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Matthew Gibson
Williams College and IZA

Jamie T. Mullins
University of Massachusetts Amherst

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Climate Risk and Beliefs in New York Floodplains*

Applying a difference-in-differences framework to a census of residential property transactions in New York City 2003-2017, we estimate the price effects of three flood risk signals: 1) the Biggert-Waters Flood Insurance Reform Act, which increased premiums; 2) Hurricane Sandy; and 3) new floodplain maps reflecting three decades of climate change. Estimates are negative for all three signals and some are large: properties included in the new floodplain after escaping flooding by Sandy experienced 11 percent price reductions. We investigate possible mechanisms, including selection of properties into the market and residential sorting. Finding no evidence for these, we develop a parsimonious theoretical model that allows decomposition of our reduced-form estimates into the effects of insurance premium changes and belief updating. Results suggest the new maps induced belief changes comparable to those from insurance reform.

JEL Classification: Q54, Q58, R30, G22
Keywords: beliefs, updating, climate change, flood risk

Corresponding author:
Matthew Gibson
Department of Economics
Williams College
24 Hopkins Hall Drive
Williamstown MA 01267
USA
E-mail: mg17@williams.edu

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1 Introduction

Climate change is increasing flood risk through both sea-level rise and growing storm intensity (Cleetus, 2013). The welfare consequences depend on human behavior. Coastal retreat, adaptation, and insurance takeup will all influence realized flood damages, so understanding the determinants of such decisions is important. We study New York residential property market responses to three flood risk signals: 1) the Biggert-Waters Flood Insurance Reform Act, which increased flood insurance premiums; 2) Hurricane Sandy; and 3) new floodplain maps produced by the Federal Emergency Management Agency (FEMA). Exploiting demographic data and a coverage cap in flood insurance contracts, we investigate the possible mechanisms behind these responses, including buyer sorting, selection into transactions, changes in insurance premiums, and belief updating.

The quasi-experimental risk signals we study provide unusual opportunities to examine behavioral responses to climate change. This is particularly true of the updated floodplain maps, which are the primary focus of this paper. In general such responses are difficult to disentangle from confounding trends, as both climate parameters and many economic outcomes evolve continuously over time. If agents are inattentive, however, then risk signals may produce sudden behavioral responses.[1] Because official maps of flood risk in New York City have not been updated since 1983, the 2013 release of proposed new floodplain maps would have confronted an inattentive New Yorker with as many as three decades of climate change in a single day. This allows us to disentangle climate change from other time-varying factors.

Using a census of residential property transactions from the New York City Department of Finance 2003-2017, we estimate treatment effects of risk signals in a hedonic difference-in-differences framework. Our identifying assumption is that absent the signals, average sale prices of treated properties would have evolved in parallel with average sale prices of control properties. Graphs of pre-treatment trends in sale prices suggest the common trends assumption is reasonable. The richness of our property transactions data allows us to employ specifications with tax lot fixed effects, using only repeated sales for identification.[2]

We find the Biggert-Waters Act of 2012, which rolled back premium subsidies on many National Flood Insurance Program (NFIP) policies, decreased sale prices of impacted properties by 3 to 5 percent. These estimates are imprecise, and we cannot reject a hypothesized null effect in any of our main specifications. Flooding during Sandy decreased prices by approximately 4.5 percent for minimally inundated properties, and 5 to 7 percent for properties that experienced average inundation. Finally, we investigate effects on the prices of properties included in the floodplain under updated maps.[3] Prices of Sandy-flooded properties included in the new floodplain fell by roughly 3 percent, with the estimate not statistically distinguishable from zero in our preferred specification. Prices of non-flooded properties included in the new floodplain fell by 11 percent.

These reduced-form price effects potentially reflect several mechanisms. Using American Community Survey data, we first test for differential sorting. Previous literature (Lindell and Hwang, 2008; Kellens et al., 2011, 2012; Mills et al., 2016) has shown that education and duration of residence, for example, are correlates of risk preferences and perceptions. We find that while these and other correlates are evolving

[1] Such inattention could be rational (Sims, 2006; Ellis, 2018) or the result of optimization failure (Kahneman, 2003). Inattention is not the only reason an agent might update her beliefs in response to a risk signal. Other possible explanations include new information, biased beliefs, and changes in salience.

[2] In New York City, a tax lot is the smallest unit at which real estate transactions take place.

[3] FEMA flood risk maps identify the geographic extent of "100-year" and "500-year" floodplains (defined as having $\geq 1\%$ and $.2\% - .99\%$ annual probability of flooding respectively). Zones within the 100-year floodplain are designated Special Flood Hazard Areas and will be the focus of this investigation. Such areas are referred to throughout as the "one percent floodplain" or simply "the floodplain."

over time, changes are strongly similar in our treatment and control groups. Analysis of price effects on fully insurable properties likewise shows no evidence of sorting on risk preferences. Together these exercises suggest that sorting does not have substantial influence on our results. On the supply side of the property market, risk signals could influence selection into our census of transactions. To test this, we first estimate a hedonic model using only pre-treatment data and generate predicted prices for all observations. We then estimate the effects of risk signals on predicted prices. Point estimates are uniformly small and the large majority are not statistically significant. This indicates selection on observables is not driving our treatment effects. Selection on unobserved, unrepaired Sandy damage remains a potential confounder. We estimate our primary specifications on a subsample excluding all sales in the 26 months following Sandy and obtain similar estimates. Two possible mechanisms remain: changes in insurance premiums and belief updating. Both Biggert-Waters and the new floodplain maps changed expected future insurance premiums. Theory predicts the present value of such premium changes will be capitalized into transaction prices. Because many New York residents report inaccurate beliefs (Botzen et al., 2015), they may also update substantially in response to risk signals.[4]

To evaluate the importance of beliefs and insurance, we extend the model of Kousky (2010) to include insurance premiums and risk ratings (floodplain maps). We then derive a novel approximation of derivatives of interest in terms of Arrow-Pratt risk aversion and value at risk. Coupled with data on insurance premiums, this allows us to recover belief changes from our reduced-form treatment effects. Under our preferred set of structural assumptions, we estimate that the Biggert-Waters Act induced an average change in subjective annual flood probability of 0.4 percentage points among buyers of affected properties. Minimal flooding during Sandy increased subjective annual flood probability by .13 percentage points. Among properties that escaped Sandy flooding, but were included in the floodplain under the new maps, subjective probability increased by .27 percentage points. While these changes are small in absolute terms, they are large relative to the one percent or greater annual flood risk estimated by FEMA for floodplain properties. Our results are consistent with homeowner beliefs lagging objective risk measures.

These findings matter because climate change continues to increase flood risk. In New York City, sea level is projected to rise by .55 to 1.4 meters by 2100. As a result, "...flood height return periods that were $\sim$500 y during the preindustrial era [2.25 meters] have fallen to $\sim$25 y at present and are projected to fall to $\sim$5 y within the next three decades" (Garner et al., 2017). Understanding the likely behavioral responses is important not only intrinsically, but also for governments contemplating long-lived defensive investments and forward-looking policies. Our results demonstrate that in some settings information signals generate considerable updating, which is potentially important when price-based policies face political constraints.[5]

To the best of our knowledge, our study is the first to examine changes in official flood risk maps for an important coastal city–New York has $129 billion in property value within the current floodplain (Stringer, 2014). This study is also the first to conduct a thorough empirical investigation of mechanisms behind the effects of flood risk signals on property markets, and the first to recover the belief changes implied by reduced-form estimates. Our paper shares an interest in flood beliefs with a more structural paper by Bakkensen and Barrage (2017) set in Providence, Rhode Island; comparisons are given in Sections 7.2 and 7.3. Our work contributes to the hedonic literature on climate change, which to date has largely focused on agricultural land (Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009; Ashenfelter and Storchmann, 2010). It also contributes to the literatures on capitalization of flood risk (Bin and Polasky, 2004; Kousky, 2010; Atreya

[4]Note that inaccurate beliefs are not a necessary condition for updating in response to risk signals.

[5]As discussed in Section 5, the large updating response to information in this setting may result in part from the previous experience of Hurricane Sandy.

et al., 2013; Bin and Landry, 2013), the NFIP (Kunreuther and Slovic, 1978; Chivers and Flores, 2002; Michel-Kerjan et al., 2012; Gallagher, 2014),[6] and Hurricane Sandy (Ortega and Taspinar, 2018; McCoy and Zhao, 2018).[7] More generally, it speaks to literatures on tail risk perceptions (Botzen et al., 2015), the relative effectiveness of price and information signals (Ferraro and Price, 2013; Jessoe and Rapson, 2014; Delaney and Jacobson, 2015), and the price effects of disaster risk ratings (Garnache, 2019).

The rest of the paper proceeds as follows. Section 2 provides policy background and detail on the three risk signals we study. Section 3 describes our data. Section 4 discusses our empirical approach and Section 5 presents our primary reduced-form results. Section 6 lays out reduced-form robustness checks. Section 7 considers empirical evidence on potential mechanisms and develops a corresponding theoretical model. Approximations of model derivatives permit recovery of belief changes from reduced-form effects. Section 8 concludes.

2 Policy background

The following brief description of the National Flood Insurance Program (NFIP) draws on Michel-Kerjan (2010) and US Government Accountability Office (2008). Congress created the NFIP in 1968 to provide residential flood insurance. The NFIP maps flood risks, sets premiums, and ultimately underwrites policies. The 1973 Flood Disaster Protection Act made coverage mandatory for properties that: 1) are located in a "Special Flood Hazard Area," an area with annual flood risk of one percent or greater; and 2) have a mortgage from a federally regulated financial institution. Despite this nominal insurance mandate, noncompliance remains considerable (Tobin and Calfee, 2005). Coverage of residential structures is capped at $250,000 per insured property and the cap is the same everywhere.[8] Private flood insurance is available in some states, but represents just 3 to 4 percent of the overall market (Carrns, 2016; Kousky et al., 2018).[9]

At inception, the NFIP offered subsidized rates (rates below actuarially fair levels) on existing homes while charging actuarially fair rates on new structures. This was designed to maintain property values and encourage participation. Purchasers of properties built (not purchased) before creation of the first risk map in their area were eligible for subsidized rates, which averaged approximately 40 percent of the actuarially fair level (Hayes et al., 2007; US Government Accountability Office, 2008). Premiums often lagged behind true risk even for properties that were supposed to face actuarially fair premiums because: 1) NFIP maps are updated infrequently; and 2) "grandfathering" allowed properties to keep their original risk ratings even when floodplain maps were updated.

Historically the NFIP maintained fiscal balance. However the 2005 hurricane season, which included Hurricanes Katrina, Rita, and Wilma, left NFIP with nearly $18 billion in debt. Payouts from Hurricane Sandy pushed NFIP debt to nearly $30 billion (Cleetus, 2013). Even as its fiscal balance has deteriorated, the NFIP has grown rapidly. In the early 1980s there were roughly 2 million NFIP policies. As of September 2017, the NFIP had more than $1.2 trillion under coverage and approximately 5 million policies in force.[10]

[6] Other important related papers include: Donnelly (1989); Shilling et al. (1989); Macdonald et al. (1990); Kunreuther (1996); Harrison et al. (2001); Hallstrom and Smith (2005); Smith et al. (2006); Morgan (2007); Bin et al. (2008a); Pope (2008); Michel-Kerjan and Kousky (2010).

[7] McCoy and Zhao (2018) consider changes in property investments via permit applications and assessment data. Ortega and Taspinar (2018) investigate the magnitudes and persistence of price effects of Sandy on residential properties. Both papers find significant impacts of damage by Sandy.

[8] An additional $100,000 in coverage is permitted for the contents of structures. Neither the structure cap nor the contents cap is indexed to nationwide inflation or the regional price level.

[9] Florida began to encourage private policies in 2014. As of mid-2016, NFIP covered 1.8mn Florida properties, while private insurers covered 3,000 properties (Carrns, 2016).

[10] FEMA Policy Statistics. https://bsa.nfipstat.fema.gov/reports/1011.htm. Last accessed December 15, 2017.

For more on the history and administrative details of the NFIP, see Michel-Kerjan (2010); Michel-Kerjan and Kunreuther (2011), and Knowles and Kunreuther (2014).

In response to the increasingly negative fiscal balance of the NFIP, Congress passed the Biggert-Waters Flood Insurance Reform Act in 2012. The bill became law on July 6 and its first provisions took effect on July 10. Beginning January 1, 2013, Biggert-Waters called for subsidized premiums to increase 25 percent per year until reaching actuarially fair levels (FEMA, 2013). It also eliminated grandfathering of risk ratings. In response to numerous complaints about the premium increases, Congress passed the Homeowner Flood Insurance Affordability Act (HFIAA) of 2014. The HFIAA lowered the maximum rate of premium increase to 18 percent per year. It restored grandfathering for incumbent policy holders, but not for new buyers of previously grandfathered homes. Because HFIAA did not change long-run premiums for properties sold after the passage of Biggert-Waters, we do not focus on it.

Hurricane Sandy was important to both the fiscal balance of the NFIP and capitalization of risk in New York City. The storm hit New York on October 29-30, 2012. In total Sandy caused roughly $50 billion in damage, surpassing the costs of all prior US hurricanes except Katrina in 2005, and led directly to 147 deaths (Blake et al., 2013). At the time Sandy hit, the existing floodplain maps had not changed substantially since 1983,[11] and the 1983 maps were based on a hydrologic model from the 1960s (US Government Accountability Office, 2008). FEMA had, however, begun the development of new maps in 2008. The agency issued the first public version of the new maps, the Advisory Base Flood Elevation (ABFE) Maps, on January 28, 2013 (Buckley, 2013). They came from the agency's new flood risk models, which reflected roughly 3.5 inches of sea level rise and increased storm activity since 1983, but not data from Sandy. These initial releases of new flood risk information were accompanied by prominent press coverage (e.g. Buckley, 2013). Subsequent versions of the new floodplain maps went by different names, but were largely unchanged: FEMA issued Preliminary Work Maps on June 10, 2013 and Preliminary Flood Insurance Rate Maps (FIRMs) on January 30, 2015. The Preliminary FIRMs represented the agency's proposed risk ratings for determining premiums under the NFIP. While the new FIRMs had not yet taken full effect as of this writing, our analysis assumes that they have been internalized by the market.[12] Appendix A presents descriptive evidence from floodplain-related Google searches that is consistent with this assumption. For a timeline of NFIP policy changes, see Table A1.

3 Data

Publicly available data on real estate sales in New York City from 2003 to August 2017 are from the New York City Department of Finance.[13] Addresses are geocoded using New York City tax lot maps and the Geocoding Services of the New York State GIS Program Office.[14] We employ 2012 tax assessment data from the Department of Finance to estimate the structure value for each transaction.[15]

Information on official flood risk estimates comes from four generations of FEMA maps. The original FIRMs were produced in 1983 and remained essentially unchanged for 30 years. Three updated flood risk maps for New York City were released on 1/28/2013 (ABFE), 6/10/2013 (Preliminary Work Maps) and

[11]"FEMA's FIRMs [Flood Insurance Rate Maps] have not been significantly updated since 1983, and the New York City maps are currently being updated by FEMA." http://www1.nyc.gov/site/floodmaps/index.page. Last accessed December 15, 2017.

[12]See Appendix B.1 for discussion of NYC's appeal of the FIRMs and Appendix D for efforts to map future flood risks.

[13]Data are available here: http://www1.nyc.gov/site/finance/taxes/property-annualized-sales-update.page.

[14]See http://gis.ny.gov/gisdata/inventories/details.cfm?DSID=1278.

[15]The New York City Department of Finance does not currently provide assessment data prior to 2009. We do not employ post-2012 assessment data because doing so might introduce measurement error correlated with the risk signals we study.

1/30/2015 (Preliminary FIRM). Each of the maps assigns a flood risk level to each property in New York City. The updated maps reflect sea-level rise and changes in storm activity since 1983, but they do not reflect Sandy data or climate change forecasts (Buckley, 2013). Flood inundation during Hurricane Sandy (also from FEMA) is also mapped onto each property. For example, Figure 1 shows the area around Coney Island, with risk maps overlaid onto the geolocated sales data.[16] For each map generation, Table A2 presents counts of properties in our main sample assigned to each of four NFIP flood risk levels, descriptions of which are provided in Table A3.

In this paper, we say a property is "in the floodplain" or "in the one percent floodplain" if it falls into what FEMA calls a "high-risk zone" (V or A). Officially estimated annual flood risk for such properties is one percent or greater. We call properties in X zones "outside the floodplain." Of the 29,698 properties in our main sample that were flooded by Hurricane Sandy, 10,067 were in Zone X and 8,652 were in Zone X500 (under the 1983 maps), meaning they were not in FEMA's one percent floodplain. Of the 18,719 properties outside the one percent floodplain that nonetheless flooded during Sandy, 3,757 (about one fifth) were still not included in the floodplain by the ABFE maps released three months later.

Our sample is comprised of properties in New York's Tax Class 1: "Most residential property of up to three units (family homes and small stores or offices with one or two apartments attached), and most condominiums that are not more than three stories."[17] We exclude transactions less than $100,000 because they may not be arm's-length (e.g. they may be deals among family members). We also exclude transactions greater than $6.75 million, which is above the 99th percentile among Tax Class 1 sales, to limit the influence of outliers.[18]

Three distinct geographic identifiers are used to control for cross-sectional differences. The neighborhood, tax block, and tax lot of each property are provided by the City of New York. There are 247 distinct neighborhoods, nearly 13,000 tax blocks, and approximately 260,000 unique tax lots included in the main sample. Tax blocks generally coincide with physical city blocks. Tax lots are the smallest unit of real estate that can be transacted independently in New York City. The data contain an average of ~1,498 sales in each neighborhood and ~29 in each block. Within each tax lot, we observe an average of 1.4 sales of the same property at different times.

Descriptive statistics for our primary samples are in Table A4. The average sale price in the broader sample, in 2010 dollars, is approximately $597,000.[19] Three percent of transactions occur in the old (1983) floodplain and eight percent of transactions occur in the new (post-2013) floodplain. One percent of observations (~4100 transactions) are treated by Biggert-Waters, two percent (~9200 transactions) by Sandy, and two percent by new floodplain maps.[20] Treatment groups are proportionally small, limiting the potential for spillover effects into the broader real estate market. Summary statistics for the repeated-sales sample are also presented in Table A4. There are 80,375 unique properties in this group.

[16] Figure A8 is a color version of this figure, showing the old floodplain, Sandy inundation, the new floodplain, and all intersections of these groups. As an additional example, Figure A9 does the same for the Red Hook neighborhood. Figures A3 through A7 display this information at the borough level across the entire city, while Figure A2 illustrates citywide cross-sectional overlap in a Venn diagram.

[17] https://www1.nyc.gov/site/finance/taxes/definitions-of-property-assessment-terms.page. Last accessed December 15, 2017. Figure A1 presents transaction counts in our main sample by year and borough.

[18] The exclusion of transactions based on a comparison of the reported sale price to the assessed value of the property was also considered. Results are similar, but because the assessment data are not available until 2009, sample sizes are substantially reduced, especially for the repeated sales sample.

[19] Sales prices are converted to 2010 dollars using the S&P/Case-Schiller Home Price Index for New York City (NYXRSA).

[20] "Treated" denotes transactions that take place in the affected geographic area after the date of the relevant risk signal.

4 Empirical strategy

We estimate difference-in-differences hedonic models whose theoretical underpinnings derive from Rosen (1974). Our identifying assumption is common trends: had the treated properties not been treated, their average potential outcome (sale price) would have differed from the average potential outcome among control properties by a constant. One can evaluate the common trends assumption indirectly for each risk signal by examining pre-treatment trends. We do so for each treatment in turn using Figures 2, 3, and 4, which plot time series of residual sale prices, net of block dummies.[21]

- Biggert-Waters: The treated group is properties in the 1983 floodplain. Figure 2 shows that sale prices in the 1983 floodplain moved in parallel with sale prices outside the floodplain until after Biggert-Waters became law on July 6, 2012. Many properties in the 1983 floodplain also flooded during Sandy in late October 2012, so the peak-to-trough drop apparent in the figure reflects both events. This raises an important point of interpretation for our Biggert-Waters estimate. If the effect of Biggert-Waters had not fully realized by the time Sandy struck, then our Biggert-Waters estimate is a lower bound on the magnitude of the true effect and our Sandy estimate is an upper bound.

- Sandy: The treated group is properties that were partially or wholly inundated by flood waters from the storm. Figure 3 plots three series: 1) properties not flooded by Sandy; 2) properties flooded by Sandy and located in the 1983 floodplain; and 3) properties flooded by Sandy and located outside the 1983 floodplain. Sale prices for flooded properties moved closely in parallel with sale prices for non-flooded properties 2003-2012.

- New floodplain maps: The treated group is properties included in the new floodplain. Figure 4 plots three series: 1) properties outside the new floodplain; 2) properties in the new floodplain and flooded by Sandy; and 3) properties in the new floodplain and not flooded by Sandy. Groups 1 and 2 exhibit common trends throughout the figure. Group 3 generally moves in parallel with the other two, but exhibits higher variance. In particular, it diverges upward 2011-2012 before converging to group 1 just before the release of the ABFE maps in January 2013. If group 3 prices would have increased relative to group 1 prices absent the new maps, then our new map estimates for properties not flooded by Sandy are biased upward (downward in magnitude). The brief March 2014 spike in group 3 prices coincides with the passage of the HFIAA (see Section 2) and may reflect short-lived buyer optimism about the law. This short-run deviation from long-run equilibrium prices likewise biases our new map estimates upward (downward in magnitude). In Table 3 we report estimates from a matched difference-in-differences estimator that forces common trends in the pre-treatment period; results are strongly similar to our main estimates.

While we have pointed out two areas of concern, the common trends assumption looks broadly reasonable. Conditional on common trends and other standard difference-in-differences assumptions, our empirical models will recover causal effects.[22]

Four years after treatment, none of the figures show clear evidence that prices in any treatment group are returning to baseline. This is superficially inconsistent with Gallagher (2014), which finds a relatively smooth decline in insurance takeup beginning two years after a flood event. It is possible that the price

[21] Appendix H presents alternative versions of these figures: 1) treatment-control differences in residual sale prices, with associated 95% confidence intervals; and 2) residual sale prices net of tax lot dummies.

[22] Other standard assumptions include, for example, SUTVA.

effects we estimate will decay in the future. It is also possible they will not, as the risk signals we study are qualitatively different. First, Gallagher (2014) examines only flood experience, which may be comparable to Sandy but not to Biggert-Waters or the new maps. Second, Biggert-Waters and HFIAA require escrow of flood insurance premiums (FDIC, 2015), which may have increased long-run compliance with the NFIP mandate by making it more difficult for homeowners to drop coverage. Third, market participants may have interpreted the risk signals we study as informative about climate change. Most New York City residents (79 percent) believe the scientific consensus on climate change (Howe et al., 2015), and media frequently linked Hurricane Sandy to climate change (Barrett, 2012, "It's Global Warming, Stupid"). In this context risk signals might reasonably be expected to produce persistent effects.

In a typical hedonic analysis, property and building attributes that might be correlated with the non-market attribute of interest are included to avoid bias. Because our data include few such variables, we rely instead on large sets of fixed effects. If properties within the groups defined by these fixed effects are sufficiently similar, this approach addresses potential endogeneity from unobserved property attributes.

The primary estimating equation is as follows.

$$\begin{aligned}
\ln\left(Y_{nblwt}\right) = {} & \alpha_1 O_l + \alpha_2 S_l + \alpha_3 N_l + \alpha_4 O_l S_l + \alpha_5 O_l N_l + \alpha_6 S_l N_l + \alpha_7 O_l S_l N_l \\
& + \beta_1 O_l P_{BW,t} \\
& + \gamma_1 S_l P_{S,t} O_l + \gamma_2 S_l P_{S,t} !O_l + \gamma_3 S_l P_{S,t} O_l D_l + \gamma_4 S_l P_{S,t} !O_l D_l \\
& + \delta_1 N_l P_{N,t} S_l + \delta_2 N_l P_{N,t} !S_l \\
& + \eta_n + \theta_w + \varepsilon_{nblwt}
\end{aligned} \tag{1}$$

In equation 1, n indexes neighborhood, b block, l lot, w year-week, and t date. O is a dummy for the old floodplain and P_{BW} is a dummy for a sale after the passage of the Biggert-Waters Act. S is a dummy for Sandy flooding, D is depth of Sandy inundation, and P_S is a dummy for a sale after Sandy. N is a dummy for the new floodplain and P_N is a dummy for a sale after the issue of the new floodplain maps. Variables preceded by a logical not (for example, $!O$) equal one when the indicated dummy (for example, O) equals zero and vice versa. Terms pre-multiplied by coefficients α control for cross-sectional differences across treatment and control groups. We also employ neighborhood fixed effects η_n in our least saturated specifications, then move to block fixed effects η_b and finally tax lot fixed effects η_l. The last approach leaves only within-tax-lot (within-property) variation to identify treatment effects and so omits the perfectly collinear cross-sectional variables. Because all specifications include a vector of year-week dummies θ_w to control flexibly for secular time trends, the "post" dummies do not enter separately.

The Biggert-Waters Act enters the equation in standard fashion and the relevant parameter is β_1. We interact the Sandy treatment with indicators for being in or out of the 1983 (old) floodplain, and with depth of inundation. The triple and quadruple interactions involving Sandy and the new floodplain maps allow for heterogeneous double-difference effects; they do not imply a triple- or quadruple-difference estimation strategy.[23] The marginal effects of Sandy on properties that experienced near-zero inundation (γ_1 and γ_2) reflect very little physical damage. We hypothesize that signals with novel information content will drive larger responses, and therefore that near-zero inundation will produce larger effects for properties that were outside the old floodplain: $\gamma_2 < \gamma_1$. The parameters γ_3 and γ_4 capture marginal effects of inundation. We

[23]Estimating equation 1 with $\gamma_1 S_l P_{S,t} O_l + \gamma_2 S_l P_{S,t} !O_l$ is equivalent to estimating with $\sigma_1 S_l P_{S,t} + \sigma_2 S_l P_{S,t} O_l$; parameter relationships are $\sigma_1 = \gamma_2$ and $\sigma_2 = \gamma_1 - \gamma_2$. In principle one could also include $\sigma_3 O_l P_{S,t}$. Conditional on the other included variables this would yield the marginal effect of Sandy on old-floodplain properties that did not experience flooding. Table A7 reports results from such a specification.

interact the new maps treatment with indicators for being flooded or not flooded by Sandy. This allows us to test the hypothesis that inclusion in the 2013 (new) floodplain produced stronger impacts on properties that were not flooded by Sandy: $\delta_2 < \delta_1$. We pool across the new map releases discussed in Section 2, as all but a handful of properties in our sample do not change floodplain status across releases.

5 Primary empirical results

Table 1 presents estimates corresponding to equation 1. All specifications include year-week fixed effects. Column 1 employs neighborhood fixed effects. Column 2 moves to block fixed effects applied to the same sample. In column 3 the sample changes to properties for which we observe repeated sales, but the specification again includes block fixed effects. Finally column 4 adds lot fixed effects, using only repeated sales of the same property to identify treatment effects. Only one dimension of the analysis–either specification or sample–changes between adjacent columns. Standard errors are clustered at the Census Tract level, allowing for arbitrary covariances of ε_{nblwt} across properties and over time within a tract.[24] While coefficient estimates vary across columns, differences are small compared to the associated standard errors.

The estimated effect of Biggert-Waters is negative in three of four specifications, and near -5.7 log points (or -5.5 percent) in the repeated sales specification, but all of these estimates are imprecise. One cannot reject a hypothesized null effect at any conventional level of significance. These point estimates are similar to the hedonic Biggert-Waters effects in Bakkensen and Barrage (2017), where estimates range from -1 to -7 percent. As mentioned in Section 4, if the effects of Biggert-Waters had not fully realized by the time Sandy hit in late October 2012, then our estimates represent lower bounds on the magnitude of the true response. Estimates are not sensitive to the inclusion of the Homeowner Flood Insurance Affordability Act (signed March 21, 2014), which slowed the rollout of insurance premium increases begun by Biggert-Waters (see Appendix Table A5).

Equation 1 interacts the Sandy treatment variable $S_l P_{S,t}$ with dummies for being in or out of the old (1983) floodplain (O_l and $!O_l$) and a continuous measure of Sandy inundation (D_l). That is, we allow the slope and intercept of the Sandy treatment to depend on whether a property was in the official floodplain when the storm hit. Our strategy is loosely analogous to that of Atreya and Ferreira (2015), who compare non-inundated houses in the floodplain to those outside. We interpret the intercepts ("Sandy*in old FP" and "Sandy*not in old FP") as effects on properties that were flooded by Sandy ($S_l = 1$), but for which the level of inundation was near zero.[25] While inundation slopes ("Sandy*in old FP*depth" and "Sandy*not in old FP*depth") vary somewhat over specifications and samples, they are in the range from -0.4 to -1.9 percent per foot of flood depth in the more saturated specifications. There is no evidence that the marginal effect of inundation is different for properties inside and outside the old (1983) floodplain. This is also the case for the intercept terms. In specifications with richer cross-sectional controls (columns 2 and 4), properties outside the old floodplain show responses of -2.2 and -4.3 log points, respectively. Corresponding estimates for properties inside the old floodplain are -4.4 and -4.8 log points, respectively.[26] None of these estimates are statistically significant at conventional levels. These Sandy results are inconsistent with the hypothesis

[24] There are 24,765 clusters in columns 1-2 and 21,400 clusters in columns 3-4. The average number of observations per cluster is 14.9 in columns 1-2 and 9.6 in columns 3-4.

[25] FEMA generally records floods up to 5 inches of inundation as zeros; these are colloquially known within the agency as "carpet soaker" floods (US Government Accountability Office, 2008).

[26] From column 4, the marginal effects of Sandy at average inundation (in log points) are $-.0483+(-.0048/ft * 4.69ft) = -.071$ in the old floodplain and $-.0432+(-.0059/ft * 2.22ft) = -.056$ outside it. They are smaller than those in Ortega and Taspinar (2018), 11 and 17 log points for flooding depths below and above 5.5 feet, perhaps suggesting that controlling for other events that occurred around the time of Sandy is important for identification.

given in Section 4, that belief updating will drive larger responses outside the old floodplain, but this pattern should be interpreted with some caution. McCoy and Zhao (2018) find that inundated properties within the floodplain see more post-flood reinvestment than inundated properties outside the floodplain. If properties were improved beyond their pre-flood state, that could bias the Sandy coefficients within the floodplain upward. If the rate of unrepaired damage differed inside and outside the floodplain, e.g. because of higher insurance takeup inside the floodplain, that could similarly confound the comparison of Sandy coefficients across these areas.[27]

In a similar spirit, equation 1 interacts the new map treatment with dummies for being flooded or not during Sandy. The estimated effect of new maps on properties flooded by Sandy ranges from -2.1 to -4.6 percent (-0.021 to 0.048 log points) across specifications, with varying levels of significance. Note that this group of properties is similar to the group of Sandy-flooded properties outside the old floodplain, so identification comes primarily from the time dimension. If the effects of Sandy on these groups had not yet fully realized by January 2013, then this estimate could be biased downward. The estimated effect of new maps on properties not flooded by Sandy, in contrast, ranges from -11.1 to -12.9 percent (-11.8 to -13.9 log points) in these specifications, with one or five percent statistical significance maintained in all columns. To put these magnitudes in context, note that Hallstrom and Smith (2005) and Carbone et al. (2006) find a larger response (-19 percent) to a near-miss by Hurricane Andrew in Lee County, Florida. In their benchmark simulation, Bakkensen and Barrage (2017) estimate 12.7 percent price declines from growing flood risk in Providence by 2040, and 16.1 percent when nearly half of all agents are over-optimistic ex ante. Bin and Landry (2013) find prices of North Carolina properties in the floodplain declined 6 to 20 percent following Hurricanes Fran and Floyd. Taken together, these papers suggest that the magnitude of our estimates is plausible, and that it does not come solely from some peculiarity of post-Sandy New York City.[28] The most directly comparable results are from Hino and Burke (2020), who exploit a large number of NFIP map revisions 1996-2017 to estimate price effects from NFIP risk ratings. In repeated-sales specifications, the average effect of a new floodplain designation is just -2.1 percent. In states with strong disclosure requirements, it is -4.1 percent, while for business buyers of residential properties, it is -6.9 percent. Finally the authors estimate that under a 3 percent discount rate and fully insurable structure value, the efficient price change would be -10.7 percent.[29] This is quite close to our preferred -11.4 percent estimate for properties not flooded by Sandy. The results from Hino and Burke (2020) do indicate that our estimated response in New York is substantially larger than the average response, and this could be due in part to Sandy-driven increases in flood information or salience throughout the New York area. On the other hand, our estimate is roughly consistent with efficient capitalization of flood risk, and inconsistent with strong overreaction by market participants.

[27]Following Hurricane Sandy, the State of New York set aside funds to purchase severely damaged properties at pre-flood market rates. As of October 2016, only 132 such acquisitions had occurred (New York City Mayor's Office of Housing Recovery Operations, 2016). It is therefore unlikely that this program meaningfully biases our estimates.

[28]All estimated effects have magnitudes within the range of cross-sectional price variation in New York City. In our main samples, Bronx and Richmond (Staten Island) Counties are approximately 22% cheaper than in Queens County, which is in turn 13-14% cheaper than Kings County (Brooklyn).

[29]As discussed in Section 7.3, the evidence of Giglio et al. (2016) and Bracke et al. (2018) suggests this discount may be slightly too high in the context of real estate. As discussed in Section 7.1, in New York City many properties have structures valued above the $250,000 NFIP cap.

6 Secondary empirical results

6.1 Robustness: specification

Table 2 reports results under block and lot fixed effects based on the full and repeat sales samples, as in columns 2 and 4 of Table 1, but using alternative specifications. Estimates are generally similar to our primary results; we comment on the differences. Our preferred specification includes a fixed effect for each week in the sample. Columns 1 and 2 of Table 2 report estimates from a specification with fixed effects in sale date. While the temporal fixed effects applied so far account for uniform time trends across New York City, area-specific trends remain a concern. Columns 3 and 4 include borough by year-month fixed effects. Estimated intercept changes from Sandy increase in magnitude and are statistically significant in some cases. Point estimates for the Biggert-Waters Act are positive, but not statistically significant. In Appendix Table A6, we present estimates from specifications with a variety of geography-specific time controls, including a specification with tax-lot-specific linear trends. Estimates from specifications that allow for differential time trends are generally consistent with our main results, though precision is substantially reduced in the most saturated models.[30] In principle impacts of Sandy not captured by our linear inundation measure could threaten identification. To test this, we include a quadratic in Sandy inundation in columns 5 and 6 of Table 2. The inclusion of inundation squared naturally changes estimates for other Sandy variables, but estimates for Biggert-Waters and the floodplain maps are unaffected. Spillover effects of Sandy on non-flooded properties are also a potential problem. The specification in Table A7 models such spillovers and our estimates of interest do not change substantially.

It is also possible that expected future defensive investments and evolution of risk bias our estimates. Appendix B.2 describes New York's proposed flood defense investments. In unreported work, we estimate specifications that include announcement dates and protected areas defining additional treatment periods and groups. Our estimates of interest are unaffected, but the coefficients on the various infrastructure announcement treatments vary substantially in magnitude, sign, and significance depending on which project announcements are included. In a similar vein, Appendix D describes the release of 2020 and 2050 forecast flood maps for New York City, and Appendix Table A9 presents estimated effects. The simultaneous release of the 2020 and 2050 predicted flood maps and strong overlap in their geographic areas suggest these coefficient estimates should be interpreted with caution. Importantly, the control for the release of this future flood risk information does not markedly impact our main estimates of interest. In particular, estimates corresponding to the 2013 floodplain map remain strongly similar to their analogs in Table 1.

Lastly we consider the potential violation of common trends for properties not flooded by Sandy but included in the new floodplain. To test whether the deviations seen in Figure 4 influence our primary estimates, we employ a matched difference-in-differences model. To simplify analysis and rule out confounding from Sandy, we use a sample of properties not flooded by Sandy. A property is treated if it is included in the floodplain under the new maps. Propensity scores are estimated for all properties based on building and lot square footage, building age, latitude, longitude, and block-level average annual price growth rate in the pre-treatment period. In addition, propensity scores depend on the level of pre-treatment average price at

[30] The specification with lot-specific time trends is especially demanding. Estimating a fixed effect and slope for each tax lot requires more than 160,000 parameters in a sample of roughly 183,000 observations. Because a lot-specific affine function will fit two sale prices perfectly, identification comes only from properties that sell three or more times, which potentially exacerbates selection. The estimated effect of the new floodplain maps on properties not flooded by Sandy changes from -.121 in our preferred specification to -.0912 (not statistically significant) in the specification with tax lot fixed effects and tax lot linear trends.

increasingly fine geographic resolution, as indicated in the column headings of Table 3.[31] Treated properties are matched to control properties based on these propensity scores, with common support required. Note that the matching on pre-treatment price growth engineers common trends in the pre-treatment period. We then estimate a double difference in prices over treatment and time, with regression adjustment for imperfect matching and year-week fixed effects. For more details on this procedure, see Appendix C. Results appear in Table 3. Point estimates of the effect of new maps on prices of unflooded properties range from approximately -9 to -14 log points, comparable to the bottom row in Table 1, and all are statistically significant at the one percent level. This suggests that our primary estimates of the new map effects do not reflect substantial bias from violation of the common trends assumption.

6.2 Robustness: sample

Table 4 again reports results under block and lot fixed effects, preserving our preferred specifications but using alternative samples. Given the spatial correlation in property values it could be that the values of properties near the border of the treated area were impacted by spillovers. Columns 1 and 2 of Table 4 report estimates after properties within 50 meters of the original one percent floodplain boundary (inside and outside) are dropped from the samples. Another potential issue is that time-varying unobserved amenities might be positively correlated in space. If so, using properties from all over New York City to construct a counterfactual price path could introduce bias. We exclude properties more than 500 meters outside the original floodplain and report estimates in columns 3 and 4 of Table 4.[32] Again the estimates are broadly similar to those in Table 1. We next consider the possibility that the risk signals we study may not impact all properties in Tax Class 1, particularly second- and third-floor condominiums that might not suffer direct damage in a flood. Columns 5 and 6 of Table 4 limit the sample to single-family homes and results are strongly similar to our primary estimates. Finally, in columns 3 and 4 of Appendix Table A10, we address outliers by Winsorizing at the one percent level, rather than dropping, and results are not meaningfully different.

It remains possible that unrepaired damage from Sandy is biasing our estimates in a way that could be hard to sign *ex ante*. To explore this possibility, we re-estimate our main regressions on a sample that omits sales between Sandy and the end of 2014. Columns 3 and 4 of Appendix Table A8 demonstrate that the resulting estimates are comparable to our main estimates. This indicates that unrepaired damage is probably not a substantial influence on our results.

Previous work has raised concerns about shifts in hedonic price functions over time and in response to market shocks (e.g., Kuminoff and Pope, 2014). We are unable to test directly for such changes in the equilibrium hedonic price function. In our particular setting, we know of no valid method by which to separately identify the hedonic slopes of interest in the pre- and post-treatment periods. Indeed it is the dearth of valid cross-sectional identification strategies that leads us to rely on information shocks. Work by Palmquist (1992) suggests that hedonic gradients take time to adjust to shocks. If so, we can test indirectly for a change in equilibrium by comparing short- and long-run estimates of our treatment effects. Columns 1 and 2 of Appendix Table A8 present estimates based only on 2012-2015 sales; they are similar to our primary estimates, especially for the new maps. There is no evidence, then, of a shift in the equilibrium price function. This is perhaps to be expected, as the shocks we study directly impacted relatively small

[31] Repeated sales are sufficiently infrequent to make matching on lot-level price growth impracticable. We match on price growth at the block level and vary the spatial matching on price level by analogy with our difference-in-differences approach.

[32] This is not our preferred sample because: 1) the parallel trends assumption appears reasonable in the larger sample; and 2) the limited sample may introduce bias from spatial spillovers.

portions, between 3 and 8 percent, of the overall population of small residential properties (see Table A4).

7 Mechanisms

7.1 Candidate mechanisms

In this section we present empirical evidence on possible mechanisms for our reduced-form results: 1) sorting; 2) selection; 3) insurance premiums; and 4) beliefs. First let us consider sorting. If the risk preferences or perceptions of the marginal buyer were evolving differently in the treatment and control groups, that could cause prices to diverge. We test for sorting on known correlates of risk preferences and perceptions, specifically: gender, age, ethnicity, permanence of residents, education, and income (Lindell and Hwang, 2008; Kellens et al., 2011, 2012; Mills et al., 2016). Table 5 presents changes in these characteristics from the 5-year period prior to our treatments (2007-2011) to the 5-year period during and after treatments (2012-2016), calculated separately for Census Tracts in the new one percent floodplain and outside.[33] The statistical power of these tests is limited given the coarseness of the observational units, imperfect treatment assignment, and the fact that ACS aggregates reflect all residents, rather than new residents. Nevertheless, we find no evidence that correlates of risk preferences or perceptions shift differently. The only statistically significant difference in Table 5 is in the mean sale price of residential properties, consistent with our reduced-form estimates in Table 1. In a separate analysis below (see Figure 5), we disaggregate the impacts of the new flood maps by structure value and find no effects for fully insurable properties. This is inconsistent with sorting on risk aversion, which would have changed willingness to pay for mandated insurance and therefore capitalization. These analyses cannot categorically exclude sorting in our setting, and previous research has found evidence of sorting on flood risk in other settings (Fan and Davlasheridze, 2016; Bakkensen and Barrage, 2017; Bakkensen and Ma, 2019). Nonetheless the small point estimates in the third column of Table 5 and among fully-insurable properties in Figure 5 suggest that sorting is not a first-order driver of our results. This could be because much of the housing stock in New York City is close to the water–median distance to the edge of the 1983 floodplain is roughly one kilometer in our larger sample–and therefore sorting on flood risk and its correlates is less pronounced than in other communities. If so, that is a limitation on the external validity of our results. Finally, we note that sorting on risk aversion would be expected to bias estimates toward zero.

The second potential mechanism is selection into the set of observed transactions. Under tax lot fixed effects such selection is not a potential source of bias, but it could raise external validity concerns. To test for selection we use transactions prior to June 1, 2012 to estimate log price as a function of quartics in lot area, floor area, building age, and number of units.[34] We then calculate fitted values for all transactions and estimate treatment effects on these fitted values. Intuitively, we are testing whether observable characteristics of transacted properties change such that we would expect price changes unrelated to the treatments we study. Table 6 presents these estimates, which are generally small and not statistically significant. In addition, we employ the method of Oster (2017) to bound the selection on unobservables that would be required to explain away our large effects of new floodplain maps on properties not flooded by Sandy. The estimated value of Oster's δ parameter corresponding to column four of Table 1 (our preferred specification)

[33]In Table 5 we include a Census Tract in the floodplain group if any part of it overlaps the floodplain. The groups of Tracts overlapping with the treatment geographies of the other risk signals are largely similar.

[34]These are the only well-populated lot-level variables available in our data.

is -1.21.[35] For our estimate to arise solely from selection on unobservables, the covariance of unobservables with treatment, scaled by the variance of those unobservables, would have to be opposite in sign and at least 1.21 times larger than the corresponding ratio for the observables in our estimating equation. Intuitively, because our coefficients are stable under the addition of controls with high partial R^2, there is limited scope for unobservables to matter and selection would have to be rather severe to generate our estimate. Additionally, as discussed previously, we find no evidence that dynamic selection via the sale of properties with unrepaired flood damage is driving our estimates. Instead, Columns 3 and 4 of Appendix Table A8 demonstrate that estimates remain stable even when sales from the 26-month period following Sandy are omitted from the analysis.

We can say little about the importance of insurance premiums using our data. Our negative point estimates for the Biggert-Waters Act (Table 1) are consistent with capitalization of insurance premiums, but could also come from another mechanism like risk salience. Prior literature has investigated premium capitalization. Harrison et al. (2001) find less than full capitalization of flood insurance premiums, but also find that capitalization responds in the expected direction to NFIP rule changes. Comparing homes in the one percent floodplain to those in the .2 percent floodplain, Bin et al. (2008b) "...find that the capitalized values of the insurance premiums are in close agreement with the sales price differentials." These results suggest premium capitalization may be one of the mechanisms behind our reduced-form estimates.

Finally, it is possible that changes in beliefs (subjective flood risk) are partially responsible for the observed price changes. To evaluate this candidate mechanism, we exploit the $250,000 NFIP structure coverage cap. Below the cap, one would expect little or no relationship between structure value and the new map effect, because there is little or no uninsured value and premiums increase slowly in structure value.[36] Above the cap, marginal effects potentially reflect belief updating over risk to uninsured structure value. In this range one would expect a negative relationship between structure value and the map effect, because the same hypothesized change in belief is being multiplied by larger uninsured value for more costly structures. We test these predictions by estimating effects of the updated floodplain maps in $100,000 structure value bins.[37] Figure 5 displays the new map effects on transaction prices for properties that were (left panel) and were not (right panel) flooded in Sandy. Estimates below the cap are small in both panels, and five of six are statistically indistinguishable from zero, consistent with buyers internalizing this feature of the insurance contract. Estimates above the cap are generally negative and their magnitudes increase in structure value. This pattern is more pronounced for properties not flooded in Sandy, and in the right panel the estimates for the two highest structure value bins are statistically significant at the ten percent level. This is consistent with belief updating. While high structure values are especially prevalent in New York City–we estimate 45 percent of small residential properties in the city had structures valued over $250,000 in 2013–they are also common in other states with high NFIP enrollment. In the five states with the highest numbers of NFIP policies, between 5 and 19 percent of residential properties contain structures valued at $250,000 or more.[38]

[35]These estimates are from Oster's psacalc Stata package. We conservatively assume that R^2 for a model including the unobservables would equal 1.

[36]Because small floods are more common than big ones, the marginal cost of $100 in coverage declines in structure value.

[37]Structure values are based on the portion of total property value not assigned to land in 2012 assessment data from the NYC Department of Finance.

[38]In particular, we estimate that 17.4%, 6.5%, 5.6%, 19.4%, and 7.3% of residential properties had structure values above $250,000 in California, Florida, Louisiana, New York, and Texas respectively, based on 2013, Zillow-aggregated assessment data. Outside of New York City, we find that 11.9% of residential properties in New York state contain structures valued over $250,000.

7.2 Theory: beliefs and insurance premiums

To better understand behavior in our setting, we seek to impose some theoretical structure. The evidence of Section 7.1 implies that such structure should accommodate both flood insurance and changes in beliefs. Given the importance of risk preferences in this setting, it should also allow for curvature of the utility function. Within the class of models with these features, we strive for maximum parsimony.[39]

With these goals in view, we extend the model of Kousky (2010), which descends from Smith (1985) and MacDonald et al. (1987). Housing supply is assumed fixed, with the number of units strictly greater than the number of agents. Prices are a function of a vector of structural, location, and environmental characteristics $\boldsymbol{Z}$ and an agent's subjective probability of a flood event p. The hedonic function is thus $H(\boldsymbol{Z}, p)$. The model is static, supposing an agent whose beliefs are stationary in the absence of parameter shocks. Such stationarity could come from inattention (Sims, 2006; Kahneman, 2003) or myopia (Thaler et al., 1997), coupled with the type of permanent updating in response to large shocks described by Kozlowski et al. (2017). This type of updating is one possible explanation for the large divergences between flood beliefs and objective risks documented in Botzen et al. (2015). Appendix G presents an alternative, dynamic model in which subjective flood probability p_t rises over time to reflect anticipated climate change.

Let Y be exogenous income and X consumption of a numeraire good. The budget constraint is then $Y = X + H(\boldsymbol{Z}, p)$. The flood insurance contract is the same in all locations, with premium I, anticipated flood loss L, and insurance payout V.[40] To simplify the theoretical exposition in this section, insurance takeup is assumed to be complete, but the empirical calculations of Section 7.3 account for the time-varying, incomplete insurance takeup observed in New York City.[41] Then we have state-dependent budget constraints

$$\begin{aligned} X_1 &= Y - H(\boldsymbol{Z}, p) - I - L + V \\ X_0 &= Y - H(\boldsymbol{Z}, p) - I \end{aligned} \tag{2}$$

where X_1 and X_0 are consumption levels in the flood and non-flood states of the world respectively.

Given the lack of evidence for differential sorting in Table 5, we assume a representative agent. The agent is assumed to have a twice continuously differentiable von Neumann-Morgenstern utility function such that $\frac{\partial U}{\partial X} > 0$ and $\frac{\partial^2 U}{\partial X^2} < 0$, but no functional form is assumed. Relative to Bakkensen and Barrage (2017), this model sacrifices heterogeneity in beliefs but avoids imposing risk neutrality (linear utility). Expected utility can then be written simply.

$$EU = pU(X_1, \boldsymbol{Z}) + (1 - p)U(X_0, \boldsymbol{Z}) \tag{3}$$

The subjective probability of a flood, p, is a function of a property's official floodplain designation F, experience with past flooding events E, and flood insurance premiums I.[42] Thus the anticipated magnitude of losses when a flood occurs depends on F, E, and I. Insurance premiums depend only on the official flood zone F and the characteristics of the property $\boldsymbol{Z}$. Expected utility can now be rewritten.

[39] A more parsimonious model simplifies exposition and makes more transparent the influence of assumptions on conclusions.

[40] Within SFHAs, risk ratings and premia for new policies are approximately equal everywhere. Differences do arise because of varying structure elevations (e.g. a house on 6-foot stilts requires a lower premium), but we abstract from such variation.

[41] That is, in our theoretical model we treat insurance takeup as exogenous. This allows us to remain agnostic about the source of observed low takeup rates while accounting for them in our empirical calculations. Possible explanations for low insurance takeup include hyperbolic discounting, biased beliefs, and mispricing by the NFIP, among others.

[42] Previous models of this type have not allowed beliefs to depend on insurance premiums; we hypothesize that a consumer whose premiums change may update her belief about the riskiness of her property.

$$
\begin{aligned}
EU &= p(F,E,I)U\left(Y - H(\boldsymbol{Z}, p(F,E,I)) - I(\boldsymbol{Z},F) - L(F,E,I) + V(\boldsymbol{Z}), \boldsymbol{Z}\right) \\
&\quad + (1 - p(F,E,I))U\left(Y - H(\boldsymbol{Z}, p(F,E,I)) - I(\boldsymbol{Z},F), \boldsymbol{Z}\right)
\end{aligned} \tag{4}
$$

The agent maximizes expected utility by choosing a location, which implies an attribute-belief bundle $(\boldsymbol{Z}, p)$. As in previous work (Smith, 1985; MacDonald et al., 1987), we assume a housing equilibrium under which all agents enjoy equal expected utility. Under this assumption one can directly differentiate expected utility (rather than the first-order conditions of the agent's problem) with respect to a parameter of interest and set the resulting derivative to zero. Intuitively, when a parameter changes the hedonic function must change to maintain equilibrium expected utility.

7.2.1 Biggert-Waters

The Biggert-Waters Act shocked insurance premiums I, removing subsidies that had previously kept premiums below the actuarially fair level. Differentiating EU with respect to I, subject to the budget constraints, allows us to solve for the marginal effect of a change in insurance premiums on housing prices.

$$
\frac{\partial H}{\partial I} = \frac{\left[U(X_1) - U(X_0)\right] \frac{\partial p}{\partial I} - p \frac{\partial U}{\partial X_1} \frac{\partial L}{\partial I} - \left[p \frac{\partial U}{\partial X_1} + (1-p) \frac{\partial U}{\partial X_0}\right]}{p \frac{\partial U}{\partial X_1} + (1-p) \frac{\partial U}{\partial X_0}} \tag{5}
$$

Recall that we assumed a twice continuously differentiable utility function. Then by the intermediate value theorem there exists a point X_c on $[X_1, X_0]$ such that $\frac{\partial U}{\partial X_c} = p \frac{\partial U}{\partial X_1} + (1-p) \frac{\partial U}{\partial X_0}$. By the mean value theorem, there exists a point X_m on $[X_1, X_0]$ such that $\frac{\partial U}{\partial X_m} = \frac{1}{X_0 - X_1} \int_{X_1}^{X_0} \frac{\partial U}{\partial X}(X)\, dX$. Then we can replace $U(X_1) - U(X_0) = (X_1 - X_0) \frac{\partial U}{\partial X_m} = (V - L) \frac{\partial U}{\partial X_m}$. Our derivative now becomes

$$
\frac{\partial H}{\partial I} = \frac{\left[(V - L) \frac{\partial U}{\partial X_m}\right] \frac{\partial p}{\partial I}}{\frac{\partial U}{\partial X_c}} - \frac{p \frac{\partial U}{\partial X_1} \frac{\partial L}{\partial I}}{\frac{\partial U}{\partial X_c}} - 1
$$

To this point, no approximations have been required. We next employ first-order Taylor expansions to approximate numerator marginal utilities in terms of denominator marginal utility $\frac{\partial U}{\partial X_c}$. We obtain $\frac{\partial U}{\partial X_m} \approx \frac{\partial U}{\partial X_c} + (X_m - X_c) \frac{\partial^2 U}{\partial X_c^2}$ and $\frac{\partial U}{\partial X_1} \approx \frac{\partial U}{\partial X_c} + (X_1 - X_c) \frac{\partial^2 U}{\partial X_c^2}$. Our derivative is now

$$
\frac{\partial H}{\partial I} \approx \frac{\left[(V - L)\left(\frac{\partial U}{\partial X_c} + (X_m - X_c) \frac{\partial^2 U}{\partial X_c^2}\right)\right] \frac{\partial p}{\partial I}}{\frac{\partial U}{\partial X_c}} - \frac{p\left(\frac{\partial U}{\partial X_c} + (X_1 - X_c) \frac{\partial^2 U}{\partial X_c^2}\right) \frac{\partial L}{\partial I}}{\frac{\partial U}{\partial X_c}} - 1 \tag{6}
$$

We wish to simplify this expression using the definition of Arrow-Pratt absolute risk aversion $r(X) = -\frac{\frac{\partial^2 U}{\partial X^2}}{\frac{\partial U}{\partial X}}$ (Arrow, 1970; Pratt, 1964). Reversing the order of the numerator subtractions and dividing yields

$$
\frac{\partial H}{\partial I} \approx (V - L)\left[1 + (X_c - X_m)\, r(X_c)\right] \frac{\partial p}{\partial I} - p\left[1 + (X_c - X_1)\, r(X_c)\right] \frac{\partial L}{\partial I} - 1 \tag{7}
$$

To the best of our knowledge, this approximation is novel. It is potentially applicable in other settings, particularly those involving low-probability events. In the expression above, X_c is the point on $[X_1, X_0]$ at which the marginal utility of consumption is equal to the expected value of the marginal utility of consumption across flood and non-flood states. If subjective flood probability p is small, X_c will be in the neighborhood of X_0. X_m is the point at which the marginal utility of consumption attains its average over the interval $[X_1, X_0]$. The model predicts a negative effect of increased premiums on home prices by way of three channels: 1) increased subjective flood probability in term one; 2) an increase in expected flood severity in term two, and 3) increased premiums in term three. Alternatively one can simplify in terms of relative risk aversion; see Appendix E.

7.2.2 Hurricane Sandy

In the analogous derivative for Hurricane Sandy, E denotes flood experience.

$$\frac{\partial H}{\partial E} = \frac{[U(X_1) - U(X_0)] \frac{\partial p}{\partial E} - p \frac{\partial U}{\partial X_1} \frac{\partial L}{\partial E}}{p \frac{\partial U}{\partial X_1} + (1-p) \frac{\partial U}{\partial X_0}} \tag{8}$$

As before, we can simplify.

$$\frac{\partial H}{\partial E} \approx (V - L) [1 + (X_c - X_m) r (X_c)] \frac{\partial p}{\partial E} - p [1 + (X_c - X_1) r (X_c)] \frac{\partial L}{\partial E} \tag{9}$$

Flood experience decreases property values through two channels: 1) increased subjective flood probability in term one; and 2) increased expected flood severity in term two.[43]

7.2.3 Updated Flood Risk Maps

Updated floodplain maps (F) may provide new information on properties not previously included in the one percent floodplain, and may increase the salience of official risk estimates among properties previously included. The housing response by an optimizing consumer is characterized by the following.

$$\frac{\partial H}{\partial F} = \frac{[U(X_1) - U(X_0)] \frac{\partial p}{\partial F} - p \frac{\partial U}{\partial X_1} \frac{\partial L}{\partial F} - \left[p \frac{\partial U}{\partial X_1} + (1-p) \frac{\partial U}{\partial X_0}\right] \frac{\partial I}{\partial F}}{p \frac{\partial U}{\partial X_1} + (1-p) \frac{\partial U}{\partial X_0}} \tag{10}$$

Again we can approximate in terms of observables.

$$\frac{\partial H}{\partial F} \approx (V - L) [1 + (X_c - X_m) r (X_c)] \frac{\partial p}{\partial F} - p [1 + (X_c - X_1) r (X_c)] \frac{\partial L}{\partial F} - \frac{\partial I}{\partial F} \tag{11}$$

The model predicts a negative effect of the updated floodplain maps on home prices by way of three channels: 1) increased subjective flood probability in term one; 2) an increase in expected flood severity in term two; and 3) increased future premiums in term three.

7.3 Estimated belief changes

We next use the analytical results from Section 7.2 to build a bridge from our reduced-form results to belief changes ($\frac{\partial p}{\partial I}$, $\frac{\partial p}{\partial E}$, and $\frac{\partial p}{\partial F}$ respectively). Equations 7, 9, and 11 characterize the marginal effects on property values of changes in insurance premiums, flood experience, and official flood zone designation. Values for these marginal effects have been empirically estimated and reported in Table 1. Our calculations require estimates of several structural parameters, which we now discuss.

[43] Our model does not include a channel by which E affects property values directly via flood damage; that is, $\boldsymbol{Z}$ is not treated as a function of E. This is partly for simplicity and partly because the empirical evidence of Table A6 suggests unrepaired damage is not a first-order source of bias in our empirical estimates.

As explained in Section 7.2, if p is small then X_c is close to X_0, consumption in the non-flood state. In such a setting, it is reasonable to employ estimates of Arrow-Pratt absolute risk aversion derived from ordinary periods, rather than the aftermath of a disaster. Empirical evidence generally supports the Arrow hypothesis that absolute risk aversion decreases in wealth (Arrow, 1970; Bar-Shira et al., 1997; Guiso and Paiella, 2008). New York home buyers are among the wealthiest people in the world, so we want to employ one of the smaller estimates. Many of the empirical papers in this literature estimate lower bounds on absolute risk aversion on the order of 10^{-3} (Saha et al., 1994; Cramer et al., 2002; Sydnor, 2010). We adopt $r(X_c) = 1.2 * 10^{-3}$ from Saha et al. (1994).[44] Appendix Table A11 shows the results of our calculations for different values of $r(X_c)$.

To annualize our marginal effects, we employ a 2.6 percent discount rate consistent with both Giglio et al. (2016) and Bracke et al. (2018). These studies estimate discount rates by comparing the prices of extremely long-term leases (99 to 1,000 years) to outright purchases of property, and obtain strongly similar estimates from the United Kingdom and Singapore. Appendix Table A12 shows the results of our calculations under different assumed discount rates.

As noted by Kousky (2010), in theory we cannot disentangle changes in subjective flood probability from changes in anticipated damages. For the calculations below we assume anticipated damages (conditional on flooding) are fixed, that is $\frac{\partial L}{\partial I} = \frac{\partial L}{\partial E} = \frac{\partial L}{\partial F} = 0$. There is empirical support for this assumption. Gallagher (2014) finds that the increase in NFIP insurance uptake following a flood does not depend on flood severity, noting that homeowners, "do not appear to use new floods to learn about expected flood damages." If this assumption does not hold, then our estimates are upper bounds on the magnitude of belief updating.

Our model derivatives assume some level of insurance coverage, but empirical insurance takeup has been less than 100 percent and has varied over time. In the calculations below we use data from RAND Corporation reports (Dixon et al., 2013, 2017) and the City of New York (NYC, 2013) to account for this.

Finally, while our theoretical model employs a representative agent, in our most saturated empirical specifications identification comes from repeated sales of the same property to different marginal buyers. This raises the question of how to interpret model derivatives if agents have different beliefs. If the ex ante (before risk signals) distributions of beliefs are on average the same for ex ante and ex post buyers, then the belief differences recovered below arise solely from belief updating. If these distributions differ, then our calculations reflect both ex ante belief differences and updating, but still recover the total difference in beliefs across ex ante and ex post marginal buyers. The key restriction imposed by the model is that ex ante and ex post buyers exhibit, on average, the same risk aversion. Despite the evidence of Table 5, it remains possible that the signals we study induce sorting on risk aversion that is not revealed by our tests. In this case the primary belief calculations below are lower bounds. To give a sense of how sorting might influence these results, we also report belief changes under an assumed decrease in absolute risk aversion across ex ante and ex post buyers, with $\Delta r(X_c) = -.00017$ set equal to the difference between employees and entrepreneurs from Cramer et al. (2002).[45]

7.3.1 Biggert-Waters

Neither uninsured nor unsubsidized properties experienced a shock to insurance premiums from the Biggert-Waters Act ($\frac{\partial H}{\partial I} = 0$), and our belief calculation must reflect this. A RAND study found that 40 percent

[44]Note von Neumann-Morgenstern expected utility is unique up to an affine transformation and Arrow-Pratt absolute risk aversion is invariant to affine transformations (Arrow, 1970; Kreps, 1990). Therefore Arrow-Pratt absolute risk aversion is unique and it is reasonable to borrow an estimate from another population, provided that population has similar preferences.

[45]This calculation also assumes common ex ante beliefs.

of the one- to four-family homes in the one percent floodplain had NFIP coverage prior to Hurricane Sandy (Dixon et al., 2017). To account for premium subsidies, we rely on a City of New York estimate that 75 percent of NFIP policies in effect during Sandy were eligible for subsidies (NYC, 2013). The following adaptation of equation 7 reflects both city-wide takeup and subsidy rates.

$$\frac{\partial H}{\partial I} \approx 0.4 \left\{ 0.75 \left[(V-L)\left(1+(X_c-X_m)\, r\,(X_c)\right) \frac{\partial p}{\partial I} - 1 \right] + 0.25(0) \right\} + 0.6\,(0)$$

We require an estimate of $X_c - X_m$. Under diminishing absolute risk aversion, if X_c were equal to X_0, then X_m would lie on the interval $\left[X_1, \frac{X_0+X_1}{2}\right]$.[46] We approximate using the midpoint of this interval $X_m \approx \frac{1}{2}\left(X_1 + \frac{X_0+X_1}{2}\right) = \frac{X_1}{2} + \frac{X_0+X_1}{4} = \frac{3}{4}X_1 + \frac{1}{4}X_0$ and substitute to obtain $X_c - X_m \approx X_0 - \left(\frac{3}{4}X_1 + \frac{1}{4}X_0\right) = \frac{3}{4}(X_0 - X_1) = \frac{3}{4}(L-V)$.

We calculate expected uninsured loss $V-L$ as follows. As of 2012, NFIP policies in New York City covered an average of \$231k in damages (FEMA, 2012), so payout V equals $min(L, \$231k)$ for insured properties and zero for uninsured properties.[47] From Aerts et al. (2013), we calculate that annual expected flood damage in New York is .6 percent of structure value $\bar{S}$. If a property is uninsured, $V-L = 0 - .006 * \bar{S}$. If a property is insured, $V-L$ depends on the distribution of losses for severe floods ($L > V$). We calibrate a property-specific loss distribution based on Aerts et al. (2013) and integrate over $V-L$ (for details, see Appendix F). For each property, we then compute a weighted average of $V-L$ across insured and uninsured states, using the 40 percent insurance rate and 60 percent uninsurance rate as weights. Next we average over properties in the treatment group. Applying the 2.6 percent discount rate yields a present value of $V - L = -\$21{,}082$.

Based on the lot fixed-effects specification in Table 1, we estimate: $\frac{\partial H}{\partial I} = -5.51\%$ (-0.0567 log points), or a reduction of \$27,109 (based on the average sale price in the old floodplain of \$492k) due to the premium increase under the Biggert-Waters Act. This is equivalent to a \$705 loss to the expected annual flow of hedonic value, so $\frac{\partial H}{\partial I} = -\$705$. Rather than a 1 unit change in insurance premiums, we are interested in the increase from the Biggert-Waters Act, which removed subsidies for NFIP insurance.[48] FEMA estimates that on average, subsidized premiums were 60 percent of the actuarially fair level [GAO, 2013; Hayes and Neal, 2011], so by eliminating these subsidies, Biggert-Waters led to 66 percent premium increases. The City of New York estimates that "the average NFIP premium paid on 1- to 4-family residential policies in New York City" was approximately \$1000 in 2012 (NYC, 2013).[49] The approximate increase in annual premiums is thus $0.66 * \$1000 = \$660$.

Combining these elements, we now have the following.

[46] The assumption of diminishing absolute risk aversion is in keeping with theoretical prediction of Arrow (1970) and a large empirical literature (Saha et al., 1994; Guiso and Paiella, 2008; Sydnor, 2010). Assuming $\frac{\partial U}{\partial X} > 0$, diminishing absolute risk aversion requires $\frac{\left(\frac{\partial^2 U}{\partial X^2}\right)^2}{\frac{\partial U}{\partial X}} - \frac{\partial^3 U}{\partial X^3} < 0$. Because $X_c < X_0$, the right endpoint of the interval containing X_m is less than $\frac{X_0+X_1}{2}$.

[47] Alternatively, one could employ the NFIP structure coverage cap of \$250k. This does not meaningfully change the results of our calculations.

[48] In addition to the simplifying assumptions already imposed, note that we are now using derivatives to investigate non-marginal changes in the values of interest.

[49] Because this figure is approximate, we do not deflate it to 2010 US dollars.

$$\begin{aligned}
\frac{\partial H}{\partial I} &\approx 0.4\left\{0.75\left[(V-L)\left(1+\frac{3}{4}(L-V)\,r(X_0)\right)\frac{\partial p}{\partial I}-1\right]\right\}\Rightarrow \\
-\$705 &\approx (0.4)(0.75)\left[(-\$21,082)\left(1+\frac{3}{4}(\$21,082)\left(1.2*10^{-3}\right)\right)\frac{\partial p}{\partial I}-\$660\right]\Rightarrow \\
\frac{\partial p}{\partial I} &\approx .0040
\end{aligned} \tag{12}$$

This calculation implies that a 66 percent increase in future flood insurance premiums led to an increase in subjective annual flood probability of 0.4 percentage points. The interval corresponding to the 95 percent confidence interval for the reduced-form estimate is $(-.0050, .012)$. Property values fell by more than the present value of the insurance premium increases, consistent with belief updating. Under the assumed sorting-driven decrease in absolute risk aversion, the estimated belief change across marginal buyers is .46 percentage points. Under an assumption of risk neutrality ($r(X_0) = 0$), this estimate would be eight percentage points. Even allowing for optimization failures, such a large estimate is difficult to credit. These estimates underscore the importance of accounting for risk aversion when considering belief changes.

7.3.2 Hurricane Sandy

Our reduced-form estimates show no evidence of updating in response to the depth of Sandy inundation, as the estimated marginal effects of depth inside and outside the floodplain are similar (see Section 5). These inundation slopes may also be confounded by differences in insurance, reinvestment, and unrepaired damage, as discussed in Section 5. Therefore we focus on estimated changes in intercept, which reflect near-zero levels of flooding and minimal physical damage. From column 4 of Table 1, the marginal effect of Sandy at near-zero inundation is -4.72 percent (-0.0483 log points) for properties that were in the floodplain at the time of the storm, and -4.23 percent for properties outside the floodplain. We will focus on the latter group, for which flood experience was more plausibly informative. The average price in the areas flooded by Sandy but outside the old floodplain is approximately \$540k, so the change in annual hedonic flow from such properties is $\frac{\partial H}{\partial E} = -.0423 * \$540K * 0.026 = -\$593$. The value of $V - L$ (calculated as described in Section 7.3.1) is -\$22,075, giving us the following.

$$\begin{aligned}
\frac{\partial H}{\partial E} &\approx (V-L)\left[1+\frac{3}{4}(L-V)\,r(X_0)\right]\frac{\partial p}{\partial E}\Rightarrow \\
-\$593 &\approx (-\$22,075)\left[1+\frac{3}{4}(\$22,075)\left(1.2*10^{-3}\right)\right]\frac{\partial p}{\partial E}-0\Rightarrow \\
\frac{\partial p}{\partial E} &\approx .0013
\end{aligned} \tag{13}$$

Subjective annual flood probability increased by .13 percentage points. The interval corresponding to the 95 percent confidence interval for the reduced-form estimate is $(-.00067, .0031)$. Under the assumed sorting-driven decrease in absolute risk aversion, the estimated belief change across marginal buyers is .15 percentage points. Again accounting for risk aversion is important, as imposing risk neutrality yields an estimate greater than 2.5 percentage points. Applying our equation 13 for Sandy-flooded properties inside the old floodplain yields $\frac{\partial p}{\partial E} = .0014$, or .14 percentage points.

7.3.3 Updated flood risk maps

In this section we focus on properties included in the new (2013) one percent floodplain as defined by the new maps, but which did not flood during Sandy. Most of these properties have little history of flooding or flood insurance, so the new maps are plausibly informative. We proceed under the assumption that buyers behave as though maps resembling the proposed ones will take effect in the near future.[50] The mean pre-treatment sale price of such properties is \$524k. Taking our reduced-form estimate (converted from log points to percentage) from column 4 of Table 1 yields: $\frac{\partial H}{\partial F} \approx -.114 * \$524K * 0.026 \approx -\$1,553$. For the group impacted by this treatment, $V - L = -\$22,272$.

The expected change in insurance premiums depends on each property's previous designation. Of the 27,953 such properties in the larger analytical sample, ~12,000 (43 percent) were within the old floodplain, while ~16,000 (57 percent) were newly designated. Properties already included in the old floodplain faced no premium increase, but takeup for this group rose from 40 to 57 percent, at a premium of \$1726, in the post-Sandy period (Dixon et al., 2017).[51] The average premium increase in this group was $(.4 * \$0) + (.17 * \$1726) \approx \$293$. Among newly designated properties before Sandy, approximately 10 percent had coverage at a premium of roughly \$484 (Dixon et al., 2013, 2017).[52] In the post-Sandy period, takeup for this group rose to 30 percent and premiums rose by \$1242 to \$1726 (Dixon et al., 2017). The average expected change in insurance cost among newly designated properties is then $(.1 * \$1242) + (.2 * \$1726) \approx \$469$. Averaging across new-floodplain properties that were already in the old floodplain and newly designated properties yields the expected change in premiums: $.43 * \$293 + .57 * \$469 \approx \$393$.[53]

Returning to equation 11 and plugging in values for observables yields the following.

$$\begin{aligned}
\frac{\partial H}{\partial F} &\approx (V-L)\left(1+\frac{3}{4}(L-V)\,r(X_0)\right)\frac{\partial p}{\partial F} - p\left(1+(L-V)\,r(X_0)\right)\frac{\partial L}{\partial F} - \frac{\partial I}{\partial F} \Rightarrow \\
-\$1,553 &\approx (-\$22,272)\left(1+\frac{3}{4}(\$22,272)\left(1.2*10^{-3}\right)\right)\frac{\partial p}{\partial F} - p\,(0) - \$393 \Rightarrow \qquad (14)\\
\frac{\partial p}{\partial F} &\approx .0027
\end{aligned}$$

The map treatment increased subjective flood probability by .27 percentage points. The estimated belief change in response to the new maps is roughly one tenth of the difference between "optimists" and "realists" in Bakkensen and Barrage (2017), and somewhat smaller than the updating generated by a flood in their simulations. The interval corresponding to the 95 percent confidence interval for the reduced-form estimate is $(-.0001, .0052)$. Under the assumed sorting-driven decrease in absolute risk aversion, the estimated belief change across marginal buyers is .31 percentage points. As in previous calculations, risk aversion matters; imposing risk neutrality returns an implausibly large estimate of over five percentage points.

In light of uncertainty not only over reduced-form estimates, but over other model parameters (see Tables A11 and A12), differences across our estimated derivatives should be interpreted cautiously. The 95 percent

[50] The reasonableness of this approach is bolstered by the widespread belief in climate change among New York City residents, the official adoption of the preliminary maps for use in zoning decisions, and the fact that the appeal of the Preliminary FIRMs was based on modeling methodology rather than the substance of the expanded floodplain.

[51] For the aggregate time series of NFIP policies in New York City, see Appendix Figure A17. Dixon et al. (2017) gives a mean premium of \$1880 in 2016 dollars. Converting to 2010 dollars using the PCE deflator yields \$1726 (U.S. Bureau of Economic Analysis, 2019). This is modestly higher than the post-Biggert-Waters figure from Section 7.3.1 for two possible reasons: differences in data and technique across Dixon et al. (2013) and Dixon et al. (2017); and small surcharges imposed by HFIAA.

[52] The figure given in Dixon et al. (2013) is \$506. Again using the PCE deflator, this is \$484 in 2010 US dollars.

[53] This calculation assumes market participants expected the new maps to take legal effect with probability 1. If participants attached subjective probability less than 1 to this event, then the calculation that follows understates belief updating.

confidence intervals reflecting uncertainty in our reduced-form estimates do overlap. Varying the risk aversion and discount parameters, or allowing for modest sorting on risk aversion, alters the levels of estimated belief changes, but not the ranking of treatments by belief change. With these caveats in mind, note that our preferred new-map estimate of .27 percentage points is more than our estimates of Sandy updating (.13 and .14 percentage points), but smaller than the 0.4 percentage point change in response to the Biggert-Waters Act. Given that FEMA classifies annual flood risks greater than one percent as high, these responses are all proportionally large.

8 Conclusion

This study examines the effect of three different flood risk signals on sale prices of small residential properties in New York City. It finds the Biggert-Waters Act decreased sale prices by 5.5 percent (not statistically significant) and Sandy flooding decreased prices by 5.5 to 7 percent (also not generally statistically significant). It also examines the 2013 release of updated FEMA floodplain maps reflecting three decades of climate change and 3.5 inches of sea-level rise. The effect of these new maps on properties flooded by Sandy was just -2.9 percent, while the effect on properties not flooded by Sandy was -11 percent.

We investigate possible mechanisms for these price effects, finding no evidence that residential sorting or selection on the supply side of the market are first-order drivers of our estimates. Using the NFIP structure coverage cap, we find evidence that the large price effect on properties that escaped Sandy flooding, but were included in the new floodplain, is driven by properties with substantial uninsurable structure value. This is consistent with belief updating being an important mechanism behind observed behavioral responses. In light of these findings, we develop a parsimonious theoretical model that includes insurance, beliefs, and risk aversion.

Using a novel approximation of derivatives from this model, we decompose our estimated price effects into changes in expected future premiums and updating. Under our preferred structural assumptions on discounting and risk aversion, we find that insurance premium increases under the Biggert-Waters Act led to average increases in subjective annual flood probability of 0.40 percentage points. Experience of minimal flooding in Sandy increased subjective annual flood probability by .14 percentage points, while the new floodplain maps increased it by .27 percentage points. These changes are proportionally large, ranging from 14 to 40 percent of FEMA's roughly one percent estimated annual risk for properties in the floodplain.

Our findings suggest several potential improvements to the NFIP program. They emphasize the importance of more rapidly updating old NFIP maps to accurately reflect current risks. New maps change floodplain boundaries and insurance premiums. Our results suggest that agents update beliefs in response to both. If such updating leads to optimizing responses, welfare gains could be considerable. More frequent updates to flood information could also allow increasing risk from climate change to be capitalized smoothly rather than discretely, spreading the costs across homeowner cohorts. Greater publicity of floodplain maps reflecting future climate risk could also produce large net benefits by facilitating better-informed buying decisions, insurance choices, and defensive investments.[54] Congress might also consider extending the NFIP insurance mandate to the current .2 percent floodplain, which would force disclosure of risk to a larger set of prospective home buyers. Such steps are particularly important in coastal cities like New York, where climate researchers project an increase in the depth of the .2 percent flood from 3.4 meters to 4-5 meters above an increased sea level by the end of the century (Garner et al., 2017).

[54]For analysis of the forecast risk maps in New York City, see Appendix D.

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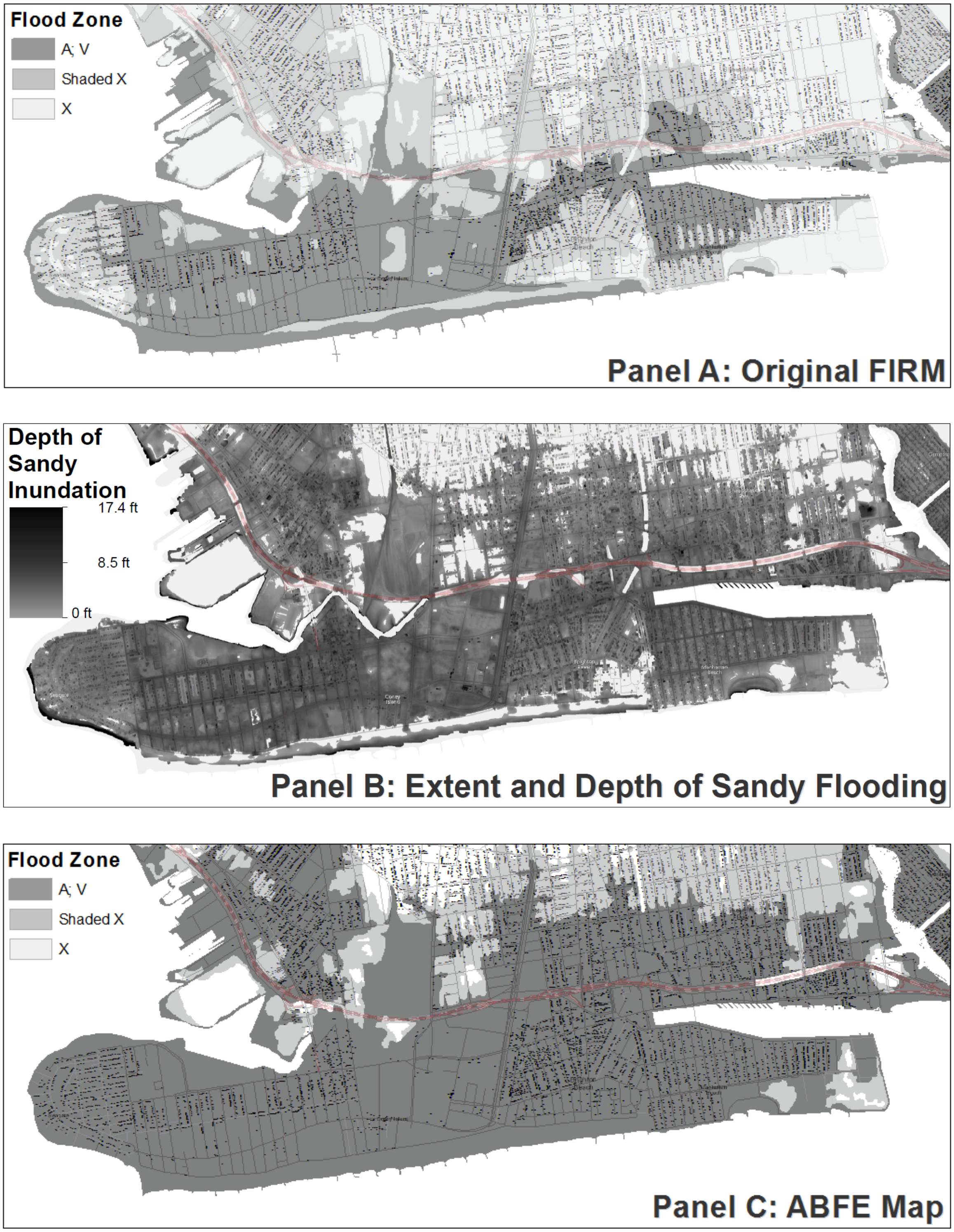
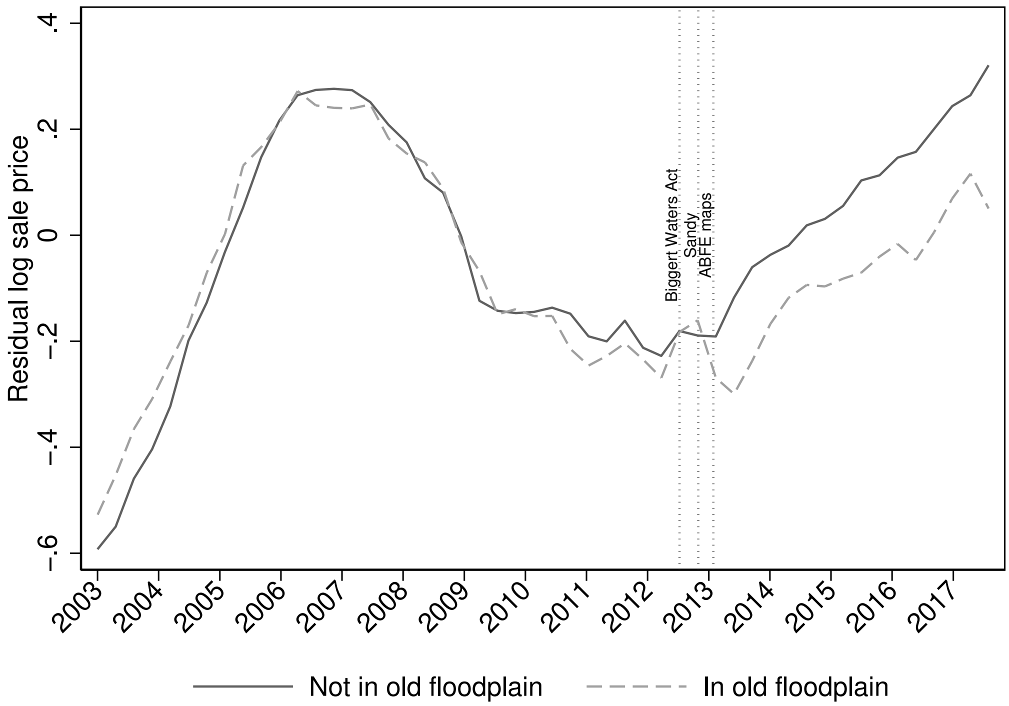
9 Figures

Figure 1: Treatment groups in Coney Island



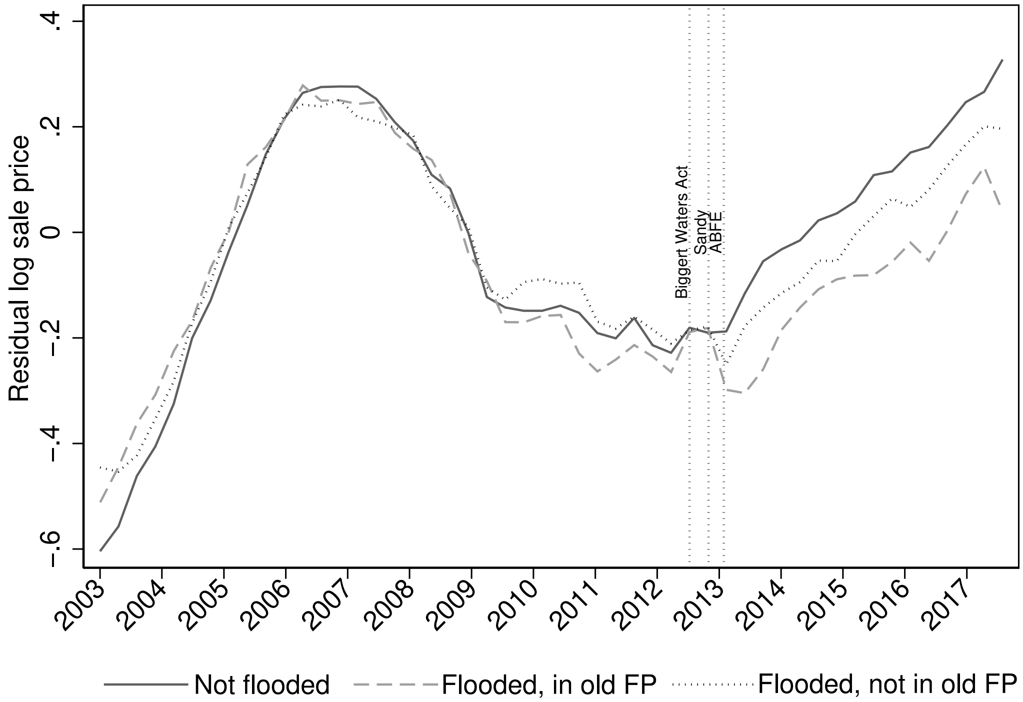
Maps depict Coney Island in south Brooklyn (Kings County). This is an example; our analyses include all five boroughs of New York City. Floodplain and inundation maps are from FEMA. Black dots represent properties for which sales are observed in the transaction data from the New York City Department of Finance 2003-2017. The one percent floodplain consists of flood zones A and V. Zone "Shaded X" is the .2 percent floodplain, and zone X is not considered to be within a floodplain as the annual flood risk is estimated at less than 0.2 percent. For a color version of this figure, see Figure A8.

Figure 2: Effect of Biggert-Waters



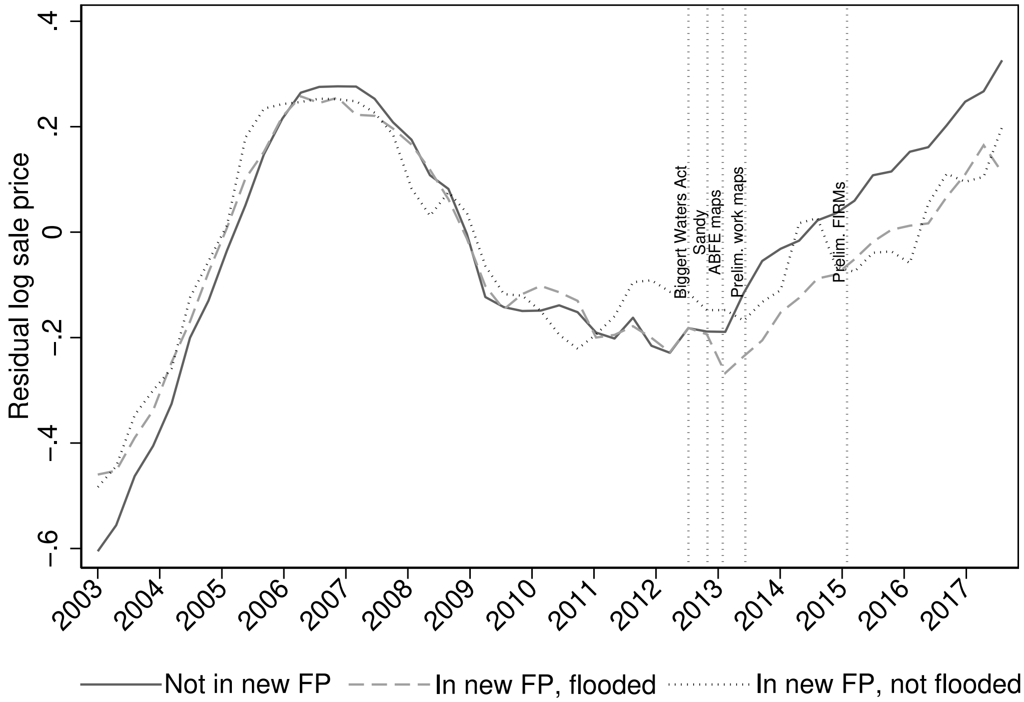
Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Sample is restricted to properties in Tax Class 1. The dependent variable is log sale price, residualized on block fixed effects. Plotted lines are local regressions. "Not in old floodplain" denotes properties not in the 1983 floodplain. "In floodplain" denotes properties in the 1983 floodplain.

Figure 3: Effect of Sandy



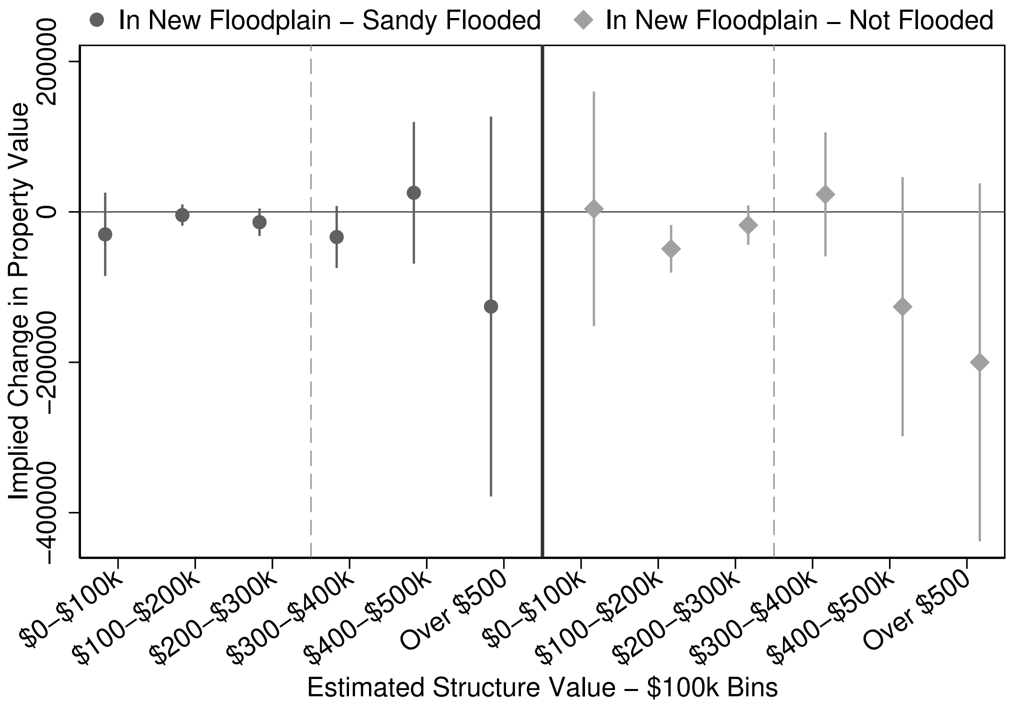
Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Sample is restricted to properties in Tax Class 1. The dependent variable is log sale price, residualized on block fixed effects. Plotted lines are local regressions. "Not flooded" denotes properties not flooded by Sandy. "Flooded, in old floodplain" denotes properties in the 1983 floodplain (which was in effect when Sandy struck) and flooded by Sandy. "Flooded, not in old floodplain" denotes properties not in the 1983 floodplain and flooded by Sandy. The greater post-Sandy fall in prices for properties within the old floodplain is explained by inundation depth (see Table 1).

Figure 4: Effect of new floodplain maps



Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Sample is restricted to properties in Tax Class 1. The dependent variable is log sale price, residualized on block fixed effects. Plotted lines are local regressions. "Not in new FP" denotes properties outside the 2013 floodplain. "In new FP, flooded" denotes properties in the 2013 floodplain that flooded during Sandy. "In new FP, not flooded" denotes properties in the 2013 floodplain that did not flood during Sandy. The brief March 2014 price increase for this group coincides with the passage of the Homeowner Flood Insurance Affordability Act (HFIAA) and may reflect short-lived buyer optimism about the law.

Figure 5: Heterogeneous new map effects by structure value



Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Sample is restricted to properties in Tax Class 1. Reported coefficient estimates are based on the larger sample using block fixed effects (as in column 2 of Table 1). Structure values are estimated by netting out land value from 2012 assessment data from the New York City Department of Finance. Sales observations are divided into bins based on the estimated structure value at the time of the sale. Indicator variables for each of those bins are added to the main specification laid out in equation 1, both directly and interacted with all treatment group and treatment period indicator variables and interactions. "In New Floodplain - Sandy Flooded" denotes properties in the 2013 floodplain that flooded during Sandy. "In New Floodplain - Not Flooded" denotes properties in the 2013 floodplain that did not flood during Sandy.

10 Tables

Table 1: Effects of flood risk signals on log transaction prices

	(1) Neighborhood FE	(2) Block FE	(3) Block FE	(4) Lot FE
Biggert-Waters	-0.0154	-0.0349	0.00654	-0.0567
	(0.0269)	(0.0256)	(0.0355)	(0.0459)
Sandy*in old FP	0.0423	-0.0437	-0.106*	-0.0483
	(0.0471)	(0.0423)	(0.0638)	(0.0880)
Sandy*not in old FP	-0.00605	-0.0218	-0.0220	-0.0432
	(0.0167)	(0.0148)	(0.0218)	(0.0332)
Sandy*depth*in old FP	-0.0363***	-0.0127**	-0.00713	-0.00481
	(0.00695)	(0.00557)	(0.00863)	(0.0115)
Sandy*depth*not in old FP	-0.0384***	-0.0189***	-0.0168*	-0.00590
	(0.00649)	(0.00554)	(0.00912)	(0.0162)
Floodplain maps*Sandy	-0.0216	-0.0480***	-0.0430*	-0.0297
	(0.0219)	(0.0173)	(0.0253)	(0.0395)
Floodplain maps*no Sandy	-0.139***	-0.118***	-0.135***	-0.121**
	(0.0328)	(0.0250)	(0.0394)	(0.0525)
Observations	369342	369342	182667	182667

* $p < .1$, ** $p < .05$, *** $p < .01$. Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Estimates correspond to equation 1. Dependent variable is log sale price. All columns include year-week fixed effects. Cross-sectional fixed effects are indicated in column headings. Standard errors, clustered at the Census Tract level, in parentheses. The estimated effect of map treatment on non-flooded properties, -.121 in the most saturated specification, corresponds to a -11 percent change: $e^{-.121} - 1 = -.114$.

Table 2: Robustness: alternative specifications

	Sale Date FE		Boro*Yr-Mo FE		Depth-Squared	
	(1)	(2)	(3)	(4)	(5)	(6)
	Block FE	Lot FE	Block FE	Lot FE	Block FE	Lot FE
Biggert-Waters	-0.0373	-0.0448	0.0329	0.0139	-0.0349	-0.0567
	(0.0256)	(0.0464)	(0.0247)	(0.0437)	(0.0256)	(0.0458)
Sandy*in old FP	-0.0402	-0.0532	-0.0942**	-0.0986	-0.0417	-0.0593
	(0.0422)	(0.0893)	(0.0415)	(0.0861)	(0.0554)	(0.119)
Sandy*not in old FP	-0.0222	-0.0406	-0.0647***	-0.0731**	-0.0156	0.000436
	(0.0145)	(0.0329)	(0.0145)	(0.0359)	(0.0157)	(0.0339)
Sandy*depth*in old FP	-0.0125**	-0.00612	-0.00589	0.00557	-0.0160	-0.0156
	(0.00550)	(0.0116)	(0.00552)	(0.0114)	(0.0173)	(0.0341)
Sandy*depth*not in old FP	-0.0185***	-0.00843	-0.0180***	-0.00596	-0.0299**	-0.0794**
	(0.00553)	(0.0169)	(0.00551)	(0.0153)	(0.0130)	(0.0370)
Floodplain maps*Sandy	-0.0496***	-0.0275	-0.0678***	-0.0641	-0.0426**	0.00626
	(0.0171)	(0.0402)	(0.0173)	(0.0408)	(0.0183)	(0.0422)
Floodplain maps*no Sandy	-0.114***	-0.131**	-0.117***	-0.108**	-0.118***	-0.120**
	(0.0254)	(0.0530)	(0.0250)	(0.0513)	(0.0250)	(0.0526)
Sandy*depth^2*in old FP					0.000309	0.000989
					(0.00157)	(0.00269)
Sandy*depth^2*not in old FP					0.00192	0.0123*
					(0.00233)	(0.00694)
Observations	368843	181958	369342	182667	369342	182667

* $p < .1$, ** $p < .05$, *** $p < .01$. Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Estimates correspond to equation 1 with noted variations. The estimates in Columns 1 & 2 use date-specific (rather than year-week) fixed effects. Note that these additional controls increase the number of singleton observations, resulting in reduced sample sizes. Columns 3 & 4 include borough-year-month fixed effects, and Columns 5 & 6 add a squared term (in addition to the linear term) for flood depth interacted with the indicator variables for floodplain, flooded by Sandy, and post-Sandy. (These final two columns include the same year-week fixed effects as our primary specification.) Dependent variable is log sale price. Cross-sectional fixed effects are indicated in column headings. Block FE estimates are based on the larger, neighborhood fixed effects sample while the Lot FE estimates use the repeated sales sample. Standard errors, clustered at the Census Tract level, in parentheses.

Table 3: Robustness: Matched difference-in-differences effects of new maps on unflooded properties

	Pre-Treatment Price Spatial Aggregation by:			
	(1)	(2)	(3)	(4)
	Neighborhood	Block	Block	Lot
Floodplain maps	-0.146***	-0.135***	-0.0931***	-0.124***
	(0.0210)	(0.0215)	(0.0215)	(0.0223)
Observations	268502	281840	138324	137365

* $p < .1$, ** $p < .05$, *** $p < .01$. Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Sample is limited to properties not flooded by Sandy. Dependent variable is log sale price. Estimates are from a propensity-score matching difference-in-differences model. Propensity scores are estimated for all properties based on building and lot square footage, building age, latitude, longitude, and block-level average annual price growth rate in the pre-treatment period. In addition, propensity scores depend on the level of pre-treatment average price at the increasingly fine geographic resolutions indicated in the column headings. Both treatment and control observations for columns 3 & 4 are restricted to the repeated sales sample. For all columns, treated properties are matched to control properties based on these propensity scores, with common support required. Estimates reflect a double difference in prices over treatment and time, with regression adjustment for differences in matching variables (except latitude and longitude) and year-week fixed effects. Standard errors, clustered at the Census Tract level, in parentheses. See Appendix C for additional details on the matching and estimation processes. Sample sizes differ due to the common support requirement.

Table 4: Robustness: alternative samples

	Exclude 50M Boundary		500M Buffer as Cntrl		Single Family Homes	
	(1)	(2)	(3)	(4)	(5)	(6)
	Block FE	Lot FE	Block FE	Lot FE	Block FE	Lot FE
Biggert-Waters	0.0113	0.0715	-0.0269	-0.0589	-0.0135	-0.0278
	(0.0360)	(0.0661)	(0.0260)	(0.0480)	(0.0336)	(0.0566)
Sandy*in old FP	-0.131**	-0.236	-0.0155	-0.00999	-0.0294	-0.0835
	(0.0655)	(0.149)	(0.0431)	(0.0923)	(0.0503)	(0.0961)
Sandy*not in old FP	-0.0118	-0.0354	0.0147	-0.00248	-0.0178	-0.0443
	(0.0291)	(0.0682)	(0.0162)	(0.0368)	(0.0171)	(0.0380)
Sandy*depth*in old FP	-0.00710	0.00474	-0.0124**	-0.00440	-0.0118*	0.00199
	(0.00793)	(0.0157)	(0.00554)	(0.0114)	(0.00661)	(0.0115)
Sandy*depth*not in old FP	-0.0208**	-0.00754	-0.0194***	-0.00525	-0.0135*	-0.00803
	(0.00850)	(0.0356)	(0.00591)	(0.0167)	(0.00707)	(0.0141)
Floodplain maps*Sandy	-0.0337	-0.00687	-0.0498***	-0.0291	-0.0313	0.0179
	(0.0326)	(0.103)	(0.0186)	(0.0437)	(0.0201)	(0.0504)
Floodplain maps*no Sandy	-0.0725	-0.146	-0.0943***	-0.0905	-0.103***	-0.104
	(0.0492)	(0.106)	(0.0266)	(0.0569)	(0.0375)	(0.0760)
Observations	341333	169329	116674	53602	173056	80365

* $p < .1$, ** $p < .05$, *** $p < .01$. Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Estimates correspond to equation 1, and different samples are considered. Columns 1 & 2 drop properties within 50 meters of the floodplain boundary. Columns 3 & 4 drop properties >500m outside the boundary of the floodplain. Columns 5 & 6 limit the sample to single-family homes. Block FE estimates are based on the larger neighborhood fixed effects sample (cf. column 2 of Table 1) while the Lot FE estimates use the repeated sales sample. Dependent variable is log sale price. All columns include year-week fixed effects. Cross-sectional fixed effects are indicated in column headings. Standard errors, clustered at the Census Tract level, in parentheses.

Table 5: Correlates of risk preferences, by overlap with new floodplain

Difference in means (2012-2016) - (2007-2011)	Census Tracts: Outside Floodplain	Census Tracts: Overlap w/ Floodplain	Difference in Differences
Census Tract Population	146.357***	185.266***	-38.908
	(9.641)	(21.826)	(23.860)
Share Population Male	.002	.003	.000
	(0.002)	(0.058)	(0.058)
Share >25 Pop: Less than HS Diploma	-.016	-.018	.002
	(0.014)	(0.077)	(0.078)
Share of Population: Age <5	.001	.001	-.001
	(0.007)	(0.044)	(0.044)
Share of Population: Age >64	.008	.007	.001
	(0.009)	(0.058)	(0.059)
Share of Population: White	-.011***	-.010	-.001
	(0.002)	(0.012)	(0.012)
Share of Population: Black	-.009***	-.003	-.007
	(0.002)	(0.016)	(0.016)
Share of Population: Native Born	-.007***	.001	-.008
	(0.002)	(0.026)	(0.026)
Share of Population: Non-Citizen	-.007**	-.004	-.003
	(0.003)	(0.030)	(0.030)
Mean Household Size	.006	.002	.003
	(0.052)	(0.456)	(0.459)
Share >15 Population: Married	-.006	.005	-.011
	(0.011)	(0.022)	(0.024)
Household Median Income	4,598.69***	4,332.68***	266.00
	(338.97)	(681.62)	(761.25)
Unemployment Rate	-.010***	-.007	-.003
	(0.001)	(0.005)	(0.005)
Share HH that Moved In Before 2000	-.097***	-.097	.000
	(0.008)	(0.075)	(0.075)
Share Units Owner Occupied	-.005*	.003	-.008
	(0.003)	(0.023)	(0.023)
Mean Room Count	-.065	-.074	.009
	(0.040)	(0.447)	(0.448)
Mean Year Built of Sales	-2.810	-3.972	-1.162
	(12.618)	(9.802)	(0.968)
Median Rent	176.05***	184.11***	-8.06
	(4.45)	(9.98)	(10.93)
Mean Sale Price	126,185.22	61,389.70	-64,795.52**
	(425,677.25)	(270,229.06)	(32,237.53)
Census Tract Count	1,746	418	2,164

* $p < .1$, ** $p < .05$, *** $p < .01$. SEs in parentheses. Means are calculated for each Census Tract 2007-2011 and 2012-2016. Year Built and Sale Price are from the main analytical sample; all other variables are from the ACS 5-year samples corresponding to these periods. Sample periods were selected to avoid overlap and because more recent ACS data are not yet available. SEs for the ACS data take into account uncertainty in ACS estimates following methods in US Census Bureau (2008).

Table 6: Tests for sample selection

	(1) Neighborhood FE	(2) Block FE	(3) Block FE	(4) Lot FE
Biggert-Waters	0.00470	0.00582	0.0256**	-0.00554
	(0.0144)	(0.0296)	(0.0107)	(0.00486)
Sandy*in old FP	1.339	1.501	-0.00608	0.00476
	(1.307)	(1.504)	(0.0188)	(0.00830)
Sandy*not in old FP	0.381	0.377	0.000679	-0.00110
	(0.378)	(0.388)	(0.00643)	(0.00433)
Sandy*depth*in old FP	-0.0904	-0.112	-0.000531	0.00199*
	(0.0834)	(0.113)	(0.00227)	(0.00106)
Sandy*depth*not in old FP	0.0650	0.0954	0.00232	0.00184
	(0.0670)	(0.0964)	(0.00303)	(0.00295)
Floodplain maps*Sandy	-0.707	-0.828	-0.0103	-0.000643
	(0.707)	(0.839)	(0.00791)	(0.00488)
Floodplain maps*no Sandy	0.0284	0.0318	-0.0166	0.00354
	(0.0241)	(0.0766)	(0.0104)	(0.00339)
N	369342	369342	182690	182689

* $p < .1$, ** $p < .05$, *** $p < .01$. Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Estimates correspond to equation 1, but with the dependent variable constructed as follows. Transactions prior to June 1, 2012 are used to estimate log price as a function of quartics in lot area, floor area, building age, and number of units. Fitted values are then calculated for all transactions and these values comprise the dependent variable in the table above. Intuitively, we are testing whether observable characteristics of transacted properties change such that we would expect price changes unrelated to the treatments we study. All columns include year-week fixed effects. Cross-sectional fixed effects are indicated in column headings. Standard errors, clustered at the Census Tract level, in parentheses.

Web Appendix: Climate risk and beliefs in New York floodplains

Matthew Gibson & Jamie T. Mullins*

A Descriptive evidence from Google Trends

Risk signals can produce the sale price effects estimated above only if the marginal buyer receives them. Using data from Google Trends, we provide descriptive, non-causal evidence consistent with signal diffusion.[1] Monthly data on web searches for floodplain-related searches are from the period 2004-2016. The finest available geographic resolution is a metropolitan area. For a given search term, Google Trends provides a normalized measure of "interest" so that the maximum value achieved in the period equals 100 and all other values are fractions of this maximum level.[2]

Figure A16 plots Google searches for "floodplain" in New York City and the entire United States, residualized on month of year dummy variables 2004-2016.[3] We limit the horizontal range of the plot in order to focus on the period in which the risk signals occurred. The global maximum of the New York City series occurs in January 2013, the month in which the first updated FEMA maps (the ABFE maps) were released. This is consistent with the marginal buyer learning about the maps around this time. We do not observe the locations or identities of those searching, however, so the correlation is merely suggestive. Later releases of the preliminary work maps (June 2013) and preliminary FIRMs (January 2015) do not produce discernible effects on the time series. This is consistent with later releases, which left the ABFE floodplain largely unchanged, conveying little new information. There is a large local maximum associated with Hurricane Sandy and a very small one associated with the Biggert-Waters Act, again consistent with transmission of the signal to the marginal buyer. It is possible these correlations arise from omitted confounders. To test this, Figure A16 includes a similar time series for the entire United States. The US series shows no evidence of local maxima associated with any of the flood risk signals we study. This suggests that the New York City maxima do not arise from nationwide time-varying confounders.

*Gibson: Department of Economics, Williams College, and IZA; mg17@williams.edu. Mullins: Department of Resource Economics, University of Massachusetts Amherst. We thank Alison Hill and Michael Ding for important and skillful research assistance. We are also grateful to participants in the following conferences and seminars: Yale FES, Iowa State, the Northeast Workshop on Energy Policy and Environmental Economics, the Heartland Environmental and Resource Economics Workshop, London School of Economics SERC, and ASSA.

[1] Web traffic data from several FEMA websites with flood risk information was also obtained. Unfortunately, accurate traffic statistics do not begin until 2015, and are therefore unhelpful in assessing the impacts of our main treatments of interest on the search for flood risk information.

[2] https://www.google.com/trends/. "Numbers represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. Likewise a score of 0 means the term was less than 1% as popular as the peak." Last accessed December 15th, 2017.

[3] There is seasonality in such searches, including a predictable increase during the Atlantic hurricane season.

B Additional policy background

B.1 Map appeal & future maps

New York City appealed the Preliminary FIRMs on technical grounds in June of 2015 (Zarrilli, 2015). Pending the outcome of the appeal, the Preliminary FIRMs were held in abeyance and the NFIP insurance mandate was not applied to properties newly placed in the proposed floodplain. In October of 2016, FEMA publicly agreed with the technical complaints of the appeal and announced that it would work closely with the City of New York to revise the Preliminary FIRMs before they would go into force. Despite the appeal, the risk information in the new flood maps was widely publicized and recognized as credible. New York City announced that its construction permitting decisions would be based on the Preliminary FIRMs during the revision period.

B.2 Flood defenses in New York City

This paper has focused on information signals that were anticipated to lead to increases in perceived flood risk levels and decreases in home prices. The announcement of flood protection infrastructure, on the other hand, could increase property values through the expectation of reductions in future flood risks. There has been much discussion of such flood-protection infrastructure in New York City since Hurricane Sandy.

In the four years since Sandy came ashore, very little additional protection has been put into place, and most proposals aimed at the installation of such additional protective measures are still in very early stages. The credibility and timing of any claims regarding protection provided through such programs is highly uncertain, and thus not yet expected to markedly impact future perceived flood risks. The only major flood-protection infrastructure proposal that appears to have gained significant traction is the "BIG U", which proposed a series of barriers be installed around the southern tip of Manhattan. Unfortunately, our focus on small residential properties in this investigation leaves us with very few observations in the potentially impacted area as there are very few small residential properties in Lower Manhattan. Nevertheless, this section applies our empirical strategy to the announcement of the BIG U and provides descriptions and maps of other major flood-protective infrastructure projects in New York City.

As early as 2013, plans were put forth to defend New York City against future major flood events. Such plans can be divided into those that aim to provide harbor-wide protections and those through which local investments are intended to provide protection to specific high-risk areas. Two primary harbor-wide protection alternatives have been proposed. The first involves three movable barriers, one each at the Narrows, Arthur Kill, and in the upper reaches of the East River. The second proposal relies on only two barriers, one in the upper reaches of the East River, and the second spanning from the Rockaway Peninsula to Sandy Hook, NJ (at ~5 miles, the widest proposed span by far, p. 49, PlaNYC, 2013). Any harbor-wide plan would be exceedingly expensive (estimates are on the order of $20 billion), need to overcome significant approval hurdles and environmental impact assessments, require fortification of coastlines adjacent to proposed barriers, and possibly exacerbate flood damage in nearby areas outside the protected areas (p. 49, PlaNYC, 2013). For these reasons and others, such harbor-wide protective plans have fallen out of favor, and recent activities have been focused exclusively on a diverse range of more localized coastal protective strategies (OneNYC Report, 2013).[4]

[4] One exception to this trend is the Blue Dunes proposal which seeks to provide protection to a large section of the Mid-Atlantic coastline through the construction of a chain of barrier islands ~10 miles off the coast to break large wave and surge events before they reach the populated coastline behind. This proposal has not garnered any serious funding, and

The most prominent of the localized protection proposals is the BIG U, also known as the Dryline. This proposal was one of six winners of the 2014 Rebuild by Design competition sponsored by the U.S. Department of Housing and Urban Development (HUD) and intended to support innovative solutions to prepare communities impacted by Hurricane Sandy for future uncertainties. The competition awarded $930 million to six projects in the coastal regions impacted by Hurricane Sandy, of which $335 million was allocated to the BIG U proposal. Put simply the BIG U proposed the installation of a protective barrier along the waterfront from the southern tip of Manhattan to 42nd Street along the East River and up to 57th Street along the Hudson River (see Figure A18).

Since the competition, the BIG U, has garnered further funding commitments from HUD and the City of New York. It has also been split up into a number of pieces, two of which have become active projects. The first has been titled the East Side Coastal Resiliency (ESCR) Project and is considered to be fully funded with $510 million budgeted (Mayor's Office of Recovery & Resillency Map, accessed 2/24/2017). The ESCR Project is currently in the design phase (OnceNYC 2016 Progress Report) with construction expected to begin in 2018 (Architeets Newspaper, 2016). The second project that has thus far come out of the BIG U proposal is known as the Lower Manhattan Coastal Resiliency (LMCR) Project and has been split further into two distinct project areas. Work in the Two Bridges area, on the East River between the Manhattan and Brooklyn Bridges, has been allocated $203 million and is in the planning phase, while studies are still underway and additional funding is being sought for coastal defenses of the waterfront extending from the Brooklyn Bridge, around the tip of Manhattan to the northern end of Battery Park City (Mayor's Office of Recovery & Resillency Map, accessed 2/24/2017).[5] "Actionable concept designs" are expected for the LMCR in 2018 (Architects Newspaper, 2016).

The initial funding of the BIG U proposal came on June 2, 2014, when it was announced as the largest winner of the Rebuild by Design competition.[6] We will treat this date as the beginning of the period during which property prices may reflect the value of future flood protection provided under the proposal. We consider all properties behind the barriers described in the BIG U proposal as potentially benefiting from reductions in perceived future flood risk, and thus increased property values. Table A13 presents the results of our main specification with the initial BIG U funding added as an additional information signal. While the neighborhood fixed effects specification suggests large and significant effects in the anticipated direction, the better controlled specifications are unable to identify any significant effects of the BIG U proposal on the sale prices of small-residential properties. Alternative specifications - for example using alternative announcement dates, considering only properties flooded by Sandy or in some definition of the one percent floodplain as potentially benefiting from the BIG U proposal, or considering only properties in the areas behind the ESCR and LMCR Projects as impacted - yield similarly unconvincing results in focused specifications. It is worth noting that our analytical sample includes only 1,357 sales that fall behind the barriers proposed by the BIG U, and only 286 are characterized as within the one percent floodplain under the updated definitions.

Below we provide basic information on four other large-scale infrastructure projects that have been

while it has generated discussion, especially among the academic community, there is currently no plan or timeline for its implementation. See the proposal website for more information: `http://www.rebuildbydesign.org/our-work/all-proposals/finalist/blue-dunes--the-future-of-coastal-protection`.

[5] The BIG U proposes development along the East River from East River Park to Battery Park. The transformation of this "J" shape to a "U" through protecting the Lower West Side of Manhattan is never talked about, though the line of protection is often drawn all the way up the West Side. A single mention of the "Westside Highway as a "raised natural landscape" was found (in this video at 3:14), but this does not appear to be part of the BIG U project (https://www.nytimes.com/2016/01/19/nyregion/new-york-city-to-get-176-million-from-us-for-storm-protections.html?_r=0).

[6] Though the BIG U Proposal was released to the public on April 3, 2014, as one of nearly 150 competitors in the Rebuild by Design competition, it was the selection of the proposal for funding which raised it to prominence.

proposed and gained some level of official support or recognition. Figure A19 depicts the location of each of these proposals as well as that of the BIG U.

- **The Living Breakwaters Project** was funded with $60M through the HUD Rebuilding by Design competition to install breakwaters off of Staten Island's southern tip with the stated goal of reducing erosion and attenuating wave action (Project Web Page). Early design work is currently underway with a final design expected by early 2018, and construction slated to begin thereafter.
- **Red Hook Integrated Flood Protection System (IFPS)** is a project seeking to protect the Red Hook neighborhood in Brooklyn through a series of flood protection measures (gates, walls, raised roads, etc.). The initial announcement of the project was made December 14, 2014 (Governor's Announcement), and the project has received $100M in funding commitments from City and Federal sources. Three possible plans have been put forth and a series of public meetings were held in 2016 to inform the community about the project and the possible plans (Project Website).
- **Atlantic Coast of New York: East Rockaway Inlet to Rockaway Inlet and Jamaica Bay:** The United States Army Corps of Engineers (USACE) has maintained Rockaway Beach since 1977. In 2003, a study was commenced to reevaluate the "long-term protection" of the area. Funding was inconsistent until the Disaster Relief Appropriates Act of 2013 (following Sandy). The new recommendations for the management of the area were released to the public in July 2016 focusing on expensive, long-term infrastructure construction ($3-4B over 50-year period) to provide "long-term coastal storm risk reduction for Rockaway and Jamaica Bay" (USACE, 2016c). The recommended plan would provide some degree of coastal flood protection to Coney Island in addition to Jamaica Bay and the Rockaway Peninsula (see Figure A19). The recommended plan aims to provide protection with a height of 17feet above average water levels with an estimated total cost of $3.78B (Study Report), but no funding source or time frame for the project have been identified.
- **South Shore of Staten Island, NY: Coastal Storm Risk Management:** The USACE released an Interim Feasibility Report in Oct 2016 (amended in Dec 2016) which recommended that barriers to address storm damages from water levels up to 15.6 feet above still water elevation (2 feet higher than Hurricane Sandy Storm tide) be constructed along the Southern Shore of Staten Island with an estimated total cost of $571M (ACE Interim Feasibility Report, 2016). The plan involves the construction of a series of levees, floodwalls, and seawalls spanning from Great Kills Park to Fort Wadsworth along the northern end of Staten Island's southeast shore. Original funding for the study of coastal storm risk management in the area was set up in May 1999 and work on the assessment began in August of 2000. Funding ran out prior to the completion and release of a report. Additional funding was allocated in 2009 (part of the ARRA stimulus) and then again in the Disaster Relief Appropriates Act of 2013 (following Sandy). The Draft Feasibility Report was released in June 2015. While the design phase of the project is currently underway, no definitive schedule has been laid out or funding source identified (Fact Sheet and ACE Page).

Each of these projects has characteristics that inhibit the application of our empirical methods to estimate the effects their announcements might have had on property values. The Living Breakwaters Project has been very slow moving, will cover a fairly small region at the southern tip of Staten Island, and doesn't seek to provide full protection, but only to mitigate damages. The Red Hook IFPS project similarly seeks to protect a very small area, and the proposed plans vary significantly in the specifics of which areas might actually benefit. While the two USACE projects aim to provide protection to large areas (and many residential properties), their announcements simply come too late for us to provide useful assessments of their effects. Further, it is far from certain when and to what extent the protections outlined in these proposals might be implemented.

C Matched Difference-in-Differences

As a validation to our main results, we estimate the impacts of the new floodplain map release on properties that were not flooded by Sandy using a regression adjusted, kernel propensity score matching difference-in-differences estimator (see: Rosenbaum and Rubin 1983; Heckman et al. 1998; Caliendo and Kopeinig 2008 for additional details). This approach addresses concerns regarding differential pre-trends between control and treatment groups by identifying a control group that is comparable to the treated group in dimensions of interest, and in particular in pre-treatment trends. This estimation is done in isolation from the direct effects of the Biggert Waters and Sandy treatments by considering only properties which were not flooded by Sandy. Treated properties - those designated as within the updated floodplain - are matched to similar untreated properties - those not identified as being within the new floodplain - that were also not flooded by Sandy. "Matching" in this case is actually done using a kernel (epanechnikov with bandwidth 0.6) weighting of all control-group properties with propensity scores within the support of the treated properties (note, treated properties outside of the propensity score support of the control properties are also dropped). Control observations with propensity scores closer to scores of treated properties are given higher weights, and weighted-regression-based difference-in-differences estimates are calculated based on mean logged sale prices at the neighborhood, block, and lot levels. Regression adjustment (i.e., inclusion of controls in the difference-in-differences regression) for observable factors which might impact sales prices corrects for some degree of poor matches, and robust standard errors are clustered by Census Tract (Robins and Rotnitzky, 1995).

Propensity scores are calculated via a probit regression of treatment status on building and lot square footage, building age, latitude, longitude, and block-level average annual price growth rate in the pre-treatment period. In addition, propensity scores depend on the level of pre-treatment average price considered at the relevant resolution of geographic aggregation: neighborhood, block, or lot. This pre-treatment average price is simply the mean sale price (in 2010 US dollars) of transactions included in our main and repeated sales samples during the period from 2003 to the passage of Biggert Waters in July 2012. Similarly, the block-level average annual price growth is calculated based on annualized changes in sale prices over time within a given block during the pre-Biggert Waters period. Untreated properties are assumed to have a treatment period beginning with the January 2013 release of the ABFE maps.

Figure A20 shows difference-in-differences estimates of the new maps treatment effect (at the lot-level of aggregation in the repeated sales sample) for five, 1-year placebo treatment periods prior to the actual release of the updated flood maps, and the estimated effect of the treatment during the actual treatment. This figure shows what we would expect, namely that there was no significant deviation in sales prices between the treatment and control groups in the matched sample leading up to the actual treatment period.

D Projected floodplains

In June 2013, the New York City Panel on Climate Change released a report titled "Climate Risk Information 2013: Observations, Climate Change Projections, and Maps".[7] The executive summary included maps of New York City with projected 100-year and 500-year flood zones for the 2020s and 2050s. These maps were generated based on a "high estimate" of sea-level rise (characterized as 90th percentile) and specifically assumed sea level rise of 11 inches by the 2020s and 31 inches by the 2050s, relative to the 2000-2004 period. Higher sea levels increase the area of inundation from a 100-year flood event. Thus the 100-year (or 1 percent annual risk) floodplain is larger in such scenarios than under the existing or proposed FIRMs. See Figure A21 for a comparison of the floodplains under the current active FIRM (Old FP), the Preliminary FIRM, the projection for the 2020s, and the projection for the 2050s.[8]

Failure to account for these projections could produce bias. To investigate, we merge projected map layers onto our sales data and estimate modified versions of our primary regression specifications. In particular, we define F^{2020} and F^{2050} as indicator variables for a tax lot falling within the projected floodplains for the 2020s and 2050s respectively. P_F is a dummy for a sale taking place after the June 2013 release of the maps showing the projected future floodplains. The following four terms are thus added to the specification detailed in equation 1: F^{2020}, $F^{2020} * P_F$, F^{2050}, and $F^{2050} * P_F$. Note that the year-week fixed effects preclude the need for P_F to enter directly.

Table A9 reports the results. Coefficients of interest (Biggert-Waters, Sandy, and the 2013 maps) are strongly similar to those in Table 1. The estimated effect of the 2020 projection is positive and insignificant in the more tightly controlled specifications (columns 2 and 4). The estimated effect of the 2050 projection is negative (-.0458) in column 2 and statistically significant at the one percent level, but near zero and not statistically significant in column 4. These estimates are consistent with the very limited media attention to these future floodplain projections. The projections have no official status and mandate no actions by citizens or officials. As their exclusion does not meaningfully affect our estimates of interest, we have opted to exclude them from our main specifications.

[7] Available: http://www.nyc.gov/html/planyc2030/downloads/pdf/npcc_climate_risk_information_2013_report.pdf. Last accessed February 7, 2019.

[8] Data available from: https://data.cityofnewyork.us/browse?q=floodplain, last accessed February 7, 2019.

E Relative risk aversion

In our primary model of Section 7.2 we approximate derivatives in terms of Arrow-Pratt absolute risk aversion. Alternatively, one can simplify using Arrow-Pratt relative risk aversion $\rho(X) = -\frac{\frac{\partial^2 U}{\partial X^2}}{\frac{\partial U}{\partial X}} X$. Beginning from equation 6, factor X_c out of the subtractions to obtain

$$\frac{\partial H}{\partial I} \approx \frac{\left[(V-L)\left(\frac{\partial U}{\partial X_c} + \left(\frac{X_m}{X_c} - 1\right)\frac{\partial^2 U}{\partial X_c^2} X_c\right)\right]\frac{\partial p}{\partial I}}{\frac{\partial U}{\partial X_c}} - \frac{p\left(\frac{\partial U}{\partial X_c} + \left(\frac{X_1}{X_c} - 1\right)\frac{\partial^2 U}{\partial X_c^2} X_c\right)\frac{\partial L}{\partial I}}{\frac{\partial U}{\partial X_c}} - 1$$

Reversing the order of the subtractions and applying the definition of relative risk aversion yields

$$\frac{\partial H}{\partial I} \approx (V-L)\left[1 + \left(1 - \frac{X_m}{X_c}\right)\rho(X_c)\right]\frac{\partial p}{\partial I} - p\left[1 + \left(1 - \frac{X_1}{X_c}\right)\rho(X_c)\right]\frac{\partial L}{\partial I} - 1$$

We do not employ the simplification in terms of $\rho(X)$ in this paper.

F Expected loss

Suppose a truncated exponential distribution $f(L)$ over loss L, with support on $\left[0, \bar{S}\right]$. The upper endpoint $\bar{S}$ is structure value, the maximum possible loss. In general the expected loss over such a distribution is as follows.

$$\begin{aligned}
E[L] &= \int_0^{\bar{S}} L f(L)\, dL \\
&= \int_0^{\bar{S}} L \frac{\lambda e^{-\lambda L}}{1 - e^{-\lambda \bar{S}}} dL \\
&= \frac{1}{1 - e^{-\lambda \bar{S}}} \int_0^{\bar{S}} L \lambda e^{-\lambda L} dL \\
&= \frac{1}{1 - e^{-\lambda \bar{S}}} \left[-L e^{-\lambda L} - \frac{1}{\lambda} e^{-\lambda L}\right]_0^{\bar{S}} \\
&= \frac{1}{1 - e^{-\lambda \bar{S}}} \left[\left(-\bar{S} e^{-\lambda \bar{S}} - \frac{1}{\lambda} e^{-\lambda \bar{S}}\right) - \left(0 - \frac{1}{\lambda} e^{0}\right)\right] \\
&= \frac{1}{1 - e^{-\lambda \bar{S}}} \left[-\bar{S} e^{-\lambda \bar{S}} - \frac{1}{\lambda} e^{-\lambda \bar{S}} + \frac{1}{\lambda}\right] \\
&= \frac{1}{1 - e^{-\lambda \bar{S}}} \left[-\bar{S} e^{-\lambda \bar{S}} + \frac{1}{\lambda}\left(1 - e^{-\lambda \bar{S}}\right)\right] \\
&= \frac{1}{\lambda} + \frac{-\bar{S} e^{-\lambda \bar{S}}}{1 - e^{-\lambda \bar{S}}}
\end{aligned}$$

Let us now set $\bar{S} = 1$, which will allow us to interpret losses as a percentage of structure value. Aerts et al. (2013) calculate annual expected loss of roughly .6 percent, or .006 in decimal terms. Matching this expected loss and solving numerically for λ yields $\lambda = 166.67$. With this parameter in hand, we can now calculate the expected loss over uninsured value for properties with NFIP coverage rate $c = \frac{\$250{,}000}{\bar{S}}$ (that is, coverage rate is the cap divided by the structure value).

$$\begin{aligned}
E\left[L \mid c\right] &= \int_0^c 0 f\left(L\right) dL + \int_c^1 L f\left(L\right) dL \\
&= \int_c^1 L \frac{\lambda e^{-\lambda L}}{1 - e^{-\lambda}} dL \\
&= \frac{1}{1 - e^{-\lambda}} \int_c^1 L \lambda e^{-\lambda L} dL
\end{aligned}$$

From above, we have the form of the definite integral.

$$\begin{aligned}
E\left[L \mid c\right] &= \frac{1}{1 - e^{-\lambda}} \left[-L e^{-\lambda L} - \frac{1}{\lambda} e^{-\lambda L}\right]_c^1 \\
&= \frac{1}{1 - e^{-\lambda}} \left[\left(-1 e^{-\lambda 1} - \frac{1}{\lambda} e^{-\lambda 1}\right) - \left(-c e^{-\lambda c} - \frac{1}{\lambda} e^{-\lambda c}\right)\right] \\
&= \frac{1}{1 - e^{-\lambda}} \left[-e^{-\lambda} - \frac{1}{\lambda} e^{-\lambda} + c e^{-\lambda c} + \frac{1}{\lambda} e^{-\lambda c}\right] \\
&= \frac{1}{1 - e^{-\lambda}} \left[-e^{-\lambda} \left(1 + \frac{1}{\lambda}\right) + e^{-\lambda c} \left(c + \frac{1}{\lambda}\right)\right]
\end{aligned}$$

This can be evaluated for any property by plugging in $\lambda = 166.67$ and coverage rate $c = \frac{\$250{,}000}{S}$.

G Dynamic model

Our primary theoretical model of Section 7.2 assumes subjective flood probability p is time-invariant unless shocked by new information through F (official flood risk rating), E (flood experience), or I (insurance premium). In this section we relax that assumption, allowing for time-varying belief $p_t = p_0(F, E, I) + \gamma t$. The period-zero subjective probability of a flood, $p_0(F, E, I)$, is a function of a property's official floodplain designation F, experience with past flooding events E, and flood insurance premiums I faced by the property owner. Subjective flood probability is assumed to grow linearly in time at rate γ, reflecting the agent's anticipation of climate change. While linearity is a restrictive assumption, it allows us to make the model dynamic while maintaining empirical tractability.

The hedonic function is now time-varying: $H(\boldsymbol{Z}, p_t)$. Let Y be exogenous income and X consumption of a numeraire good. The budget constraint is then $Y = X_t + H(\boldsymbol{Z}, p_t)$. We denote flood insurance premium $I(F)$, anticipated flood loss $L(F, E, I)$, and insurance payout $V(Z)$. Then we have state-dependent budget constraints:

$$\begin{aligned} X_{1t} &= Y - H(\boldsymbol{Z}, p_t) - I(F) - L(F, E, I) + V(Z) \\ X_{0t} &= Y - H(\boldsymbol{Z}, p_t) - I(F) \end{aligned} \tag{1}$$

where X_{1t} and X_{0t} are consumption levels in the flood and non-flood states of the world respectively. Assume a twice continuously differentiable, time-separable von Neumann-Morgenstern utility function, with $\frac{\partial U}{\partial X} > 0$ and $\frac{\partial^2 U}{\partial X^2} < 0$. Given a utility discount rate δ, expected utility can then be written as follows.

$$EU = \sum_{t=0}^{T} \frac{p_t U(X_{1t}, \boldsymbol{Z}) + (1 - p_t) U(X_{0t}, \boldsymbol{Z})}{(1+\delta)^t} \tag{2}$$

The passage of the Biggert-Waters Act served as a shock to insurance premiums I. As before we assume a housing equilibrium under which all agents enjoy equal expected utility, which allows us to set the derivative of expected utility with respect to the insurance premium to zero.

$$\frac{\partial}{\partial I} EU = \sum_{t=0}^{T} \frac{1}{(1+\delta)^t} \left\{ [U(X_{1t}) - U(X_{0t})] \frac{\partial p_t}{\partial I} - p_t \frac{\partial U}{\partial X_{1t}} \frac{\partial L}{\partial I} - \left[p_t \frac{\partial U}{\partial X_{1t}} + (1 - p_t) \frac{\partial U}{\partial X_{0t}} \right] \frac{\partial H}{\partial I} - \left[p_t \frac{\partial U}{\partial X_{1t}} + (1 - p_t) \frac{\partial U}{\partial X_{0t}} \right] \right\} \tag{3}$$

We wish to solve for the housing price effect $\frac{\partial H}{\partial I} = \frac{\partial H}{\partial p_t} \frac{\partial p_t}{\partial I}$. Concretely, we assume linearity of the hedonic function, $H(p_t) = \pi_0 + \pi_1 p_t$, and a constant derivative of p_0 with respect to I such that $\frac{\partial p_t}{\partial I} = \frac{\partial p}{\partial I}$ for all t.[9] This allow us to rearrange terms.

$$\frac{\partial H}{\partial I} = \frac{\sum_{t=0}^{T} \frac{1}{(1+\delta)^t} \left\{ [U(X_{1t}) - U(X_{0t})] \frac{\partial p}{\partial I} - p_t \frac{\partial U}{\partial X_{1t}} \frac{\partial L}{\partial I} - \left[p_t \frac{\partial U}{\partial X_{1t}} + (1 - p_t) \frac{\partial U}{\partial X_{0t}} \right] \right\}}{\sum_{t=0}^{T} \frac{1}{(1+\delta)^t} \left[p_t \frac{\partial U}{\partial X_{1t}} + (1 - p_t) \frac{\partial U}{\partial X_{0t}} \right]} \tag{4}$$

The model predicts a negative effect of increased premiums on home prices by way of three channels: 1) increased subjective flood probability in term one; 2) an increase in expected flood severity in term two, and

[9] Recall that $p_t = p_0(F, E, I) + \gamma t$, so a constant derivative of p_0 with respect to I implies a constant derivative of p_t with respect to I.

3) increased premiums in term three.

This expression is not empirically tractable. We now derive an approximation that will allow us to take this model to the data. First, distributing the summation allows us to simplify.

$$\frac{\partial H}{\partial I} = \frac{\sum_{t=0}^{T} \frac{1}{(1+\delta)^t} \left\{ \left[U(X_{1t}) - U(X_{0t}) \right] \frac{\partial p}{\partial I} - p_t \frac{\partial U}{\partial X_{1t}} \frac{\partial L}{\partial I} \right\}}{\sum_{t=0}^{T} \frac{1}{(1+\delta)^t} \left[p_t \frac{\partial U}{\partial X_{1t}} + (1-p_t) \frac{\partial U}{\partial X_{0t}} \right]} - 1 \tag{5}$$

By the intermediate value theorem there exists a point X_{ct} on $[X_{1t}, X_{0t}]$ such that $\frac{\partial U}{\partial X_{ct}} = p_t \frac{\partial U}{\partial X_{1t}} + (1 - p_t) \frac{\partial U}{\partial X_{0t}}$. If initial subjective flood probability p_0 is small, X_{c0} will be in the neighborhood of $X_{0,0}$. As p_t increases, X_{ct} will decrease relative to $X_{0,t}$. By the mean value theorem, there exists a point X_{mt} on $[X_{1t}, X_{0t}]$ such that $\frac{\partial U}{\partial X_{mt}} = \frac{1}{X_{0t} - X_{1t}} \int_{X_{1t}}^{X_{0t}} \frac{\partial U}{\partial X}(X)\, dX$. Then we can replace $U(X_{1t}) - U(X_{01}) = (X_{1t} - X_{0t}) \frac{\partial U}{\partial X_{mt}} = (V - L) \frac{\partial U}{\partial X_{mt}}$. The last equality is possible because $H(p_t)$ enters both budget constraints identically; while X_{1t} and X_{0t} increase over time, the distance between them remains constant at $(V - L)$. Our derivative now becomes simpler.

$$\frac{\partial H}{\partial I} = \frac{\sum_{t=0}^{T} \frac{1}{(1+\delta)^t} \left[(V-L) \frac{\partial U}{\partial X_{mt}} \right] \frac{\partial p}{\partial I}}{\sum_{t=0}^{T} \frac{1}{(1+\delta)^t} \left[\frac{\partial U}{\partial X_{ct}} \right]} - \frac{\sum_{t=0}^{T} \frac{1}{(1+\delta)^t} p_t \frac{\partial U}{\partial X_{1t}} \frac{\partial L}{\partial I}}{\sum_{t=0}^{T} \frac{1}{(1+\delta)^t} \left[\frac{\partial U}{\partial X_{ct}} \right]} - 1 \tag{6}$$

To this point the intermediate value theorem and mean value theorem have allowed us to avoid approximation. We next employ first-order Taylor expansions to approximate numerator marginal utilities in terms of denominator marginal utility $\frac{\partial U}{\partial X_{ct}}$. We obtain $\frac{\partial U}{\partial X_{mt}} \approx \frac{\partial U}{\partial X_{ct}} + (X_{mt} - X_{ct}) \frac{\partial^2 U}{\partial X_{ct}^2}$ and $\frac{\partial U}{\partial X_{1t}} \approx \frac{\partial U}{\partial X_{ct}} + (X_{1t} - X_{ct}) \frac{\partial^2 U}{\partial X_{ct}^2}$. Our derivative is now as follows.

$$\frac{\partial H}{\partial I} \approx \frac{\sum_{t=0}^{T} \frac{1}{(1+\delta)^t} \left[(V-L) \left(\frac{\partial U}{\partial X_{ct}} + (X_{mt} - X_{ct}) \frac{\partial^2 U}{\partial X_{ct}^2} \right) \right] \frac{\partial p}{\partial I}}{\sum_{t=0}^{T} \frac{1}{(1+\delta)^t} \left[\frac{\partial U}{\partial X_{ct}} \right]} - \frac{\sum_{t=0}^{T} \frac{1}{(1+\delta)^t} p_t \left(\frac{\partial U}{\partial X_{ct}} + (X_{1t} - X_{ct}) \frac{\partial^2 U}{\partial X_{ct}^2} \right) \frac{\partial L}{\partial I}}{\sum_{t=0}^{T} \frac{1}{(1+\delta)^t} \left[\frac{\partial U}{\partial X_{ct}} \right]} - 1 \tag{7}$$

Recall that X_{1t} and X_{0t} are increasing over time, while X_c is moving leftward within the interval $[X_{1t}, X_{0t}]$. Assuming locally constant absolute risk aversion, $X_{ct} = X_c$ and one can simplify further.

$$\frac{\partial H}{\partial I} \approx \frac{\frac{\partial p}{\partial I}(V-L) \sum_{t=0}^{T} \frac{1}{(1+\delta)^t} \left(\frac{\partial U}{\partial X_c} + (X_{mt} - X_c) \frac{\partial^2 U}{\partial X_c^2} \right)}{\frac{\partial U}{\partial X_c} \sum_{t=0}^{T} \frac{1}{(1+\delta)^t}} - \frac{\sum_{t=0}^{T} \frac{1}{(1+\delta)^t} p_t \left(\frac{\partial U}{\partial X_c} + (X_{1t} - X_c) \frac{\partial^2 U}{\partial X_c^2} \right) \frac{\partial L}{\partial I}}{\frac{\partial U}{\partial X_c} \sum_{t=0}^{T} \frac{1}{(1+\delta)^t}} - 1 \tag{8}$$

In the denominator, we can now apply the formula for the sum of a geometric series. We wish to use the definition of Arrow-Pratt absolute risk aversion $r(X) = -\frac{\frac{\partial^2 U}{\partial X^2}}{\frac{\partial U}{\partial X}}$ (Arrow, 1970; Pratt, 1964). Reversing the order of the numerator subtractions and dividing yields the following.

$$\frac{\partial H}{\partial I} \approx \frac{\frac{\partial p}{\partial I}\left(V-L\right)\sum_{t=0}^{T}\frac{1}{(1+\delta)^t}\left(1+\left(X_c-X_{mt}\right)r\left(X_c\right)\right)}{\frac{1-\left(\frac{1}{1+\delta}\right)^{T+1}}{1-\frac{1}{1+\delta}}} - \frac{\sum_{t=0}^{T}\frac{1}{(1+\delta)^t}p_t\left(1+\left(X_c-X_{1t}\right)r\left(X_c\right)\right)\frac{\partial L}{\partial I}}{\frac{1-\left(\frac{1}{1+\delta}\right)^{T+1}}{1-\frac{1}{1+\delta}}} - 1 \qquad (9)$$

Based on the work of Gallagher (2014), we set $\frac{\partial L}{\partial I} = 0$ and the second term vanishes. It remains to find an empirically useful approximation for $X_c - X_{mt}$. In the expression above, X_c is the point on all $[X_{1t}, X_{0t}]$ at which the marginal utility of consumption is equal to the expected value of marginal utility of consumption across flood and non-flood states. This is true in particular for period zero. If initial subjective flood probability p_0 is small, X_c will be approximately equal to $X_{0,0}$. X_{mt} is the average marginal utility of consumption over the interval $[X_{1t}, X_{0t}]$. Under diminishing absolute risk aversion X_m would lie on the interval $\left[X_{1t}, \frac{X_{0t}+X_{1t}}{2}\right]$.[10] We approximate using the midpoint of this interval $X_{mt} \approx \frac{1}{2}\left(X_{1t} + \frac{X_{0t}+X_{1t}}{2}\right) = \frac{X_{1t}}{2} + \frac{X_{0t}+X_{1t}}{4} = \frac{3}{4}X_{1t} + \frac{1}{4}X_{0t}$. Next we substitute into $X_c - X_{mt}$ and obtain the following.

$$\begin{aligned} X_c - X_{mt} &\approx X_{0,0} - \left(\frac{3}{4}X_{1t} + \frac{1}{4}X_{0t}\right) \\ &\approx X_{0,0} - \frac{1}{4}X_{0t} - \frac{3}{4}X_{1t} \end{aligned}$$

Now we substitute the budget constraint in the non-flood state of the world.

$$X_c - X_{mt} \approx \left(Y - H\left(p_0\right) - I\right) - \frac{1}{4}\left(Y - H\left(p_t\right) - I\right) - \frac{3}{4}X_{1t}$$

We next add and subtract $H\left(p_t\right)$ on the right-hand side of the expression.

$$\begin{aligned} X_c - X_{mt} &\approx \left(Y - H\left(p_t\right) - I\right) - \frac{1}{4}\left(Y - H\left(p_t\right) - I\right) - \frac{3}{4}X_{1t} + H\left(p_t\right) - H\left(p_0\right) \\ &\approx \frac{3}{4}\left(X_{0t} - X_{1t}\right) + \left(H\left(p_t\right) - H\left(p_0\right)\right) \\ &\approx \frac{3}{4}\left(L - V\right) + \left(H\left(p_t\right) - H\left(p_0\right)\right) \end{aligned}$$

We previously assumed $H\left(p_t\right) = \pi_0 + \pi_1 p_t$ and $p_t = p_0\left(F, E, I\right) + \gamma t$. Combining these functions we obtain $H\left(t\right) = \left(\pi_0 + \pi_1 p_0\right) + \left(\pi_1 \gamma\right) t$. For notational convenience, let $\pi_0 + \pi_1 p_0 \equiv \Gamma_0$ and $\pi_1 \gamma \equiv \Gamma_1$ so that $H\left(t\right) = \Gamma_0 + \Gamma_1 t$. Then $H\left(t\right) - H\left(0\right) = \left(\Gamma_0 + \Gamma_1 t\right) - \left(\Gamma_0\right) = \Gamma_1 t$. Plugging back into our approximation, we simplify further.

$$X_c - X_{mt} \approx \frac{3}{4}\left(L - V\right) + \Gamma_1 t$$

[10] The assumption of diminishing absolute risk aversion is in keeping with theoretical prediction of Arrow (1970) and a large empirical literature (Saha et al., 1994; Guiso and Paiella, 2008; Sydnor, 2010). Assuming $\frac{\partial U}{\partial X} > 0$, diminishing absolute risk aversion requires $\frac{\left(\frac{\partial^2 U}{\partial X^2}\right)^2}{\frac{\partial U}{\partial X}} - \frac{\partial^3 U}{\partial X^3} < 0$.

This expression can now be substituted into our approximate derivative.

$$\frac{\partial H}{\partial I} \approx \frac{\frac{\partial p}{\partial I}\left(V-L\right)\sum_{t=0}^{T}\frac{1}{(1+\delta)^{t}}\left(1+\left(\frac{3}{4}\left(L-V\right)+\Gamma_{1}t\right)r\left(X_{c}\right)\right)}{\frac{1-\left(\frac{1}{1+\delta}\right)^{T+1}}{1-\frac{1}{1+\delta}}} - 1 \tag{10}$$

Following similar steps, we can derive comparable expressions for $\frac{\partial H}{\partial E}$ and $\frac{\partial H}{\partial F}$ based on the dynamic model described in equation 1 and 2:

$$\frac{\partial H}{\partial E} \approx \frac{\frac{\partial p}{\partial E}\left(V-L\right)\sum_{t=0}^{T}\frac{1}{(1+\delta)^{t}}\left(1+\left(\frac{3}{4}\left(L-V\right)+\Gamma_{1}t\right)r\left(X_{c}\right)\right)}{\frac{1-\left(\frac{1}{1+\delta}\right)^{T+1}}{1-\frac{1}{1+\delta}}} \tag{11}$$

$$\frac{\partial H}{\partial F} \approx \frac{\frac{\partial p}{\partial F}\left(V-L\right)\sum_{t=0}^{T}\frac{1}{(1+\delta)^{t}}\left(1+\left(\frac{3}{4}\left(L-V\right)+\Gamma_{1}t\right)r\left(X_{c}\right)\right)}{\frac{1-\left(\frac{1}{1+\delta}\right)^{T+1}}{1-\frac{1}{1+\delta}}} - \frac{\partial I}{\partial F} \tag{12}$$

These three expressions (for $\frac{\partial H}{\partial I}$, $\frac{\partial H}{\partial E}$, and $\frac{\partial H}{\partial F}$) are analogs to equations 7, 9, and 11 in the main paper, the difference being that the expressions here allow for the anticipated evolution of flood risk under climate change. Here again we can use these expressions to estimate the implied changes in subjective risk perceptions associated with our information signal. As before, such calculations require estimates for value at risk $(V-L)$, the utility discount rate δ, and Arrow-Pratt absolute risk aversion $r\left(X_c\right)$. We will use the same values here as in the body of the paper. We must also additionally obtain values for Γ_1, the rate at which housing expenditures fall over time as subjective flood probability increases, and T, the agent's time horizon. Given these inputs, we can obtain empirical estimates of the objects of ultimate interest: $\frac{\partial p}{\partial I}$, $\frac{\partial p}{\partial E}$, and $\frac{\partial p}{\partial F}$, the changes in the intercept of the time series of beliefs $p_t = p_0\left(F,E,I\right)+\gamma t$.

G.1 Belief Updating

In order to derive an estimate of the change in housing expenditures in response to increasing flood risks, Γ_1, we decompose the term into its constituent parts: π_1 and γ. π_1 characterizes the relationship between increased flood risk and home values. A recent review article estimated the price penalty for properties within the one percent floodplain to be (on average) 4.6%, suggesting an approximate reduction of 4.6 percent in home prices for a one percent change in flood risk (Beltrán et al., 2018). We therefore assume $\pi_1 = -4.6 * H\left(p_0\right) = -\$58,843$.

We rely on the work of Garner et al. (2017) to estimate a value for the expected annual change in flood risk, γ. Specifically, Garner et al. (2017) report that floods that occur with frequency "∼25 y at present... are projected to [occur every] ∼5 y within the next three decades" (Garner et al., 2017). This suggests an increase in annual flood risk (for a fixed severity of flood) from 4% to 20% over a 30 year period, which is an average annual increase of 16%/30=0.533% per year. We therefore set $\gamma = 0.00533$.

The agent's time horizon T depends on preferences and a number of parameters, including p_0, γ, π_1, and δ. We bound T by finding the period in which agent would gain no additional expected utility be remaining in the home. Setting expected utility for the final period to zero and solving yields

$T \approx \left(\frac{1}{\gamma}\right)\left(\frac{Y-\pi_0-\pi_1 p_0-I}{-(V-L)}-p_0\right)\left(\frac{V-L}{V-L+\pi_1}\right)$. Assuming $\pi_0 = \$596790 * .026 \approx \$15517$ (from the sample mean transaction price), $p_0 = 0$, $V-L = -\$22000$ (roughly the mean over the three calculations below), $I = \$1726$, and $Y = \$94,000$ (median household income in New York was $\$57,782$ 2013-2017, but home buyers are substantially wealthier), it follows that $T \approx 178$. The agent is assumed to abandon the home at that time. In a more general model including the possibility of moving outside New York City, T would likely be smaller. Because later periods are heavily discounted, changes of +/- 100 in T have negligible effects on the calculations below.

G.1.1 Biggert-Waters

Following the same procedure laid out in Section 7.3.1 and applying the 2.6 percent discount rate yields a present value of $(V-L) = -\$21,182$. While we use a finite time horizon in these calculations, the buyer is assumed to internalize annual expected costs after the end of the time horizon (and in perpetuity) through lower future sales prices to subsequent buyers. Similarly, the estimate: $\frac{\partial H}{\partial I} = -1.73\%$ translates to a reduction of \$8,512 (based on the average sale price in the old floodplain of \$492k) in value which impacts the expected annual hedonic flow in perpetuity (not only during the time horizon of ownership considered). This is equivalent to a \$221 loss to the expected annual flow of hedonic value. Thus, on an annual basis, $\frac{\partial H}{\partial I} = -\$221$. As before we are interested in the increase in premiums from the Biggert-Waters Act rather than a one unit change in premiums, thus the minus one is again replaced with: \$660. Again, the impacts of the subsidy rollbacks of Biggert-Waters are assumed to impact only the properties receiving subsidies (~75% of properties in New York City) and the portion of the population that purchases flood insurance (about 55% in New York City at the time of Biggert-Waters). Finally, the denominator term of all the expressions above is: $\frac{1-\left(\frac{1}{1+\delta}\right)^{T+1}}{1-\frac{1}{1+\delta}}$ which equals 39.14 for $\delta = 0.026$ and $T = 187$. This yields:

$$\frac{\partial H}{\partial I} \approx 0.4\left\{0.75\left[\frac{\frac{\partial p}{\partial I}(V-L)\sum_{t=0}^{T}\frac{1}{(1+\delta)^t}\left[1+\left(\frac{3}{4}(L-V)+\pi_1*\gamma*t\right)r(X_c)\right]}{\frac{1-\left(\frac{1}{1+\delta}\right)^{T+1}}{1-\frac{1}{1+\delta}}}-1\right]+0.25(0)\right\}+0.6(0) \Rightarrow$$

$$-\$221 \approx 0.4\left\{0.75\left[\frac{\frac{\partial p}{\partial I}(-\$21,182)\sum_{t=0}^{187}\frac{1}{(1.026)^t}\left[1+\left(\frac{3}{4}(\$21,082)+(-\$58,843)*(0.00533)*t\right)(1.2*10^{-3})\right]}{39.14}-\$660\right]\right\} \Rightarrow$$

$$\frac{\partial p}{\partial I} \approx .00047$$

As in the static model, the estimate is very small.

G.1.2 Sandy

Using $\frac{\partial H}{\partial E} = -\$913$ and $(V-L) = -22,075$, we can estimate the subjective risk updating implied by our reduced form estimates for properties flooded by Sandy that were not in the designated one percent floodplain. As in the paper, estimates only take into account the change in intercept and should therefore be interpreted as the effect of flooding once the depth of flooding is separately controlled for or was zero.

$$
\begin{aligned}
\frac{\partial H}{\partial E} &\approx \frac{\frac{\partial p}{\partial E}(V-L)\sum_{t=0}^{T}\frac{1}{(1+\delta)^t}\left[1+\left(\frac{3}{4}(L-V)+\pi_1 * \gamma * t\right)r(X_c)\right]}{\frac{1-\left(\frac{1}{1+\delta}\right)^{T+1}}{1-\frac{1}{1+\delta}}} \\
\$913 &\approx \frac{\frac{\partial p}{\partial E}(-\$22,075)\sum_{t=0}^{187}\frac{1}{(1.026)^t}\left[1+\left(\frac{3}{4}(\$22,075)+(-\$58,843)*(0.00533)*t\right)(1.2*10^{-3})\right]}{39.14} \\
\frac{\partial p}{\partial E} &\approx .0047
\end{aligned}
$$

This estimate is proportionally large, more than twice the magnitude of the corresponding estimate from the static model. (The repetition of the last two digits from the Biggert-Waters estimate is coincidental.) Such magnitudes cannot be summarily ruled out, given the evidence of Bakkensen and Barrage (2017) on belief bias and belief updating.

G.1.3 Updated flood risk maps

In order to consider the impacts of assignment to the one percent floodplain under the new flood risk maps among properties that avoided flooding from Sandy, we set $\frac{\partial H}{\partial F} = -\$2,452$,$(V-L) = -\$22,272$, and $\frac{\partial I}{\partial F} = \$393$. Please see Section 7.3.3 of the paper for details on the underlying sources and calculations behind these values. Together with equation 12, this yields:

$$
\begin{aligned}
\frac{\partial H}{\partial F} &\approx \frac{\frac{\partial p}{\partial F}(V-L)\sum_{t=0}^{T}\frac{1}{(1+\delta)^t}\left[1+\left(\frac{3}{4}(L-V)+\pi_1 * \gamma * t\right)r(X_c)\right]}{\frac{1-\left(\frac{1}{1+\delta}\right)^{T+1}}{1-\frac{1}{1+\delta}}} - \frac{\partial I}{\partial F} \\
-\$2,452 &\approx \frac{\frac{\partial p}{\partial F}(-\$22,272)\sum_{t=0}^{187}\frac{1}{(1.026)^t}\left[1+\left(\frac{3}{4}(\$22,272)+(-\$58,843)*(0.00533)*t\right)(1.2*10^{-3})\right]}{39.14} - \$393 \\
\frac{\partial p}{\partial E} &\approx .0108
\end{aligned}
$$

Again this is more than twice the magnitude of the corresponding estimate from the static model. Intuitively, if agents' beliefs already incorporate rising future risk, a greater shift in the intercept of beliefs is required to generate a given marginal effect on transaction prices than in the case where beliefs are static, absent shocks.

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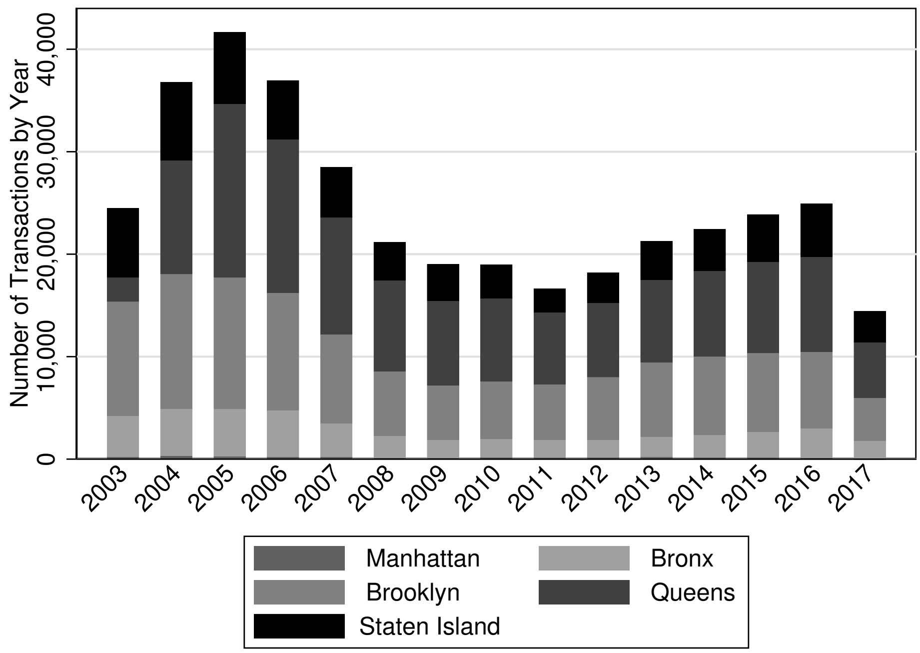
H Additional figures

Figure A1: Sample sales by year and borough



Transaction data are from the New York City Department of Finance 2003-8/2017. Figure includes only properties in the main sample and is therefore restricted to properties in Tax Class 1. The majority of sales are in Brooklyn and Queens.

Figure A2: Cross-sectional groups

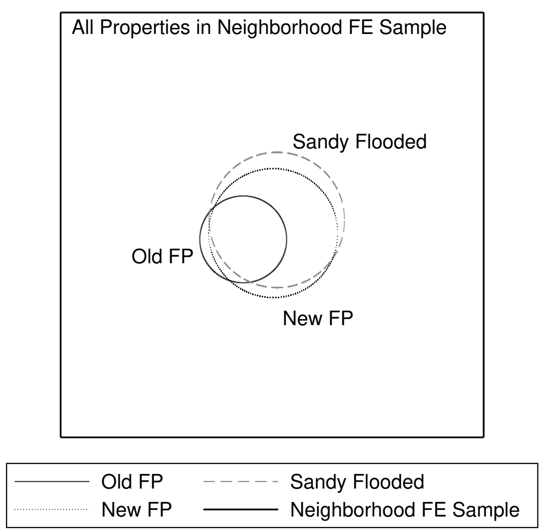
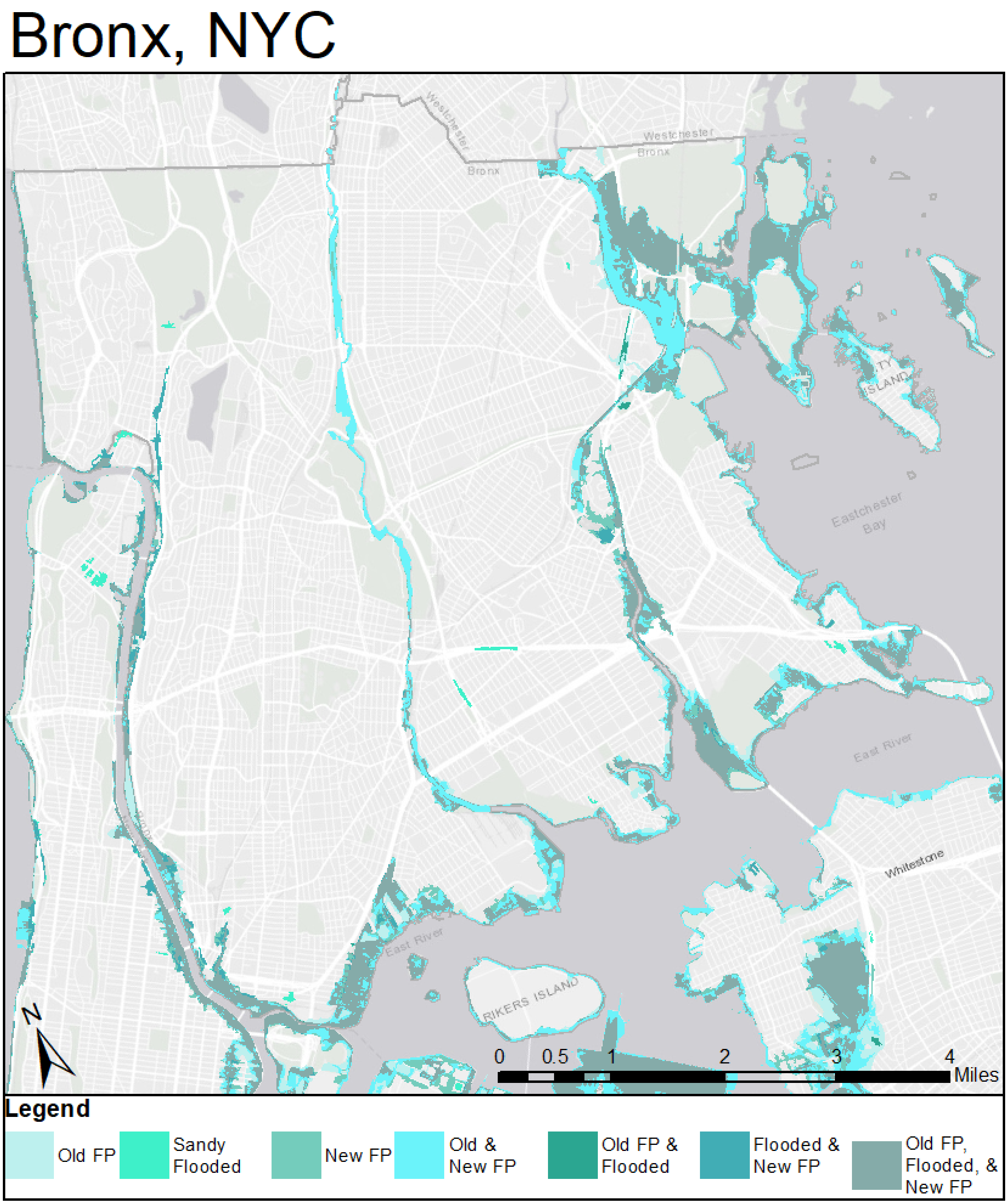


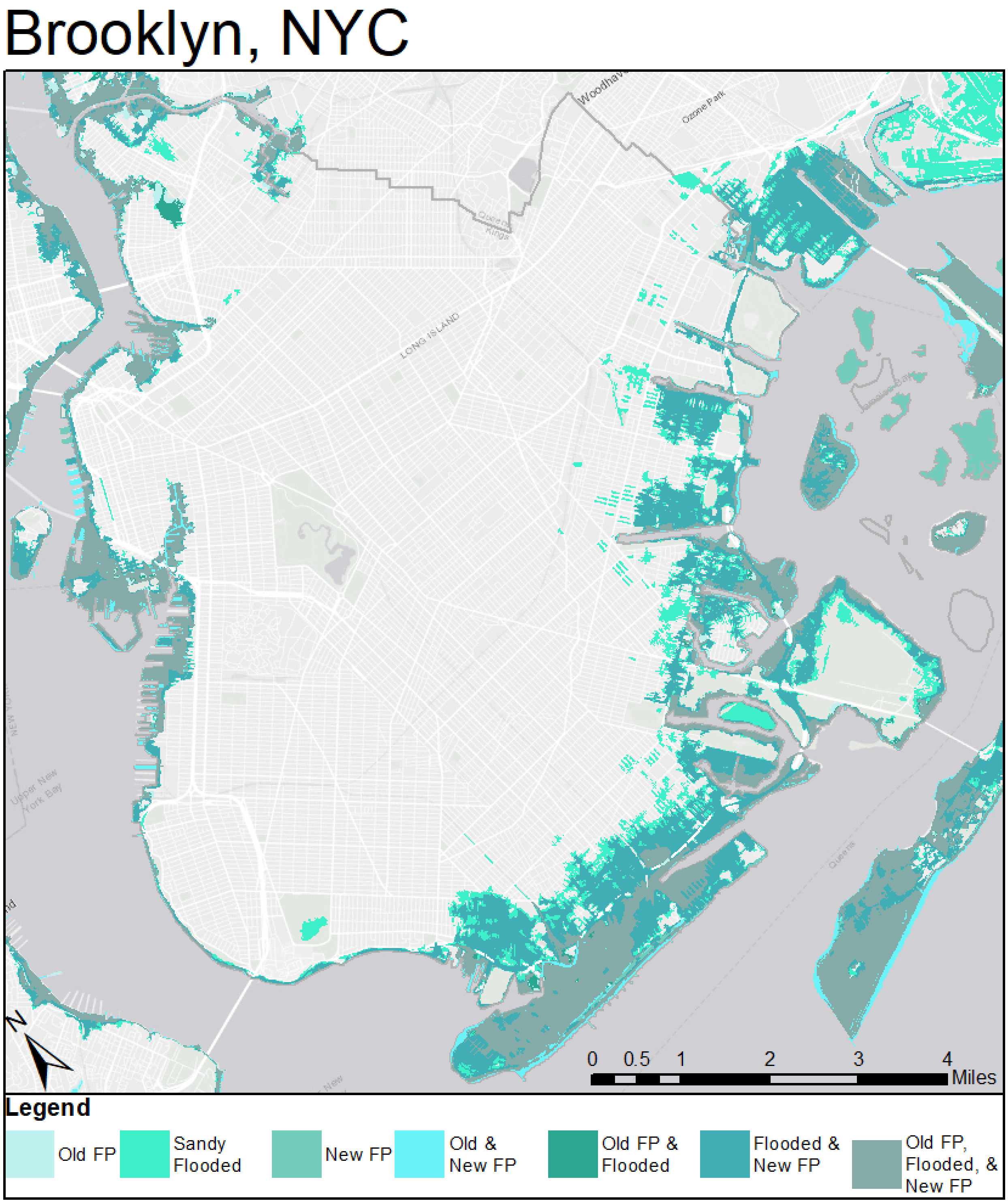
Diagram illustrates cross-sectional overlap in treatment groups for the larger (neighborhood FE) sample. The analogous diagram for the repeated-sales sample is visually indistinguishable and we omit it for brevity.

Figure A3: Cross-sectional groups in the Bronx



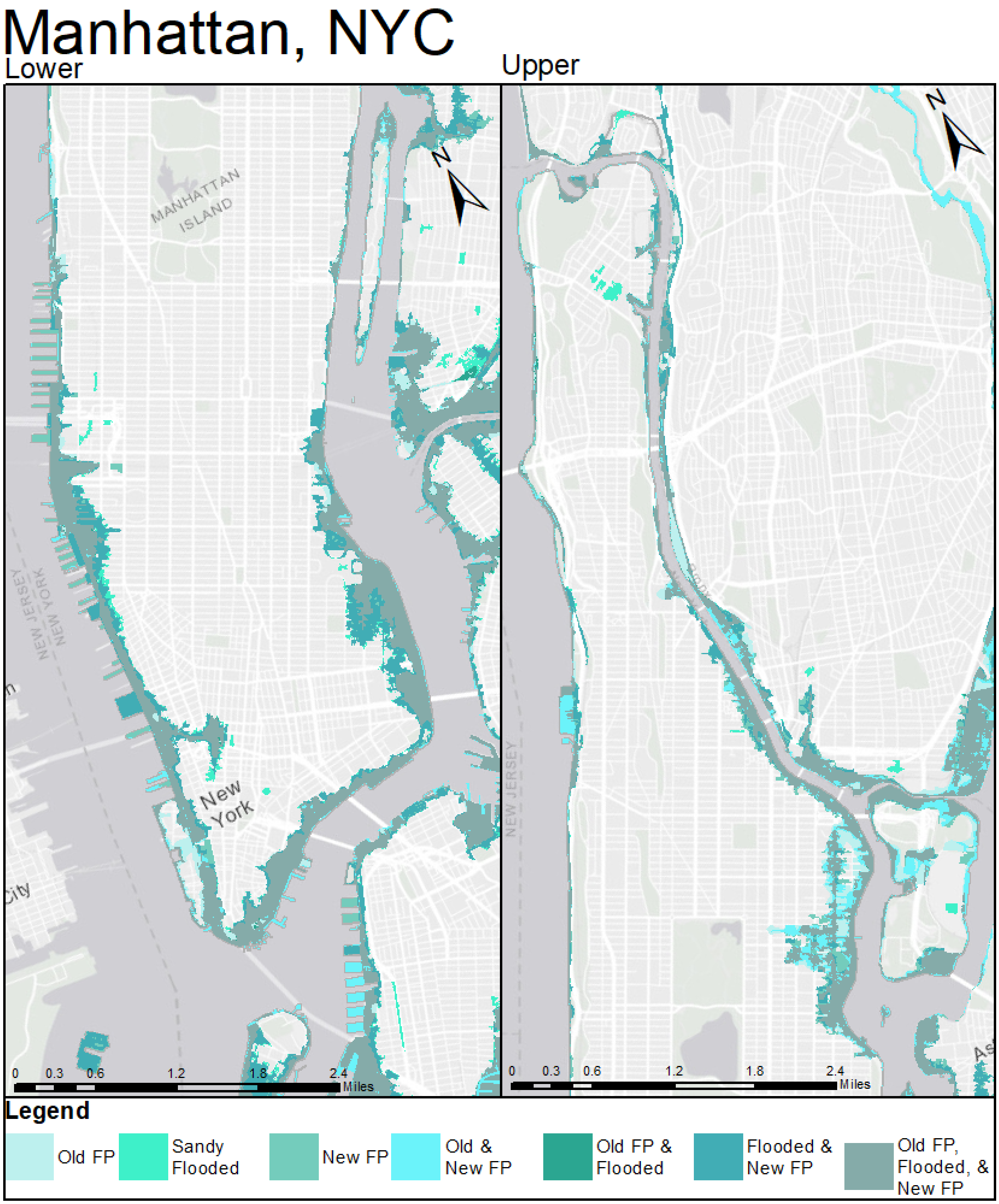
Floodplain and inundation maps are from FEMA.

Figure A4: Cross-sectional groups in Brooklyn



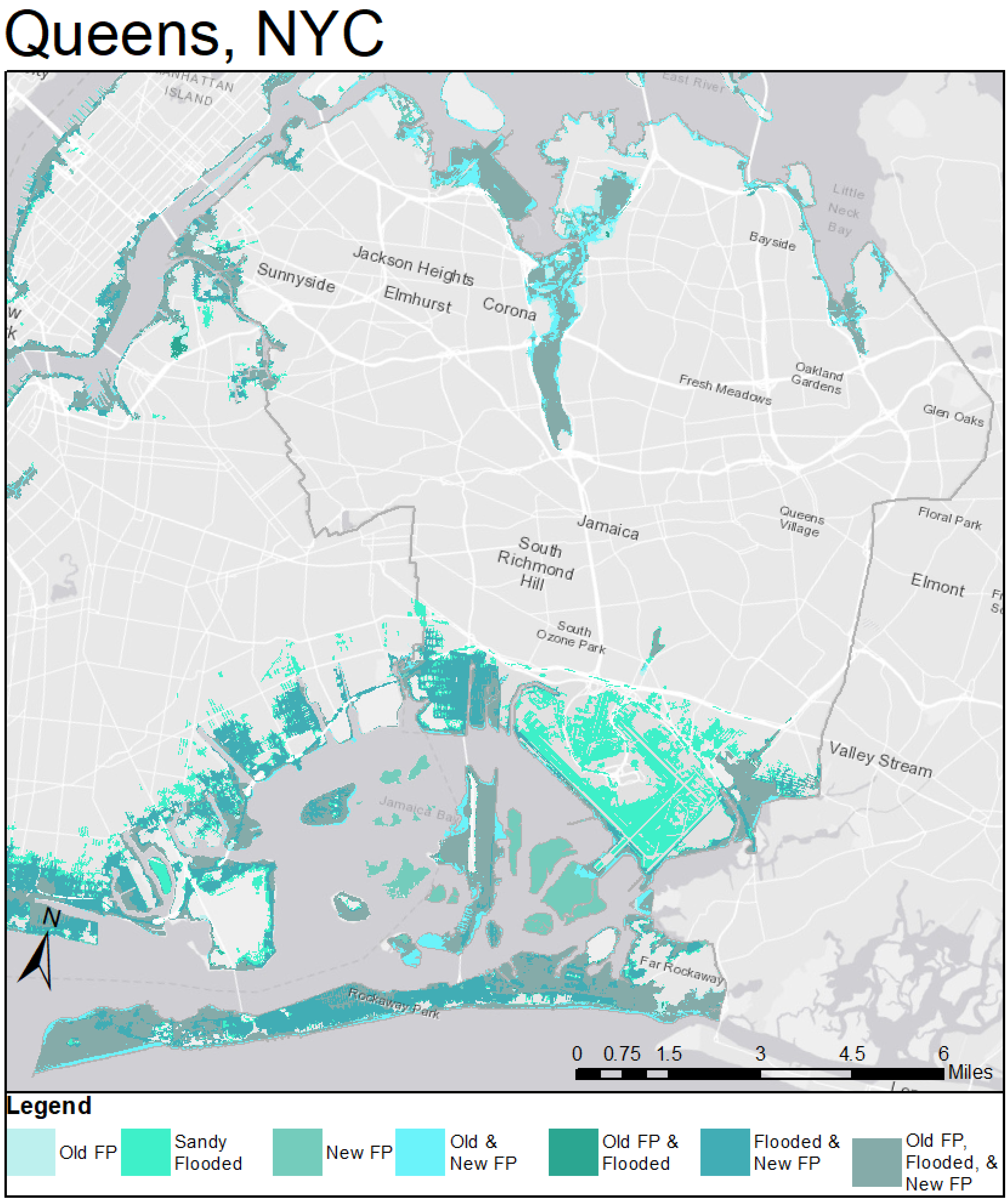
Floodplain and inundation maps are from FEMA.

Figure A5: Cross-sectional groups in Manhattan



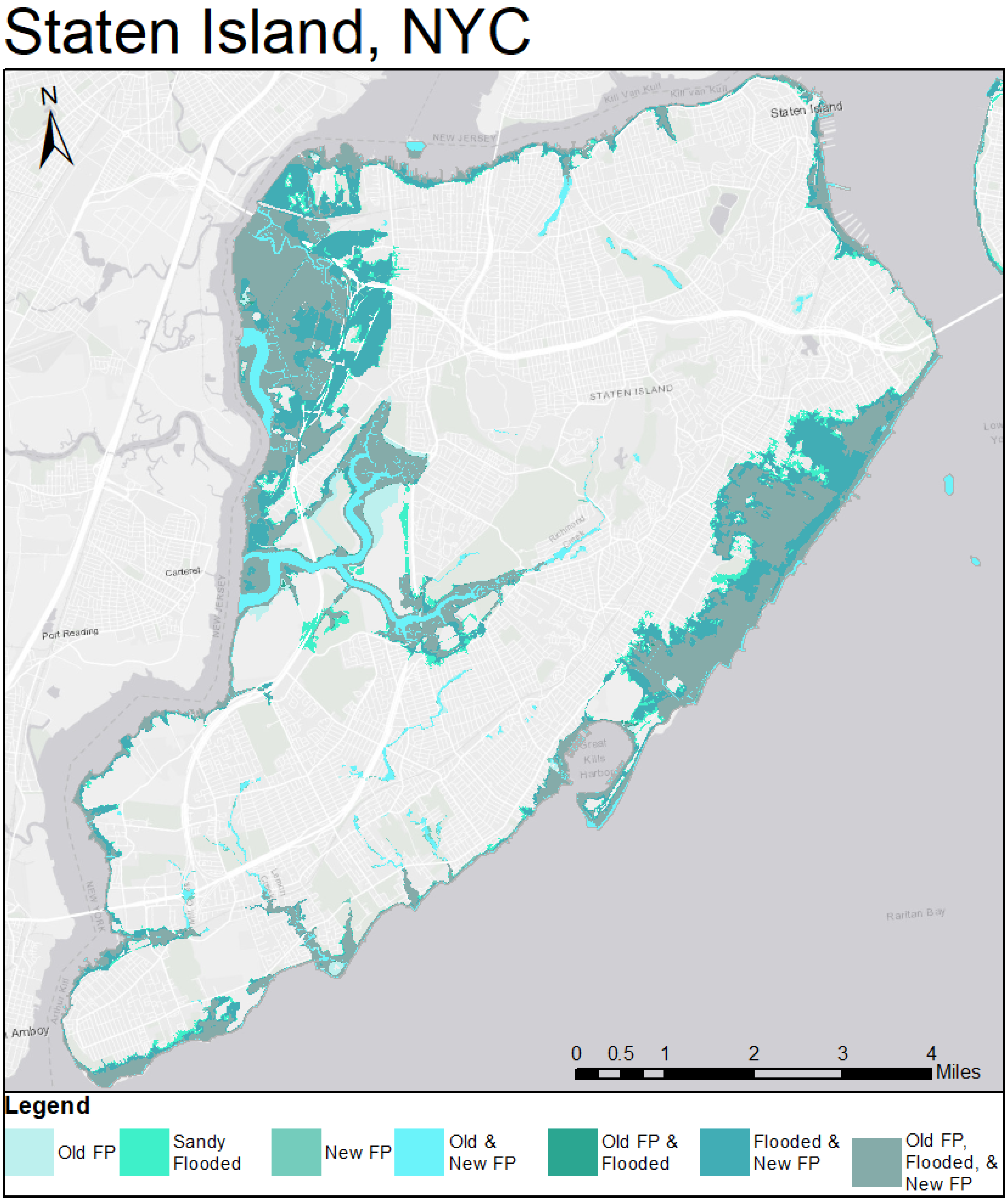
Floodplain and inundation maps are from FEMA.

Figure A6: Cross-sectional groups in Queens



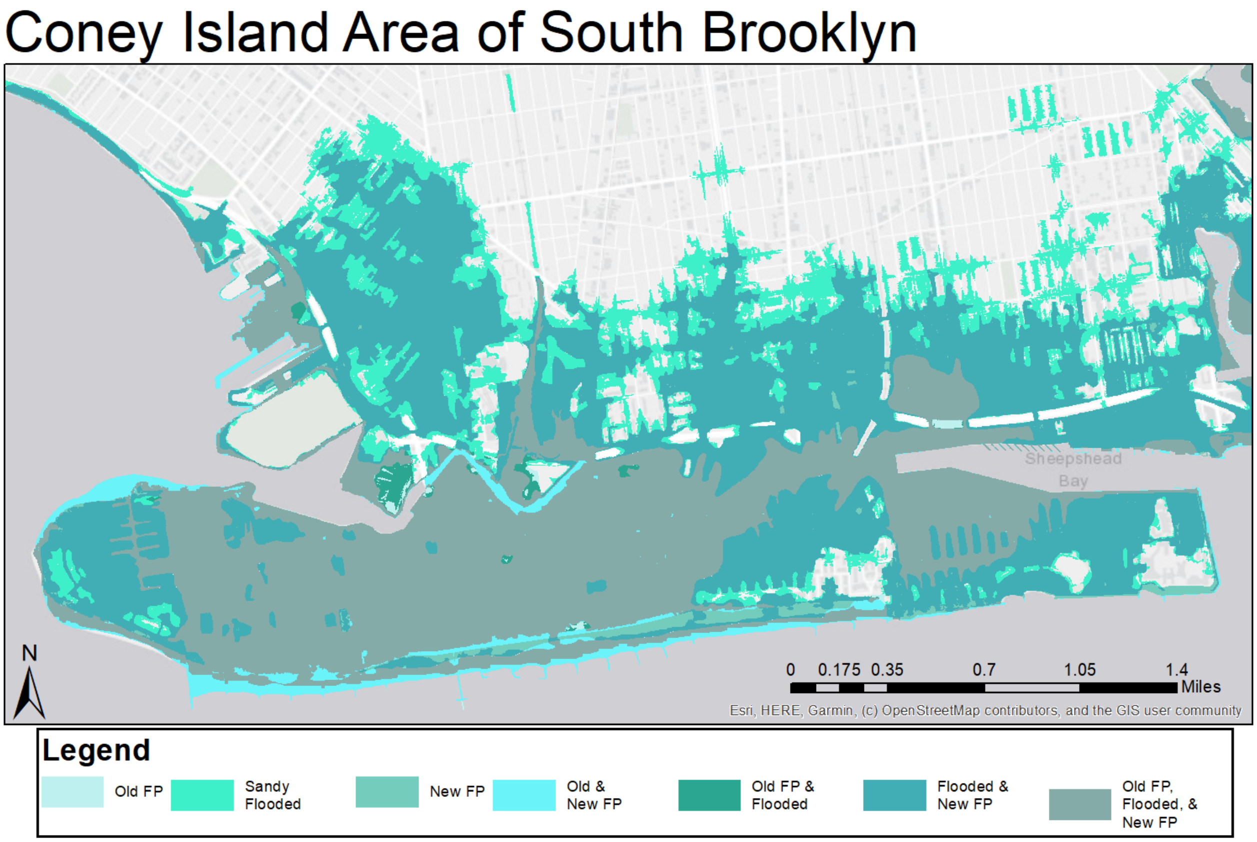
Floodplain and inundation maps are from FEMA.

Figure A7: Cross-sectional groups in Staten Island



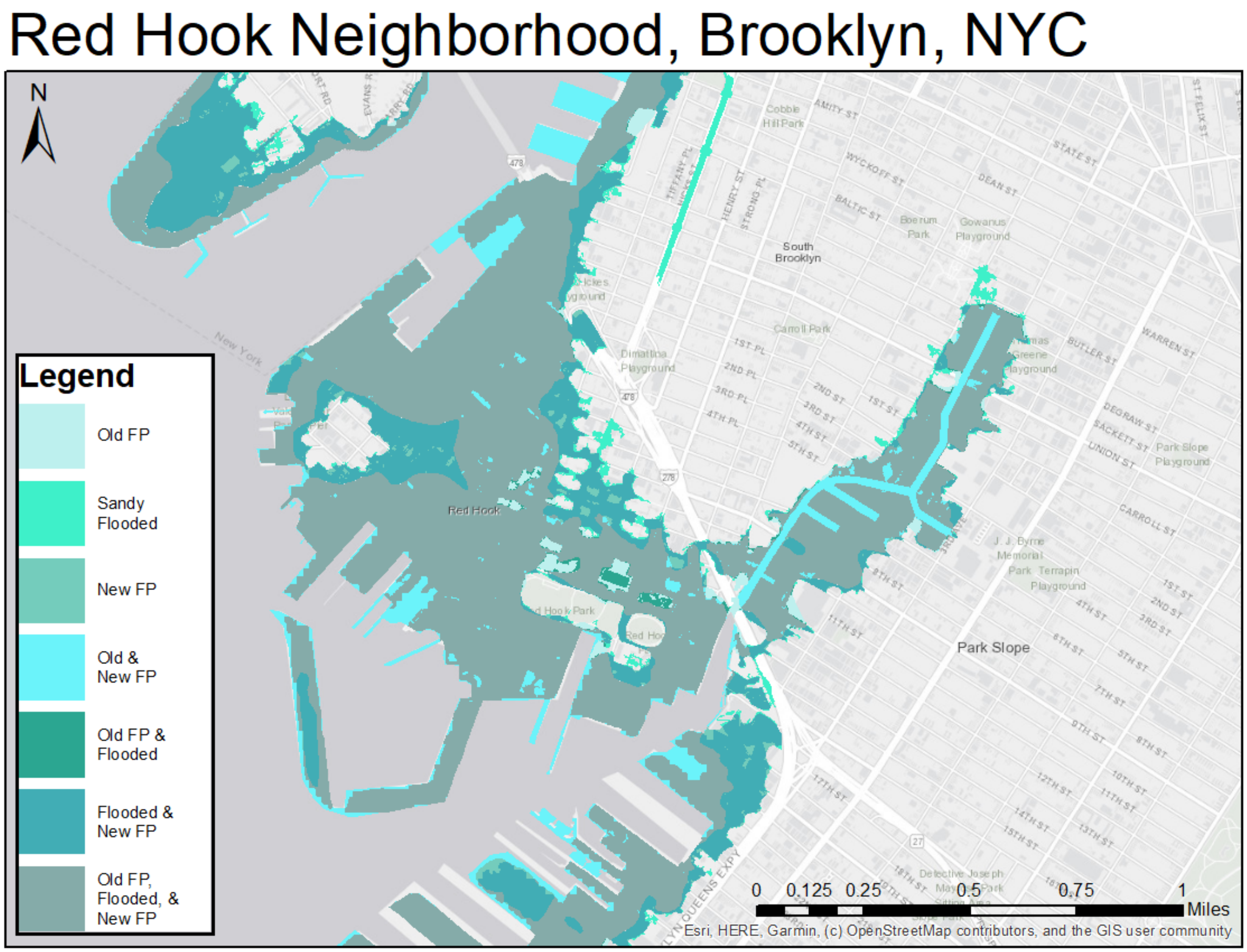
Floodplain and inundation maps are from FEMA.

Figure A8: Cross-sectional groups in Coney Island



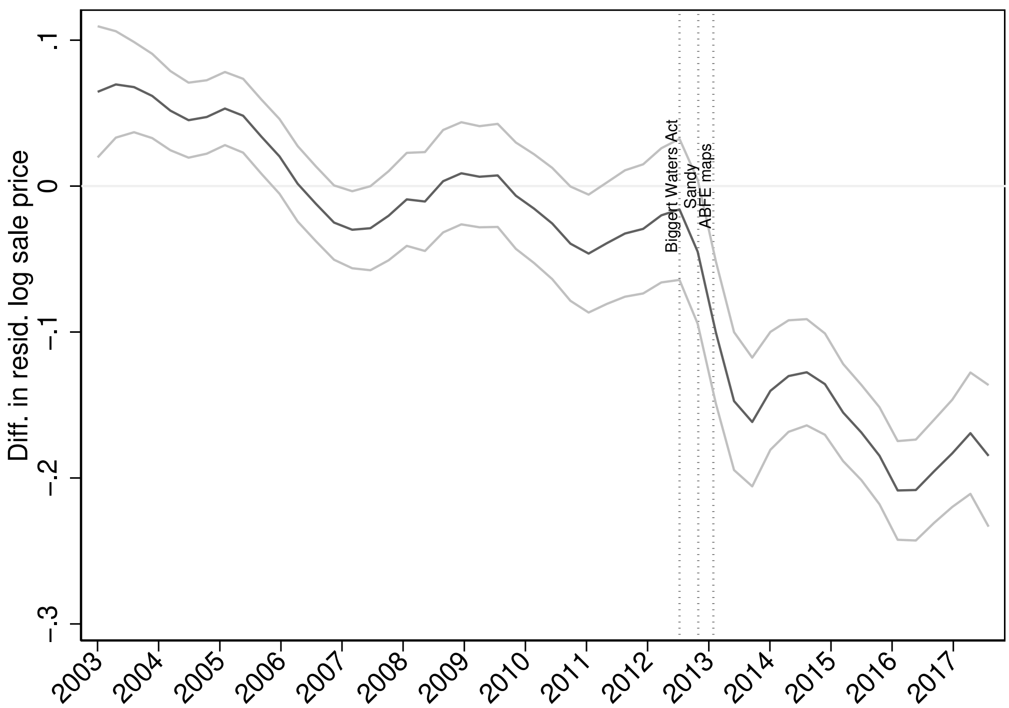
Floodplain and inundation maps are from FEMA.

Figure A9: Cross-sectional groups in Red Hook



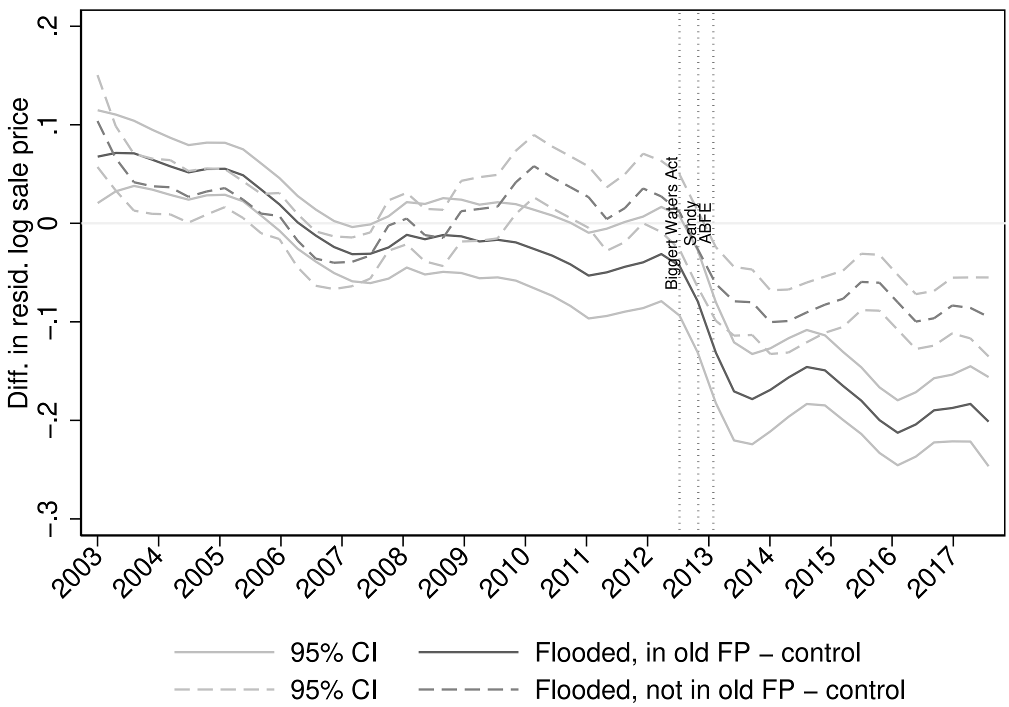
Floodplain and inundation maps are from FEMA.

Figure A10: Effect of Biggert-Waters, treatment-control difference



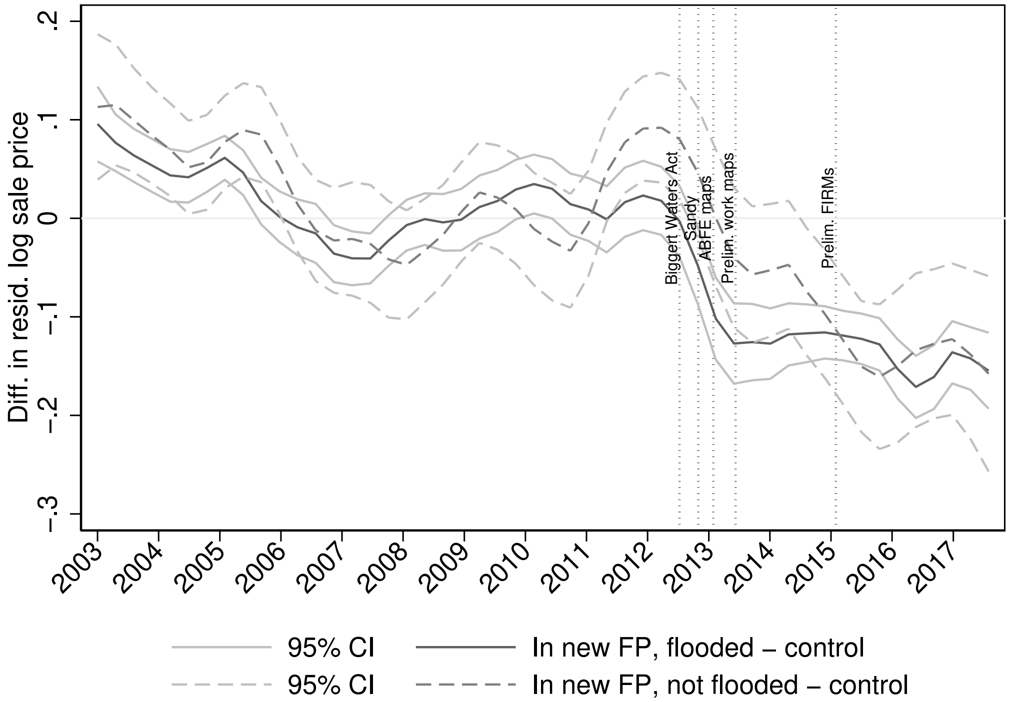
Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Sample is restricted to properties in Tax Class 1. The dependent variable is log property value, residualized on block fixed effects. Plotted lines are local regressions and 95% confidence intervals. "Not in old floodplain" denotes properties not in the 1983 floodplain. "In floodplain" denotes properties in the 1983 floodplain.

Figure A11: Effect of Sandy, treatment-control differences



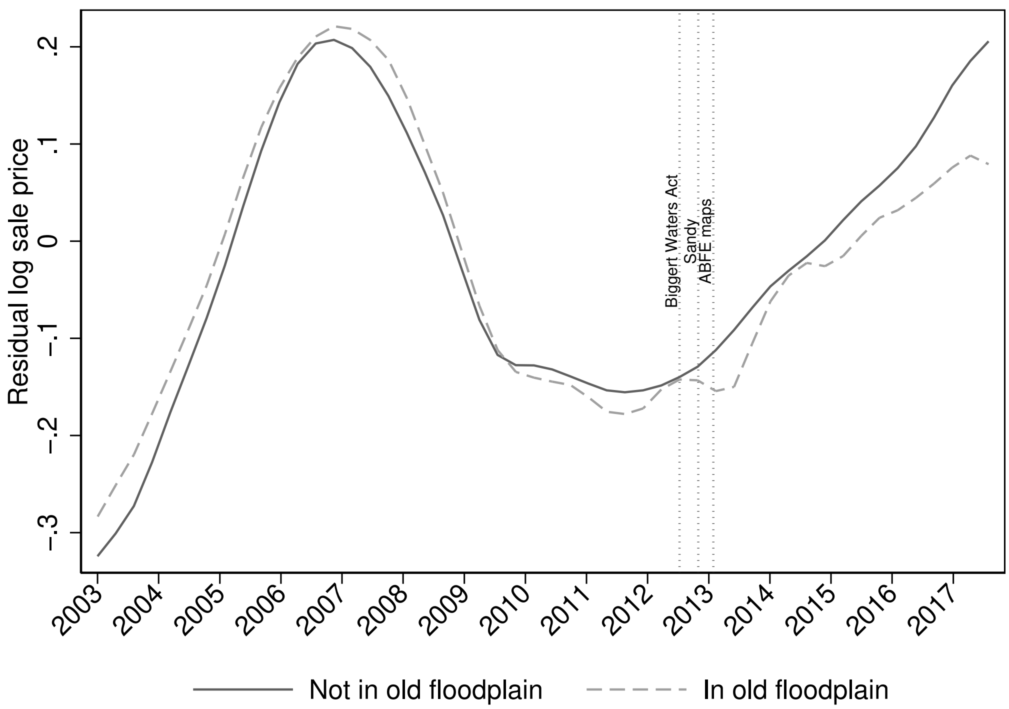
Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Sample is restricted to properties in Tax Class 1. The dependent variable is log property value, residualized on block fixed effects. Plotted lines are local regressions and 95% confidence intervals. "Not flooded" denotes properties not flooded by Sandy. "Flooded, in old floodplain" denotes properties in the 1983 floodplain (which was in effect when Sandy struck) and flooded by Sandy. "Flooded, not in old floodplain" denotes properties not in the 1983 floodplain and flooded by Sandy. The greater post-Sandy fall in prices for properties within the old floodplain is explained by inundation depth (see Table 1).

Figure A12: Effect of new floodplain maps, treatment-control differences



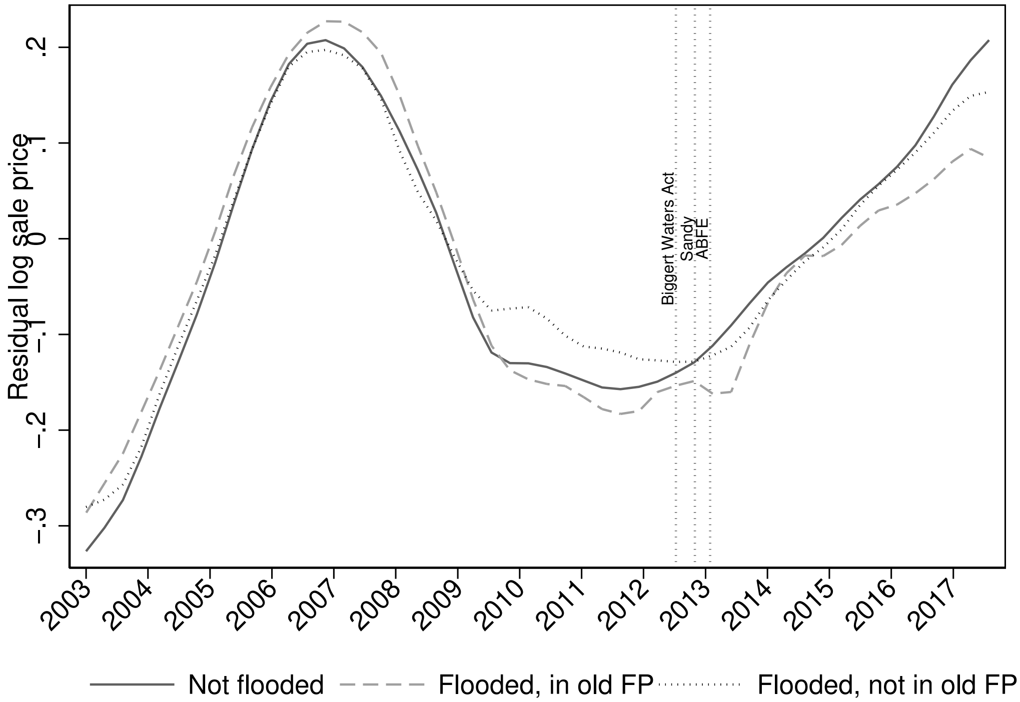
Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Sample is restricted to properties in Tax Class 1. The dependent variable is log property value, residualized on block fixed effects. Plotted lines are local regressions and 95% confidence intervals. "Not in new FP" denotes properties outside the 2013 floodplain. "In new FP, flooded" denotes properties in the 2013 floodplain that flooded during Sandy. "In new FP, not flooded" denotes properties in the 2013 floodplain that did not flood during Sandy.

Figure A13: Effect of Biggert-Waters, tax lot FE



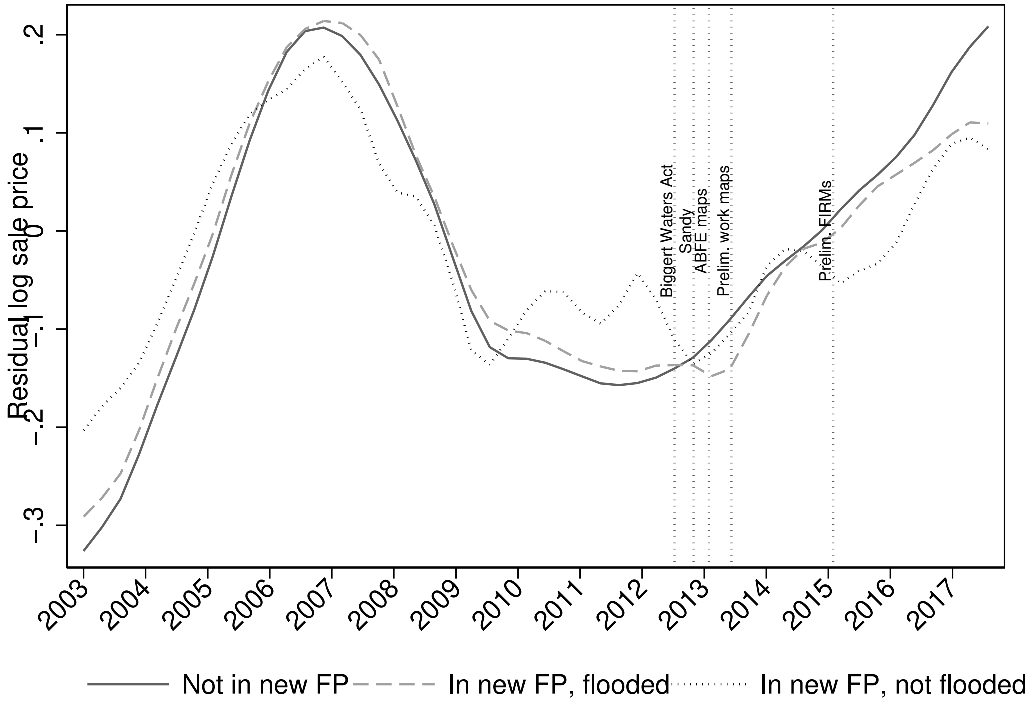
Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Sample is restricted to properties in Tax Class 1. The dependent variable is log property value, residualized on tax lot fixed effects. Plotted lines are local regressions. "Not in old floodplain" denotes properties not in the 1983 floodplain. "In floodplain" denotes properties in the 1983 floodplain.

Figure A14: Effect of Sandy, tax lot FE



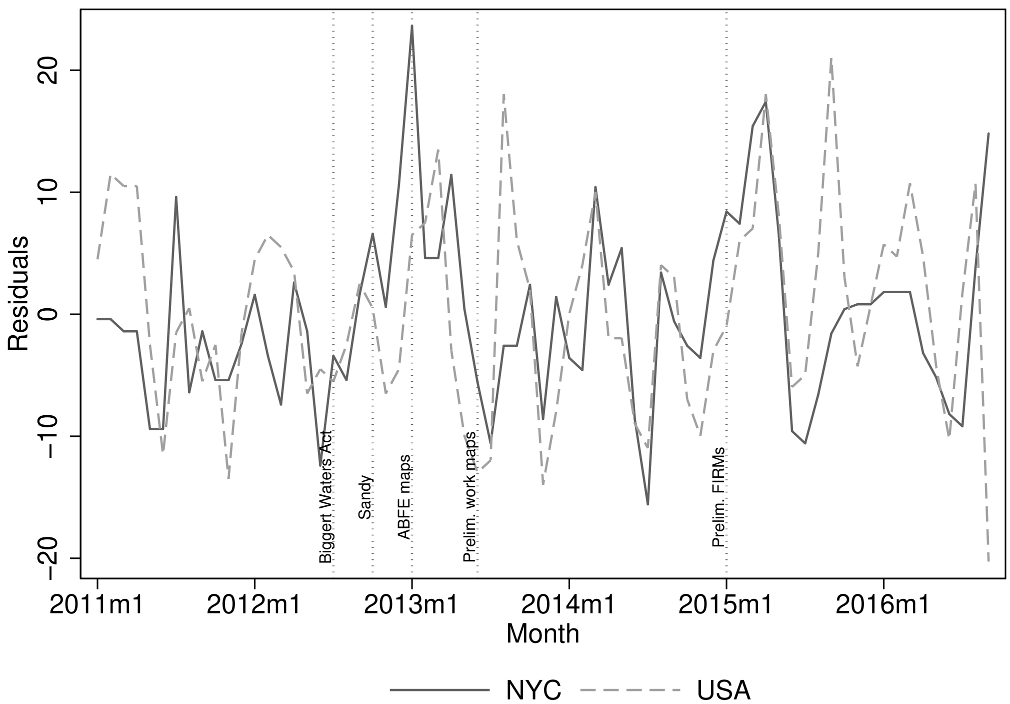
Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Sample is restricted to properties in Tax Class 1. The dependent variable is log property value, residualized on tax lot fixed effects. Plotted lines are local regressions. "Not flooded" denotes properties not flooded by Sandy. "Flooded, in old floodplain" denotes properties in the 1983 floodplain (which was in effect when Sandy struck) and flooded by Sandy. "Flooded, not in old floodplain" denotes properties not in the 1983 floodplain and flooded by Sandy. The greater post-Sandy fall in prices for properties within the old floodplain is explained by inundation depth (see Table 1).

Figure A15: Effect of new floodplain maps, tax lot FE



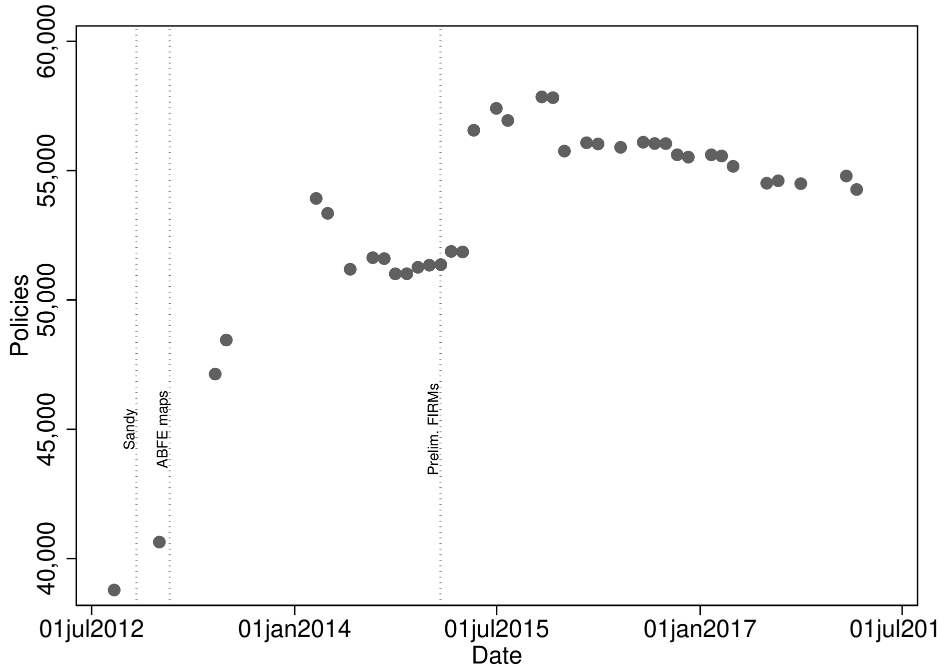
Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Sample is restricted to properties in Tax Class 1. The dependent variable is log property value, residualized on tax lot fixed effects. Plotted lines are local regressions. "Not in new FP" denotes properties outside the 2013 floodplain. "In new FP, flooded" denotes properties in the 2013 floodplain that flooded during Sandy. "In new FP, not flooded" denotes properties in the 2013 floodplain that did not flood during Sandy.

Figure A16: Google searches for "floodplain," in New York City and nationwide



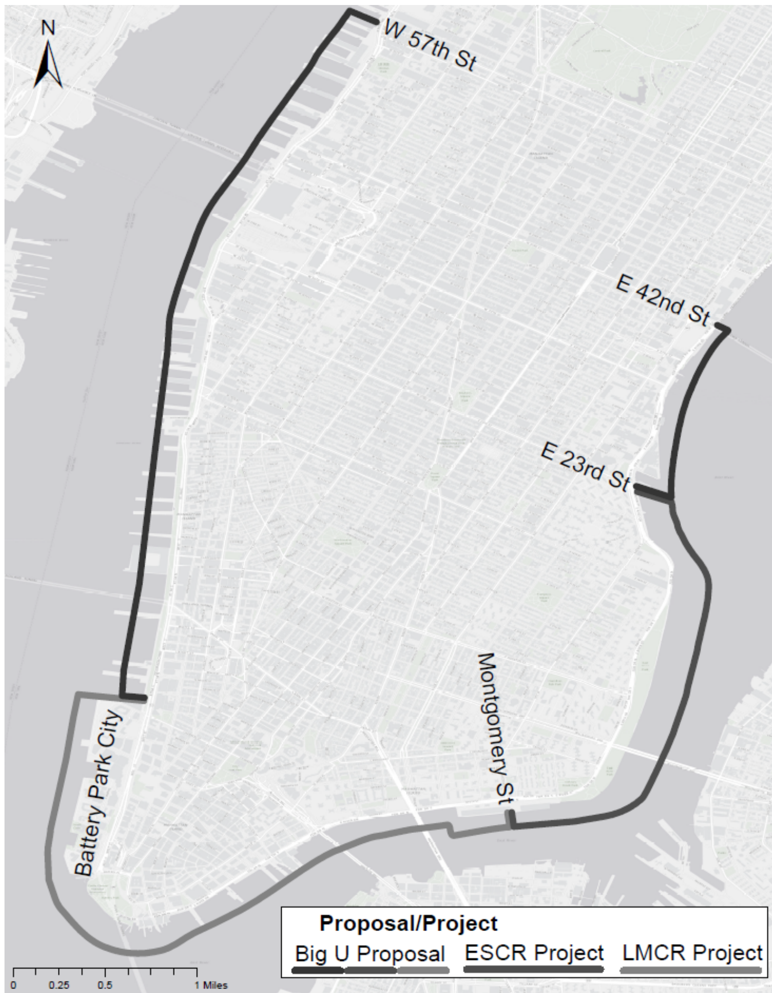
Data from Google Trends for the search term "floodplain" in New York City and the entire United States, 2004-2016. The horizontal range of the plot is limited for clarity. Google normalizes these data such that the maximum search volume over the period equals 100. The vertical axis reflects residuals from a regression of the full time series on month-of-year dummies. Dashed vertical lines correspond to flood risk signals.

Figure A17: NFIP policies in New York City



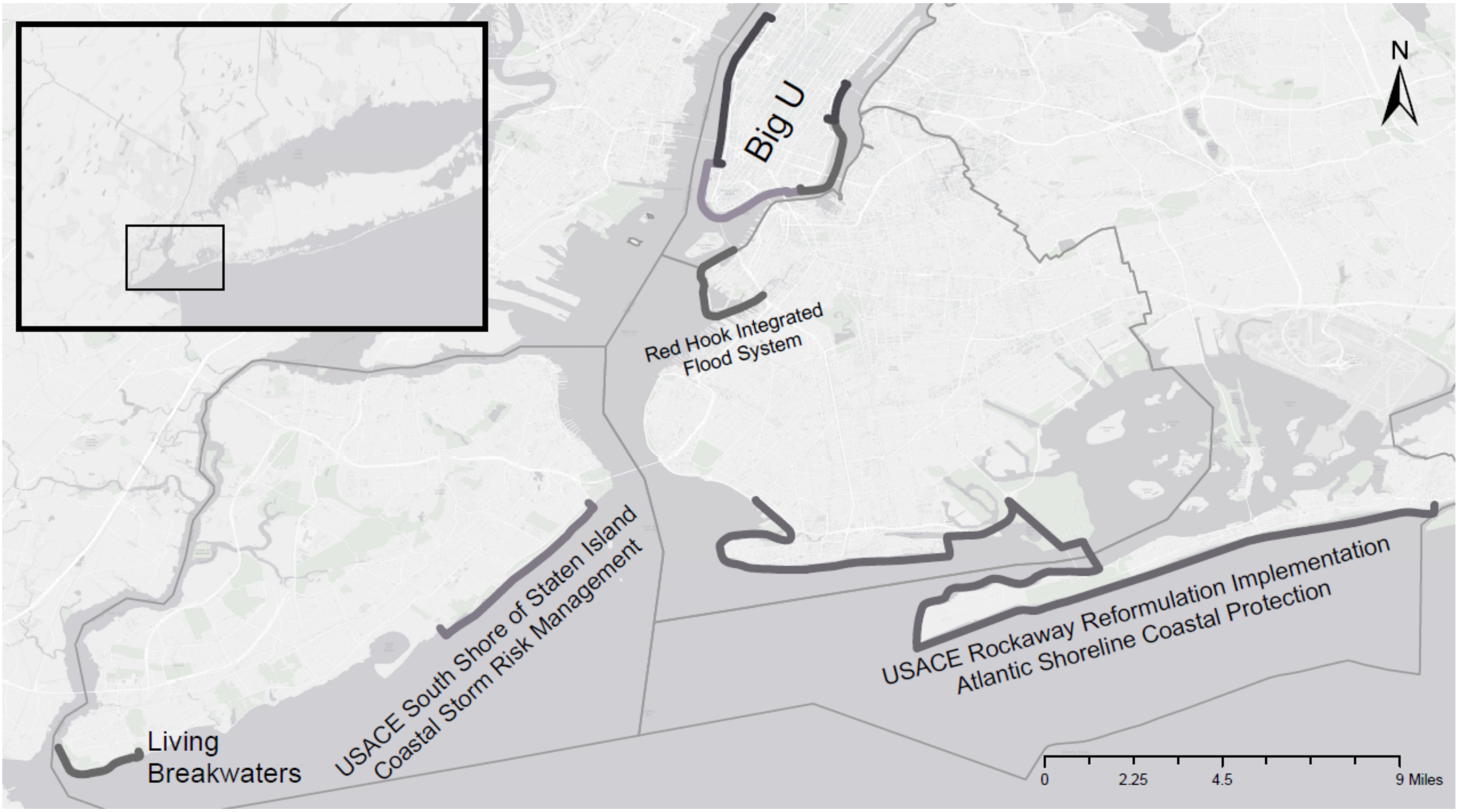
Vertical coordinates are the number of NFIP policies in force in New York City as of the date given by the horizontal coordinate. Data are from FEMA (2018). Previous versions of this online report were scraped using the Wayback Machine (https://web.archive.org/web/*/https://bsa.nfipstat.fema.gov/reports/1011.htm). Archived versions are not available for all months. The oldest available archived version is from Nov. 10, 2012 and records policies in force as of Aug. 31, 2012. NFIP takeup as of this date was a approximately 55%, so the increase in policies shown in this figure implies takeup of approximately 75% in the period after Sandy.

Figure A18: Lower Manhattan protective infrastructure - proposal and projects



Data from NYC Map of Recovery and Resiliency (https://maps.nyc.gov/resiliency/, accessed 3/24/2017) and the BIG U Design Proposal (https://portal.hud.gov/hudportal/documents/huddoc?id=BIG_IP_Briefing_Book.pdf, accessed 3/24/2017). The BIG U Proposal includes protection for the areas to be protected by the ESCR and LMCR Projects. Construction on the ESCR Project is slated to begin in 2018 while design and plan for the LMCR Project are also to be finalized in the same year (Wachs, 2016).

Figure A19: Flood-protection infrastructure: projects, proposals, and studies



USACE stands for United States Army Corps of Engineers. Data on proposed protective infrastructure are pulled from: 1. NYC Map of Recovery and Resiliency (https://maps.nyc.gov/resiliency/, accessed 3/24/2017); 2. the BIG U Design Proposal (https://portal.hud.gov/hudportal/documents/huddoc?id=BIG_IP_Briefing_Book.pdf, accessed 3/24/2017), 3. USACE (2016a); 4. USACE (2016b); and 5. Living Breakwaters Website (https://stormrecovery.ny.gov/learn-more-about-living-breakwaters-project, accessed 4/5/2017). The depicted infrastructure from the USACE Atlantic Shoreline Coastal Protection study is the Storm Surge Barrier alignment C-1E, denoted as the "likely... Recommended Plan". All depictions of proposal coverage and extents are provided for illustrative purposes only and do not capture feature types or placement. Thin gray lines denote county/borough boundaries.

Figure A20: Matched difference-in-differences pre-trends

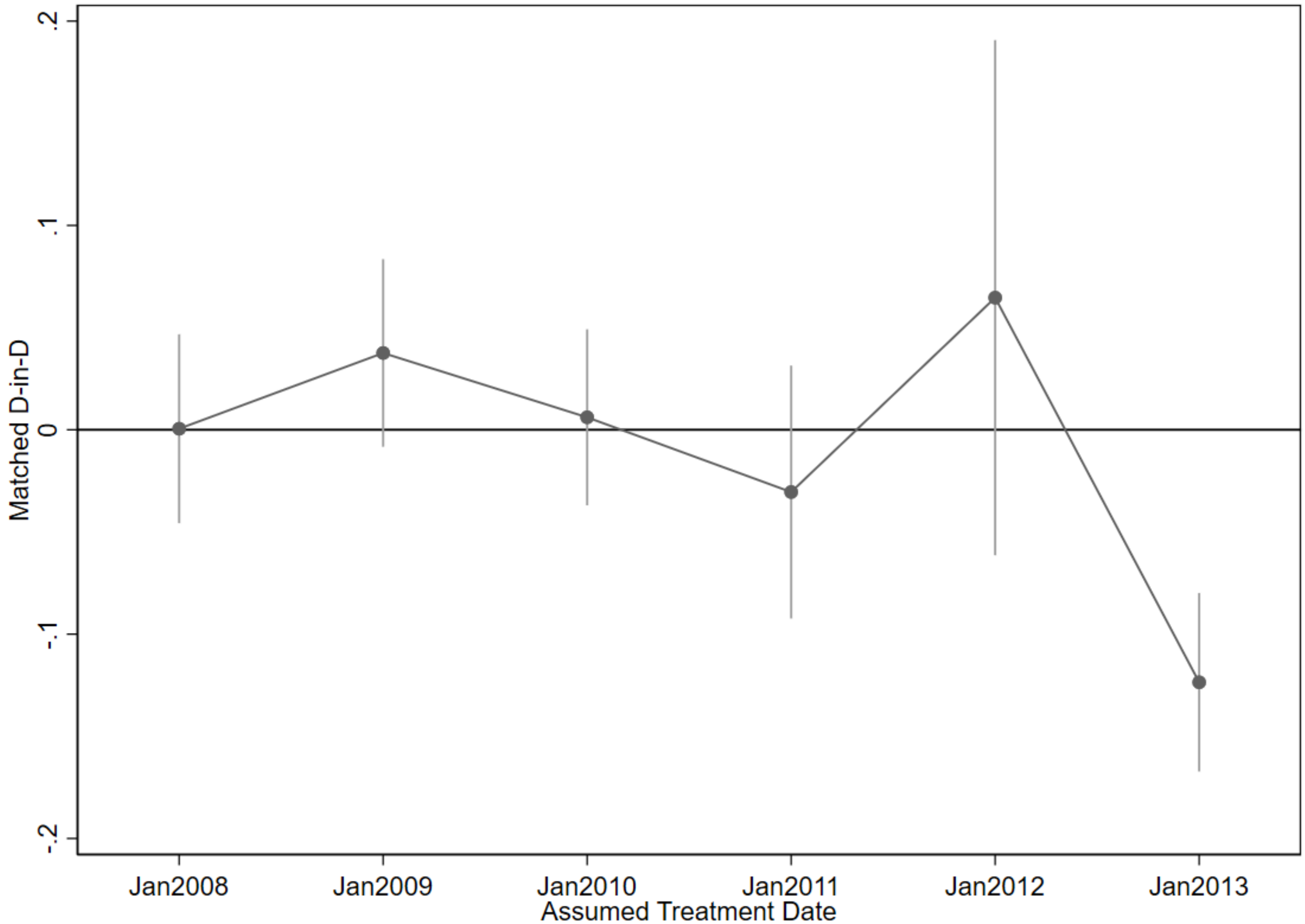


Figure depicts estimates and 95% confidence intervals from the lot-level, matched difference-in-differences estimator of the effect of new floodmaps on properties unflooded by Sandy. The first five estimates are based on one year placebo-treatment periods in the period prior to the the release of the new maps. The last point captures the actual estimated treatment effect of the new floodplains on properties that were not flooded by Sandy. The small magnitude and insignificance of the first five estimates points to the parallel evolution of prices among control and treatment properties in the matched sample prior to the release of the new maps in 2013. Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Sample is limited to properties not flooded by Sandy. Dependent variable is log sale price. Propensity scores are estimated for all properties based on building and lot square footage, building age, latitude, longitude, mean-sale price of each lot in the pre-Biggert Waters period, and block-level average annual price growth rate in the pre-Biggert Waters period. Both treatment and control observations are restricted to the repeated sales sample. Treated properties are matched to control properties based on these propensity scores, with common support required. Estimates reflect a double difference in prices over treatment and treatment-period, with regression adjustment for differences in matching variables (minus latitude and longitude) plus year-week fixed effects. Standard errors are clustered at the Census Tract level. The wider confidence interval in 2012 may be due to higher variance in sales prices in the year of Biggert Waters and Sandy in New York City.

Figure A21: Floodplain extents

Map depicts the area around (and including) Coney Island in south Brooklyn (Kings County). This is an example; our analyses include all five boroughs of New York City. Current and Preliminary Floodplain maps are from FEMA. Projected Floodplain maps are from NYC Open Data. Black dots represent properties for which sales are observed in the transaction data from the New York City Department of Finance 2003-2017. The one percent floodplain consists of flood zones A and V.

I Additional tables

Table A1: Timeline

Event	Date
Biggert-Waters Act	7/6/2012
Hurricane Sandy	10/29-30/2012
ABFE Map Release	1/28/2013
Preliminary Work Maps	6/10/2013
Homeowner Flood Insurance Affordability Act	3/21/2014
Preliminary FIRMs	1/30/2015
NYC Appeals Preliminary FIRMs	6/26/2015
FEMA Agrees to further Revise Preliminary FIRMs	10/17/2016

Table A2: Property counts in the main sample by flood zone and map

Map:	Original FIRM	ABFE	Prelim Work Map	Prelim FIRM
Date:	1983	1/2013	6/2013	1/2015
V	151	1,413	29	25
A	8,584	18,938	18,832	18,912
X500	9,104	10,381	11,812	11,814
X	243,443	230,552	230,611	230,533

Notes: Counts include all 261,284 unique properties in the main sample which sold between 2003 and August 2017. Subcategorizations have been dropped for simplicity.

Table A3: FEMA flood risk groups

	Description
V	annual flood risk $\geq 1\%$ and risk of wave action (also called "velocity hazard")
A	annual flood risk $\geq 1\%$
X500	$1\% \geq$ annual flood risk $\geq 0.2\%$
X	annual flood risk $< 0.2\%$

Notes: Descriptions taken from http://www.mass.gov/anf/docs/itd/services/massgis/q3floodzonescodetable.pdf. Subcategorizations have been dropped for simplicity.

Table A4: Descriptive statistics, neighborhood and lot fixed effects samples

	Count	Mean	Stdev	Min	Max
Sale price (2010USD)		595243.94	453159.4	85565.07	8344827
Old floodplain	12164	0.03	.1784647	0	1
Post Biggert-Waters	116220	0.31	.464384	0	1
Old floodplain*Post Biggert-Waters	3920	0.01	.1024737	0	1
Flooded by Sandy	29582	0.08	.2714387	0	1
Post Sandy	109988	0.30	.4572893	0	1
Flooded by Sandy*Post Sandy	9100	0.02	.1550207	0	1
New floodplain	26866	0.07	.2597099	0	1
Post ABFE	105747	0.29	.4520375	0	1
Post prelim. work maps	98698	0.27	.4425122	0	1
Post prelim. FIRMs	61601	0.17	.372785	0	1
New floodplain*post new maps	8120	0.02	.1466348	0	1
Observations	369342				

	Count	Mean	Stdev	Min	Max
Sale price (2010USD)		557925.29	424871.7	85565.07	8344827
Old floodplain	6331	0.03	.1829143	0	1
Post Biggert-Waters	54501	0.30	.4575407	0	1
Old floodplain*Post Biggert-Waters	1895	0.01	.1013238	0	1
Flooded by Sandy	13808	0.08	.2643435	0	1
Post Sandy	51669	0.28	.4503897	0	1
Flooded by Sandy*Post Sandy	3967	0.02	.1457587	0	1
New floodplain	12385	0.07	.2514047	0	1
Post ABFE	49765	0.27	.445214	0	1
Post prelim. work maps	46293	0.25	.4349752	0	1
Post prelim. FIRMs	28918	0.16	.3650324	0	1
New floodplain*post new maps	3550	0.02	.138046	0	1
Observations	182667				

Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. The first table includes property sales for which needed spatial, temporal, and control variables are available, and for which non-unique neighborhood classification exists. The second table summarizes sales observations of properties for which two or more transactions are observed in the data, and for which other needed spatial, temporal, and control variables are available. This second sample could alternatively be characterized as being composed of properties with repeated sales in the data.

Table A5: Effects of flood risk signals on log transaction prices with HFIAA

	(1) Neighborhood FE	(2) Block FE	(3) Block FE	(4) Lot FE
Biggert-Waters	-0.0191	-0.0357	0.00601	-0.0565
	(0.0268)	(0.0256)	(0.0355)	(0.0459)
Sandy*in old FP	0.0610	-0.0412	-0.0856	-0.0588
	(0.0626)	(0.0554)	(0.0885)	(0.119)
Sandy*not in old FP	-0.00735	-0.0162	0.000660	0.000125
	(0.0183)	(0.0158)	(0.0232)	(0.0340)
Sandy*depth*in old FP	-0.0428**	-0.0158	-0.0244	-0.0157
	(0.0201)	(0.0173)	(0.0260)	(0.0341)
Sandy*depth*not in old FP	-0.0405**	-0.0291**	-0.0560***	-0.0790**
	(0.0160)	(0.0132)	(0.0209)	(0.0373)
Floodplain maps*Sandy	-0.0235	-0.0467**	-0.0228	0.00848
	(0.0248)	(0.0198)	(0.0308)	(0.0452)
Floodplain maps*no Sandy	-0.129***	-0.120***	-0.132***	-0.118**
	(0.0328)	(0.0250)	(0.0400)	(0.0529)
HFIAA	-0.000998	0.00472	-0.00205	-0.00293
	(0.0150)	(0.0129)	(0.0225)	(0.0276)
N	369342	369342	182667	182667

* $p < .1$, ** $p < .05$, *** $p < .01$. This table reproduces the estimates reported in Table 1 with the addition the passage of the Homeowner Insurance Affordability Act as an additional treatment. The relevant treatment period begins with passage of the bill, March 21, 2014, and the impacted geography is assumed to be the 1% floodplain as defined by the Preliminary Work Maps (released in June 2013) which were the most up-to-date floodplain delineations available for New York City at the time of HFIAA passage. Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Dependent variable is log sale price. All columns include year-week fixed effects. Cross-sectional fixed effects are indicated in column headings. Standard errors, clustered at the Census Tract level, in parentheses.

Table A6: Effects of flood risk signals on log transaction prices with additional time trend controls

	(1) Block FE	(2) Lot FE	(3) Block FE	(4) Lot FE	(5) Block FE	(6) Lot FE	(7) Block FE	(8) Lot FE	(9) Block FE	(10) Lot FE
Biggert-Waters	-0.0349	-0.0567	-0.0352	-0.0606	-0.0352	0.0517	-0.0465*	-0.0704	-0.0211	-0.0479
	(0.0256)	(0.0458)	(0.0257)	(0.0459)	(0.0257)	(0.100)	(0.0266)	(0.0544)	(0.161)	(0.171)
Sandy*in old FP	-0.0417	-0.0593	-0.0408	-0.0596	-0.0408	-0.277	-0.0259	-0.0764	-0.0400	-0.00694
	(0.0554)	(0.119)	(0.0554)	(0.119)	(0.0554)	(0.176)	(0.0586)	(0.144)	(0.335)	(0.345)
Sandy*not in old FP	-0.0156	0.000436	-0.0152	-0.00210	-0.0152	0.0105	-0.0117	-0.00580	0.0876	0.0852
	(0.0157)	(0.0339)	(0.0157)	(0.0341)	(0.0157)	(0.0610)	(0.0169)	(0.0405)	(0.115)	(0.115)
Sandy*depth*in old FP	-0.0160	-0.0156	-0.0165	-0.0151	-0.0165	0.0502	-0.0190	-0.0108	-0.0444	-0.0464
	(0.0173)	(0.0341)	(0.0174)	(0.0342)	(0.0174)	(0.0512)	(0.0187)	(0.0406)	(0.104)	(0.105)
Sandy*depth*not in old FP	-0.0299**	-0.0794**	-0.0300**	-0.0776**	-0.0300**	-0.0505	-0.0287**	-0.0800*	-0.187*	-0.185*
	(0.0130)	(0.0370)	(0.0130)	(0.0370)	(0.0130)	(0.0540)	(0.0142)	(0.0439)	(0.105)	(0.105)
Floodplain maps*Sandy	-0.0426**	0.00626	-0.0431**	0.00744	-0.0431**	0.0256	-0.0439**	0.0191	0.0439	0.0437
	(0.0183)	(0.0422)	(0.0183)	(0.0419)	(0.0183)	(0.0774)	(0.0190)	(0.0474)	(0.130)	(0.129)
Floodplain maps*no Sandy	-0.118***	-0.120**	-0.118***	-0.120**	-0.118***	-0.141	-0.110***	-0.0958	-0.106	-0.0923
	(0.0250)	(0.0526)	(0.0251)	(0.0528)	(0.0251)	(0.0948)	(0.0255)	(0.0604)	(0.166)	(0.174)
N	369342	182667	369342	182665	369342	118543	369342	182667	182676	182667

* $p < .1$, ** $p < .05$, *** $p < .01$. Columns 1 and 2 reproduce our main results from columns 2 and 4 of Table 1. Subsequent column pairs control for geographically differential time trends as follows: Columns 3 and 4 include neighborhood-specific linear trends (in week-of-sale); columns 5 and 6 include neighborhood-by-week-of-sale fixed effects; columns 7 and 8 include tax-block-specific linear time trends (in week-of-sale); and columns 9 and 10 include lot-specific time trends. This last specification is especially taxing on the data given that a slope (time trend) and intercept (fixed effect) is estimated for every individual property in the analysis. Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Dependent variable is log sale price. All columns include year-week fixed effects. Cross-sectional fixed effects are indicated in column headings. Standard errors, clustered at the Census Tract level, in parentheses.

Table A7: Heterogeneity among unflooded properties by distance to Sandy inundation

	Main Estimates		Hetero by Dist	
	(1)	(2)	(3)	(4)
	Block FE	Lot FE	Block FE	Lot FE
Biggert-Waters	-0.0349	-0.0567	-0.0339	-0.0420
	(0.0256)	(0.0459)	(0.0262)	(0.0471)
Sandy*in old FP	-0.0442	-0.0483	-0.0461	-0.0636
	(0.0423)	(0.0880)	(0.0426)	(0.0888)
Sandy*not in old FP	-0.0224	-0.0432	-0.0223	-0.0432
	(0.0148)	(0.0332)	(0.0148)	(0.0332)
Sandy*depth*in old FP	-0.0127**	-0.00481	-0.0125**	-0.00470
	(0.00557)	(0.0115)	(0.00557)	(0.0115)
Sandy*depth*not in old FP	-0.0188***	-0.00590	-0.0189***	-0.00590
	(0.00554)	(0.0162)	(0.00554)	(0.0162)
Post-Sandy*in old FP*unflooded			-0.0507	-0.253
			(0.109)	(0.303)
Post-Sandy*in old FP*dist to fld			0.0207	0.199
			(0.195)	(0.509)
Floodplain maps*Sandy	-0.0476***	-0.0297	-0.0475***	-0.0296
	(0.0173)	(0.0395)	(0.0173)	(0.0395)
Floodplain maps*no Sandy	-0.118***	-0.121**	-0.117***	-0.113**
	(0.0250)	(0.0525)	(0.0247)	(0.0515)
Observations	369342	182667	369342	182667

* $p < .1$, ** $p < .05$, *** $p < .01$. Columns 1 and 2 duplicate those of Columns 2 and 4 in Table 1 of the paper for comparison. Columns 3 and 4 report estimates with the addition of: 1) Post-Sandy*in old FP*unflooded, the product of a post-Sandy indicator, an old floodplain indicator, and an unflooded indicator; and 2) Post-Sandy*in old FP*dist to fld, the product of a post-Sandy indicator, an old floodplain indicator, and the distance to Sandy inundation (in hundreds of meters). Distance to inundation for flooded properties is 0. Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Dependent variable is log sale price. All columns include year-week fixed effects. Cross-sectional fixed effects are indicated in column headings. Standard errors, clustered at the Census Tract level, in parentheses.

Table A8: Effects of flood risk signals on log transaction prices with period-restricted samples

	(1) 2012-2015 Neighborhood FE	(2) 2012-2015 Block FE	(3) Post-Sandy Omitted Neighborhood FE	(4) Post-Sandy Omitted Block FE
Biggert-Waters	0.0252	0.0399	-0.00800	-0.0390
	(0.0495)	(0.0496)	(0.0291)	(0.0278)
Sandy*in old FP	0.150*	-0.0721	-0.00176	-0.0584
	(0.0832)	(0.0884)	(0.0688)	(0.0592)
Sandy*not in old FP	0.00693	-0.0403	-0.00560	-0.0268
	(0.0315)	(0.0312)	(0.0244)	(0.0200)
Sandy*depth*in old FP	-0.0664***	-0.0155	-0.0436**	-0.0134
	(0.0244)	(0.0283)	(0.0207)	(0.0172)
Sandy*depth*not in old FP	-0.0471**	-0.00901	-0.0651***	-0.0257*
	(0.0190)	(0.0190)	(0.0192)	(0.0154)
Floodplain maps*Sandy	-0.0746**	-0.0613*	0.0182	-0.0339
	(0.0336)	(0.0339)	(0.0285)	(0.0234)
Floodplain maps*no Sandy	-0.151***	-0.134***	-0.199***	-0.155***
	(0.0528)	(0.0392)	(0.0361)	(0.0288)
N	82308	82308	322325	322325

* $p < .1$, ** $p < .05$, *** $p < .01$. This table reproduces the estimates reported in Table 1 for the period restricted samples denoted in the column titles. Columns 1 and 2 limit the sample to the years 2012-2015. Columns 3 and 4 drop transactions that take place in 2012 after Sandy, as well as all transactions from 2013 and 2014. Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Dependent variable is log sale price. All columns include year-week fixed effects. Cross-sectional fixed effects are indicated in column headings. Standard errors, clustered at the Census Tract level, in parentheses.

Table A9: Accounting for projected floodplains

	(1) Neighborhood FE	(2) Block FE	(3) Block FE	(4) Lot FE
Biggert-Waters	-0.0121	-0.0297	0.0113	-0.0566
	(0.0269)	(0.0255)	(0.0353)	(0.0460)
Sandy*in old FP	0.0549	-0.0280	-0.0914	-0.0463
	(0.0472)	(0.0426)	(0.0646)	(0.0891)
Sandy*not in old FP	0.00926	0.000481	-0.00187	-0.0412
	(0.0187)	(0.0167)	(0.0253)	(0.0368)
Sandy*depth*in old FP	-0.0365***	-0.0127**	-0.00707	-0.00484
	(0.00695)	(0.00557)	(0.00861)	(0.0115)
Sandy*depth*not in old FP	-0.0384***	-0.0193***	-0.0168*	-0.00561
	(0.00649)	(0.00555)	(0.00912)	(0.0162)
Floodplain maps*Sandy	-0.0250	-0.0477***	-0.0488*	-0.0366
	(0.0229)	(0.0178)	(0.0261)	(0.0412)
Floodplain maps*no Sandy	-0.128***	-0.102***	-0.124***	-0.123**
	(0.0335)	(0.0254)	(0.0405)	(0.0540)
2020 1pct Floodplain	0.0402**	0.0319**	0.0414*	0.0308
	(0.0176)	(0.0159)	(0.0227)	(0.0320)
2050 1pct Floodplain	-0.0539***	-0.0558***	-0.0576***	-0.0263
	(0.0131)	(0.0118)	(0.0169)	(0.0233)
N	369342	369342	182691	182691

* $p < .1$, ** $p < .05$, *** $p < .01$. Transaction data are from the New York City Department of Finance 2003-2017. Projected Floodplain maps are from NYC Open Data. Estimates correspond to equation 1 with the addition of four terms: F^{2020}, $F^{2020} * P_F$, F^{2050}, and $F^{2050} * P_F$. The coefficient estimates for the two added interaction terms are reported above. Dependent variable is log sale price. All columns include year-week fixed effects. Cross-sectional fixed effects are indicated in column headings. Standard errors, clustered at the Census Tract level, in parentheses. The estimated effect of map treatment on non-flooded properties, -.201 in the most saturated specification, corresponds to a -18 percent change: e^{-.201}-1=-.182.

Table A10: Effects of flood risk signals on log transaction prices with additional hedonic controls or Winsorized prices

	Additional Hedonic Controls		Winsorized Sale Prices	
	(1)	(2)	(3)	(4)
	Block FE	Lot FE	Block FE	Lot FE
Biggert-Waters	-0.0429*	-0.0489	-0.0349	-0.0567
	(0.0229)	(0.0452)	(0.0256)	(0.0458)
Sandy*in old FP	-0.0281	-0.0709	-0.0417	-0.0594
	(0.0477)	(0.119)	(0.0554)	(0.119)
Sandy*not in old FP	-0.0142	-0.0208	-0.0156	0.000408
	(0.0153)	(0.0349)	(0.0157)	(0.0339)
Sandy*depth*in old FP	-0.0175	-0.0155	-0.0160	-0.0156
	(0.0149)	(0.0358)	(0.0173)	(0.0341)
Sandy*depth*not in old FP	-0.0265**	-0.0664*	-0.0299**	-0.0794**
	(0.0112)	(0.0345)	(0.0130)	(0.0370)
Floodplain maps*Sandy	-0.0450***	0.0153	-0.0426**	0.00626
	(0.0165)	(0.0435)	(0.0183)	(0.0422)
Floodplain maps*no Sandy	-0.130***	-0.111**	-0.118***	-0.120**
	(0.0225)	(0.0527)	(0.0250)	(0.0526)
N	358304	177136	369343	182678

* $p < .1$, ** $p < .05$, *** $p < .01$. Columns 1 & 2 reproduce the estimates reported in columns 2 & 4 of Table 1 with the addition of property-specific hedonic controls to the specification detailed in equation 1. Hedonic controls include building age at time of sale, a cubic in land area and building square footage, fixed effects for each number of residential units, commercial units, and total units, and fixed effects for building class at the time of sale. Columns 3 & 4 address sale price outliers by Winsorizing at the 1 percent level rather than dropping. Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Dependent variable is log sale price. All columns include year-week fixed effects. Cross-sectional fixed effects are indicated in column headings. Standard errors, clustered at the Census Tract level, in parentheses.

Table A11: Belief updating sensitivity to risk aversion parameter

	Coeff. Abs. Risk Aversion $r(X_c)$:	(1) Biggert-Waters	(2) Sandy*not in old FP	(3) Floodplain maps*no Sandy
Guiso and Paiella (2008)				
(1) Baseline	1.2×10^{-3}	0.02%	0.20%	0.46%
(2) Lower	1.2×10^{-4}	0.13%	1.38%	3.22%
(3) Higher	1.2×10^{-2}	0.00%	0.02%	0.05%
Cramer et al. (2002)				
(4) Employees	1.56×10^{-3}	0.01%	0.15%	0.36%
(5) Entrepreneurs	1.38×10^{-3}	0.02%	0.17%	0.40%
Sydnor (2010)				
(6) Low Bound	1.72×10^{-3}	0.01%	0.14%	0.33%
(7) Upper Bnd.	1.58×10^{-2}	0.00%	0.02%	0.04%
Guiso and Paiella (2008)				
(8) Low	2.0×10^{-4}	0.09%	0.96%	2.23%
(9) High	3.3×10^{-2}	0.00%	0.01%	0.02%

Values estimated from equations 7, 9, and 11 as described in the body of the text with the value of $r(X)$ changed between rows. Row 1 reports our main estimates based on $r(X) = 1.2 * 10^{-3}$ from Saha et al. (1994). Rows 2 and 3 simply deflate and inflate (respectively) this value by an order of magnitude. Columns 4 and 5 use the risk aversion estimates for employees and entrepreneurs identified in Cramer et al. (2002). Columns 6 and 7 rely on upper and lower bounds on the median CARA coefficient from Sydnor (2010) assuming home owners (observed purchasing insurance with a $500 deductible) have a lifetime wealth of $1 million. Columns 8 and 9 use the mean coefficients of absolute risk aversion from respondents identified as having low vs. high risk aversion in a study by Guiso and Paiella (2008).

Table A12: Belief updating sensitivity to discount rate

	Discount Rate δ:	(1) Biggert-Waters	(2) Sandy*not in old FP	(3) Floodplain maps*no Sandy
Giglio et al. (2016)				
(1) Baseline	2.6%	0.02%	0.20%	0.46%
Drupp et al. (2015)				
(2) 10th Percentile	1.0%	0.00%	0.01%	0.07%
(3) Mean	2.25%	0.01%	0.13%	0.35%
(4) 90th Percentile	3.0%	0.02%	0.30%	0.61%
(5) **Stern (2006)**	1.4%	0.01%	0.03%	0.14%
(6) **Nordhaus (2013)**	4.0%	0.04%	0.70%	1.06%
(7) **Gollier (2013)**	4.6%	0.06%	1.06%	1.39%

Values estimated from equations 7, 9, and 11 as described in the body of the text with the discount rate, δ, changed between rows. Row 1 reports our main estimates based on $\delta = 0.026$ from Giglio et al. (2016). Rows 2, 3, and 4 are based on the 10th percentile, mean, and 90th percentile values of the social discount rate from a survey of 197 experts by Drupp et al. (2015) . Rows 5, 6, and 7 use discount rate levels suggested by Stern (2006), Nordhaus (2013), and Gollier (2013) respectively.

Table A13: Effects of flood risk signals including protective infrastructure

	(1) Neighborhood FE	(2) Block FE	(3) Block FE	(4) Lot FE
Biggert-Waters	-0.0155	-0.0350	0.00640	-0.0570
	(0.0269)	(0.0256)	(0.0355)	(0.0458)
Sandy*in old FP	0.0519	-0.0443	-0.0876	-0.0603
	(0.0624)	(0.0553)	(0.0884)	(0.119)
Sandy*not in old FP	-0.00194	-0.0210	-0.00498	-0.00740
	(0.0185)	(0.0156)	(0.0227)	(0.0340)
Sandy*depth*in old FP	-0.0446**	-0.0157	-0.0248	-0.0156
	(0.0201)	(0.0173)	(0.0260)	(0.0341)
Sandy*depth*not in old FP	-0.0515***	-0.0275**	-0.0539***	-0.0757**
	(0.0160)	(0.0129)	(0.0206)	(0.0371)
Floodplain maps*Sandy	-0.0125	-0.0407**	-0.0217	0.00814
	(0.0229)	(0.0183)	(0.0272)	(0.0422)
Floodplain maps*no Sandy	-0.139***	-0.118***	-0.136***	-0.122**
	(0.0328)	(0.0250)	(0.0394)	(0.0526)
Big U Protection	0.0915	0.139**	0.408***	0.451***
	(0.0659)	(0.0647)	(0.111)	(0.173)
N	369342	369342	182667	182667

* $p < .1$, ** $p < .05$, *** $p < .01$. Transaction data are from the New York City Department of Finance 2003-2017. Floodplain and inundation maps are from FEMA. Sample is restricted to properties in Tax Class 1. Estimates correspond to equation 1. Dependent variable is log sale price. All columns include year-week fixed effects. Cross-sectional fixed effects are indicated in column headings. Standard errors, clustered at the Census Tract level, in parentheses.