Adaptation and Adverse Selection in Markets for Natural Disaster Insurance: Online Appendix

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Contents

A Comparative Statics Derivations

This section derives comparative statics for the effects of changes in natural disaster insurance price p, adaptation α, and frictions ϕ on homeowners' willingness to pay for insurance and insurers' costs. Denote the change in the share of insured homeowners by $s_\theta \equiv \frac{\partial s(p,\alpha,\phi)}{\partial \theta}$ for $\theta \in \{p, \alpha, \phi\}$. $\tilde{D}_\theta$ and AC_θ are the equivalent expressions for the partial derivatives of willingness to pay and average costs. $u_c \equiv \frac{\partial u(\cdot)}{\partial c}$ is the marginal utility of consumption.

A.1 Willingness To Pay

To derive comparative statics for willingness to pay, I use the identities that define the share insured $s(p, \alpha, \phi)$ as a function of the exogenous parameters:

$$\tilde{D}(s(p,\alpha,\phi),\alpha,\phi) = p \tag{8}$$

and the willingness to pay for insurance for any given type s_i:

$$u(y_i - \tilde{D}(s_i, \alpha, \phi_i)) = \phi_i \mathbb{E}[u(y_i - f(s_i, \alpha))|s_i]. \tag{9}$$

Prices

Totally differentiating (8) holding constant adaptation α and frictions ϕ yields $\tilde{D}_s s_p = 1$. Rearranging, the effect of a marginal price change on the share of homeowners purchasing insurance is $s_p = \frac{1}{\tilde{D}_s} < 0$. This expression is negative because $\tilde{D}_s$ is the change in willingness to pay for a marginal increase in type s_i, which is negative by construction. This result shows the equivalence between assuming willingness to pay decreases in homeowner type and assuming that the demand curve slopes downwards.

Adaptation

Totally differentiating (8) holding constant frictions ϕ and price p yields $\tilde{D}_s s_\alpha + \tilde{D}_\alpha = 0$. The total effect of increasing adaptation is made up of two partial effects. The first term $\tilde{D}_s s_\alpha$ is the movement along the demand curve from the change in the identity of the marginal type, so that $\tilde{D}(s(p,\alpha,\phi),\alpha,\phi) = p$ continues to hold at the new value of α. The derivative $\tilde{D}_s$ is negative by construction.

The second term $\tilde{D}_\alpha$ is the shift of the demand curve from the adaptation policy. The demand curve shifts inward when adaptation increases because expected utility when uninsured increases, lowering willingness to pay for all types. To see this, fix a type s_i and totally differentiate (9) with respect to α. This yields:

$$\tilde{D}_\alpha = \frac{-\phi_i}{u_c} \frac{\partial}{\partial \alpha} \mathbb{E}[u(y_i - f(s_i, \alpha^*))|s_i]$$

I evaluate this expression at the new level of adaptation, $\alpha^* = \alpha + d\alpha$. We know $\phi_i \geq 1$, so $\frac{-\phi_i}{u_c} < 0$. The exact expression for $\frac{\partial}{\partial \alpha}\mathbb{E}[u(y_i - f(s_i, \alpha^*))|s_i]$ depends on how adaptation affects the distribution of damages and, by extension, consumption. However, as long as a marginal increase in adaptation does not reduce expected utility, willingness to pay weakly decreases in adaptation.[1] The assumption that homeowners are weakly better off with adaptation than without it is equivalent to assuming that the distribution of consumption at higher levels of adaptation first order stochastically dominates the distribution at lower levels of adaptation. If adaptation makes homeowners strictly better off, then $\tilde{D}_\alpha$ is strictly negative. In this case, $s_\alpha = \frac{-\tilde{D}_\alpha}{\tilde{D}_s} < 0$, and I expect fewer insured homeowners at higher levels of adaptation.

Frictions in Uptake

Following the same approach and totally differentiating (8) holding constant α and p yields $\tilde{D}_s s_\phi + \tilde{D}_\phi = 0$. The first term $\tilde{D}_s s_\phi$ again is the movement along the demand curve that ensures that $\tilde{D}(s(p,\alpha,\phi),\alpha,\phi) = p$ continues to hold at the new value of ϕ_i. The second term $\tilde{D}_\phi$ is the shift of the demand curve that results from increasing the wedge between perceived and actual expected utility in the uninsured state, for any type s_i. Totally differentiating (9) with respect to ϕ_i yields:

$$\tilde{D}_\phi = \frac{-1}{u_c}\mathbb{E}[u(y_i - f(s_i,\alpha))|s_i]$$

This expression is unambiguously negative. Hence, $s_\phi = \frac{-\tilde{D}_\phi}{\tilde{D}_s} < 0$ and I expect fewer insured homeowners when the wedge between perceived and actual expected utility when uninsured is larger.

A.2 Insurer Average Costs

To derive comparative statics for the effect of changes in the exogenous parameters price p, adaptation α, and frictions ϕ on insurer costs, I start from the definition of average costs:

$$AC(p,\alpha,\phi) = \frac{1}{s(p,\alpha,\phi)} \int_0^{s(p,\alpha,\phi)} \mathbb{E}[f(s_i,\alpha)]ds_i \tag{10}$$

Prices

Totally differentiating (10) with respect to price p and evaluating at the new price $p^* = p + dp$ yields:

$$\begin{aligned} AC_p &= \frac{s_p}{s(p^*,\alpha,\phi)}\left[\mathbb{E}[f(s(p^*,\alpha,\phi),\alpha)] - \frac{1}{s(p^*,\alpha,\phi)}\int_0^{s(p^*,\alpha,\phi)} \mathbb{E}[f(s_i,\alpha)]ds_i\right] \\ &= \frac{s_p}{s(p^*,\alpha,\phi)}\left[MC(p^*,\alpha,\phi) - AC(p^*,\alpha,\phi)\right] \end{aligned}$$

The first term, $\frac{s_p}{s(p^*,\alpha,\phi)}$, is the change in market size from the price increase; I showed above that $s_p < 0$. The second, bracketed term is the selection effect: if marginal homeowners have lower costs than the average of the insured homeowners, then this term is negative and the market is adversely selected. In this case, $AC_p > 0$ and average costs are increasing in price.

[1] The effect of adaptation on demand will depend on whether adaptation increases expected consumption, reduces the variance of consumption, or both. This is an open empirical question. Consistent with my empirical context, this discussion presumes that there is an *ex ante* level of adaptation and abstracts from costs of e.g., elevating one's house.

Adaptation

Totally differentiating (10) with respect to the level of adaptation α and evaluating this expression at the new value of $\alpha^* = \alpha + d\alpha$ yields:

$$AC_\alpha = \frac{1}{s(p,\alpha^*,\phi)}\left[\int_0^{s(p,\alpha^*,\phi)} \frac{\partial}{\partial\alpha}\mathbb{E}[f(s_i,\alpha^*)]ds_i + s_\alpha\left[\mathbb{E}[f(s(p,\alpha^*,\phi),\alpha^*)] - \frac{1}{s(p,\alpha^*,\phi)}\int_0^{s(p,\alpha^*,\phi)} \mathbb{E}[f(s_i,\alpha^*)]ds_i\right]\right]$$

$$= \underbrace{\frac{1}{s(p,\alpha^*,\phi)}\int_0^{s(p,\alpha^*,\phi)} \frac{\partial}{\partial\alpha}\mathbb{E}[f(s_i,\alpha^*)]ds_i}_{\text{protection effect (-)}} + \underbrace{\frac{s_\alpha}{s(p,\alpha^*,\phi)}\left[MC(p,\alpha^*,\phi) - AC(p,\alpha^*,\phi)\right]}_{\text{selection effect (?)}}$$

The first term is the mechanical effect of adaptation on the mean of the distribution of damages in the insured population. This is weakly negative by assumption. The second term is the selection effect, and its sign depends on how adaptation changes the distribution of costs of homeowners who continue to buy insurance. I showed above that $s_\alpha < 0$. If the marginal individuals who opt out of insurance when they are more protected are also lower cost than average, then the selection effect is positive. If the selection effect is large enough, then increasing adaptation may actually *increase* average costs to the insurer.

Frictions in Uptake

The expression for the effect of a change in frictions ϕ on cost has a similar form to the expression for the effect of a price change. Totally differentiating (10) with respect to ϕ_i and evaluating at $\phi_i^* = \phi_i + d\phi_i$ yields:

$$AC_\phi = \frac{s_\phi}{s(p,\alpha,\phi^*)}\left[\mathbb{E}[f(s(p,\alpha,\phi^*),\alpha)] - \frac{1}{s(p,\alpha,\phi^*)}\int_0^{s(p,\alpha,\phi^*)} \mathbb{E}[f(s_i,\alpha)]ds_i\right]$$

$$= \frac{s_\phi}{s(p,\alpha,\phi^*)}\left[MC(p,\alpha,\phi^*) - AC(p,\alpha,\phi^*)\right]$$

The term $\frac{s_\phi}{s(p,\alpha,\phi^*)}$ is the change in the market size from the marginal increase in ϕ_i, which I showed is negative. The overall sign of the expression depends on the selection effect: if reducing the wedge between expected and perceived utility results in higher cost marginal individuals taking up insurance, then average insurance costs can increase. This resorting could arise, for example, if informing homeowners about their actual level of flood risk leads high-risk homeowners to increase their take-up of insurance and low-risk homeowners to substitute away from insurance.

B Derivation of Willingness to Pay

Evaluating the welfare effects of counterfactual price increases and an insurance mandate requires information on the marginal cost and frictionless willingness to pay curves.

First, I obtain the marginal cost curve using the observed demand and average cost curves that I estimate in Section 6 in the main text. Using these empirical quantities, I derive the marginal cost curve as the change in total cost from an incremental change in demand, i.e., $MC(p,\alpha,\phi) = \frac{\partial(AC(p,\alpha,\phi)\times s(p,\alpha,\phi))}{\partial s(p,\alpha,\phi)}$ (Einav et al., 2010). The pre-2013 levels of prices p', average costs $AC(p',\alpha,\phi)$, and share of insured homeowners $s(p',\alpha,\phi)$ locate the initial equilibrium in the market.

Next, I show that we can write the frictionless willingness to pay curve as a function of the marginal cost curve as well as a coefficient of absolute risk aversion and the effect of insurance on the variance of consumption. Hendren (2019) provides a method to estimate risk aversion using observed demand and cost curves and the effect of insurance on the variance of consumption; I invert this approach to recover the risk premium that homeowners should be willing to pay for natural disaster insurance in the absence of frictions. This risk premium can be calibrated with information on homeowners' willingness to bear risk from natural disasters and on the difference in the variance of consumption when insured relative to when uninsured.

The model in Section 2 is based on the assumption of full insurance. Here, I derive the expression for willingness to pay for the more general case of partial insurance. Relative to the full insurance case, the natural disaster insurer only reimburses a fraction δ of damages $f(s_i,\alpha)$, where $0 < \delta \leq 1$. If $\delta = 1$, the model collapses to the full insurance special case in Section 2 of the main text.

With partial insurance, the budget constraint for insured homeowners is:

$$c^I(s_i,\alpha,p,\delta,y_i) + p + (1-\delta)f(s_i,\alpha) \leq y_i$$

The budget constraint for uninsured homeowners is identical to the full insurance case:

$$c^U(s_i,\alpha,y_i) + f(s_i,\alpha) \leq y_i$$

The highest price $\tilde{D}(s_i,\alpha,\phi_i,\delta)$ that a homeowner of type s_i with frictions ϕ_i is willing to pay for insurance solves:

$$\mathbb{E}\left[u(y_i - \tilde{D}(s_i,\alpha,\phi_i,\delta) - (1-\delta)f(s_i,\alpha))|s_i\right] = \phi_i\mathbb{E}\left[u(y_i - f(s_i,\alpha))|s_i\right] \tag{11}$$

and the fraction of insured homeowners $s(p,\alpha,\phi,\delta)$ is defined by $\tilde{D}(s(p,\alpha,\phi,\delta),\phi,\alpha,\delta) = p$.[2]

To derive an expression for frictionless willingness to pay for each type s_i, the first step is to take a second-order Taylor expansion of (11) around the average consumption $\bar{c}$ of homeowners of type s_i. This yields:

$$u(\bar{c}) + u_c\mathbb{E}\left[(y_i - \tilde{D}(s_i,\alpha,\phi_i,\delta) - (1-\delta)f(s_i,\alpha)) - \bar{c})|s_i\right] + \frac{u_{cc}}{2}\mathbb{E}\left[(y_i - \tilde{D}(s_i,\alpha,1,\delta) - (1-\delta)f(s_i,\alpha)) - \bar{c})^2|s_i\right]$$
$$= \phi_i\left(u(\bar{c}) + u_c\mathbb{E}[(y_i - f(s_i,\alpha) - \bar{c})|s_i] + \frac{u_{cc}}{2}\mathbb{E}[(y_i - f(s_i,\alpha) - \bar{c})^2|s_i]\right)$$

Note that $u_c = \frac{\partial u(\bar{c})}{\partial c}$ and $u_{cc} = \frac{\partial^2 u(\bar{c})}{\partial c^2}$ are evaluated at the average consumption $\bar{c}$ of all homeowners of type s_i. Subtracting the Taylor expansion of $\mathbb{E}\left[u(y_i - f(s_i,\alpha))|s_i\right]$ from both sides and canceling deterministic terms from the expectation yields an expression that implicitly defines willingness to pay

[2] To allow more generally for the possibility of negative utility functions, replace ϕ_i in equation (1) by $\phi_i^{sgn(u(y_i))}$.

$\tilde{D}(s_i, \alpha, \phi_i, \delta)$ of each type s_i:

$$\tilde{D}(s_i, \alpha, \phi_i, \delta) = \delta\mathbb{E}[f(s_i, \alpha)|s_i] + \frac{1}{2} \times \frac{-u_{cc}}{u_c} \times \left(\mathbb{E}\left[(y_i - f(s_i, \alpha) - \bar{c})^2|s_i\right] - \mathbb{E}\left[(y_i - \tilde{D}(s_i, \alpha, \phi_i, \delta) - (1-\delta)f(s_i, \alpha) - \bar{c})^2|s_i\right]\right) + (1-\phi_i) \times \frac{1}{u_c} \times \left(u(\bar{c}) + u_c\mathbb{E}[(y_i - f(s_i, \alpha) - \bar{c})|s_i] + \frac{u_{cc}}{2}\mathbb{E}[(y_i - f(s_i, \alpha) - \bar{c})^2|s_i]\right) \quad (12)$$

We can write the last bracketed term more concisely as $\mathbb{E}\left[u(y_i - f(s_i, \alpha))|s_i\right]$. For the marginal individual who purchases insurance at price p, willingness to pay is given by the identity $\tilde{D}(s(p, \alpha, \phi, \delta), \alpha, \phi, \delta) = p$. Replacing this identity into equation (12) yields an expression for the market observed willingness to pay curve as a function of p:

$$D(p, \alpha, \phi, \delta) = \underbrace{\delta\mathbb{E}\left[f(s_i, \alpha)|s_i = s(p, \alpha, \phi, \delta)\right]}_{\text{reimbursed share of costs}} + \frac{1}{2} \times \frac{-u_{cc}}{u_c} \times \underbrace{\left[\mathbb{E}\left[(y_i - f(s_i, \alpha) - \bar{c})^2|s_i = s(p, \alpha, \phi, \delta)\right] - \mathbb{E}\left[(y_i - p - (1-\delta)f(s_i, \alpha) - \bar{c})^2|s_i = s(p, \alpha, \phi, \delta)\right]\right]}_{\text{difference in the variance of consumption between the insured and the uninsured states}} + \underbrace{(1-\phi_i) \times \frac{1}{u_c} \times \left(\mathbb{E}\left[u(y_i - f(s_i, \alpha))|s_i = s(p, \alpha, \phi, \delta)\right]\right)}_{\text{distortion from frictions } \phi > 1} \quad (13)$$

The term $\mathbb{E}[f(s_i, \alpha)|s_i]$ is the homeowner's expected cost, $\frac{-u_{cc}}{u_c}$ is their coefficient of absolute risk aversion, and $\mathbb{E}\left[(y_i - f(s_i, \alpha) - \bar{c})^2|s_i = s(p, \alpha, 1, \delta)\right] - \mathbb{E}\left[(y_i - p - (1-\delta)f(s_i, \alpha) - \bar{c})^2|s_i = s(p, \alpha, 1, \delta)\right]$ is the difference in the variance of consumption when uninsured relative to when insured. The last term in (13) is the distortion from frictions in uptake, which is negative for $\phi_i > 1$. In the absence of frictions, $\phi_i = 1$ for all homeowners, and so homeowners accurately equate expected utility in the insured and the uninsured states. Therefore, $\tilde{D}(s_i, \alpha, \phi_i, \delta) < \tilde{D}(s_i, \alpha, 1, \delta)$ for all s_i: frictions distort willingness to pay downward, possibly below expected payouts.

Replacing $\phi_i = 1$ into (13) yields an expression for the frictionless willingness to pay curve:

$$D(p, \alpha, 1, \delta) = \delta\mathbb{E}[f(s_i, \alpha)|s_i = s(p, \alpha, 1, \delta)] + \frac{1}{2} \times \frac{-u_{cc}}{u_c} \times \left(\mathbb{E}\left[(y_i - f(s_i, \alpha) - \bar{c})^2|s_i = s(p, \alpha, 1, \delta)\right] - \mathbb{E}\left[(y_i - p - (1-\delta)f(s_i, \alpha) - \bar{c})^2|s_i = s(p, \alpha, 1, \delta)\right]\right) \quad (14)$$

The second line of (14) is positive for risk-averse homeowners with $u_{cc} < 0$. Therefore, this expression says that, in the absence of frictions, risk-averse homeowners should be willing to pay a risk premium over reimbursed costs that depends on risk aversion and on the reduction in risk provided by insurance.

With full insurance, $\delta = 1$ and we can further simplify (14) to obtain the full insurance special case in the main text. Suppressing δ as an argument in willingness to pay, this yields the frictionless willingness to pay curve:

$$D(p,\alpha,\phi=1) = \underbrace{\mathbb{E}[f(s_i,\alpha)|s_i = s(p,\alpha,\phi=1)]}_{\text{expected cost}} + \\ \frac{1}{2} \times \underbrace{\frac{-u_{cc}}{u_c}}_{\text{coef. of absolute risk aversion}} \times \underbrace{\left(E[(y_i - f(s_i,\alpha) - \bar{c})^2|s_i = s(p,\alpha,\phi=1)] - (y_i - p - \bar{c})^2\right)}_{\text{effect of insurance on the variance of consumption}} \quad (15)$$

The full insurance frictionless willingness to pay curve (15) differs from the partial insurance frictionless willingness to pay curve (14) in two ways. First, the risk premium depends on deterministic income and prices when insured, rather than the variance of consumption in the insured state.[3] Second, the expected benefit from insurance is equal to the full amount of expected costs because they are fully reimbursed by the insurer.

It is worth noting what information is not required by this approach for calibrating frictionless willingness to pay. Related papers that use insurance demand and costs curves to analyze welfare in the presence of choice frictions calibrate a frictionless willingness to pay curve by adjusting the observed willingness to pay curve using information on how frictions are distributed (Handel et al., 2019; Spinnewijn, 2017). By contrast, this paper's approach does not require information on the distribution of frictions; frictions ϕ_i do not appear in equation (15). Instead, this approach uses other information on the distribution of the consumption variance and risk aversion, as well as on marginal costs. As a result, the frictionless willingness to pay curve is robust to homeowners with lower observed willingness to pay making bigger or smaller mistakes. Any correlation between individual frictions and observed willingness to pay is reflected in the relative slopes of the two willingness to pay curves. In comparison with a fully structural model (e.g., Handel and Kolstad, 2015), the main benefit of this approach is that it does not require specifying how frictions in uptake affect homeowners' decisions. Section 7.1 discusses some possible explanations for low willingness to pay, but disentangling the roles of different behavioral frictions is an interesting area for future work.

C Data

This section provides details on the data sources, the construction of the analysis sample, and the linking of the data sets.

C.1 Sample Construction

Flood Insurance Policies and Claims – The administrative flood insurance data are from FEMA's BureauNet database, which the NFIP uses to track current and historical flood insurance policies and claims. The data include over 70 million policies written for single and multi-family residences, condominiums, vacation homes, and businesses in the 20 Atlantic and Gulf Coast states. The 20 states are Alabama, Connecticut, Delaware, Florida, Georgia, Louisiana, Maine, Maryland, Massachusetts, Mis-

[3] With full insurance and deterministic income y_i for each type s_i, $(y_i - p - \bar{c})^2$ will be small if there is little variation in income conditional on willingness to pay.

sissippi, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Texas, Vermont, and Virginia.

The policies data set includes premium paid, purchased coverage for building and contents, year of construction of the structure, flood zone, the minimum elevation requirement, and a few dwelling characteristics, as well as the date the policy was written, NFIP community identifiers and 5-digit zip codes. The claims data include the same identifying information, along with the amount of the claim, the flood event number assigned by FEMA, and the depth of water that flooded the house.

I impose several sample exclusions during the cleaning of this data set. I first restrict the analysis to the 25 million policies written for single-family, primary residences in high-risk flood zones. I follow the NFIP rating system and classify high-risk flood zones as A, numbered A, V, or numbered V zones. I drop 1% of policies that are missing the flood zone or the house's date of construction since this information is needed to identify whether a house is treated by the price reforms that I study. Additionally, I exclude 4% of policies for which coverage exceeds the maximum allowable coverage for single-family residential properties or is less than or equal to 0. Since some prices are miscoded relative to the rate schedule published by NFIP for residential properties (e.g., total premia that exceed \$60,000 per year or \$16,000 per \$1,000 of insurance coverage or less than \$0.10 per \$1,000 of insurance), I exclude policies that are smaller than the first or greater than the ninety-ninth percentile of premia.[4] I similarly drop the less than 0.5% of claims that are missing the house's construction year or the flood zone. I exclude the 7% of claims reporting damages or payouts that are zero or negative, or realized payouts that exceed purchased coverage. Zero entries for damages or payouts indicate either that no payout was made or that the claim is still outstanding.

For the years 2010-2017, 5-10% of policies are missing zip codes. My conversation with the FEMA FOIA office indicates that these were erroneously deleted when the detailed addresses were removed during the anonymizing of the FOIA request for the 2010-2017 data. I reconstruct these zip codes by building a concordance from zip code to flood map panel identifier. The flood map panel identifier is the subsection of a flood map that is included in one specific hydrological study, is the size of several city blocks, and is typically fully contained in a 5-digit zip code. I identify policies with the same flood map panel identifier as the policies with the missing zip codes, and assign the same zip code to policies with the same flood map panel code. This procedure recovers approximately 75% of the missing zip codes.

I do not observe flood insurance prices for houses that do not purchase insurance. I impute prices linearly based on characteristics of the NFIP rate schedule, specifically date of construction relative to map year, year built, flood zone, minimum elevation requirement, and community id. These variables alone account for 60% of the variation in prices. The NFIP additionally adjusts prices based on elevation of the house relative to the construction requirement and on basement, but these variables are not available in the housing data set.

Minimum Elevation Requirement – I construct a measure of the mean zip code elevation requirement for new construction using the policy data. The policy data set includes the minimum elevation requirement for adapted houses. Non-adapted houses are not required to meet minimum construction

[4] Prices are generally in the range of \$1-15 per \$1,000 of coverage (NFIP, 2019).

standards, and so this information is not available for these houses; it is also missing for approximately 1% of adapted houses. Averaging over the requirement for policies with available data yields an average measure of the construction requirement for adapted houses in each zip code. I measure the extent to which this requirement binds using the available data on the elevation difference between the minimum requirement and the actual construction height in the policy data set.

Flood Type – I use the flood event number from the claims data to identify the types of floods that strike each zip code, in each year. FEMA assigns claims an event number of 0 if they are made during localized "nuisance" floods, while claims made during flood events that are large enough for FEMA to set up a local claims office are assigned a three-digit code that uniquely identifies the catastrophe. The latter includes named disasters, such as Hurricanes Harvey and Katrina. I take the maximum over the flood event numbers in each zip code-year to determine whether FEMA classifies the worst flood to strike each zip code as a "nuisance" flood or a catastrophe. I assign zip codes with no claims to a third, "not flooded" category.

Flood Depth – I construct an annual measure of flood water depth in each zip code using information on the number of feet of water that flooded each house, available from the claims data. This flood water depth variable captures the amount of water that enters the house during the flood. I assign a flood depth of zero to policies without claims. Since water depths are rounded to the nearest foot, I set claims with water depths of zero to 0.0001 to distinguish small floods from no floods. Approximately 2% of water depths are negative. I impute the flood depth for these claims using the average water depth for claims made by the same type of house (i.e., adapted or non-adapted) in the same flood zone with the same flood event number (e.g., no. 653 is Hurricane Katrina). An additional 7% of claims have water depths that exceed 25 feet. I treat these flood depths as missing and impute them following the same procedure as the negative values. I calculate the annual average level of inundation in feet for high-risk houses in each zip code by averaging over the water depths for all high-risk policies in each zip code for each year. To define an index of flood severity, I bin the average flood depth into quintiles. Approximately 40% of zip codes are not flooded, so this yields three categories of flood severity and a fourth "not flooded" category. Appendix Table A.2 shows that average payouts are higher in deeper floods and in catastrophes. For medium and deep floods, I distinguish between "nuisance" floods and catastrophes according to FEMA's classification to obtain six monotonically increasing water depth categories.[5]

I conduct several analyses to verify that the flood water depths that I measure using the claims data provide an accurate representation of the inundation level of each zip code. An ideal measure of flood water depth would come from external data for all floods between 2001 and 2017 for the 20 states in the analysis, rather than measures based on data from the insurance claims. Unfortunately, to the best of my knowledge, no such external data set is available for most of these floods.[6] The National Oceanic

[5]Appendix Table A.2 shows that less than 1% of policies are written for houses that experience floods of the lowest water depth that are classified as catastrophes. To avoid thin bins in the post-reform period in equation (6), I therefore do not distinguish between "nuisance" floods and catastrophes for floods of the lowest water depth.

[6]Some remote sensing data sets (e.g., the MODIS Near Real-Time Global Flood Mapping Project) record if an area flooded in recent years, but not water depth.

and Atmospheric Administration (NOAA) did compile detailed flood water depth data for New Orleans in the aftermath of Hurricane Katrina in 2005. Appendix Figure A.7 shows that my measured flood water depth is strongly positively correlated with these external flood water depth measures in the zip codes affects by this flood event. My flood water depth measure is consistently higher, which is to be expected because the NOAA measures are the average flood water depth over the whole zip code during Hurricane Katrina and my measures are over the part of the zip code in a high-risk flood zone only (i.e., the part of the zip code that is most likely to be badly flooded). This validation of the water depth measure helps to reduce any concern about the endogeneity of the flood depth measure to the insurance purchase decision and about the distributions of adapted and non-adapted houses in a zip code affecting the claims measures of the amount of water that entered the home; Appendix Table A.3 shows the similarity between the distributions of the number of adapted and non-adapted houses in high-risk zip codes.

To further examine the importance of the distributions of adapted and non-adapted houses for my measures of flood depth, I also reconstruct the measure of flood severity using only claims made by non-adapted houses and re-estimate the model. This robustness check avoids the possibility that differences in flood water depth between zip codes are driven by any differences in the distribution of adapted and non-adapted houses that are not captured by the zip code fixed effects, and also the possibility that there are differences in the extent of construction requirements amongst adapted houses. Appendix Tables A.4, A.5, and A.6 show estimates that are very similar in sign, magnitude and precision to the main estimates, and also to the estimates that exclude flood severity controls entirely that are shown in the same tables.

Finally, I note that the potential endogeneity of the water depth measure would be most concerning if there are many zip codes without purchases, in which case no claims or water depth information is observed. In contrast, 90% of zip codes have non-zero flood insurance purchases; of the zip codes without purchases, these typically have very few houses in high-risk flood zones (only approximately 7, as compared with 162 on average), and therefore comprise less than 5% of the total number of houses in the sample. As a result, the regression estimates are unchanged if the zip codes without insured homes are excluded from the analysis.

Housing – I obtain assessment data on the universe of residential houses from the Zillow Transaction and Assessment Database (ZTRAX), for all states for which I have flood insurance data. These proprietary data are collected from county assessors' records. Coverage of different variables depends on the legal reporting requirements of each county. Zip code, latitude, and longitude are populated for almost all properties. I exclude approximately 1% of houses that are missing latitude or longitude coordinates. Construction year is not a reporting requirement for all counties and is missing for approximately 38% of residential houses in the Zillow data. Since I cannot categorize houses as built either before or after the map year of their community (i.e., treated by price changes or not) if I do not observe the construction year, I exclude houses missing year of construction from the demand analysis.

Using the latitude and longitudes for each house, I merge all single-family residential houses with the NFIP's publicly available National Flood Hazard Layer (NFHL). I use the Zillow property use code to identify single-family residences, excluding residential houses in the following categories: Rural Residence (farm/productive land), Cluster Home, Condominium, Cooperative, Planned Unit Development, Patio Home, and Landominium. For each house, I extract the flood zone, the community identifier, and the years of the initial flood map, the current flood map, and any map revisions from the NFHL. The initial and current flood map years are missing from the NFHL for approximately 10% of houses. I fill in the missing dates using the online NFIP Community Status Books, which records the same information for each community. I verify that the dates of the initial map years recorded in the NFHL are accurate by cross-referencing with the Community Status Books.

I impose several sample restrictions on the merged policies and housing data set. First, as discussed above, I restrict the analysis to single-family, primary residences in high-risk flood zones because my variation in prices and construction codes affects these houses. Subsequently, I exclude houses built in the 2000s so that every house has a positive claim probability in each year of the sample and so that the composition of the adapted control group does not change. The number of homeowners who elevate their houses after they have been built is vanishingly small due to the prohibitive cost (Hurley, 2017). Finally, I drop policies written for houses built during the initial map year since it is unclear whether they are adapted or non-adapted.

I approximate the flood insurance market size for each year between 2001 and 2017 by repeating the cross-sectional assessment data to build a panel and dropping houses built after the sample year. The main analysis focuses on the panel of 13,433,549 houses built within a 30-year window centered on the year of a community's first flood map. I focus on houses built around the same time because the match quality of insurance contracts to houses is poorer for early construction than for late construction. The year of construction for older houses is more likely to be subject to measurement error (e.g., a house built in 1953 is reported as built in 1950, whereas a house built in 1993 is reported as 1993).

Both the housing and flood insurance data sets are administrative records, but several sources of measurement error are possible. First, the NFHL lists current (i.e., 2017) flood zone designations, but revisions occur during the time period of my study. To the extent that high-risk flood zone boundaries change, merging the housing data set with the NFHL introduces some noise in the market size of high-risk houses. Second, the latitudes and longitudes in the Zillow data are property centroids, which may not correspond to the exact location of the house. This also potentially introduces noise in the number of houses in high-risk flood zones. Third, as discussed above, some construction dates seem to be approximated (i.e., rounded to nearest decade). These sources of measurement error mean that I do not obtain an exact match on construction year, flood zone, zip code, and community id for all houses. Table 1 suggests that the match rate is somewhat better for newer construction; this means that the higher rates of uptake that I find for older houses may be a lower bound on the difference in take-up between the two house types. Back-of-the-envelope calculations suggest that the share of insured houses including houses without dates of construction is comparable to the share insured in the matched subsample. Measurement error from map updates or approximated latitude and longitude coordinates are not likely to differentially affect new and old construction, though may generally attenuate the magnitudes of the coefficient estimates.

C.2 Matching Algorithm

I match policies to houses using zip code, community id, flood zone, and construction year. In accordance with federal FOIA disclosure requirements, the flood insurance policies and claims are anonymized and do not include street addresses. However, whether a house is subject to higher prices after 2012 and minimum elevation requirements depends on when it was built relative to the community-specific map year and whether it is in a high- or low-risk flood zone. This means that it important for me to know the share of insured houses and average insurer costs for the group of houses built in a given year in each zip code and flood zone, but not which specific house purchased the policy. I therefore link each policy to a house built in the same year in the same zip code and flood zone.

I follow a four-step matching procedure. I first match 14 million policies to houses based on zip code, flood zone, and year of construction. Zip codes change over time, and are occasionally missing in the NFIP data. Therefore, in step 2, I match an additional 2 million policies and houses based on community id, flood zone, and year of construction. Since there is bunching on decades and five-year bins for the year built variable in the Zillow data (e.g., houses built in 1953 reported as 1950), I conduct a tertiary match of 1 million policies on community id, flood zone, and the most recent year ending in 5. In a fourth step, I match an additional 150,000 policies based on community id, flood zone, and the most recent decal year. In steps 3 and 4, I include the additional constraint that the house and policy written must both be for houses that are adapted or non-adapted.

This procedure yields a match for approximately 17 million policies, or 70% of the total number of residential policies in high-risk flood zones. Of the unmatched policies, approximately 60% are in counties for which the date of construction variable is populated less than 85% of the time because it is not included in the reporting requirements of the assessment offices of these counties.

I can obtain an almost exact match of claims to policies because the date the policy was written, construction year of the house, flood zone, and zip code uniquely identify 90% of claims. The match rate of claims to policies is 99%, though only 60% of these policies are matched to houses. The unmatched policies are concentrated in Louisiana, where the date of construction of the house is not collected for around 88% of houses but which is responsible for many claims during the time period of my sample because of Hurricane Katrina. This drives some differences in costs between the two samples, as shown in Appendix Table A.1.

D Sensitivity Analyses

D.1 Demand and Cost Estimates

This section discusses sensitivity analyses of the effects of adaptation and price on demand and cost. The results are generally similar in sign, magnitude, and precision across a range of specifications and subsamples. I highlight differences between the instrumental variables and the OLS estimates.

D.1.1 Extensive Margin Demand

Appendix Table A.4 reports sensitivity analyses of equation (2) for the extensive margin demand outcomes (i.e., the probability of purchasing any policy, a policy that includes building coverage, and a policy that includes contents coverage). Columns 1-8 show similar results to the estimates in the main text using different sets of controls. Column 1 shows that the estimates are quantitatively similar if decade built×flood severity controls are excluded. Columns 2-5 show that the results are robust to using different proxies for flood severity in equation (2), respectively the water depth quintile only, FEMA's classification the flood event type only, the unique FEMA catastrophe number assigned to the event, and the date that a claim was made. Column 6 reports similar results using decade built time trends that do not vary by flood severity; defining flood severity using the FEMA catastrophe number, which is unique for each catastrophic flood in each year, means that decade built time trends also do not vary by flood severity in Column 4. Column 7 constructs the flood water depth variable using water depths only from adapted houses, which avoids any influence of the composition of the housing stock on the measurement of flood severity. Column 8 includes a separate linear time trend for adapted houses in addition to decade built×flood severity time trends, which increases the demand elasticity somewhat.

Columns 9-12 consider different subsamples of the data. Column 9 excludes the 13% of houses in zip codes that experience catastrophic flooding (i.e., the houses shown in the last column of Appendix Table A.2). Excluding these catastrophes has no effect on the demand estimates, but increases the precision of the zero effect of prices on cost, which I discuss in more detail below. Columns 10 and 11 show that the results are robust to estimating the results on houses built within 20- and 10-year windows around the year a community is mapped, rather than a 30-year window. These results exclude older houses for which the match quality is poorer. Column 12 excludes Louisiana because Figures 2 and 3 show that Hurricane Katrina in 2005 is an outlier that creates a large subsidy to Louisiana residents. The results in Column 12 show that Hurricane Katrina is not a primary driver of the results.

Column 13 shows that the main estimates are robust to using predicted prices for all houses, rather than only those which do not purchase insurance. This analysis emphasizes that the price variation is from changes in the list price, and not due to changes in the amount or composition of coverage.

Columns 14 presents results from estimating equation (2) using OLS. These results show that instrumenting for prices is important: the OLS estimates of the price elasticities are biased upward, particularly for the probability of purchasing any insurance or a policy with building coverage. The positive omitted variables bias is consistent with aggregate NFIP price increases and with spikes in insurance uptake after floods, for example.

Appendix Table A.7 compares estimates of equation (5) using a probit regression (Panel A) and a linear probability model (Panel B). For computational tractability, I compare the differences-in-differences estimates of the price reform using equation (5) and state×year fixed effects, rather than instrumental variables probit regressions with high-dimensional zip code×year fixed effects. Since around 60% of homeowners purchase insurance, the linear probability model provides a good approximation of the effects of prices and adaptation on the probability of purchasing insurance, and I focus on the linear probability model in the main analysis (Wooldridge, 2002).

D.1.2 Intensive Margin Demand

Appendix Table A.5 reports different estimates of the effects of prices and adaptation on purchased coverage. In general, adapted houses purchase more insurance and the effect of prices on amounts of coverage are small. Contents coverage is slightly more elastic than building coverage.

Columns 1 and 2 report results using only zip code×year fixed effects, for real and nominal coverage amounts respectively. These results show that including decade built time trends are important because adapted houses purchase more nominal coverage throughout the time period of the analysis. Since the effects of the price change do not offset the differences in the amounts of nominal coverage purchased, deflating total coverage purchased to \$2017 creates the appearance that adapted houses purchase more insurance in the early years of the sample. Deflating to \$2017 therefore results in a positive price elasticity, which vanishes when controlling for decade built time trends in the main estimates or estimating using nominal coverage (column 2).

Columns 3-9 report results with different sets of controls. As above, the intensive margin results are similar in sign, magnitude, and precision when I define flood severity using the quintile of water depth, the flood event type, the claim date, the catastrophe number, or using flood water depths from adapted houses only, or estimate the model without flood severity-specific time trends. Column 9 suggests that controlling for differential time trends for adapted and non-adapted houses slightly increases the sensitivity of building coverage to prices, but decreases the sensitivity of contents coverage purchased to prices.

Columns 10-14 show the results of estimating the model on subsamples of the data. The results are very similar to the estimates in the main text when I exclude houses experiencing catastrophic flooding, use only observations for houses built within 20 or 10 years of the map year, restrict the analysis to policies that can be matched to houses, or exclude Louisiana.

Column 15 shows the results without instrumenting for prices. The OLS estimates of the price elasticity are biased downward. This is consistent with both price increases after severe floods and coverage choices that reflect declining house value after floods.

Finally, column 16 reports estimates of the effect of prices and adaptation on the log of the amount of coverage purchased, plus 1. Conditional on purchase, almost all homeowners purchase building coverage, but the log of one plus the coverage amount accounts for policies with zero coverage for either contents or building. Consistent with the results in levels, the log results for building coverage are small and statistically insignificant and the results for contents suggest that contents coverage purchased is slightly more elastic than building coverage.

D.1.3 Insurer Costs

Appendix Table A.6 shows that the effects of prices and adaptation on insurer costs are robust to a range of alternative specifications. Columns 1-8 report results using different sets of controls. Column 1 shows similar results to the main estimates excluding decade build×flood severity controls. Importantly, these results underscore that the lack of evidence of selection is not because unobservable information is correlated with these covariates. Columns 2-7 show that the results are robust to using the alternative definitions of flood severity discussed above as well. Controlling for flood severity in column 5 using the date that a claim was made increases the precision of the price effects; the effect of prices on average cost allows us to reject that adverse selection in this market is greater than half of the amount in health insurance markets at 95% (e.g., Hackmann et al., 2015). The results in column 8, which include separate linear trends for adapted and non-adapted houses, are similar in sign and magnitude to the main estimates, but are less precisely estimated due to the relatively limited number of policies that make claims.

Columns 9-13 report results on the different subsamples of the data discussed above. Column 9 excludes the 13% of houses in zip codes that experience catastrophic flooding (i.e., the houses shown in the last column of Appendix Table A.2). Excluding catastrophic flooding greatly increases the precision of the estimated zero effect of price on cost. The results are insensitive to excluding the oldest and newest houses in columns 10 and 11. The results on the matched data sample and the sample that excludes Louisiana are qualitatively similar, though less precise because they are estimated on fewer observations.

Column 14 reports OLS results. These results highlight that panel regressions that do not instrument for prices would lead to erroneous conclusions about selection in this market. Prices are positively correlated with costs in the OLS regressions because the NFIP can adjust prices in response to flood events; the instrumental variables regressions isolate price variation that is uncorrelated with changes in risk or flood severity, conditional on the variables in the model.

Column 15 reports results using an inverse hyperbolic sine transformation of the cost outcomes; I do not estimate log specifications since few policies make claims. The results again are qualitatively similar. The inverse hyperbolic sine transformation in the presence of many zero values means that the coefficients on price and adaptation in the payouts regression are smaller and primarily capture differences in the probability of a non-zero payout.

D.2 Flood Severity

The estimates of equation (6) are robust to using different definitions of flood severity and also to excluding Hurricane Katrina. Table 6 reports the main estimates that define flood severity using six monotonically increasing flood water depths; Figure 6 shows the coefficients from this regression. Appendix Table A.8 shows that the results across all outcomes are robust to defining flood severity only using the water depth quintile or only using the FEMA flood event type. The results in this table are summarized graphically in Appendix Figures A.13 and A.14. Appendix Table A.9 reports the results from estimating equation (6) excluding Louisiana. The effects of adaptation before and after the reform are very similar to the estimates discussed in the main text, which shows that adaptation matters during catastrophes that are less extreme than Hurricane Katrina. None of these specifications show any evidence of selection since the relative differences in claim probabilities and average costs after the price reform are never statistically different from zero.

E Welfare Calculations

This section provides the details of the calculations of the welfare effects of counterfactual policies in Appendix Table A.10. I discuss the general approach for calculating each entry in the table and then illustrate the welfare calculations for both counterfactuals in row 1. These calculations require simplifying assumptions about the distribution of risk aversion, the effect of insurance on the variance of consumption, the importance of other economic costs (e.g., hassle costs), and the shape of the demand and cost curves outside the range of observed price variation. However, they suggest overall that the welfare effects of proposed natural disaster insurance reforms may be large. The magnitudes of the welfare effects hinge on estimates of risk aversion and the effect of natural disaster insurance on the variance of consumption, and suggest that estimating both of these parameters for this market would be a useful avenue for future research.

E.1 Calibration of the Frictionless Willingness to Pay Curve

Welfare analysis requires information on the marginal cost and frictionless willingness to pay curves. Equation (15) defines the frictionless willingness to pay curve $D(p, \alpha, \phi = 1)$ for a given level of adaptation α. In terms of the model parameters, $D(p, \alpha, 1) = MC(p, \alpha, \phi) + \frac{\frac{1}{2}\times\gamma(p)\times V(p)}{240.7}$. The first term, $MC(p, \alpha, \phi)$, is the marginal cost curve and the second term is the risk premium, which depends on the coefficient of absolute risk aversion $\gamma(p)$ and the effect of insurance on the variance of consumption $V(p)$. To convert the risk premium into dollars per \$1,000 of insurance, I divide by the average amount of insurance purchase in thousands, 240.7. The parameters $\gamma(p)$ and $V(p)$ are functions of price because the risk aversion or the variance of damages of the homeowner of type $s(p, \alpha, \phi)$ who is marginal at price p may differ from the risk aversion and the variance of natural disaster damages of infra-marginal homeowners. I also consider a case where $\gamma(\cdot)$ and $V(\cdot)$ depend on adaptation α.

I calibrate separate frictionless willingness to pay curves for adapted and non-adapted homeowners because I estimate that their expected costs are different. This difference in expected costs also means that the actuarially fair prices are different for the two types of houses. I therefore calculate the welfare effects of counterfactual reforms separately in the adapted and non-adapted housing markets. The total welfare effect is the sum of the welfare effects in the two markets.

I derive the frictionless willingness to pay curves for adapted and non-adapted homeowners by calculating the risk premium for the average homeowner and considering different calibrations of the slope of the curve. The risk premium for the average homeowner of type $\bar{s} = 0.5$ locates a point on the frictionless willingness to pay curve. This average risk premium equals $\frac{\frac{1}{2}\times\gamma(\bar{p})\times V(\bar{p})}{240.7}$, where $\bar{p}$ is the price at which the homeowner of type $\bar{s}$ is indifferent between having insurance and not having it.

With the assumption of constant absolute risk aversion, it is possible to calibrate the coefficient of absolute risk aversion using estimates from the literature. Standard estimates of risk aversion based on health insurance contract choices are generally around 5×10^{-4} (Handel et al., 2015; Handel et al., 2019). Individuals' willingness to bear risk from natural disasters may differ from other risks such as health (Einav et al., 2012). I therefore also consider estimates based on property insurance deductible choices, though there is limited analysis in this area and existing parameter estimates are considered implausibly large (Snydor, 2010).

The effect of natural disaster insurance on the variance of consumption does not exist in the literature to my knowledge and is difficult to calculate based on available data. It requires information on the conditional distribution of consumption for individuals with and without flood insurance, which is unobserved. However, approximating the effect of insurance on the variance of consumption with the variance of forgone payouts directly from the claims data provides a plausible upper bound on the average risk premium. The variance of payouts is considerable because of the high variance of flood severity. Table 1 shows that the standard deviation of insurance payouts is about \$12,000, which combined with standard estimates of risk aversion of around 5×10^{-4} implies that homeowners should be willing to pay an average risk premium of \$141 to \$165 per \$1,000 of insurance coverage.[7] However, homeowners can draw on other sources of income to smooth consumption after natural disasters, and so the difference in the variance of consumption between the insured and the uninsured states is likely smaller than the variance of payouts.

I incorporate estimates from the literature of the effects of floods on household finance to approximate the effect of consumption smoothing on the variance of forgone payouts. Consumption smoothing reduces the variance of payouts and lowers the average risk premium to between \$82 and \$95 per \$1,000 of insurance coverage. Several studies show that homeowners cope with floods by using an average of \$2,500 from savings withdrawals and tax refunds (Deryugina et al., 2018), accumulating an average of \$500 of credit card debt (Gallagher and Hartley, 2017), and receiving \$1,000 of social security payments (Deryugina, 2017). Homeowners can also apply for up to \$33,000 of public assistance from FEMA's Individuals and Households Program. After deducting the maximum of these amounts from the claims, the payouts standard deviation is about \$9,000.

Appendix Table A.10 shows estimates of the welfare effect of counterfactual flood insurance reforms under these alternative parametrizations of the risk premium. The baseline welfare estimates (row 1) and variants with alternative assumptions on the slope (rows 2-4) use a standard estimate of risk aversion $\gamma(\bar{p}) = 5 \times 10^{-4}$ (Hendren, 2019) and the variance of payouts that incorporates consumption smoothing estimates from the literature $V(\bar{p}) = 9,000^2$. Row 5 allows $V(\bar{p})$ to depend on adaptation α using $V(\bar{p}, \alpha = 0) = 10,000^2$ and $V(\bar{p}, \alpha = 1) = 8,000^2$, which are the variances for non-adapted and adapted houses that incorporate consumption smoothing. Row 6 uses $V(\bar{p}) = 7,000^2$, which is the variance of payouts incorporating consumption smoothing and excluding payouts from Hurricane Katrina. Row 7 uses $V(\bar{p}) = 6,000^2$, which is the variance of payouts if they are capped at \$80,000 (i.e., the average income in the zip codes included in the analysis). Row 8 uses $V(\bar{p}) = 2,500^2$, which is the variance of payouts if they are capped at the U.S. annual average mortgage payment of \$20,000. This is the most conservative scenario in the table, which assumes that homeowners fully mitigate their risk by moving *ex post*. Row 9 uses $V(\bar{p}) = 12,000^2$, which is the variance of payouts directly from the claims data, without consumption smoothing. Row 10 uses the consumption smoothing variance $V(\bar{p}) = 9,000^2$, but

[7] Based on equation (15), the average risk premium per \$1,000 of coverage is calculated as $\frac{\frac{1}{2} \times \gamma \times V}{240.7}$, where $\gamma = \frac{-u_{cc}}{u_c}$ is the coefficient of absolute risk aversion, V is the variance of forgone insurance payouts, and 240.7 is the average amount of insurance purchased in thousands.

uses a risk aversion parameter of $\gamma(\bar{p}) = 1.7 \times 10^{-3}$ estimated from property insurance deductible choices (Snydor, 2010).

The slope of the frictionless willingness to pay curve depends on how natural disaster damages vary across distribution of underlying homeowner types as well as possible heterogeneity in risk aversion. I consider several alternative parametrizations. The first is a level shift of the observed demand curve, as illustrated in Figure 1.b. This parametrization is agnostic about differences in risk aversion and consumption variance that give rise to the estimated slope of $s_p = -0.03$. Equation (15) shows that the frictionless willingness to pay curve may be more or less steep than the observed demand curve. Rows 2 and 3 of Appendix Table A.10 relax the assumption of a level shift. Calculating the risk premium for the homeowner with the lowest willingness to pay $s(p^{full}, \alpha, \phi)$, together with the risk premium for the homeowner with the average willingness to pay, implies a slope for the frictionless willingness to pay curve. Row 2 assumes heterogeneity in risk aversion across the willingness to pay distribution. In this case, I calculate the risk premium for the homeowner with the lowest willingness to pay using $\gamma(p^{full}) = 1.8 \times 10^{-4}$, which is the extreme value considered by Hendren (2019). Row 3 assumes heterogeneity in the variance of consumption. Here, I calculate the risk premium for the homeowner with the lowest willingness to pay using $V(p^{full}) = 804^2$, which is the variance of payouts in the lowest severity flood in my data (Appendix Table A.2).

Row 4 of Appendix Table A.10 considers an iso-elastic frictionless willingness to pay curve, instead of a linear functional form. I parametrize the observed demand curve as $s(p, \alpha, \phi) = \delta p^{\beta}$, where $\beta = -0.25$ is the demand elasticity implied by my estimates (Table 3). I solve for δ using initial equilibrium prices and quantities. I approximate the frictionless willingness to pay curve as a shift of observed willingness to pay through the point defined by the average risk premium of the average homeowner.

With the frictionless willingness to pay and marginal cost curves in hand, calculating the welfare effects of counterfactual reforms is straightforward. The welfare loss from increasing prices and the welfare gain from the mandate are equal to the sums of the risk premia of the homeowners who cease to purchase insurance and who become insured, respectively.

E.2 Counterfactual 1: Actuarially Fair Pricing

E.2.1 Actual Welfare Loss

The welfare loss from increasing prices toward actuarially fair levels is equal to the sum of the risk premia of homeowners who become uninsured. Figure 1.b shows that the welfare loss for non-adapted homeowners is equal to the dark grey area between the frictionless willingness to pay and the marginal cost curves. Using the geometry of the figure, the total effect on social welfare for all owners of non-adapted, single-family homes in high-risk flood zones in the 20 Atlantic and Gulf Coast states is calculated as:

$$\begin{aligned} \Delta W &= ((D(p^{mc}, 0, 1) - MC(p^{mc}, 0, \phi)) + (D(p', 0, 1) - MC(p', 0, \phi))) \times (s' - s^{mc}) \times \frac{1}{2} \times 217.1 \times 1,043,345 \\ &= (92.00 - 8.54 + 89.00 - 8.54) \times (0.52 - 0.61) \times \frac{1}{2} \times 217.1 \times 1,043,345 \qquad (16) \end{aligned}$$

The first multiplicative term is the sum of the risk premia for the homeowners who are marginal at the actuarially fair price and at the inital price, respectively. To obtain $D(p^{mc}, 0, 1)$, I calculate the change in the frictionless willingness to pay for homeowners of type s^{mc} relative to $\bar{s} = 0.5$ using $\gamma = 5 \times 10^{-4}$ and $V = 9,000^2$ for the average homeowner: $D(p^{mc}, 0, 1) = D(\bar{p}, 0, 1) + \frac{(s^{mc} - 0.5)}{s_p} = 8.54 + \frac{\frac{1}{2} \times 5 \times 10^{-4} \times 9,000^2}{240.7} - \frac{(0.52-0.5)}{0.03} = 92.00$. An analogous calculation using s' instead of s^{mc} yields $D(p', 0, 1) = 89.00$. The second multiplicative term is the change in demand from the price increase, which is determined by the observed demand curve. The last two multiplicative terms in this expression convert the graphical welfare effect in dollars per \$1,000 insurance coverage per high-risk homeowner into the total effect on social welfare for this market. First, I translate the welfare effect from dollars per \$1,000 of insurance purchased to dollars per person by multiplying by the average amount of insurance coverage purchased by non-adapted homeowners, in thousands. Second, I multiply by the total number of non-adapted, single-family homes in high-risk flood zones.[8]

To obtain the analogous welfare effect for adapted houses, I replace prices and quantities in equation (16) with the equivalent amounts for adapted houses. I estimate the effect of adaptation on the price schedule θ_2^p, on extensive margin demand θ_2^s, on intensive margin demand θ_2^i, and on average costs θ_2^c using the differences-in-differences equation (5). These parameters give the distances from the pre-reform non-adapted equilibrium to the initial equilibrium in the market for adapted houses and are shown in Panel A of Tables 2, 3, 4, and 5.[9] I calculate $D(p^{mc}, 1, 1)$ and $D(p', 1, 1)$ as for non-adapted houses. The analogous quantities for adapted houses are the marginal cost curve $MC(p, 1, \phi) = MC(p, 0, \phi) + \theta_2^c$, the share of adapted houses that are insured at actuarially fair prices $s^{mc} + \theta_2^s$, and the initial share insured $s' + \theta_2^s$. Using the estimates that include decade built and flood severity controls, the expression for the welfare effect in the adapted housing market is:

$$\begin{aligned}\Delta W = &((D(p^{mc}, 1, 1) - (MC(p^{mc}, 0, \phi) + \theta_2^c)) + (D(p', 1, 1) - (MC(p', 0, \phi) + \theta_2^c))\times \\ &((s^{mc} + \theta_2^s) - (s' + \theta_2^s)) \times \frac{1}{2} \times (217.1 + \theta_2^i) \times 1,043,345 \\ = &(95.67 - 8.54 + 2.21 + 92.67 - 8.54 + 2.21) \times (0.52 - 0.61) \times \frac{1}{2} \times (217.1 + 26.3) \times 1,043,345\end{aligned}$$

Summing across the two markets yields a total welfare loss from the price reform of \$3.7 billion per year, or approximately \$1,770 per high-risk homeowner annually.

E.2.2 Perceived Welfare Gain

Calculating the perceived welfare gain uses the observed willingness to pay and marginal cost curves only. If the observed willingness to pay curve is used as the welfare-relevant metric, then the removal of the subsidy leads to a perceived welfare improvement because the marginal cost curve is above

[8] I include houses for which dates of construction are unavailable in the Zillow data. Table 1 shows that approximately half of high-risk houses are non-adapted. Therefore, I calculate the non-adapted market size as the total number of residential houses in high-risk flood zones divided by 2.

[9] The initial equilibrium for adapted houses relative to non-adapted houses is based on the differences-in-differences estimates from Panel A, rather than the instrumental variables estimates from Panel B. The differences-in-differences estimates include the effects of differential risk and prices; the instrumental variables estimates would have to be adjusted to account for the differences in the price schedule.

observed willingness to pay at pre-2013 prices. The welfare effect is equal to the light grey area between the marginal cost and the observed willingness to pay curves in Figure 1.b. Summing across the two markets yields an expression for the perceived welfare effect:

$$\begin{aligned}\Delta W =&(p^{mc} - p') \times (s' - s^{mc}) \times \frac{1}{2} \times 217.1 \times 1,043,345+\\ &((p^{mc} + \theta_2^c) - (p' + \theta_2^p)) \times ((s^{mc} + \theta_2^s) - (s' + \theta_2^s)) \times \frac{1}{2} \times (217.1 + \theta_2^i) \times 1,043,345\\ =&(8.54 - 5.49) \times (0.61 - 0.52) \times \frac{1}{2} \times 217.1 \times 1,043,345+\\ &((8.54 - 2.21) - (5.49 - 1.53)) \times (0.61 - 0.52) \times \frac{1}{2} \times (217.1 + 26.3) \times 1,043,345\end{aligned}$$

Replacing prices and quantities into this expression yields a perceived welfare gain of about \$60.0 million per year, or approximately \$30 per high-risk homeowner annually.

E.3 Counterfactual 2: Insurance Mandate

The magnitudes of the risk premia that I calculate suggest that all homeowners would benefit in expectation from purchasing flood insurance. In Figure 1.b, the welfare gain for a representative individual is equal to the black area between the frictionless willingness to pay and the marginal cost curves. This figure illustrates the case where the homeowner with the lowest willingness to pay has a risk premium of zero. More generally, the willingness to pay of the last homeowner to purchase insurance can be written as $D(p^{full}, 0, 1) = D(\bar{p}, 0, 1) - (\frac{1-0.5}{s_p}) = 76.00$. Calculating $D(p', 0, 1)$ as above, the welfare effect for the entire market of non-adapted houses is:

$$\begin{aligned}\Delta W &= (D(p', 0, 1) - MC(p', 0, 1) + D(p^{full}, 0, 1) - MC(p^{full}, 0, 1)) \times (1 - s') \times \frac{1}{2} \times 217.1 \times 1,043,345\\ &= (89.00 - 8.54 + 76.00 - 8.54) \times (1 - 0.61) \times \frac{1}{2} \times 217.1 \times 1,043,345\end{aligned}$$

For adapted houses, we again use the differences in the initial equilibrium from the differences-in-differences regressions to calculate the welfare effect of the mandate for this market:

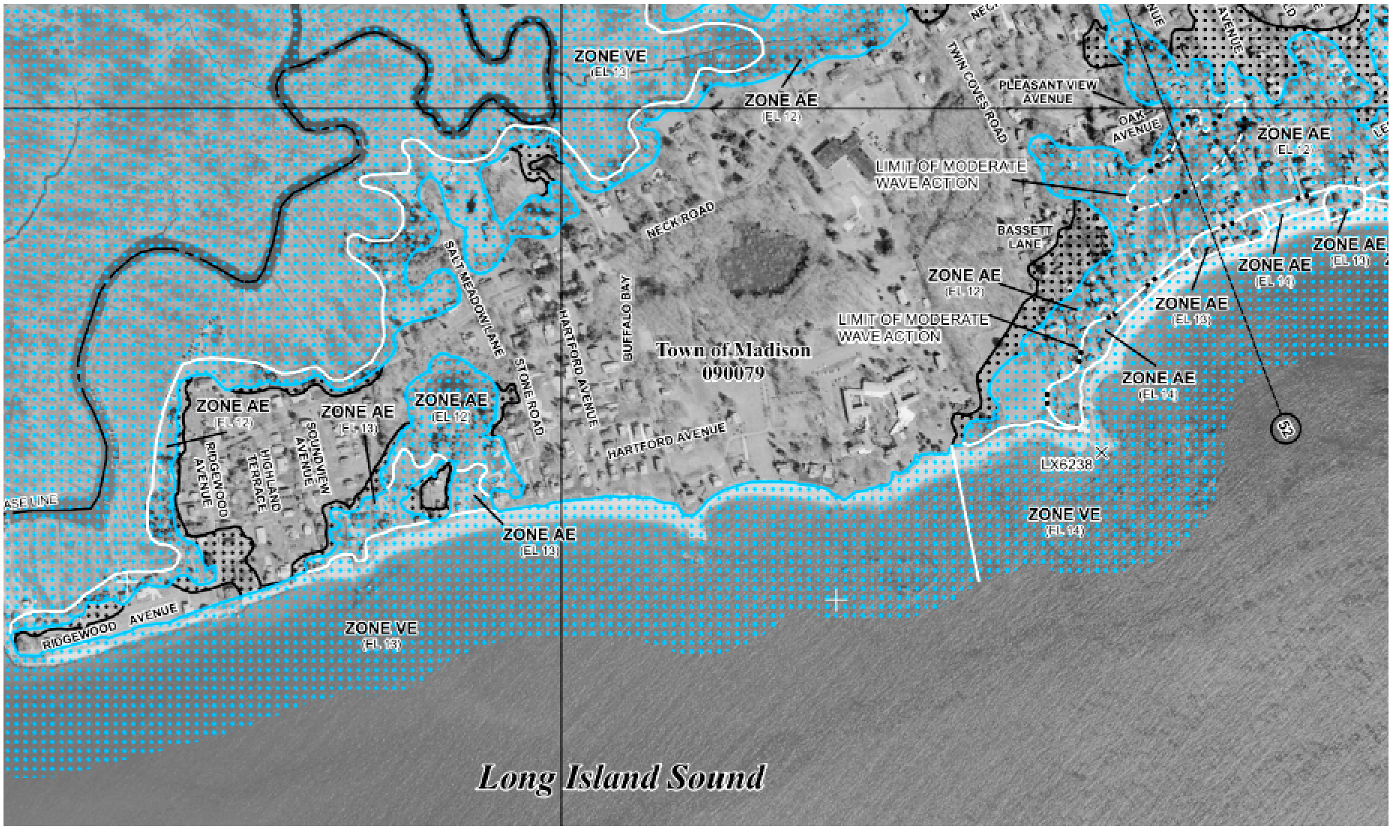
$$\begin{aligned}\Delta W = &(D(p', 1, 1) - MC(p', 1, 1) + D(p^{full}, 1, 1) - MC(p^{full}, 1, 1))\times\\ &(1 - (s' + \theta_s^s)) \times \frac{1}{2} \times (217.1 + \theta_2^i) \times 1,043,345\\ = &(92.67 - 8.54 + 2.21 + 76.00 - 8.54 + 2.21) \times (1 - (0.61 - 0.11)) \times \frac{1}{2} \times (217.1 + 26.3) \times 1,043,345\end{aligned}$$

Summing across the two markets yields a total gain from the mandate for all high-risk homeowners of approximately \$16.4 billion per year, or \$7,900 per high-risk homeowner annually.

Reducing the subsidy with or without an accompanying mandate also reduces the deadweight loss from the distortionary effect of taxation required to fund this subsidy. Using a marginal cost of public funds of 0.3, the welfare gain from reducing distortionary taxation is \$110 per high-risk homeowner per year.

F Appendix Figures

Figure A.1: Flood Insurance Rate Map (FIRM) Example

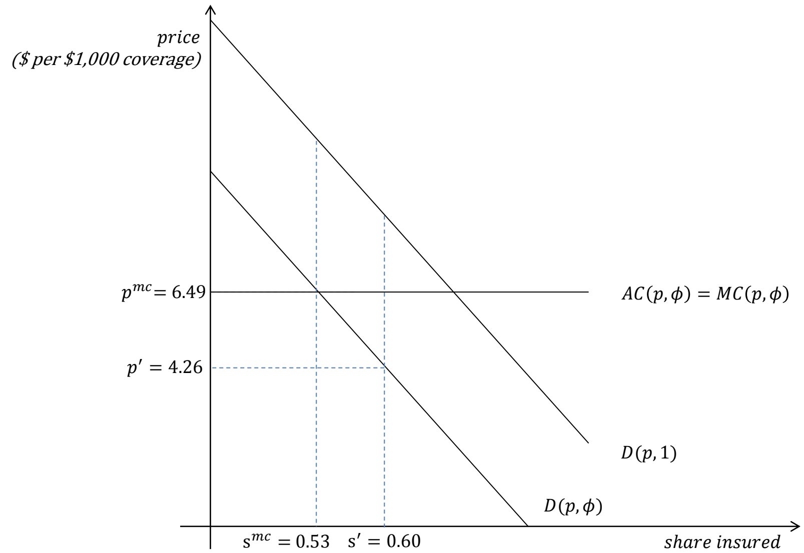


Notes: This map shows the Flood Insurance Rate Map (FIRM) for the town of Madison, CT (NFIP, 2018b). Dotted areas are high-risk flood zones. Minimum elevation requirements (in feet) for new construction are in parentheses for each detailed zone.

Figure A.2: Adapted Houses

Notes: This figure shows houses that are built to the National Flood Insurance Program minimum elevation requirements in the Bolivar Peninsula in Texas (source: Caller/Time).

Figure A.3: Empirical Willingness to Pay and Cost Curves for Adapted and Non-adapted Houses

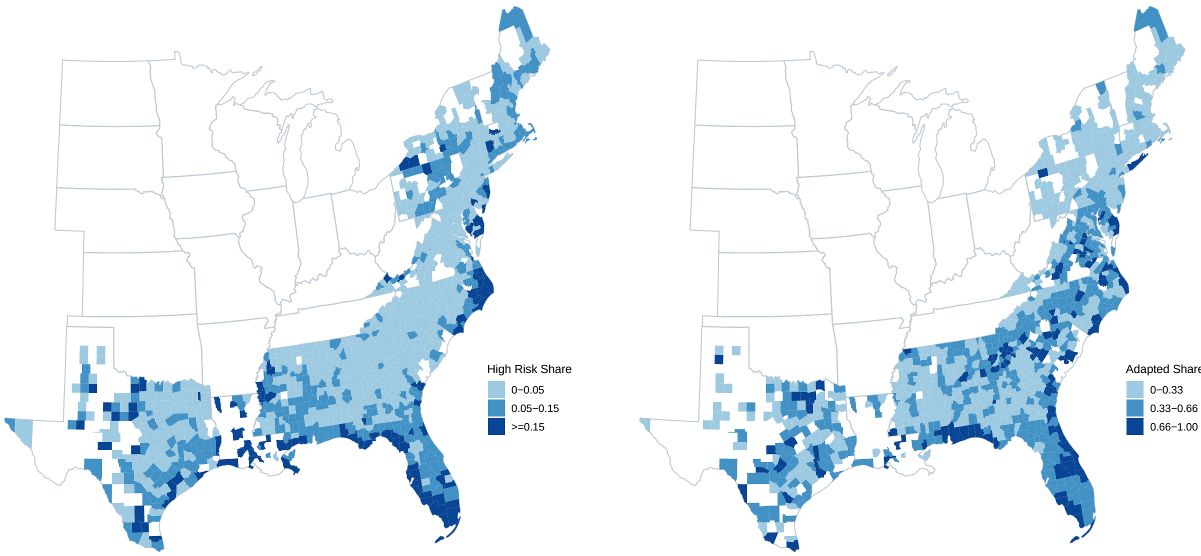


Notes: This figure shows the empirical average cost curve $AC(p, \phi)$, the empirical marginal cost curve $MC(p, \phi)$, the empirical observed willingness to pay curve $D(p, \phi)$, and the frictionless willingness to pay curve $D(p, \phi = 1)$ for the pooled market of adapted and non-adapted houses, given frictions ϕ. See text for a detailed description.

Figure A.4: Risk of Housing Stock, By County

Panel A: High-Risk Share of Houses

Panel B: Adapted Share of High-Risk Houses

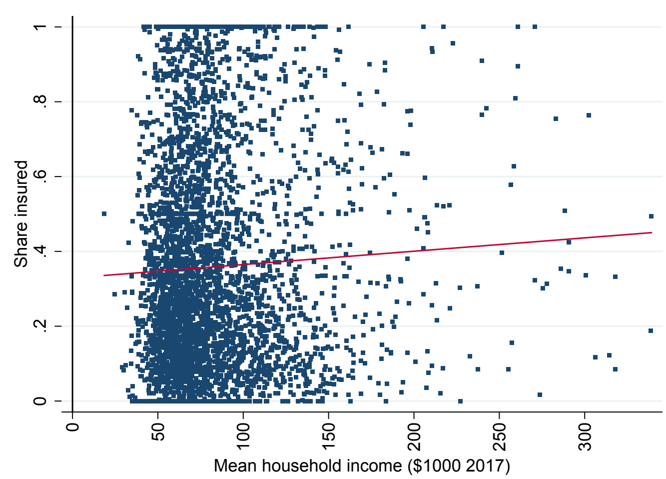


Notes: This map shows the share of the residential housing stock in high-risk flood zones (Panel A) and the share of high-risk houses that is adapted (Panel B), by county. Adapted houses are built after a community is formally mapped by the National Flood Insurance Program and are required to meet minimum elevation requirements for their foundation.

Figure A.5: Average Flood Insurance Subsidy v. Take-Up

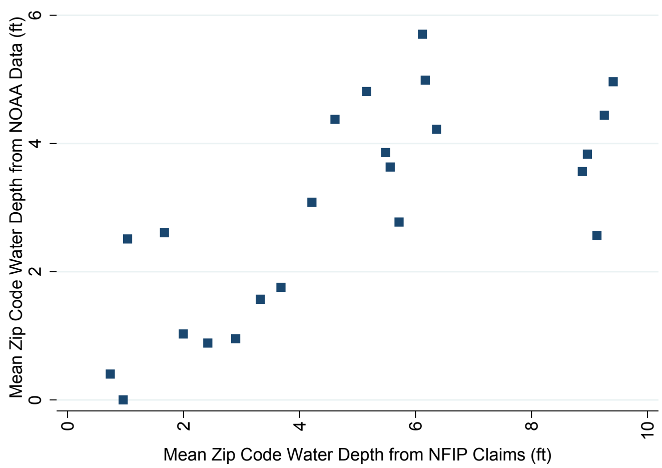
Notes: These graphs show the correlation between the average flood insurance subsidy and average take-up rate in high-risk flood zones by community, for non-adapted houses (Panel A) and adapted houses (Panel B). The subsidy is calculated as average payout minus average premium per \$1,000 of coverage (\$2017). For visual clarity, the subsidy is winsorized at 1% and 99%. Each point shows a community's average subsidy and take-up rate for the years 2001-2017.

Figure A.6: Average Household Income v. Take-Up



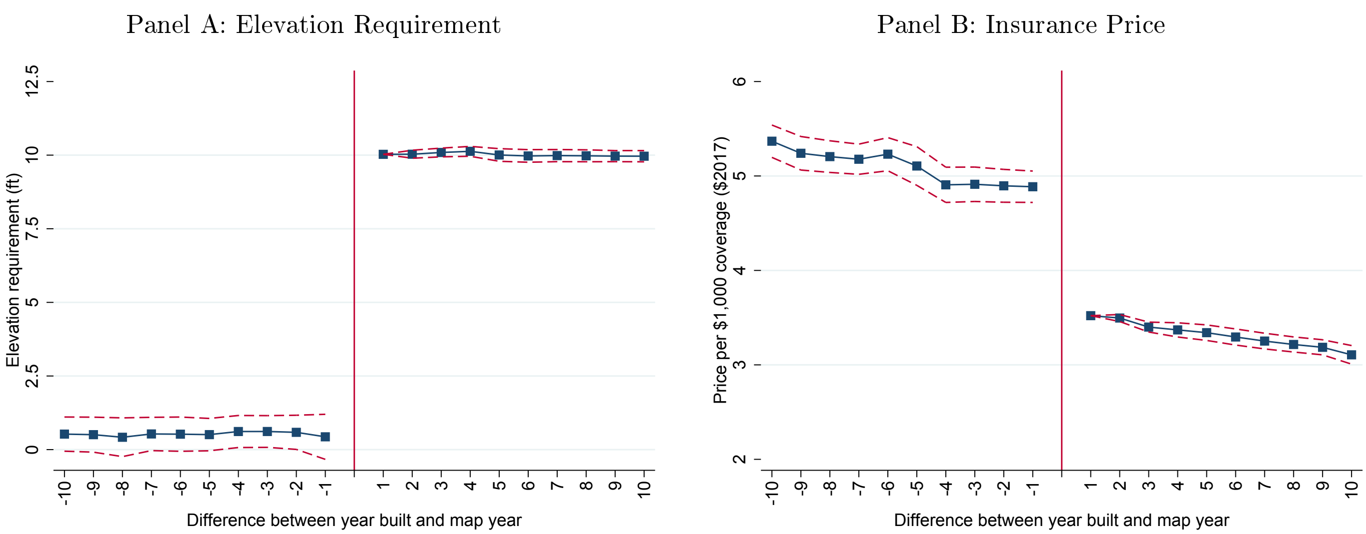
Notes: This graph shows the correlation between average household income and average take-up rate in high-risk flood zones by community. Take-up increases by 0.4 percentage points for every \$10,000 increase in mean household income. Each point shows a community's average income and take-up rate for the years 2001-2017.

Figure A.7: Correlation between Flood Water Depths from NFIP Claims Data and NOAA Depth Data



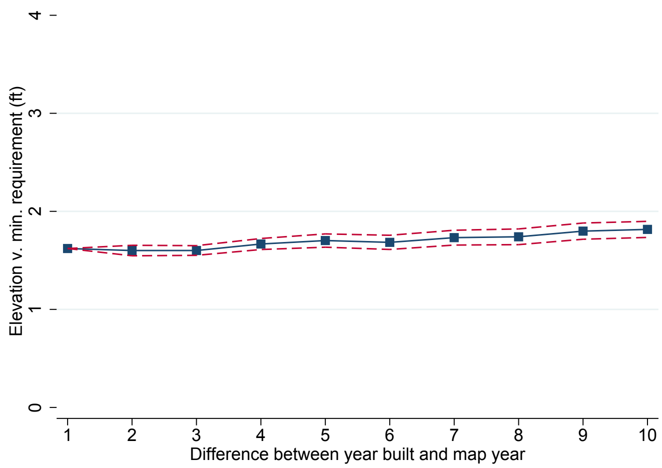
Notes: This graph shows the correlation between the reported average water depth in high-risk flood zones in the claims data and the measured average flood water depth from the National Oceanic and Atmospheric Administration (NOAA) in zip codes affected by Hurricane Katrina.

Figure A.8: Differences in Elevation Requirement and Prices for Adapted and Non-Adapted Houses, By Construction Date



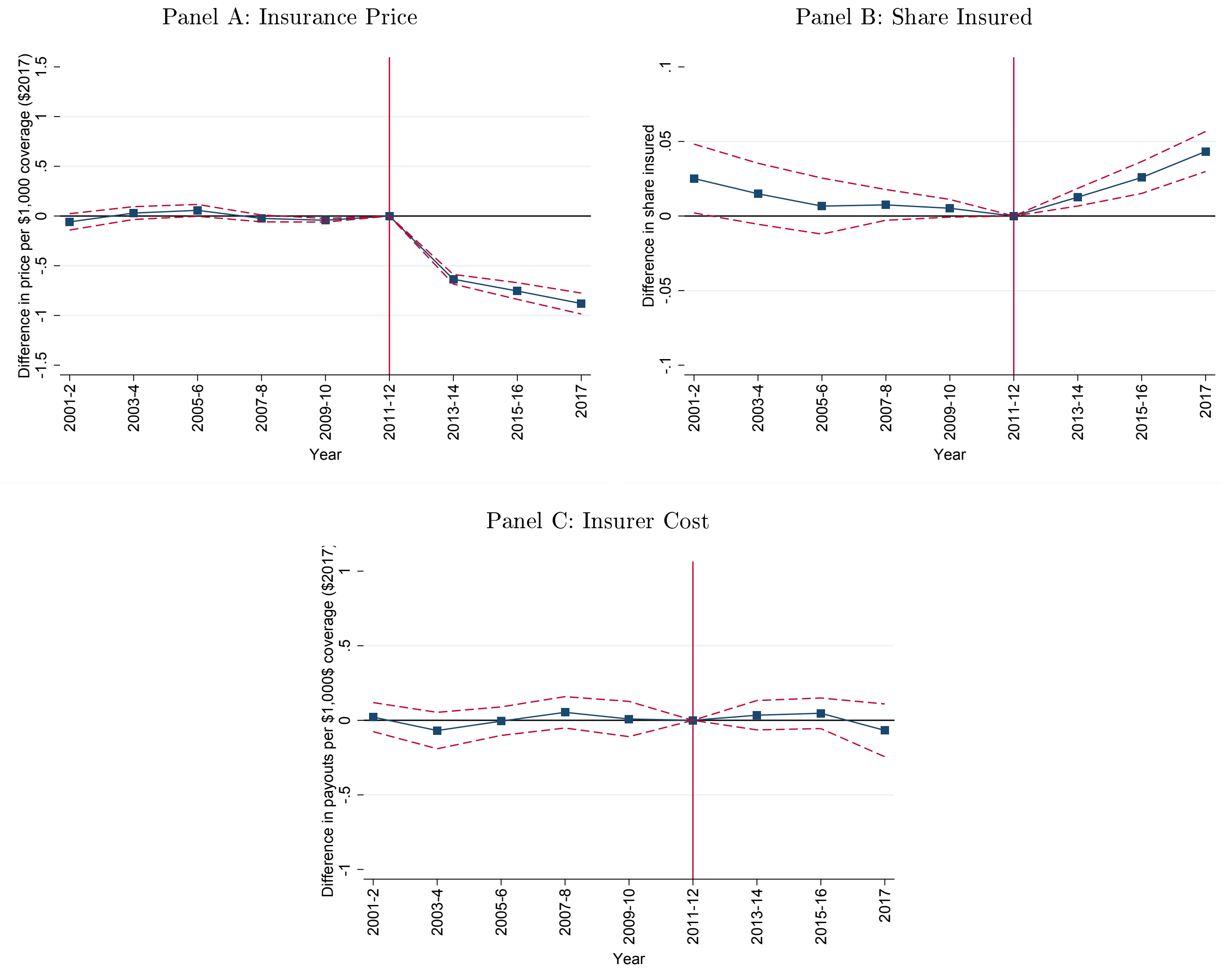
Notes: These graphs show the minimum elevation requirement for new construction (Panel A) and prices (Panel B), by year of house construction relative to the year of the initial flood map in the community in which the house is located. Adapted houses are built after communities are mapped and are required to be elevated. The coefficients are estimated from equation (7) in the text. Data are from the years 2001-2012, before Congress increased prices for non-adapted houses in 2013. Solid lines show average outcomes. Dashed lines are 95% confidence intervals. Standard errors are clustered by community.

Figure A.9: Difference Between Elevation and Minimum Requirement for Adapted Houses, By Construction Date



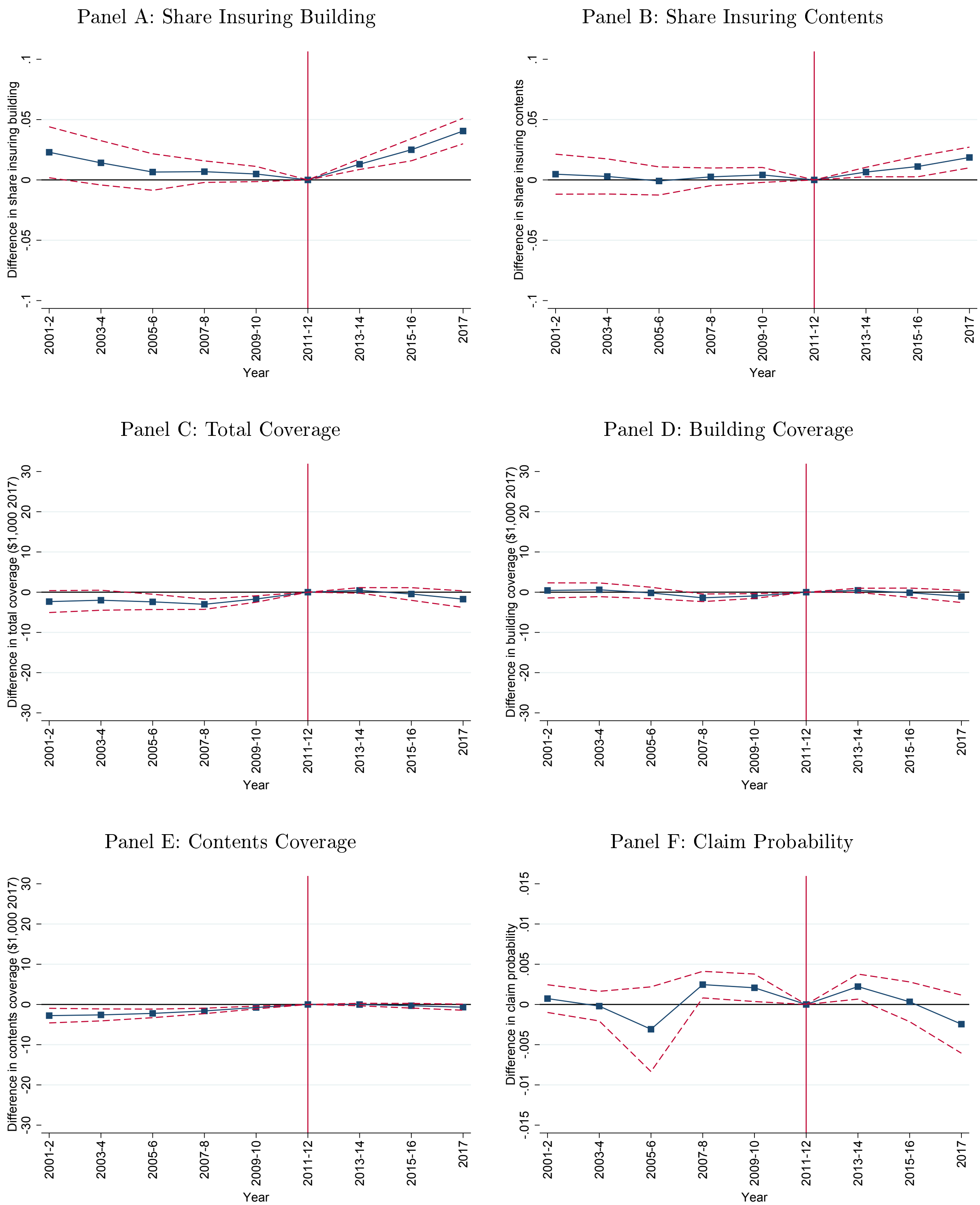
Notes: This graph shows the difference between the height of a house's foundation and the minimum construction requirement, measured from the flood insurance policy data set. The coefficients are estimated from equation (7) in the text, excluding non-adapted policies that are not subject to minimum elevation requirements and for which these data are not available. Data are from the years 2001-2012, before Congress increased prices in 2013. Solid lines show the average difference between the actual construction height and the minimum requirement. Dashed lines are 95% confidence intervals. Standard errors are clustered by community.

Figure A.10: Effects of Flood Insurance Reform on Relative Price, Demand, and Cost for Adapted Houses, Excluding Most Severe Floods



Notes: These graphs show the average price of flood insurance, share insured, and cost for adapted houses relative to non-adapted houses in high-risk flood zones, excluding zip codes struck by catastrophic "depth 6" floods (see text). Adapted houses are built after communities are mapped and are required to be elevated. The coefficients are estimated from equation (4) in the text. Solid lines show differences in outcomes between adapted and non-adapted houses relative to the difference in 2011-2012. Dashed lines are 95% confidence intervals. Standard errors are clustered by community.

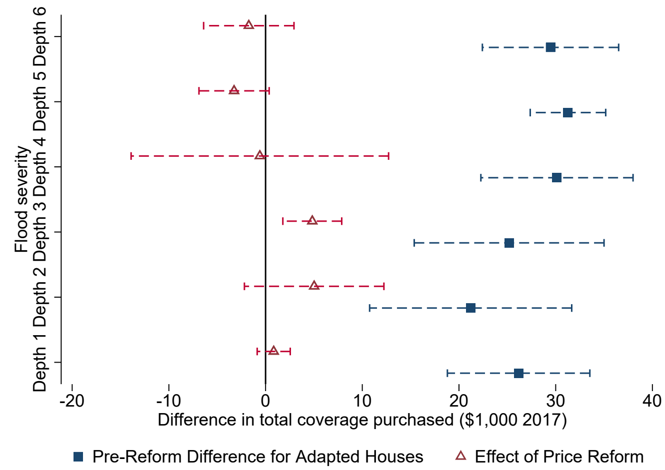
Figure A.11: Effects of Flood Insurance Reform on Demand and Cost Outcomes for Adapted Houses



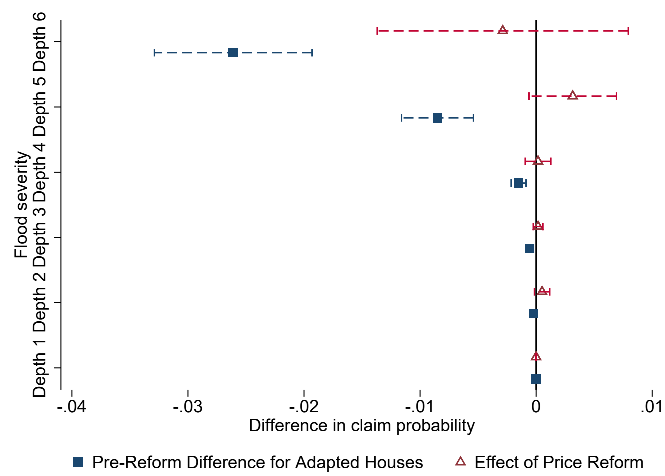
Notes: These graphs show the time series of demand and cost outcomes for adapted houses relative to non-adapted houses in high-risk flood zones. The coefficients are estimated from equation (4) in the text. Solid lines show differences in outcomes between adapted and non-adapted houses relative to the difference in 2011-2012. Dashed lines are 95% confidence intervals. Standard errors are clustered by community.

Figure A.12: Effects of Flood Insurance Reform on Other Demand and Cost Outcomes for Adapted Houses, By Flood Severity

Panel A: Total Coverage

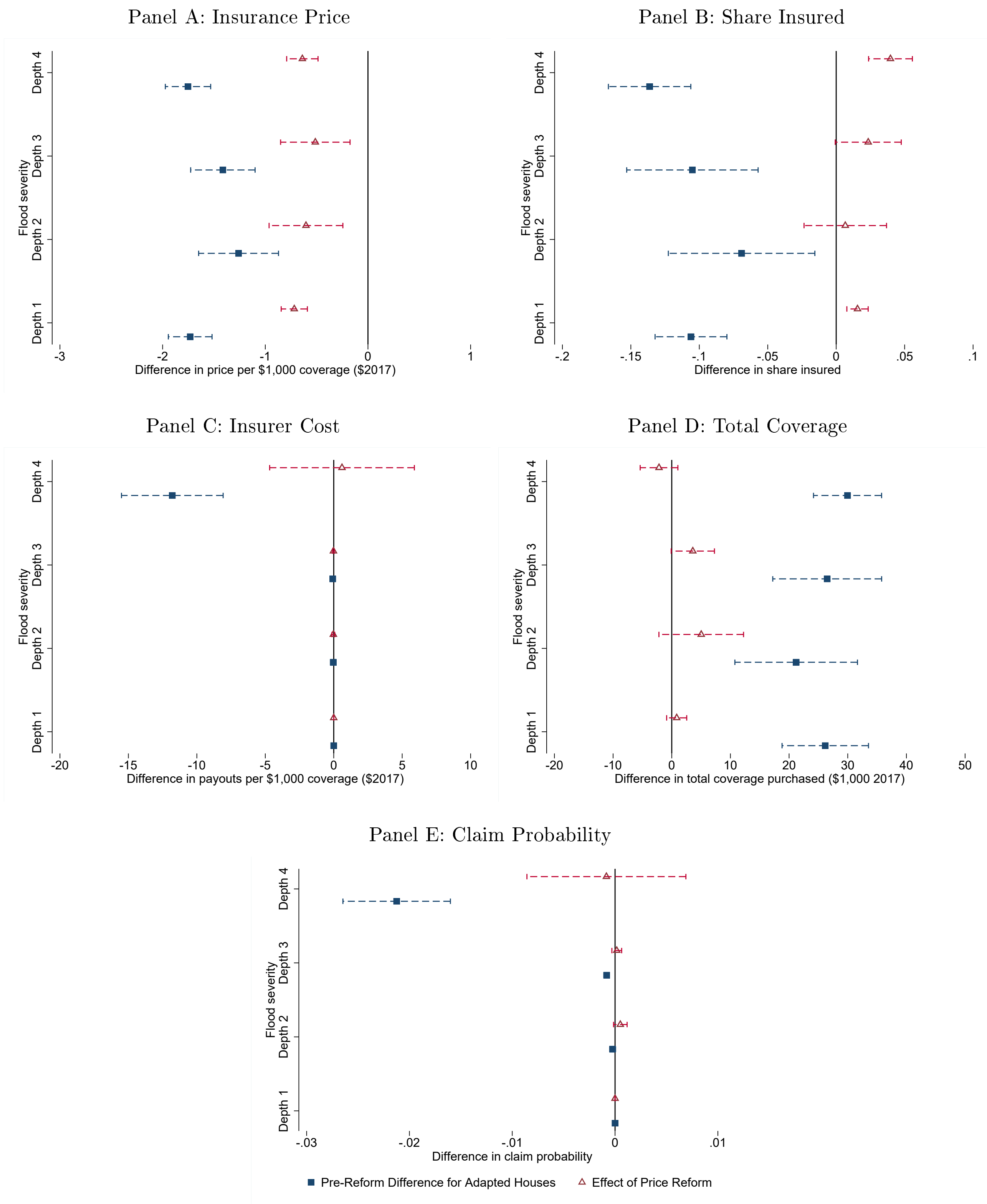


Panel B: Claim Probability



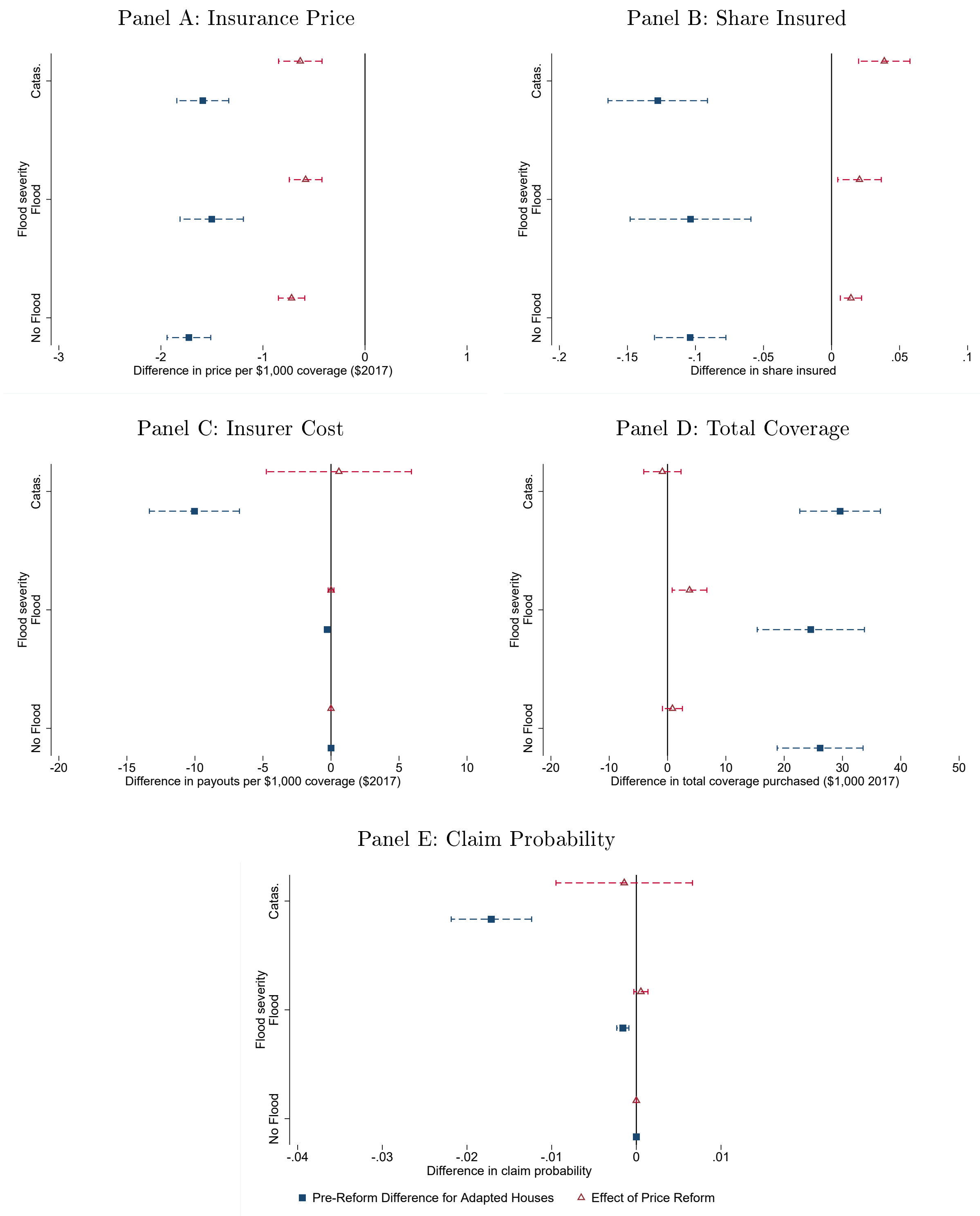
Notes: These graphs show total coverage purchased and claim probability for adapted houses relative to non-adapted houses in high-risk flood zones, by flood severity. The coefficients are estimated from equation (6) in the text. Squares are the difference between adapted and non-adapted houses in the 2001-2012 pre-reform period, and triangles are the effect of the price reform on this difference. Dashed lines are 95% confidence intervals. Standard errors are clustered by community.

Figure A.13: Effects of Flood Insurance Reform on Price, Demand, and Cost for Adapted Houses, By Water Depth Quintile



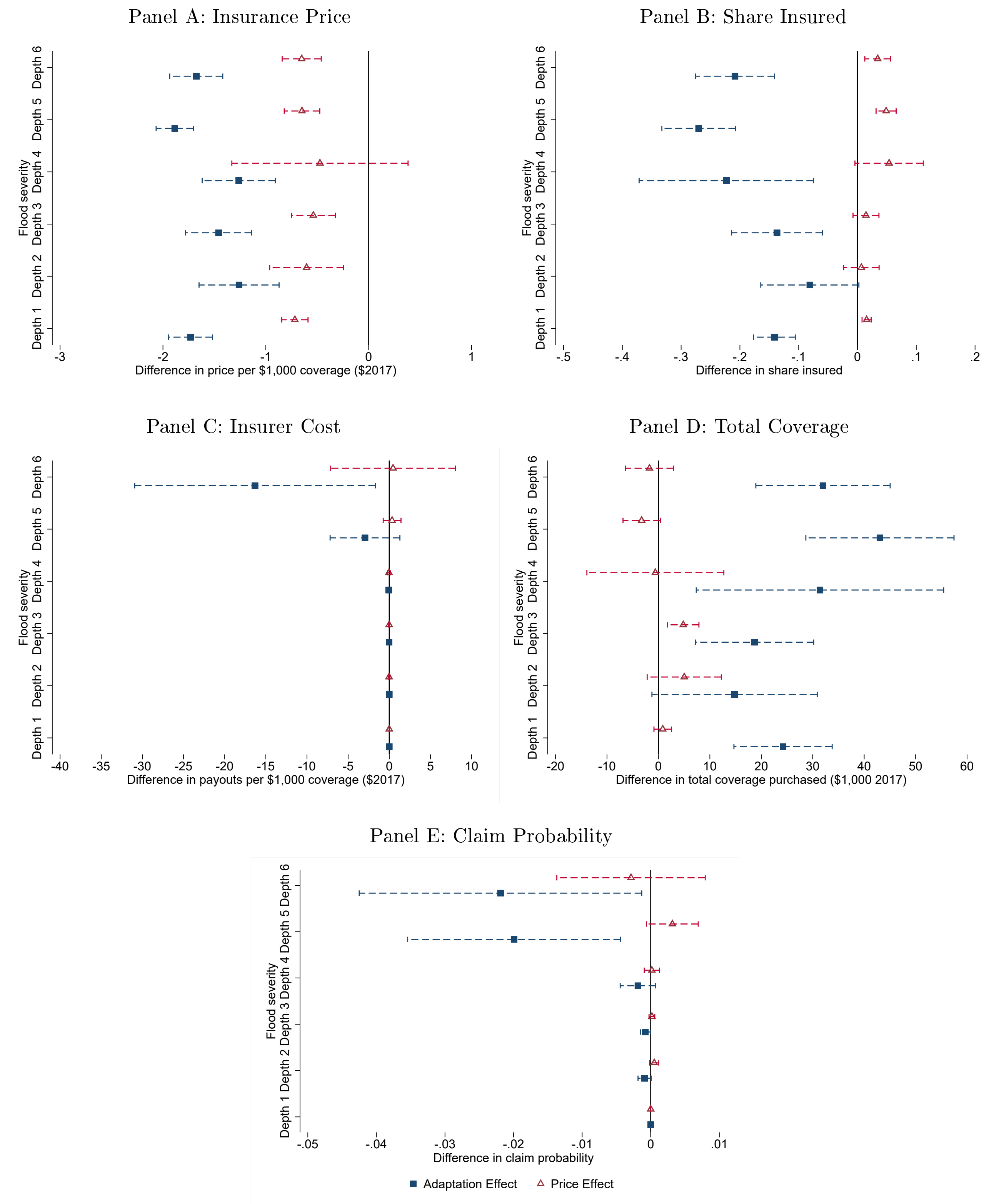
Notes: These graphs show price, demand, and cost outcomes for adapted houses relative to non-adapted houses in high-risk flood zones, by water depth quintile. The coefficients are estimated from equation (6) in the text using four categories for flood severity (no flood, three increasing water depths). Squares are the difference between adapted and non-adapted houses in the 2001-2012 pre-reform period, and triangles are the effect of the price reform on this difference. Dashed lines are 95% confidence intervals. Standard errors are clustered by community.

Figure A.14: Effects of Flood Insurance Reform on Price, Demand, and Cost for Adapted Houses, By Flood Event Type



Notes: These graphs show price, demand, and cost outcomes for adapted houses relative to non-adapted houses in high-risk flood zones, by flood event type. The coefficients are estimated from equation (6) in the text using three categories for flood severity (no flood, flood, catastrophe). Catastrophic floods are identified using the Federal Emergency Management Agency's Flood Insurance Claims Office number. Squares are the difference between adapted and non-adapted houses in the 2001-2012 pre-reform period, and triangles are the effect of the price reform on this difference. Dashed lines are 95% confidence intervals. Standard errors are clustered by community.

Figure A.15: Effects of Prices and Adaptation on Demand and Cost, By Flood Severity



Notes: These graphs show the separate effects of adaptation and prices on demand and cost outcomes by flood severity. Squares are the effects of adaptation and triangles are the effects of prices. Dashed lines are 95% confidence intervals. The coefficients are estimated from equation (6) in the text; the effect of adaptation is calculated from these coefficients and from the price difference for adapted houses in Panel A as "Adapted - Price x Price Difference" because adapted houses also pay lower prices for insurance. Standard errors are clustered by community.

G Appendix Tables

Table A.1: Summary Statistics for All High-Risk Policies and Matched Subsample, All Years

	All High-Risk Policies			Matched High-Risk Policies		
	All	Adapted	Non-Adapted	All	Adapted	Non-Adapted
	(1)	(2)	(3)	(4)	(5)	(6)
N	11,983,183	5,317,675	6,665,508	7,720,218	3,893,683	3,826,535
Elevation Requirement (ft)	4.35	9.79	0.00	5.13	10.2	0.00
	(6.16)	(5.66)	(0.00)	(6.29)	(5.18)	(0.00)
Premium per $1,000 Cov.	4.12	2.79	5.18	4.08	2.78	5.39
	(3.23)	(2.40)	(3.41)	(3.19)	(2.43)	(3.32)
Total Premium ($)	803.6	636.6	936.8	819.1	632.3	1,010.7
	(646.4)	(513.5)	(707.7)	(677.6)	(544.0)	(744.2)
Total Cov. Bought ($1,000s)	240.7	267.6	217.1	241.1	262.7	219.1
	(111.5)	(107.0)	(107.4)	(110.1)	(105.7)	(110.0)
Building Cov. Bought ($1,000s)	194.9	213.9	176.8	197.4	212.2	182.2
	(84.0)	(78.8)	(82.8)	(83.5)	(78.7)	(83.2)
Contents Cov. Bought ($1,000s)	45.8	53.7	40.3	43.7	50.5	36.9
	(42.4)	(44.1)	(40.5)	(41.5)	(42.5)	(39.9)
Payout per $1,000 Cov.	6.23	3.79	8.18	3.74	2.12	5.43
	(61.06)	(47.47)	(69.99)	(43.86)	(32.80)	(52.77)
Payout per $1,000 Cov., wo. 2005	3.60	1.95	4.92	3.36	1.81	4.95
	(43.51)	(31.02)	(51.32)	(40.76)	(28.76)	(50.10)
Total Payout ($)	1,216.8	859.5	1,501.8	775.2	508.3	1,047.5
	(12,736.6)	(11,272.9)	(13,786.7)	(9,673.1)	(8,051.3)	(11,079.1)
Total Payout ($), wo. 2005	711.6	453.3	918.0	701.4	433.7	974.7
	(9,111.1)	(7,515.5)	(10,203.6)	(9,011.0)	(7,176.1)	(10,552.0)
Claim Probability	0.019	0.014	0.023	0.015	0.011	0.020
	(0.136)	(0.117)	(0.150)	(0.123)	(0.107)	(0.138)
Claim Probability, wo. 2005	0.014	0.010	0.017	0.014	0.011	0.018
	(0.118)	(0.101)	(0.130)	(0.119)	(0.106)	(0.134)

Notes: Adapted houses are built after communities are mapped and are required to be elevated. Columns 1-3 show summary statistics for all high-risk policies written; columns 4-6 present summary statistics for the subsample of policies that are matched to houses. Data are from the years 2001-2017, for single-family primary residences in the 20 Atlantic and Gulf Coast states built within 15 years of a community's first map. All monetary values are in $2017. Standard errors are in parentheses.

Table A.2: Summary Statistics for Insurer Cost, By Flood Severity

	No Flood	Water Depth 1		Water Depth 2		Water Depth 3	
		Flood	Catas.	Flood	Catas.	Flood	Catas.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N	5,793,255	1,193,849	117,114	1,884,257	684,522	730,591	1,579,595
Water Depth (ft x 100)	0.000	0.005	0.004	0.180	0.243	6.467	33.368
	(0.000)	(0.009)	(0.008)	(0.145)	(0.154)	(17.153)	(59.112)
Total Payout ($)	0.0	13.1	91.0	14.4	37.5	461.9	8,740.0
	(0.0)	(804.0)	(2,506.2)	(637.9)	(1,281.9)	(5,726.3)	(33,004.6)
Payout per $1,000 Cov.	0.000	0.084	0.540	0.081	0.210	3.071	45.550
	(0.000)	(4.903)	(14.283)	(4.064)	(7.300)	(35.727)	(160.726)
Claim Probability	0.000	0.001	0.005	0.001	0.003	0.019	0.131
	(0.000)	(0.034)	(0.072)	(0.038)	(0.056)	(0.014)	(0.337)

Notes: Summary statistics are shown for all policies written for high-risk houses in the 20 Atlantic and Gulf Coast states built within 15 years of a community's first map. Catastrophic floods are identified according to the Federal Emergency Management Agency's Flood Insurance Claims Office number. Data are from the years 2001-2017. All monetary values are in $2017. Standard errors are in parentheses.

Table A.3: Distribution of Houses by Zip Code, 2017

	Mean	Std. Error	Minimum	Maximum
	(1)	(2)	(3)	(4)
Panel A: All Houses				
Number of Houses	162.2	422.7	2	7918
Number of Insured Houses	75.0	259.8	0	5275
Panel B: Adapted				
Number of Houses	90.5	254.6	1	6794
Number of Insured Houses	38.0	136.6	0	2261
Panel C: Non-Adapted				
Number of Houses	82.0	236.3	1	4896
Number of Insured Houses	41.8	163.5	0	5266

Notes: Summary statistics by zip code are shown for all high-risk houses in the 20 Atlantic and Gulf Coast states for which dates of construction are available and which are built within 15 years of a community's first map. Adapted houses are built after communities are mapped by the National Flood Insurance Program and are required to be elevated. The analysis includes 4,886 zip codes.

Table A.4: Sensitivity: Extensive Margin Demand

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel A: Any Policy														
Price	-0.033***	-0.026***	-0.027***	-0.028***	-0.026***	-0.027***	-0.026***	-0.038***	-0.024***	-0.022***	-0.026**	-0.028***	-0.025***	-0.002*
	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.006)	(0.008)	(0.011)	(0.006)	(0.006)	(0.001)
Adapted	-0.115***	-0.148***	-0.148***	-0.151***	-0.146***	-0.149***	-0.147***	-0.173***	-0.142***	-0.143***	-0.150***	-0.153***	-0.145***	-0.105***
	(0.032)	(0.022)	(0.022)	(0.023)	(0.022)	(0.021)	(0.022)	(0.032)	(0.021)	(0.022)	(0.023)	(0.022)	(0.021)	(0.015)
Panel B: Building Policy														
Price	-0.032***	-0.025***	-0.025***	-0.027***	-0.025***	-0.026***	-0.024***	-0.038***	-0.023***	-0.020***	-0.025**	-0.027***	-0.023***	-0.003***
	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.006)	(0.008)	(0.011)	(0.006)	(0.006)	(0.001)
Adapted	-0.113***	-0.144***	-0.144***	-0.147***	-0.142***	-0.145***	-0.143***	-0.170***	-0.138***	-0.138***	-0.146***	-0.149***	-0.141***	-0.106***
	(0.032)	(0.022)	(0.022)	(0.022)	(0.021)	(0.021)	(0.022)	(0.032)	(0.021)	(0.022)	(0.023)	(0.022)	(0.021)	(0.014)
Panel C: Contents Policy														
Price	-0.026***	-0.012**	-0.012**	-0.013**	-0.012**	-0.012**	-0.011*	-0.012*	-0.011**	-0.013*	-0.018**	-0.013**	-0.011**	-0.019***
	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)	(0.005)	(0.007)	(0.009)	(0.006)	(0.005)	(0.002)
Adapted	-0.051*	-0.069***	-0.069***	-0.071***	-0.067***	-0.070***	-0.068***	-0.070***	-0.065***	-0.072***	-0.082***	-0.071***	-0.068***	-0.081***
	(0.029)	(0.020)	(0.019)	(0.020)	(0.020)	(0.019)	(0.020)	(0.026)	(0.019)	(0.020)	(0.021)	(0.020)	(0.019)	(0.012)
K-P F−stat	588	488	503	536	484	531	464	820	340	420	244	470	310	–
Zip code × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Decade Built × Flood Severity Controls		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Water Depth Quintile Only		✓												
Flood Event Type Only			✓											
Flood Event Number Controls				✓										
Date of Claim Controls					✓									
Decade Built Trends w.o. Flood Severity				✓		✓								
Water Depth from Non-Adapted Only							✓							
Adapted × Linear Trend								✓						
Exclude Catastrophes									✓					
20-year Window Around Map (not 30)										✓				
10-year Window Around Map (not 30)											✓			
Exclude Louisiana												✓		
Predicted Prices													✓	
OLS														✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variables are indicators for purchasing any policy (Panel A), a policy that includes building coverage (Panel B), and a policy that includes contents coverage (Panel C). All models are estimated using equation (2) in the text; price is instrumented using the interaction of indicators for adapted and post-2012, except in the OLS model in Column 14. Adapted houses are built after communities are mapped and are required to be elevated. Decade built×flood severity controls are zip code×decade built×flood severity fixed effects and decade built×flood severity time trends. Flood severity is defined using flood water depth and flood event type (see text), unless otherwise noted. Date of claim controls are zip code×decade built×claim date fixed effects. The number of observations is 13,433,549 in all specifications except for Column 9 (N=11,930,969), Column 10 (N=8,848,988), Column 11 (N=4,076,271), and Column 12 (N=13,201,251). Standard errors clustered by community are in parentheses.

Table A.5: Sensitivity: Intensive Margin Demand

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: Total Coverage																
Price	2.86**	-3.78***	-1.88*	-1.87*	-2.52**	-1.98*	-1.85*	-1.76	-1.07	-2.62***	-1.49	-1.22	2.04	-0.71	-15.87***	-0.013**
	(1.23)	(0.86)	(1.11)	(1.05)	(1.09)	(1.11)	(1.09)	(1.07)	(1.09)	(1.32)	(1.10)	(1.12)	(1.45)	(1.09)	(0.47)	(0.006)
Adapted	47.11***	26.22***	23.85***	23.84***	22.87***	23.65***	23.89***	24.00***	25.43***	22.50***	25.95***	25.56***	29.30***	22.60***	3.01**	0.132***
	(4.74)	(2.77)	(4.36)	(4.36)	(4.22)	(4.35)	(4.40)	(4.40)	(5.05)	(4.17)	(3.61)	(3.10)	(3.30)	(4.80)	(1.53)	(0.025)
Panel B: Building Coverage																
Price	4.54***	-0.39	-0.88	-0.92	-1.24	-0.93	-0.83	-0.77	-2.38***	-1.28	-0.28	0.18	1.84*	-0.15	-12.19***	-0.005
	(1.04)	(0.69)	(0.84)	(0.80)	(0.82)	(0.87)	(0.82)	(0.84)	(0.74)	(0.95)	(0.81)	(0.83)	(1.07)	(0.84)	(0.33)	(0.006)
Adapted	38.25***	22.90***	17.07***	17.00***	16.52***	16.94***	17.15***	17.22***	14.10***	16.23***	18.94***	18.85***	21.52***	16.06***	0.22	0.133***
	(4.17)	(2.53)	(3.74)	(3.71)	(3.65)	(3.74)	(3.75)	(3.78)	(3.32)	(3.65)	(3.37)	(3.16)	(2.79)	(4.13)	(1.14)	(0.026)
Panel C: Contents Coverage																
Price	-1.69***	-3.39***	-1.00**	-0.96**	-1.28***	-1.05**	-1.02**	-0.99**	1.31**	-1.33**	-1.48***	-1.55***	0.20	-0.56	-3.67***	-0.057***
	(0.36)	(0.33)	(0.46)	(0.44)	(0.46)	(0.47)	(0.46)	(0.45)	(0.50)	(0.57)	(0.48)	(0.56)	(0.48)	(0.47)	(0.16)	(0.017)
Adapted	8.87***	3.32***	6.78***	6.84***	6.35***	6.70***	6.74***	6.79***	11.33***	6.27***	5.99***	5.97***	7.78***	6.54***	2.80***	0.190***
	(1.07)	(0.82)	(1.12)	(1.13)	(1.10)	(1.12)	(1.13)	(1.12)	(1.92)	(1.12)	(1.13)	(0.84)	(0.74)	(1.27)	(0.61)	(0.039)
K-P F−stat	300	300	334	345	324	326	337	331	297	242	309	214	66	269	–	332
Zip code × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Nominal Coverage		✓														
Decade Built × Flood Severity Controls			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Water Depth Quintile Only			✓													
Flood Event Type Only				✓												
Flood Event Number Controls					✓											
Date of Claim Controls						✓										
Decade Built Trends w.o. Flood Severity					✓		✓									
Water Depth from Non-Adapted Only								✓								
Adapted × Linear Trend									✓							
Exclude Catastrphes										✓						
20-year Window Around Map (not 30)											✓					
10-year Window Around Map (not 30)												✓				
Complete Data Sample													✓			
Exclude Louisiana														✓		
OLS															✓	
Logs (not Levels)																✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variables are amounts of insurance purchased in total (Panel A), for building coverage (Panel B), and for contents coverage (Panel C), in 1,000s (\$2017). All models are estimated using equation (2) in the text; price is instrumented using the interaction of indicators for adapted and post-2012, except in the OLS model in Column 15. Adapted houses are built after communities are mapped and are required to be elevated. Decade built×flood severity controls are zip code×decade built×flood severity fixed effects and decade built×flood severity time trends. Flood severity is defined using flood water depth and flood event type (see text), unless otherwise noted. Date of claim controls are zip code×decade built×claim date fixed effects. The number of observation is 11,983,183 in all models except for Column 10 (N=10,403,588), Column 11 (N=8,346,588), Column 12 (N=4,045,360), Column 13 (N=7,720,218), and Column 14 (N=10,077,506). Standard errors clustered by community are in parentheses.

Table A.6: Sensitivity: Insurer Cost

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A: Any Claim															
Price	-0.073	-0.025	-0.010	-0.094	0.025	-0.005	-0.004	0.073	-0.041*	-0.026	-0.078	-0.010	0.070	0.109***	-0.025
	(0.096)	(0.098)	(0.111)	(0.083)	(0.029)	(0.090)	(0.010)	(0.132)	(0.021)	(0.109)	(0.123)	(0.174)	(0.087)	(0.008)	(0.089)
Adapted	-0.752***	-0.451***	-0.560***	-0.548***	-0.027	-0.419***	-0.473***	-0.265	-0.128***	-0.464**	-0.539**	-0.635*	-0.233*	-0.252***	-0.401**
	(0.223)	(0.175)	(0.200)	(0.161)	(0.045)	(0.159)	(0.177)	(0.230)	(0.041)	(0.194)	(0.224)	(0.325)	(0.124)	(0.045)	(0.158)
Panel B: Average Cost															
Price	-0.187	-0.354	-0.684	-0.338	-0.438	-0.329	-0.372	-0.561	-0.027	-0.276	-0.612	-0.867	-0.188	0.670***	-0.006
	(0.603)	(0.640)	(0.732)	(0.492)	(0.322)	(0.611)	(0.635)	(1.067)	(0.048)	(0.674)	(0.799)	(1.043)	(0.581)	(0.066)	(0.007)
Adapted	-3.301**	-2.683**	-3.172**	-2.637**	-1.894***	-2.645**	-2.711**	-3.106	-0.161**	-2.643**	-3.131**	-3.148*	-1.862*	-1.159***	-0.040***
	(1.395)	(1.212)	(1.391)	(1.045)	(0.677)	(1.166)	(1.208)	(1.951)	(0.077)	(1.301)	(1.530)	(1.806)	(0.966)	(0.280)	(0.014)
K-P $F-$stat	300	334	345	324	326	337	331	297	242	309	214	66	269	–	332
Zip code × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Decade Built × Flood Severity Controls		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Water Depth Quintile Only		✓													
Flood Event Type Only			✓												
Flood Event Number Controls				✓											
Date of Claim Controls					✓										
Dec. Built Trends w.o. Flood Severity				✓		✓									
Water Depth from Non-Adapted Only							✓								
Adapted × Linear Trend								✓							
Exclude Catastrophes									✓						
20-year Window Around Map (not 30)										✓					
10-year Window Around Map (not 30)											✓				
Complete Data Sample												✓			
Exclude Louisiana													✓		
OLS														✓	
Inverse Hyperbolic Sine (not Levels)															✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variables are an indicator for making a claim (Panel A) or the payout per $1,000 of insurance coverage (Panel B). Claim probabilities are multiplied by 100. All models are estimated using equation (2) in the text; price is instrumented using the interaction of indicators for adapted and post-2012, except in the OLS model in Column 14. Adapted houses are built after communities are mapped and are required to be elevated. Decade built×flood severity controls are zip code×decade built×flood severity fixed effects and decade built×flood severity time trends. Flood severity is defined using flood water depth and flood event type (see text), unless otherwise noted. Date of claim controls are zip code×decade built×claim date fixed effects. The number of observation is 11,983,183 in all models except for Column 9 (N=10,403,588) Column 10 (N=8,346,588), Column 11 (N=4,045,360), Column 12 (N=7,720,218), and Column 13 (N=10,077,506). Standard errors clustered by community are in parentheses.

Table A.7: Effect of Prices on Extensive Margin Demand: Probit

	Any Policy (1)	Building Policy (2)	Contents Policy (3)
Panel A: Probit			
Adapted × $1[t \geq 2013]$	0.027***	0.027***	0.022**
	(0.010)	(0.010)	(0.010)
Adapted	-0.057***	-0.056***	-0.006
	(0.020)	(0.020)	(0.017)
Panel B: Linear Probability Model			
Adapted × $1[t \geq 2013]$	0.025**	0.024**	0.022**
	(0.010)	(0.010)	(0.009)
Adapted	-0.055***	-0.054***	-0.006
	(0.020)	(0.020)	(0.018)
Non-Adapted Dep. Var. Mean	0.619	0.615	0.423
N		13,433,549	
State × Year FE	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variables are indicators for purchasing any policy, a policy that includes building coverage, and a policy that includes contents coverage. Panel A estimates equation (5) in the text using probit and state×year fixed effects, and Panel B estimates the same equation using OLS. Adapted houses are built after communities are mapped and are required to be elevated. The dependent variable mean is for non-adapted houses during the 2001-2012 pre-reform period. Mean marginal effects are shown for the probit models. Standard errors clustered by community are in parentheses.

Table A.8: Effects of Prices and Adaptation on Demand and Cost, Other Flood Severity Definitions

	Prices (1)	Any Policy (2)	Total Cov. (3)	Any Claim (4)	Average Cost (5)
Panel A: Water Depth Quintile					
No Flood × Adapted	-1.73***	-0.106***	26.17***	0.000	0.000
	(0.11)	(0.013)	(3.76)	(0.000)	(0.000)
Depth 2 × Adapted	-1.26***	-0.069**	21.21***	-0.024	-0.036*
	(0.20)	(0.027)	(5.33)	(0.015)	(0.019)
Depth 3 × Adapted	-1.41***	-0.105***	26.50***	-0.082***	-0.071***
	(0.16)	(0.025)	(4.74)	(0.014)	(0.014)
Depth 4 × Adapted	-1.75***	-0.136***	29.96***	-2.124***	-11.792***
	(0.11)	(0.015)	(2.96)	(0.267)	(1.894)
No Flood × Adapted × $1[t \geq 2013]$	-0.72***	0.016***	0.84	0.000	0.000
	(0.07)	(0.004)	(0.87)	(0.000)	(0.000)
Depth 2 × Adapted × $1[t \geq 2013]$	-0.60***	0.007	5.02	0.051	-0.027
	(0.18)	(0.015)	(3.68)	(0.034)	(0.052)
Depth 3 × Adapted × $1[t \geq 2013]$	-0.51***	0.023*	3.59*	0.017	-0.020
	(0.17)	(0.012)	(1.88)	(0.024)	(0.031)
Depth 4 × Adapted × $1[t \geq 2013]$	-0.64***	0.040***	-2.17	-0.084	0.604
	(0.08)	(0.008)	(1.64)	(0.394)	(2.697)
Panel B: Flood Event Type					
No Flood × Adapted	-1.73***	-0.104***	26.17***	0.000	0.000
	(0.11)	(0.013)	(3.76)	(0.000)	(0.000)
Flood × Adapted	-1.50***	-0.104***	24.57***	-0.160***	-0.276***
	(0.16)	(0.023)	(4.69)	(0.037)	(0.070)
Catastrophe × Adapted	-1.59***	-0.128***	29.59***	-1.711***	-10.038***
	(0.13)	(0.019)	(3.53)	(0.242)	(1.689)
No Flood × Adapted × $1[t \geq 2013]$	-0.72***	0.014***	0.84	0.000	0.000
	(0.07)	(0.004)	(0.87)	(0.000)	(0.000)
Flood × Adapted × $1[t \geq 2013]$	-0.58***	0.021**	3.77**	0.054	0.005
	(0.08)	(0.008)	(1.52)	(0.043)	(0.109)
Catastrophe × Adapted × $1[t \geq 2013]$	-0.63***	0.039***	-0.88	-0.143	0.581
	(0.11)	(0.010)	(1.63)	(0.411)	(2.721)
Zip code × Year FE	✓	✓	✓	✓	✓
Decade Built × Flood Severity Controls	✓	✓	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variables are flood insurance prices per $1,000 of coverage, an indicator for purchasing a policy, total coverage in 1,000s, an indicator for making a claim, and the insurer payout per $1,000 of coverage. Claim probabilities are multiplied by 100. The coefficients are estimated from equation (6) in the text using four categories for flood severity (no flood, three increasing water depths) in Panel A and using three categories for flood severity (no flood, flood, catastrophe) in Panel B. Adapted houses are built after communities are mapped and are required to be elevated. Decade built×flood severity controls are zip code×decade built×flood severity fixed effects and decade built×flood severity time trends. Flood severity is defined using flood water depth and flood event type (see text). Catastrophic floods are identified using the Federal Emergency Management Agency's Flood Insurance Claims Office number. Columns 1 and 2 are estimated on the sample of high-risk houses with and without insurance (N=13,433,549); Columns 3-5 are estimated on all high-risk policies (N=11,983,183). All monetary values are in $2017. Standard errors clustered by community are in parentheses.

Table A.9: Effects of Prices and Adaptation on Demand and Cost Excluding Louisiana, By Flood Severity

	Price (1)	Any Policy (2)	Total Cov. (3)	Any Claim (4)	Average Cost (5)
No Flood × Adapted	-1.57***	-0.108***	25.69***	0.000	0.000
	(0.09)	(0.013)	(4.01)	(0.000)	(0.000)
Depth 2 × Adapted	-1.24***	-0.072**	16.36***	-0.015	-0.021
	(0.18)	(0.028)	(4.44)	(0.016)	(0.020)
Depth 3 × Adapted	-1.42***	-0.107***	19.66***	-0.056***	-0.028**
	(0.14)	(0.025)	(4.37)	(0.015)	(0.013)
Depth 4 × Adapted	-1.27***	-0.112***	25.06***	-0.135***	-0.148***
	(0.15)	(0.028)	(4.27)	(0.038)	(0.039)
Depth 5 × Adapted	-1.69***	-0.148***	29.89***	-0.788***	-1.721***
	(0.06)	(0.014)	(2.21)	(0.187)	(0.352)
Depth 6 × Adapted	-1.63***	-0.132***	24.62***	-2.334***	-13.522***
	(0.11)	(0.018)	(3.91)	(0.282)	(2.385)
No Flood × Adapted x $1[t \geq 2013]$	-0.70***	0.017***	-0.22	0.000	0.000
	(0.03)	(0.004)	(0.75)	(0.000)	(0.000)
Depth 2 × Adapted × $1[t \geq 2013]$	-0.70***	0.012	2.69	0.054	-0.025
	(0.13)	(0.016)	(2.84)	(0.039)	(0.059)
Depth 3 × Adapted × $1[t \geq 2013]$	-0.63***	0.014	0.97	0.021	0.010
	(0.08)	(0.011)	(1.49)	(0.023)	(0.018)
Depth 4 × Adapted × $1[t \geq 2013]$	-0.62**	0.054*	-9.65**	-0.094	-0.186
	(0.29)	(0.030)	(4.01)	(0.069)	(0.116)
Depth 5 × Adapted × $1[t \geq 2013]$	-0.65***	0.052***	-2.75	0.336*	0.281
	(0.06)	(0.009)	(2.18)	(0.198)	(0.575)
Depth 6 × Adapted × $1[t \geq 2013]$	-0.72***	0.034***	2.53	-0.344	2.891
	(0.06)	(0.011)	(2.46)	(0.550)	(4.047)
Zip code × Year FE	✓	✓	✓	✓	✓
Decade Built × Flood Severity Controls	✓	✓	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variables are flood insurance prices per \$1,000 of coverage, an indicator for purchasing a policy, total coverage in 1,000s, an indicator for making a claim, and the insurer payout per \$1,000 of coverage. Claim probabilities are multiplied by 100. The coefficients are estimated from equation (6) in the text. Adapted houses are built after communities are mapped and are required to be elevated. Decade built×flood severity controls are zip code×decade built×flood severity fixed effects and decade built×flood severity time trends. Flood severity is defined using flood water depth and flood event type (see text). Columns 1 and 2 are estimated on the sample of high-risk houses with and without insurance (N=13,218,697); Columns 3-5 are estimated on all high-risk policies (N=10,077,506). All monetary values are in \$2017. Standard errors clustered by community are in parentheses.

Table A.10: Effects of Counterfactual Policy Reforms on Annual Welfare per High-Risk Homeowner

Calibration of Frictionless WTP Curve	Counterfactual Policy: Actuarially Fair Prices (1)	Counterfactual Policy: Insurance Mandate (2)
1. Consumption smoothing baseline estimates:	-\$1,770	\$7,900
Alternative slopes:		
2. Heterogeneous risk aversion:	-\$1,810	\$5,740
3. Heterogeneous consumption variance:	-\$1,750	\$3,970
4. Iso-elastic (not linear):	-\$1,090	\$7,610
Alternative consumption variances:		
5. Consumption smoothing + adaptation-specific variance:	-\$1,840	\$7,800
6. Consumption smoothing + exclude Katrina:	-\$1,120	\$5,370
7. Consumption smoothing + cap losses at avg. income:	-\$830	\$3,490
8. Cap losses at avg. mortgage payment:	-\$140	\$300
9. No consumption smoothing:	-\$3,100	\$17,280
Alternative risk aversion:		
10. Risk aversion estimated using property insurance:	-\$6,190	\$30,000

Notes: This table shows the welfare effects of counterfactual reforms (\$ per high-risk homeowner, per year) using different calibrated parameters for the coefficient of absolute risk aversion γ and the effect of natural disaster insurance on the variance of consumption V. The baseline estimates in row 1 calculate the average risk premium using a standard estimate of risk aversion of $\gamma = 5 \times 10^{-4}$ (Hendren, 2019) and the variance of insurance payouts that incorporates consumption smoothing $V = 9,000^2$. Subsequent rows use different functional forms, different consumption variances, or different risk aversion parameters. Row 2 sets $\gamma = 1.8 \times 10^{-4}$ for the homeowner with the lowest willingness to pay, which is the risk aversion for the low-income population in Hendren (2019). Row 3 sets $V = 804^2$ for the homeowner with the lowest willingness to pay, which is the variance of payouts in the lowest severity flood in the claims data. Row 4 uses a level shift of an iso-elastic observed willingness to pay curve. Row 5 uses $V = 8,000^2$ and $V = 10,000^2$ to calculate the average risk premium separately for adapted and non-adapted houses respectively, which are the variances of payouts for each of these types of houses incorporating consumption smoothing. Row 6 uses $V = 7,000^2$, which is the variance of payouts incorporating consumption smoothing and excluding payouts from Hurricane Katrina. Row 7 uses $V = 6,000^2$, which is the variance of payouts including consumption smoothing and capping payouts at average income in the zip codes in the analysis. Row 8 uses $V = 2,500^2$, which is the variance of payouts if they are capped at the average annual mortgage payment. Row 9 uses $V = 12,000^2$, which is the variance of payouts in the data without consumption smoothing. Row 10 uses $\gamma = 1.7 \times 10^{-3}$ from Snydor (2010), which is the risk aversion parameter estimated using property insurance deductible choice. Except in rows 2 and 3, frictionless willingness to pay is a level shift of observed willingness to pay. See text for a detailed description of the calculation of the risk premium.

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