	0.145	0.176	0.143	0.173	0.056	0.057

Notes: This table reports long-difference regressions of NFIP claims growth between 1999–2003 and 2014–2018 on local wetland change from 2001–2016. Column (1) replicates the baseline TD long-difference specification. Columns (2)–(3) winsorize both claims growth and wetland change at the 0.5/99.5 and 1/99 percentiles, respectively. Columns (4)–(5) winsorize only claims growth at the same cutoffs. Columns (6)–(7) winsorize only wetland change at the same cutoffs. All specifications include the baseline TD controls and fixed effects, use the full TD sample, and cluster standard errors at the county level.

Table A3: Long Difference Regressions with Added Controls

	<i>Dependent variable:</i>								
	Change in zip code-level NFIP claims (US\$)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Local wetland change (ha)	-229.2 (127.7)	-755.3 (514.4)	-166.8 (448.1)	-339.7 (435.5)	-594.2 (460.5)	-1,002.8 (758.2)	-18,860.0 (7,040.9)	-26,538.4 (25,825.4)	-36,534.0 (10,977.5)
Harvey indicator			3,063,823.0 (533,134.2)						
Max Harvey flood height				887,171.5 (199,866.3)					
Harvey high-water marks count					273,258.6 (85,402.0)				
Elevation						-1,709.5 (393.4)			-29,576.6 (10,735.5)
Flood zone share								122,378.3 (101,317.8)	
Local wetland change $\times$ Harvey indicator			-16,451.5 (6,693.0)						
Local wetland change $\times$ max Harvey flood height				-1,086.3 (1,233.4)					
Local wetland change $\times$ Harvey high-water marks count					81.7 (447.1)				
Local wetland change $\times$ elevation						0.5 (0.8)			993.7 (426.1)
Local wetland change $\times$ flood zone share								292.0 (572.1)	
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Full sample	✓								
TX/LA only		✓	✓	✓	✓	✓			
Harvey zips only							✓	✓	✓
Mean dep. var. (US\$000s)	99.54	1047.85	1047.85	1047.85	1047.85	1047.85	5286.5	5286.5	5286.5
Observations	25,734	1,982	1,982	1,982	1,982	1,982	242	242	242
R ²	0.057	0.114	0.166	0.184	0.152	0.121	0.208	0.235	0.231
Adjusted R ²	0.055	0.110	0.161	0.180	0.148	0.116	0.181	0.202	0.198

Notes: Dependent variable is the change in NFIP claims at the zip-code-level from 1999–2003 to 2014–2018. Column (1) replicates the baseline TD long-difference specification; columns (2)–(6) restrict the data to Texas and Louisiana; columns (7)–(9) further restrict the sample to Harvey-impacted zip codes. Baseline estimates using only TD controls appear in columns (1), (2), and (7). NFHL share is calculated as the sum of Zone A share (100-year floodplain) and Zone V share (storm-surge zone) in percentage points (0–100) for readability. All specifications include the baseline TD controls and fixed effects. Standard errors are clustered at the county level.

Table A4: Long Difference Regressions with NFHL Layer Controls

	<i>Dependent variable:</i>				
	Change in zip code-level NFIP claims (US\$)				
	(1)	(2)	(3)	(4)	(5)
Local wetland change (ha)	-18,860.0 (7,040.9)	-14,996.8 (8,524.7)	-9,291.8 (8,380.7)	-26,538.4 (25,825.4)	-29,274.8 (25,116.7)
Flood zone share		110,316.0 (93,248.5)		122,378.3 (101,317.8)	
Zone A share			199,342.7 (117,029.5)		227,714.6 (123,273.1)
Zone V share			-68,924.3 (42,360.9)		-61,131.6 (45,913.5)
Local wetland change $\times$ flood zone share				292.0 (572.1)	
Local wetland change $\times$ Zone A share					576.1 (611.7)
Local wetland change $\times$ Zone V share					168.9 (537.6)
Baseline controls	✓	✓	✓	✓	✓
Harvey zips only	✓	✓	✓	✓	✓
Mean dep. var. (US\$000s)	5286.5	5286.5	5286.5	5286.5	5286.5
Observations	242	242	242	242	242
R ²	0.208	0.234	0.267	0.235	0.271
Adjusted R ²	0.181	0.204	0.235	0.202	0.233

Notes: Dependent variable is the change in NFIP claims at the zip-code level from 1999–2003 to 2014–2018. Sample restricted to Harvey-affected zip codes in Texas and Louisiana. NFHL share is calculated as the sum of Zone A share (100-year floodplain) and Zone V share (storm-surge zone) in percentage points (0–100) for readability. All specifications include TD baseline controls and TD state fixed effects; standard errors are clustered at the county level.

Table A5: Harvey Exposure and Wetland Change in Texas and Louisiana

	<i>Dependent variable: Local wetland change (ha)</i>			
	(1)	(2)	(3)	(4)
Harvey indicator	−20.441 (7.830)			
Max Harvey flood height		−4.744 (1.539)		
Harvey high-water marks count			−1.593 (0.769)	
Elevation				−0.030 (0.028)
Baseline controls	✓	✓	✓	✓
TX/LA only	✓	✓	✓	✓
Mean dep. var. (ha)	−14.30	−14.30	−14.30	−14.30
Observations	1,982	1,982	1,982	1,982
R ²	0.022	0.022	0.022	0.022
Adjusted R ²	0.018	0.018	0.018	0.018

Notes: Dependent variable is local wetland change (hectares), 2001–2016. The sample is restricted to Texas and Louisiana zip codes. The table reports the TX/LA-only identification checks corresponding to Table 4. Columns test whether Hurricane Harvey exposure or elevation predict wetland change after conditioning on TD baseline controls. Standard errors are clustered at the county level.

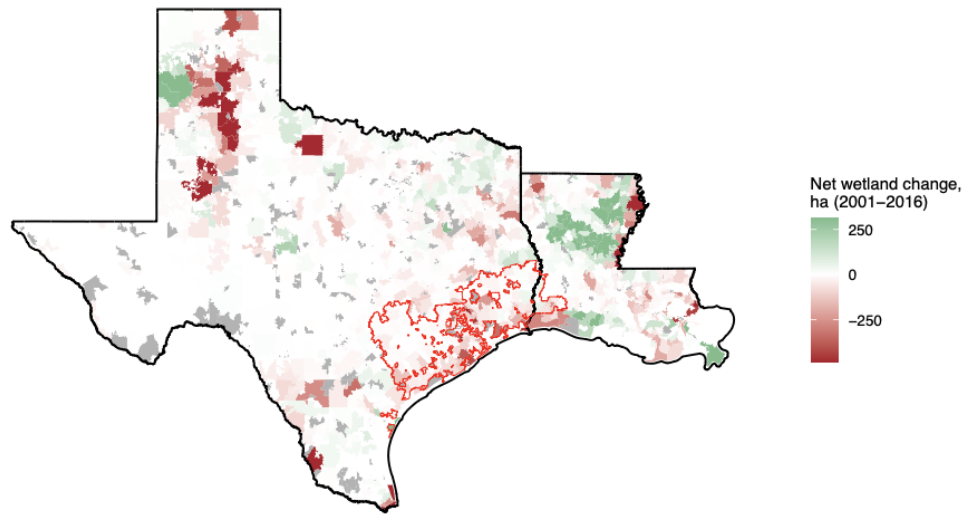
Table A6: Harvey Exposure and Wetland Loss in Texas and Louisiana

	<i>Dependent variable: Local wetland loss (ha)</i>				
	(1)	(2)	(3)	(4)	(5)
Harvey indicator	−17.559 (7.191)				
Max Harvey flood height		−4.446 (1.468)			
Harvey high-water marks count			−1.565 (0.728)		
Flood zone share				−0.758 (0.335)	
Elevation					0.335 (0.101)
Baseline controls	✓	✓	✓	✓	✓
TX/LA only	✓	✓	✓		
Harvey zips only				✓	✓
Mean dep. var. (ha)	−32.52	−32.52	−32.52	−50.55	−50.55
Observations	1,982	1,982	1,982	242	242
R ²	0.015	0.016	0.016	0.445	0.437
Adjusted R ²	0.011	0.012	0.012	0.426	0.417

Notes: Dependent variable is local wetland loss (hectares), 2001–2016. Columns examine whether hurricane exposure, flood intensity, flood-zone shares, or elevation predict wetland loss across Texas and Louisiana zip codes. Share of nfhl is calculated as the sum of share of zone A (100-year floodplain) and V (storm surge) in percentage points (0–100) for readability. All models include TD baseline controls. Standard errors are clustered at the county level.

Online Appendix – Supplementary Figures

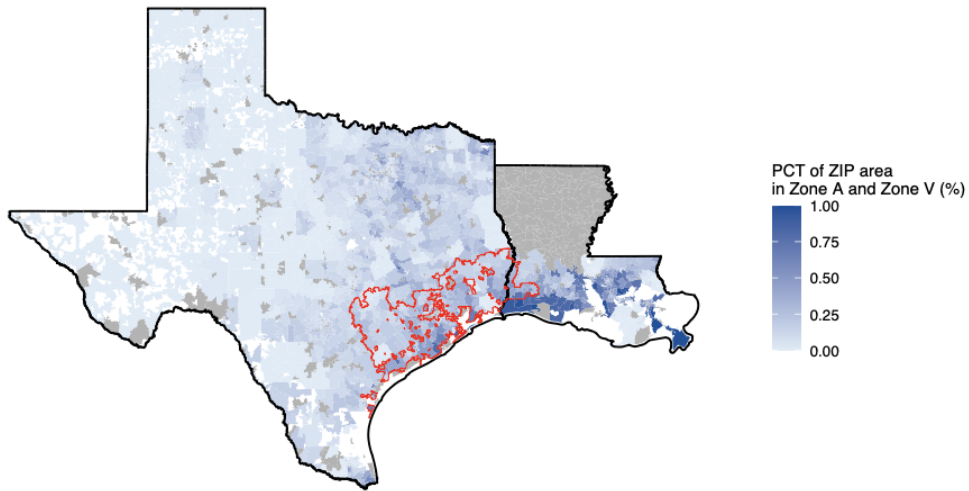
A1	Net Wetland Change in Texas and Louisiana	A-8
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A7	Wetland Area in Texas and Louisiana, 2016	A-14



zip-level change in wetland area, 2001–2016.

Figure A1: Net Wetland Change in Texas and Louisiana

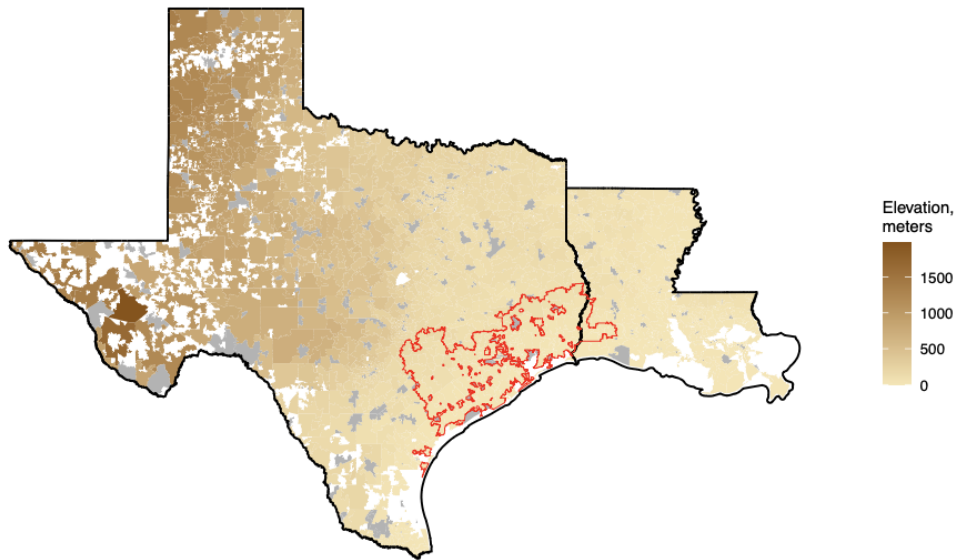
Notes: Red outline denotes the zip codes struck by Hurricane Harvey. The color scale is capped at the 1st and 99th percentiles of wetland change, with values beyond those limits capped to the scale endpoints. Gray areas are not covered by the sample used for the fill.



PCT of zip land area in Special Flood Hazard Areas (Zones A and V).

Figure A2: FEMA Flood Hazard (NFHL) Exposure in Texas and Louisiana

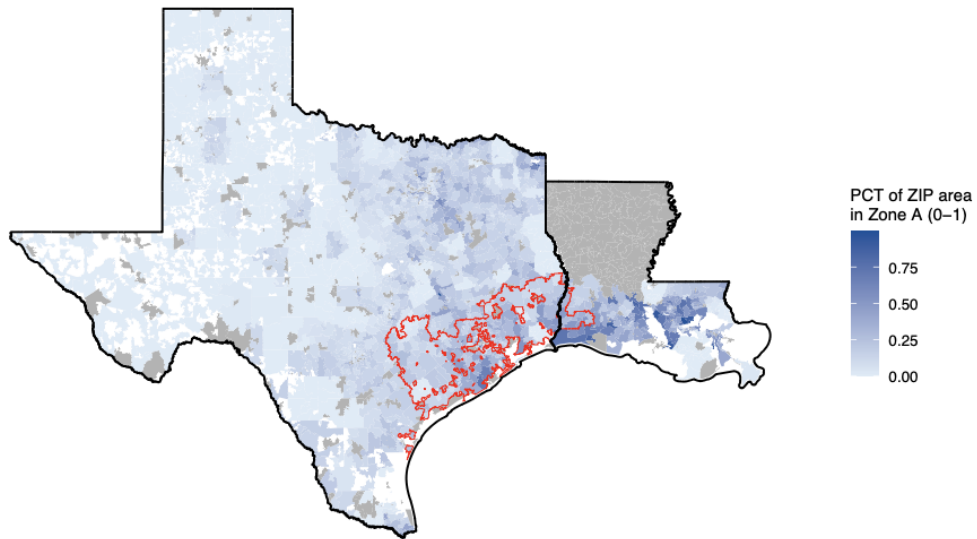
Notes: Red outline denotes the zip codes struck by Hurricane Harvey. Gray areas are not covered by the sample used for the fill. Interior gaps and holes reflect sample construction (TD's omitted coastal zip codes and a small number of unaffected zip polygons). The outline corresponds to the 242 zip codes identified as Harvey-impacted in the earlier regression sample.



zip-level elevation, in meters.

Figure A3: Elevation in Texas and Louisiana

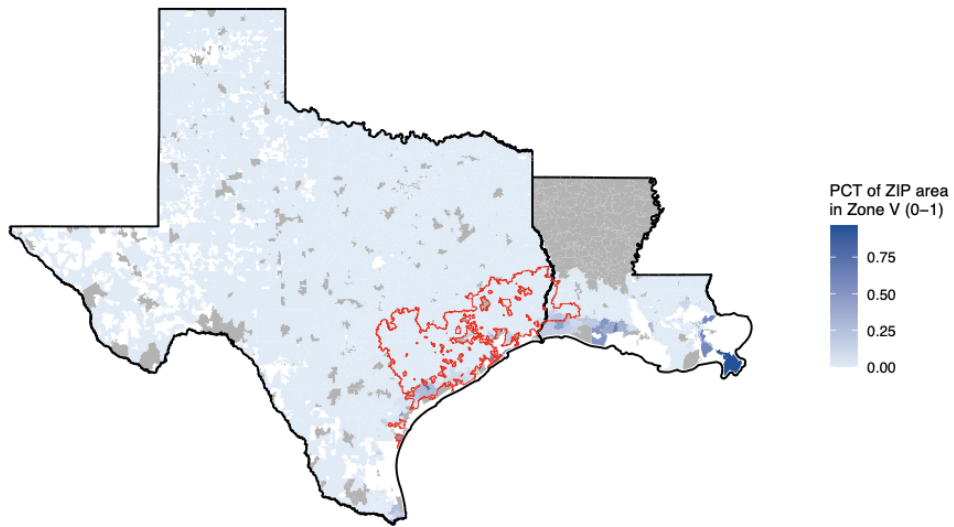
Notes: Red outline denotes the zip codes struck by Hurricane Harvey. Gray areas are not covered by the sample used for the fill. Interior gaps and holes reflect sample construction (TD's omitted coastal zip codes and a small number of unaffected zip polygons). The outline corresponds to the 242 zip codes identified as Harvey-impacted in the earlier regression sample.



PCT of zip land area in Zone A flood hazard areas.

Figure A4: FEMA Flood Hazard Zone A Exposure in Texas and Louisiana

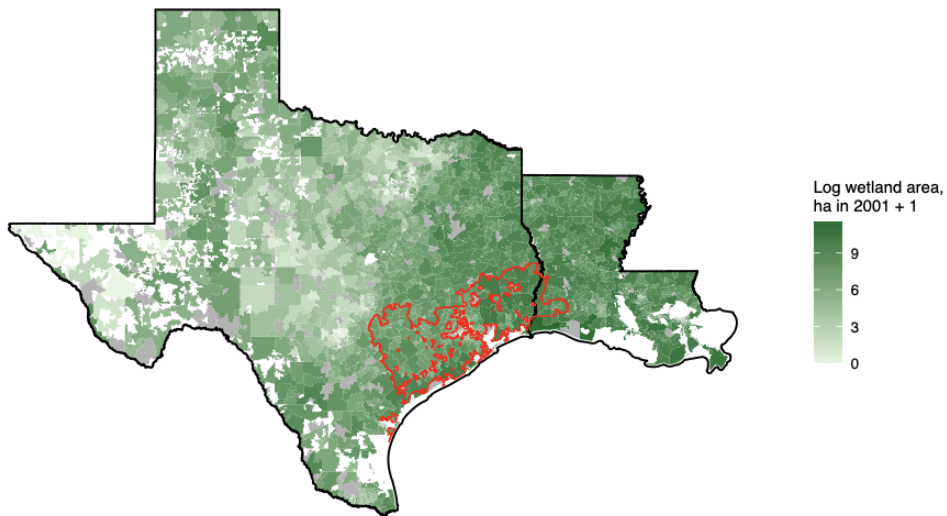
Notes: Red outline denotes the zip codes struck by Hurricane Harvey. Gray areas are not covered by the sample used for the fill. Interior gaps and holes reflect sample construction (TD's omitted coastal zip codes and a small number of unaffected zip polygons). The outline corresponds to the 242 zip codes identified as Harvey-impacted in the earlier regression sample.



PCT of zip land area in Zone V flood hazard areas.

Figure A5: FEMA Flood Hazard Zone V Exposure in Texas and Louisiana

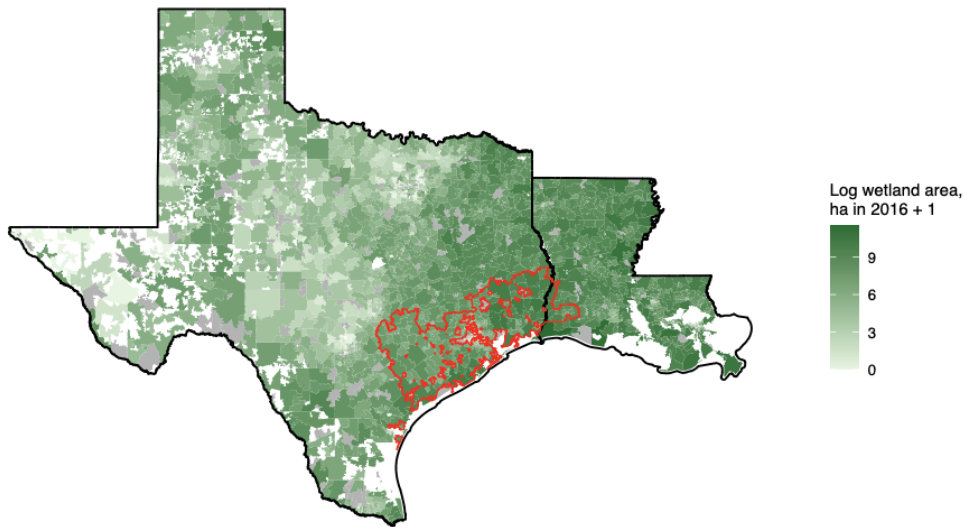
Notes: Red outline denotes the zip codes struck by Hurricane Harvey. Gray areas are not covered by the sample used for the fill. Interior gaps and holes reflect sample construction (TD's omitted coastal zip codes and a small number of unaffected zip polygons). The outline corresponds to the 242 zip codes identified as Harvey-impacted in the earlier regression sample.



Wetland area in 2001 by zip code.

Figure A6: Wetland Area in Texas and Louisiana, 2001

Notes: Red outline denotes the zip codes struck by Hurricane Harvey. Gray areas are not covered by the sample used for the fill. Interior gaps and holes reflect sample construction (TD's omitted coastal zip codes and a small number of unaffected zip polygons). The outline corresponds to the 242 zip codes identified as Harvey-impacted in the earlier regression sample.



Wetland area in 2016 by zip code.

Figure A7: Wetland Area in Texas and Louisiana, 2016

Notes: Red outline denotes the zip codes struck by Hurricane Harvey. Gray areas are not covered by the sample used for the fill. Interior gaps and holes reflect sample construction (TD's omitted coastal zip codes and a small number of unaffected zip polygons). The outline corresponds to the 242 zip codes identified as Harvey-impacted in the earlier regression sample.

A Data Sources and Sample Construction

Here we describe the additional data sources and sample restrictions used in our analysis. We start with the zip-code-level long-difference dataset from Taylor and Druckenmiller (2022). We then add three measures of flood risk and storm exposure across USGS/NOAA point data, SimpleMaps and the Open-Elevation API, and FEMA’s National Flood Hazard Layer (NFHL). These variables are used to evaluate whether the TD estimates are sensitive to observed measures of storm exposure and omitted flood risk geography.

A.1 Baseline TD estimating sample

We begin with the V1 [2022-03-25] TD zip-code long-difference dataset from Taylor and Druckenmiller (2022), available at <https://www.openicpsr.org/openicpsr/project/153221>. TD restrict the baseline estimating sample to zip codes with nonmissing values for NFIP claims growth (the difference between the 2014–2018 and 1999–2003 annual averages), wetland change from 2001–2016, developed area change, income change, population change, housing unit change, housing value change, Community Rating System (CRS) discounts, state FIPS, and county FIPS. We then merge in TD’s coastal zip code file by zip code. The resulting baseline sample contains 25,734 zip codes.

A.2 Hurricane Harvey zip indicator

The key new Harvey variable is a zip-code-level indicator for exposure to Hurricane Harvey. This variable is constructed from the USGS (2017) Harvey peak-summary data, which contain point observations with longitude and latitude coordinates, including measurements of peak stage and height above ground. We convert these observations to spatial points and assign them to zip Code Tabulation Area (ZCTA) polygons using a point-in-polygon overlay. We use the TD zip-state crosswalk to restrict the ZCTA polygons to Texas and Louisiana for the Harvey analysis. Throughout the paper, we refer to these ZCTA-based geographic units as zip codes for consistency with TD.

The variable `ind_Harvey` equals one for zip codes containing at least one Harvey peak-summary point and zero otherwise. This definition captures whether Hurricane Harvey flooding was directly observed in a zip code by the USGS/NOAA peak-summary data. It is not a modeled storm-track polygon or a continuous inundation map; it is a binary indicator for zip codes containing at least one observed Harvey peak-summary measurement.

The point-in-polygon overlay identifies 261 Texas and Louisiana ZCTAs containing at least one Harvey peak-summary observation. Of these, 242 appear in the final TD estimating sample after applying the baseline nonmissing-data and merge restrictions. The remaining 19 Harvey-identified ZCTAs are therefore excluded because they do not appear in the final regression sample.

A.3 Hurricane Harvey intensity measures

We also construct zip-level measures of Harvey intensity from USGS Harvey point data. The main intensity variable used in the paper is `height_above_gnd_max`, defined as the maximum reported height above ground among Harvey peak-summary observations contained within a zip code. Zip codes with no matched Harvey peak-summary point are coded as zero for this variable.

We also construct `harvey_hwm_count` using a filtered USGS Harvey high-water-mark file. After assigning the high-water-mark observations to ZCTA polygons, `harvey_hwm_count` is defined as the number of high-water-mark observations contained within each zip code. We interpret this variable as a measure of documented Harvey flooding or measurement density, rather than as a complete measure of all flooding in the zip code.

A.4 Elevation

We measure zip-code level elevation using the latitude and longitude coordinate associated with each zip/ZCTA in the SimpleMaps zip database (SimpleMaps, 2026). We submit this coordinate to the Open-Elevation API (Open-Elevation, 2026) and record the returned elevation in meters. The resulting variable, `elevation_m`, is a representative-point elevation for the zip code rather than an area-weighted average elevation over the zip polygon. When we report mean elevation for a group of zip codes, such as in Table 3, we calculate the average of these zip-level representative-point elevations across zips.

A.5 Flood zone maps

We use the FEMA (2023) National Flood Hazard Layer (NFHL) to measure baseline floodplain exposure. Each state needs to be downloaded separately. We downloaded these files between August–October 2023 by visiting <https://msc.fema.gov/portal/advanceSearch>, selecting **A STATE**, **ANY COU**, **ANY COMM**, choosing **CURRENT**, then downloading the **NFHL DATA-STATE (1)**, a GDB file. The exact versions used in this analysis are:

Product ID	Latest Study	Effective Date	Latest LOMR	Effective Date	Size
NFHL_01_20230901	09/24/2021	07/21/2023	1356MB		
NFHL_02_20220910	09/18/2020	N/A	68MB		
NFHL_04_20230714	03/21/2023	07/14/2023			
NFHL_05_20230628	09/15/2022	06/28/2023	262MB		
NFHL_06_20230711	09/01/2022	07/12/2023	537MB		
NFHL_08_20230714	05/09/2023	11/05/2021	190MB		
NFHL_09_20230702	04/03/2020	09/14/2022	89MB		
NFHL_10_20230222	01/22/2020	02/23/2023	101MB		
NFHL_11_20211216	09/27/2010	04/19/2021	4MB		
NFHL_12_20230714	01/26/2023	07/14/2023	2358MB		
NFHL_13_20230523	05/23/2023	N/A	1544MB		
NFHL_66_20070928	09/28/2007	N/A	3MB		
NFHL_15_20230503	02/26/2021	05/03/2023	33MB		
NFHL_16_20230703	08/24/2021	07/03/2023	69MB		
NFHL_17_20230712	05/17/2022	07/13/2023	247MB		
NFHL_18_20230706	02/23/2023	07/05/2023	326MB		
NFHL_19_20230623	12/15/2022	06/23/2023	2138MB		
NFHL_20_20230402	11/17/2022	04/03/2023	878MB		
NFHL_21_20230902	05/23/2023	08/10/2023	1262MB		
NFHL_22_20230223	02/23/2023	N/A	1208MB		
NFHL_23_20230902	07/19/2023	N/A	422MB		
NFHL_24_20230902	08/01/2023	08/04/2023	691MB		
NFHL_25_20230902	06/21/2023	08/25/2023	424MB		
NFHL_26_20230902	08/15/2023	N/A	800MB		
NFHL_27_20230826	12/01/2022	01/18/2018	540MB		
NFHL_28_20230902	08/16/2022	08/25/2023	716MB		
NFHL_29_20230902	08/15/2023	N/A	1302MB		
NFHL_30_20230902	08/15/2023	N/A	201MB		
NFHL_31_20230523	10/07/2021	05/23/2023	536MB		
NFHL_32_20230902	05/23/2023	08/22/2023	102MB		
NFHL_33_20221013	01/29/2021	10/11/2022	91MB		
NFHL_34_20230122	06/15/2022	03/21/2019	477MB		
NFHL_35_20230902	11/04/2016	08/14/2023	203MB		
NFHL_36_20230707	03/21/2023	03/07/2023	1092MB		
NFHL_37_20230902	07/19/2022	08/10/2023	1669MB		

NFHL_38_20230324	07/05/2022	11/16/2021	161MB
NFHL_39_20230902	06/07/2023	07/18/2023	793MB
NFHL_40_20230705	07/05/2023	N/A	611MB
NFHL_41_20230902	04/20/2022	08/10/2023	239MB
NFHL_42_20230902	08/16/2022	09/01/2023	1438MB
NFHL_44_20230902	07/19/2023	04/28/2023	157MB
NFHL_45_20230901	05/09/2023	07/20/2023	1113MB
NFHL_46_20230511	09/01/2022	05/11/2023	383MB
NFHL_47_20230902	05/09/2023	08/28/2023	688MB
NFHL_48_20230902	07/19/2023	08/31/2023	2827MB
NFHL_49_20230901	05/09/2023	10/03/2022	113MB
NFHL_50_20211216	12/02/2015	06/02/2010	42MB
NFHL_51_20230902	06/21/2023	09/01/2023	1442MB
NFHL_53_20230902	08/15/2023	12/18/2015	364MB
NFHL_54_20230902	08/01/2023	07/06/2015	368MB
NFHL_56_20221104	06/01/2022	10/21/2022	258MB

The NFHL provides spatial flood hazard designations, including Zone A and Zone V. Zone A corresponds to areas with one-percent annual chance flood risk, commonly referred to as 100-year floodplains, while Zone V corresponds to coastal high-hazard areas subject to wave action and storm surge risk.

We calculate the fraction of each zip code’s land area that falls in FEMA Zone A and Zone V. In the raw data, `pct_A` is the fraction of zip land area in Zone A, and `pct_V` is the fraction of zip land area in Zone V. We define `pct_nfhl` as the sum of these two fractions. These raw variables are measured from 0 to 1. For the tables, we rescale these variables to percentage points, so a one-unit increase in `share_nfhl` corresponds to a one percentage point increase in the share of zip land area located in FEMA Zone A or Zone V. NFHL-based specifications are restricted to zip codes that match to the NFHL exposure data.

A.6 Sample restrictions and observation counts

Several specifications use restrictions of the 25,734-zip baseline TD estimating sample. The 99pct sample excludes observations below the 0.5th percentile and above the 99.5th percentile of NFIP claims growth, leaving 25,476 zip codes. The 98pct sample excludes observations below the 1st percentile and above the 99th percentile of NFIP claims growth, leaving 25,218 zip codes. The No TX/LA sample excludes Texas and Louisiana zip codes, leaving 23,752 zip codes. The TX/LA sample restricts the baseline sample to Texas and Louisiana, leaving 1,982 zip codes.

The Harvey-only specifications use the 242 zip codes with `ind_Harvey` equal to one in the final TD estimating sample. The NFHL specification in Table 1 contains 22,680 observations, compared with 25,734 observations in the full baseline sample; this difference reflects the observations available after merging the FEMA NFHL exposure variables into the baseline TD sample.

For the city labels in Figure 1, we intersect 2020 Census ZCTA polygons with Census place boundaries for Amarillo, Houston, and Galveston, retaining ZCTAs that appear in the TD estimating sample and have nontrivial overlap with the city boundary, defined as at least 1 hectare of overlap and at least 1 percent of the ZCTA’s area. This yields 11 zips for Amarillo, 106 for Houston, and 3 for Galveston. For each city label, elevation is the mean of zip-level representative-point elevation, upstream wetland change is the mean of TD’s net upstream wetland-change variable across included zips, and claims change is the annual mean of zip-level NFIP claims changes between the periods 1999–2003 and 2014–2018.