Adaptation and Adverse Selection in Markets for Natural Disaster Insurance

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Abstract

This paper quantifies frictions in uptake, tests for adverse selection, and analyzes welfare effects of proposed reforms in natural disaster insurance markets. I find that willingness to pay is remarkably low. In high-risk flood zones, fewer than 60% of homeowners purchase flood insurance even though premia are only two-thirds of own costs. Estimating flood insurance demand and cost elasticities using house-level variation in premia from recent U.S. Congressional reforms reveals that these homeowners select into insurance based on observable differences in adaptation, but not private information about risk. These findings change the sign of predicted welfare effects of proposed policies.

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Homeowners are increasingly experiencing the effects of climate change firsthand. In 2017, total damages from hurricanes and wildfires in the United States exceeded \$300 billion. These losses reflect a global trend of progressively more severe and costly natural disasters. For example, public flood insurance payouts in the U.S. have increased twentyfold in the past two decades—approximately seven times the growth rate of public spending on Medicaid over the same period. This trend in flood insurance claims is predicted to continue because projected sea level rise threatens over \$1 trillion-worth of U.S. property (Gaul, 2019; Rudowitz et al., 2018). In response to the rising financial burden on flood, fire, and earthquake insurers, natural disaster insurance market reform is the current focus of seven U.S. Congressional bills and extensive policy debate. Proposed natural disaster insurance reforms include rate increases, insurance mandates, and adaptation policies such as more stringent building codes (Horn and Brown, 2018).

This paper estimates homeowners' willingness to pay for natural disaster insurance, analyzes how willingness to pay affects homeowners' insurance costs, and evaluates the welfare effects of these proposed reforms. Natural disaster insurance markets are adversely selected if homeowners with higher willingness to pay for insurance are also costlier to insure (Einav et al., 2010). The welfare cost of adverse selection in insurance markets is a classic result in public economics, and a central question in this paper is the extent to which currently proposed price increases will lead to changes in the risk pool of insured homeowners. For example, administrators of the public National Flood Insurance Program (NFIP), which underwrites almost all flood risk in the U.S., hypothesize that "relatively low-risk homeowners might leave the NFIP because of these price increases, but the full impact is unclear" (GAO, 2014). Such a response would increase the average cost of providing insurance to homeowners and undermine the financial objectives of the price reform, and "the concerns of some Members of Congress about adverse selection are among the most pressing issues likely to be addressed in any long-term NFIP re-authorization" (Horn and Webel, 2019).

Despite these concerns, much applied research on selection focuses on health and, to a lesser extent, unemployment, long-term care, and disability insurance. Natural disaster insurance contracts, which pay out only when infrequent, high-cost, and spatially correlated disasters occur, differ from most insurance contracts in these other domains. The seminal model of selection of Rothschild and Stiglitz (1976) does not apply to "risks that cannot be diversified i.e., the risk of nuclear war (or of a flood or a plague)" (p. 632). The extreme variability and geographic concentration of losses threaten the solvency of private natural disaster insurers, distort homeowners' perceptions of risk, and distinguish natural disaster insurance from other types of insurance (Jaffee and Russell, 1997). Moreover, local governments can take actions to reduce natural disaster damages. Hence, in addition to adverse selection, optimal policy in natural disaster insurance markets must consider frictions in uptake due to, for example, discounting of extreme events or misperception of risk, as well as interactions with public policies that mitigate climate risk through adaptation.

The first part of this paper develops a model that incorporates these key features of natural disaster insurance markets. The model provides a framework to analyze the social welfare implications of implementing actuarially fair insurance pricing and an insurance mandate for homeowners in high-risk flood zones. These counterfactual welfare effects are relevant for policy: flood and fire insurance markets are moving toward actuarially fair pricing as soon as 2021 (CDI, 2018; FEMA, 2019b). High-risk homeowners with federally backed mortgages are supposed to purchase flood insurance, but this requirement is not enforced (NRC, 2015).

The second part of the paper estimates two key parameters that are necessary to understand how *any* natural disaster insurance market reform will affect social welfare: homeowners' willingness to pay for insurance and the marginal cost of providing insurance to them. To do so, I compile a novel data set by linking the characteristics of residential houses, flood insurance policies, and flood insurance claims. The data set covers 20 Atlantic and Gulf Coast U.S. states for the years 2001-2017. These states account for 83% of total flood insurance policies written nationwide (NRC, 2015). This data set includes both proprietary parcel-level data on the residential housing stock and administrative data on over 70 million flood insurance contracts underwritten by the NFIP. Compiling these data required five Freedom of Information Act (FOIA) requests and over 14 months of processing by the Federal Emergency Management Agency (FEMA). To the best of my knowledge, this is the most comprehensive set of natural disaster insurance and housing data in existence.

I estimate homeowners' willingness to pay and cost curves using a differences-in-differences research design that exploits exogenous, house-level variation in flood insurance prices from Congressional reforms in 2012 and 2014. These reforms imposed annual rate increases for houses in high-risk flood zones that were built before the implementation of construction standards mandating a minimum elevation for their foundation. I assess the validity of the identifying assumptions of this research design using event study graphs, sensitivity analyses with different controls and data subsamples, and triple-difference regressions that compare outcomes for houses that experience floods of similar severity before and after the price reform. The evidence supports the identifying assumptions.

The research design also allows me to test for selection. NFIP administrators have expressed concern that homeowners could have private information about their flood risk because flood insurance prices are based on a small number of dwelling characteristics and on flood maps that are often many years out of date (Horn and Webel, 2019). The slope of the average cost curve provides the basis for a test for selection on private information: in an adversely selected market in which people have private information about their risk, infra-marginal individuals who purchase insurance are more costly to insure than marginal individuals offered the same price (Einav et al., 2010). If this is the case, then average costs increase when prices do. Comparing demand and costs for elevated and non-elevated houses (controlling for any insurance price differences) also provides a test for selection on observable determinants of natural disaster risk. In a market that is adversely selected on the elevation of a house's foundation, houses that are not elevated are more likely to be insured and are costlier to insure than elevated houses that pay the same price.

The paper's first main results document that, throughout high-risk flood zones in the eastern U.S., the mean price of flood insurance is only about two-thirds of homeowners' own expected payouts, but over 40% of homeowners are uninsured. Using these descriptive facts and exogenous price variation, I estimate that only about half of high-risk homeowners are willing to pay an amount equal to their expected payout for a flood insurance contract. These results contradict standard models of insurance demand, where risk-averse individuals are willing to pay a risk premium *above* cost. In textbook models, all risk-averse homeowners purchase insurance if it is actuarially fair. Flood insurance premia are *better* than actuarially fair on average. I show that market failures typically identified in other insurance markets, such as adverse selection, moral hazard, public bail-outs, and credit constraints, seem to play smaller roles in rationalizing low willingness to pay in this setting. Behavioral frictions, such as underestimation of flood risk, appear to be important in explaining low uptake. Homeowners' low valuation of flood insurance is surprising because floods decrease land value and labor income in addition to house value; correlated risks make the consumption smoothing benefit of insurance more valuable.

The paper's second main finding is that homeowners select into insurance based on differences in observable house characteristics, but not on private information about risk. I estimate that minimum elevation requirements for new construction reduce demand for natural disaster insurance by 25% and insurer costs by 31%, conditional on prices. I also estimate a price elasticity of demand of -0.25, but find that while homeowners are price sensitive, the slope of the average cost curve is statistically indistinguishable from zero after controlling for whether or not a house is elevated. Despite the NFIP's coarse rate schedule, these results suggest that selection on private information is limited, but that natural disaster insurance markets are adversely selected because homeowners' willingness to pay and cost are positively correlated with observables (i.e., house elevation) that the insurer does not price efficiently. In the textbook model of an adversely selected market, insurance take-up is inefficiently low because the benefit from insurance for some individuals is below prices set at average cost. By contrast, I find that the expected benefit from insurance appears to be constant and equal to average cost across the price distribution that I observe, conditional on house elevation. Differences between marginal and average costs therefore cannot rationalize low take-up in this market.

These empirical results have important implications for the social welfare effects of natural disaster insurance reforms. I discuss the effects of increases in mean insurance prices to actuarially fair levels and also consider a mandate for all homeowners in high-risk flood zones to purchase insurance. In most settings, revealed preference demand accurately reflects a good's value to consumers and forms the basis for policy recommendations. However, in this setting, I find that frictions (e.g., underestimation of true flood risk or discounting of tail events) appear to cause homeowners to substantially undervalue natural disaster insurance, and so welfare analysis based on observed demand excludes a large expected benefit. Observed willingness to pay is actually so low that accounting for frictions changes the sign of the predicted welfare effect. Whereas the wedge between observed willingness to pay and cost suggests that making flood insurance actuarially fair would improve welfare, allowing for behavioral frictions in my analysis suggests that increasing prices actually *decreases* social welfare. If demand is low because of such frictions, I calculate that enforcing an insurance mandate increases social welfare, because it efficiently extends insurance coverage to include many homeowners who seem likely to purchase it in the absence of any distortions in demand. A mandate is the typical solution to adverse selection on private information (Akerlof, 1970), but is also useful in the absence of such selection because it corrects any distortions from frictions. Under some simplifying assumptions, the model suggests that these welfare effects may be as large as billions of dollars per year.

This paper seeks to contribute to existing literature in four main ways. I believe that this is the first paper to test for or provide evidence of adverse selection into any natural disaster insurance market. In so doing, the paper also provides the first instrumental variables estimate of the price elasticity of demand for natural disaster insurance. These results extend a voluminous literature on selection in insurance markets, the focus of which is largely on health (Bundorf et al., 2008; Einav et al., 2010; Finkelstein et al., 2019b; Handel, 2013; Hackmann et al., 2015). Chetty and Finkelstein (2013) review empirical methods that public economists use to study selection in health insurance, disability insurance, and specific settings such as annuity markets or automobile insurance.[1] The omission of natural disaster insurance from this literature is particularly significant in light of the NFIP's concern about the financial implications of proposed price changes and the necessity of marginal cost estimates for welfare analysis. There is also limited evidence on the extent to which homeowners are sensitive to prices for natural disaster insurance—a prerequisite for selection. The price elasticity of demand for flood insurance is of independent interest because many proposed flood insurance reforms involve price changes. Most estimates of flood insurance price elasticities use panel regressions on a few thousand policies or state-level policy totals without instruments or an explicit research design to address endogeneity of prices (Browne and Hoyt, 2000; Dixon et al., 2006; Kriesel and Landry, 2004). The only quasi-experimental estimate that I am aware of uses an OLS panel regression with 66 policy counts (Mulder, 2019). I show that instrumenting for prices is important because OLS estimates of demand and cost elasticities are biased upward substantially, which is consistent with increases in both insurance demand and prices after floods.

In addition to selection, the empirical insurance literature also commonly studies moral hazard, which arises when insurance changes behavior in a way that affects cost. I discuss the implications for my welfare analysis of spatial distortions created by subsidies and by public disaster relief pay-

[1]The only work I am aware of applying any of these methods to natural disaster insurance markets is research in progress by Matthew Gibson, Jamie Mullins, and Carolyn Kousky. One contemporaneous study suggests that there is a correlation between average lifetime claims and duration of flood insurance tenure, which it labels "dynamic adverse selection" (Mulder, 2019). This other study does not test whether homeowners selectively take up natural disaster insurance based on observed or unobserved variables; its measure is novel and interesting though differs from the standard measure of adverse selection (Einav et al., 2010).

ments (Bakkensen and Barrage, 2019; Baylis and Boomhower, 2019; Fried, 2019). I also discuss how changes in homeowners' decisions to invest in adaptive capital could affect welfare, though I leave the test for this type of moral hazard for future work. Homeowners' private capital investments are difficult to observe, but the effect of an elevated foundation on cost, which I estimate, suggests that the range of plausible moral hazard costs have small welfare consequences.

The paper's second main contributions are the first estimates of the wedge between homeowners' willingness to pay for a natural disaster insurance contract and its expected benefit, and of the social welfare implications of flood insurance subsidies and low take-up. Previous studies measure take-up using aggregated estimates of houses and contracts or matched microdata for smaller geographies, such as individual cities, without calculating willingness to pay (Dixon et al., 2006; Kousky et al., 2018; Kriesel and Landry, 2004).[2] Gregory (2017) and Bakkensen and Ma (2019) use location-choice models to estimate observed willingness to pay for the provision of public natural disaster relief and for the avoidance of flood risk, respectively. Other work measures flood insurance subsidies using various methods, such as published NFIP rate tables or actuarial models (CBO, 2017; GAO, 2014; Kunreuther et al., 2017). My paper departs from these studies by comparing observed willingness to pay for natural disaster insurance to estimates of risk premia and costs, which allows me to analyze the normative implications of descriptive patterns of insurance purchase choices. This analysis contributes to a literature that examines how economic frictions (e.g., hassle costs) and behavioral biases (e.g., risk misperception) distort take-up of insurance and social programs (Abaluck and Gruber, 2011; Finkelstein and Notowidigdo, 2018; Spinnewijn, 2015). A subset of this literature shows that homeowners appear to underestimate their flood risk (Bakkensen and Barrage, 2019; Gallagher, 2014; Royal and Walls, 2019), which provides one plausible explanation for the wedge between willingness to pay for natural disaster insurance and the expected benefit that this insurance provides.

Additionally, I provide the first empirical estimates of the effects of minimum construction standards on natural disaster insurance demand and individuals' average costs. I show that these defensive investments deliver the largest cost reduction during catastrophic events. In addition to providing evidence of adverse selection on observables (i.e., house elevation), these estimates quantify the benefits of adaptation policies in mitigating the effects of extreme weather on homeowners. These findings contribute to a burgeoning literature that models climate change impacts on economic outcomes under different assumptions on adaptive behavior (Balboni, 2019; Barreca et al., 2016; Houser et al., 2015). An advantage of merging microdata on houses, insurance contracts, and claims is that this allows me to estimate the expected benefit of adaptation for individuals, rather than on aggregate or only using claims data, which provides a measure of the reduction in average costs that should be incorporated into insurance prices. Studies of the reduction in natural disaster damages from residential construction standards, barriers against natural hazards, and

[2] NRC (2015) reviews flood insurance take-up estimates in specific settings.

land-use planning typically rely on engineering estimates or calibrated model-based simulations (EPA, 2017; NIBS, 2018). Kousky and Michel-Kerjan (2017) examine correlations between flood insurance payouts and house characteristics conditional on making a claim.

Finally, I contribute to a methodological literature on welfare analysis in insurance markets using "sufficient statistics" (Chetty, 2009; Einav et al., 2010; Handel et al., 2019; Spinnewijn, 2017). Standard approaches in public economics that measure welfare using demand and cost curves rely on the assumption that observed demand reflects individuals' true valuation of insurance. In the presence of behavioral frictions, this assumption fails. I derive the welfare-relevant demand curve as a function of empirically estimable parameters by inverting a method for calculating risk aversion (Hendren, 2019). This approach requires few assumptions on the distribution of any frictions, and provides a framework for studying welfare in natural disaster insurance markets.

The rest of this paper proceeds as follows. Section 1 describes the NFIP. Section 2 outlines a model of natural disaster insurance markets. Section 3 describes the data. Section 4 presents descriptive evidence on natural disaster insurance subsidies and purchasing behavior. Section 5 outlines the empirical strategy, and Section 6 presents estimates of the effects of prices and adaptation on insurance demand and cost. Section 7 discusses alternative explanations for the empirical results and the welfare implications for insurance reforms. Section 8 concludes.

1 Institutional Background

Since its inception in 1968, the NFIP has been the primary provider of flood insurance in the United States. Standard property insurance contracts do not cover floods, but floods account for over 90% of natural disasters and cause more damage than wildfires, tornadoes, and earthquakes combined (GAO, 2007; Gaul, 2019). The NFIP therefore annually underwrites over 5 million flood insurance policies that represent \$3.2 billion of premia revenue and \$1.2 trillion of coverage for buildings and their contents. Insurance purchased through the NFIP is backed by the federal government, which bears essentially all flood risk. The small private market for flood insurance currently accounts for only 3.5 to 4.5% of residential policies written in the country (Kousky et al., 2018). This differs from insurance markets for other natural disasters such as wildfires, windstorms, and earthquakes, which are mostly private. As a result of cumulative damages from recent hurricanes, the NFIP is currently over \$20 billion in debt, despite regularly borrowing from the U.S. Department of the Treasury (Horn and Brown, 2018).

In addition to underwriting insurance, the NFIP coordinates hydrological studies to provide communities with a detailed Flood Insurance Rate Map (FIRM).[3] Appendix Figure A.1 shows an example. These maps serve two primary purposes. First, they delineate two types of local areas—those at high and at low risk of flooding. In theory, homeowners with federally backed

[3]NFIP communities are "political subdivisions with the authority to enforce floodplain management" and correspond roughly to metropolitan statistical areas (FEMA, 2011).

mortgages are required to purchase flood insurance if they live in high-risk flood zones, but this condition is not enforced and many homeowners are unaware of its existence (Horn and Brown, 2018; NRC, 2015).[4] The second main purpose of the maps is to provide information about the height of the flood that has a 1% probability of occurring. The NFIP requires that the foundations of new construction in high-risk flood zones are elevated to at least the height of the 1% chance flood. This minimum construction requirement affects all houses built in high-risk flood zones after the later of December 31, 1974 or the date of their community's first map. Appendix Figure A.2 shows that these "post-FIRM" houses are visibly better built to withstand flooding than "pre-FIRM" structures with no minimum height requirements. Based on these differences in adaptation policy (i.e., minimum elevation requirements), in this paper I refer to post- and pre-FIRM houses as adapted and non-adapted respectively.

Flood insurance prices are based primarily on whether houses throughout the country are in high- or low-risk flood zones and whether they are built before or after communities are mapped.[5] Both adapted and non-adapted homeowners receive an implicit subsidy because many flood maps use out-of-date information about risk and because insurance premia have not increased at the same rate as the cost of flooding. Real premia were largely unchanged throughout the 1990s and 2000s, but cumulative claims since 2005 exceed the total from the NFIP's entire prior history (DHS, 2017). However, the NFIP purposefully sets premia for non-adapted houses in high-risk flood zones below expected costs based on actuarial models. Flood insurance for these houses was initially subsidized to maintain property values when the NFIP began and to encourage uptake. Flood maps are revised periodically, and prior construction is grandfathered into new flood zone designations without price increases (Horn and Brown, 2018).

Congress is now phasing out the statutory subsidies for non-adapted structures. The Biggert-Waters Flood Insurance Reform Act of 2012 (Biggert-Waters) mandated premia increases of 25% per year beginning in 2013 for non-adapted primary residences that are sold, paying subsidized rates due to grandfathering, or classified as "severe repetitive loss" properties.[6] The Homeowner Flood Insurance Affordability Act of 2014 (HFIAA) extends the rate increase to all subsidized non-adapted residences (i.e., including those that were initially unaffected by Biggert-Waters). Premia will increase each year until they reach actuarially fair levels, though the HFIAA limits this annual rate increase to between 5% and 18% for all residential properties except "severe repetitive loss"

[4] There is limited government oversight of lender compliance with the purchase requirement. One case study finds that flood insurance take-up by high-risk homeowners was 16%, but that 45% of the total had federally backed mortgages and therefore should have been required to purchase it (NRC, 2015). Gallagher (2014) calculates that 97% of NFIP policyholders purchase flood insurance by choice rather than requirement.

[5] The NFIP also adjusts prices if houses have a basement and comply with any elevation standards. High-risk flood zones are subdivided depending on, for example, whether they are subject to storm surge. Prices are quoted per $100 of coverage, and the first $60,000 of building coverage and the first $25,000 of contents coverage are more expensive than subsequent amounts. NFIP (2019) discusses these rate setting details.

[6] FEMA classifies about 0.2% of insured structures as "severe repetitive loss" because they have made at least 4 claims that exceed $5,000, or at least 2 claims that, in total, exceed the property's value (Horn and Brown, 2018).

(NRC, 2015).[7] These Congressional reforms provide exogenous price variation that affects non-adapted houses only. I use this variation to estimate the slopes of the flood insurance demand and cost curves.

2 Conceptual Framework

The model of natural disaster insurance markets extends standard models of insurance demand and cost (Einav et al., 2010; Spinnewijn, 2017) by incorporating adaptation and a more general expression for frictions in uptake. The welfare implications of natural disaster insurance reforms depend on marginal costs and on (unobserved) willingness to pay in the absence of any frictions.

2.1 A Model of Natural Disaster Insurance Markets

2.1.1 Demand

Each year, risk-averse homeowner i with exogenous income y_i chooses whether to purchase a natural disaster insurance policy. These contracts are perfectly elastically supplied by the government at a subsidized price p and provide full insurance in case of damages.[8] Houses are characterized by a level of *ex ante* adaptation α that provides protection against natural disasters. For floods, this adaptation takes the form of minimum elevation requirements for the residential housing stock. There are frictions that affect homeowners' decision to purchase insurance, denoted by $\phi_i \geq 1$. The model is agnostic about which microfoundations give rise to these frictions. Some evidence suggests that homeowners' underestimation of their flood risk is an important friction (Bakkensen and Barrage, 2019; Gallagher, 2014; Royal and Walls, 2019). However, ϕ_i could also represent other frictions, such as inattention, that have not been tested in the existing literature.[9]

Homeowners have an underlying type s_i that captures unobservable factors that affect willingness to pay for natural disaster insurance. These unobserved variables could include risk preferences and private information about location-specific natural disaster risk, for example. I assume that these types are uniformly distributed on the unit interval in the population and that willingness to pay decreases in s_i, so that $s_i = 1$ is the lowest willingness to pay type. These assumptions are standard (Finkelstein et al., 2019b; Hendren, 2019). The assumption that willingness to pay declines in s_i means that s has a convenient interpretation as the x-axis on the demand curve because all types $s_i < s$ purchase insurance if homeowner of type s does.

[7] Biggert-Waters and the HFIAA introduced other changes, such as a $25 surcharge for all policies and a new deductible option, which did not differentially affect adapted and non-adapted houses (FEMA, 2015).

[8] The small intensive margin demand elasticities that I estimate in Section 6 motivate the model's focus on the extensive margin purchase choice. The assumption of full insurance is based on the empirical observation that total coverage is non-binding for 93% of claims. Appendix B relaxes this assumption.

[9] Friction parameters that are weakly greater than 1 allow distortions such as overoptimism about flood risk, inattention to exclusions from property insurance, inertia when uninsured, myopia, and other frictions that increase the perceived costs of purchasing insurance. This parametrization rules out overvaluation of insurance or, for example, inertia when insured. This is consistent with my empirical evidence on low levels of flood insurance uptake.

In the presence of selection, type s_i also determines the homeowner's realized cost $f(s_i, \alpha)$ to the natural disaster insurer. The correlation between willingness to pay and cost is the defining feature of selection markets; a positive and negative correlation respectively indicate adverse and advantageous selection. Damages also depend on the extent of adaptation α. For full insurance contracts, the terms damages and costs are interchangeable. Realized damages are distributed $F_{s,\alpha}$ in the population.

Homeowners maximize a well-behaved utility function $u(c_i)$, subject to a budget constraint that depends on whether they purchase insurance at price p. With full insurance, the budget constraint for insured homeowners with consumption $c^I(p, y_i)$ is:

$$c^I(p, y_i) + p \leq y_i$$

Uninsured homeowners bear the full costs of any realized damages $f(s_i, \alpha)$. This yields the budget constraint for uninsured homeowners with consumption $c^U(s_i, \alpha, p)$:

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

Consider a homeowner of type s_i with adaptation α and frictions ϕ_i and suppress dependence on y_i. The maximum price $\tilde{D}(s_i, \alpha, \phi_i)$ that this homeowner is willing to pay for insurance equates expected utility over the distribution of possible natural disaster costs when insured or uninsured:

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

Homeowners buy insurance if willingness to pay exceeds price, i.e., when $\tilde{D}(s_i, \alpha, \phi_i) \geq p$. Since all homeowners with types $s_i < s$ purchase insurance if homeowner of type s does, the type s of the marginal homeowner, who has $\tilde{D}(s, \alpha, \phi) = p$, measures the share of homeowners who purchase insurance at price p, given the distribution of frictions ϕ. The identity $\tilde{D}(s(p, \alpha, \phi), \alpha, \phi) = p$ implicitly defines the inverse demand curve $s(p, \alpha, \phi)$. To simplify notation, I denote the market willingness to pay curve by $D(p, \alpha, \phi) \equiv \tilde{D}(s(p, \alpha, \phi), \alpha, \phi)$.

Frictions $\phi_i > 1$ create a wedge between observed willingness to pay $\tilde{D}(s_i, \alpha, \phi_i)$ and frictionless willingness to pay $\tilde{D}(s_i, \alpha, \phi_i = 1)$. If $\phi_i = 1$, homeowners accurately equate expected utility in the insured and uninsured states of the world, and the model simplifies to the standard model of insurance demand and cost (Einav et al., 2010). If $\phi_i > 1$, individuals perceive the uninsured state to be more attractive than it actually is. One example of $\phi_i > 1$ is underestimation of the probability of being flooded. Note that the probability of flooding does not appear separately in equation (1) because it is included in the expectation over the distribution of damages.[10]

In Appendix A.1, I derive comparative statics for how willingness to pay responds to changes in the model's exogenous parameters by totally differentiating equation (1). These expressions show

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

that insurance take-up is declining in insurance prices, adaptation, and frictions.

2.1.2 Insurer Costs

The expected insurance cost of the marginal type $s(p, \alpha, \phi)$ who purchases insurance at price p is:

$$MC(p, \alpha, \phi) = \mathbb{E}[f(s_i, \alpha)|s_i = s(p, \alpha, \phi)].$$

I assume insurer costs are equal to claims paid and costs $f(s_i, \alpha)$ are independent of the premiums charged for insurance, which are standard assumptions (Finkelstein et al., 2019b; Hendren, 2019). The insurer's expected average costs are the expectation over the *ex ante* distribution of costs of the homeowners who purchase insurance:

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

with uniform distribution over s_i. Appendix A.2 derives the effects of changes in the exogenous parameters p, α, and ϕ on average costs. Adaptation shifts the average cost curve. Conditional on adaptation, selection on private information changes the slope of the average cost curve. In general, the comparative statics could all take either sign, which motivates testing empirically for selection on both observable and unobservable determinants of natural disaster risk.

2.2 Empirical Tests for Selection and Frictions

Data on prices, quantities, costs, and house characteristics permit two tests for selection and one test for frictions in uptake.

First, the sign of the slope of the average cost curve $\frac{\partial AC(p,\alpha,\phi)}{\partial p}$ is a test for selection on unobservable determinants of natural disaster risk (Einav et al., 2010). If the market is adversely selected, homeowners' costs are positively correlated with willingness to pay, and so infra-marginal homeowners are costlier to insure than marginal individuals. In this case, $\frac{\partial AC(p,\alpha,\phi)}{\partial p} > 0$ because lower cost individuals cease to purchase insurance at higher prices (Akerlof, 1970). Homeowners' costs could also be negatively correlated with willingness to pay, which would lead to advantageous selection. The NFIP's coarse pricing structure, based primarily on flood zone and a limited number of dwelling characteristics, creates the possibility for adverse selection: homeowners may base their insurance purchase decisions on location-specific information that the NFIP does not observe or price, such as groundwater intrusion or the behavior of local sewer systems during storms. The NFIP considers the potential for such adverse selection to be a barrier to establishing a private flood insurance market because profit-maximizing insurers with sophisticated risk models may be able to selectively enroll profitable homeowners at lower rates, transforming the NFIP into a residual market for high-risk properties (Horn and Webel, 2019).

Second, we can test for adverse selection on observable house characteristics by estimating the effects of adaptation policies on insurance demand and costs. Natural disaster insurance markets are adversely selected if adapted houses that are required to be elevated are both less costly to insure and less likely to be insured, conditional on prices. In terms of the model, this is equivalent to testing for $\frac{\partial AC(p,\alpha,\phi)}{\partial \alpha} < 0$ and $\frac{\partial s(p,\alpha,\phi)}{\partial \alpha} < 0$. If adaptation policies such as minimum elevation requirements are negatively correlated with demand and cost even conditional on the prices that the different types of houses pay, then this is evidence that the insurer does not fully incorporate these *ex ante* differences in adaptation into the rate schedule. Such tests in other settings (e.g., health insurance and annuity markets) indicate that adverse selection on observable characteristics is an important source of pricing inefficiencies (Finkelstein and Poterba, 2014; Shepard, 2016). This second test for "asymmetrically used" information is based on correlations and does not require that I observe exogenous changes in house characteristics. By contrast, testing for selection using the slope of the average cost curve requires exogenous price variation that is uncorrelated with shocks to demand and cost.

Finally, whether homeowners' observed willingness to pay exceeds the marginal cost of providing insurance to them provides a general test for frictions $\phi_i > 1$. In standard models of insurance demand, risk-averse individuals are willing to pay their expected benefit from insurance *plus* a risk premium. If homeowners do not purchase insurance when prices are below their own expected payouts, then this suggests that behavioral frictions are present in this market. This provides a simple empirical test for $\phi_i > 1$, though I consider other explanations in Section 7.1. Appendix A.1 uses a novel approach to derive an expression for homeowners' frictionless willingness to pay curve as a function of marginal cost and a risk premium that depends on a coefficient of absolute risk aversion and the effect of natural disaster insurance on the variance of consumption.

I derive homeowners' marginal cost curve and compare it to my estimates of observed willingness to pay. Estimating the observed demand and average cost curves allows me to obtain 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). I estimate the slopes of the observed demand and average cost curves using the exogenous price variation from the Biggert-Waters and HFIAA Congressional reforms. 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.

2.3 Welfare Implications

Einav et al. (2010) provide a framework for quantifying the welfare implications of counterfactual policy interventions in insurance markets based on observed willingness to pay and cost curves.[11] In the presence of frictions in uptake, revealed preference demand does not reflect the

[11] A limitation of this approach is that it relies on uncompensated (Marshallian) demand curves for welfare analysis. Accounting for income effects would require imposing more structure on the primitives of the utility function and the ways in which frictions in uptake affect homeowners' decisions.

full value of insurance (Spinnewijn, 2017). Instead, the welfare-relevant willingness to pay curve is the frictionless willingness to pay curve, which I derive in Appendix B as equation (15).

Figure 1.a shows a graphical representation of the market equilibrium for a given level of adaptation α and distribution of frictions ϕ. The horizontal axis shows the share of insured homeowners in the market and the vertical axis shows price, cost, and willingness to pay. The downward-sloping marginal cost curve $MC(p, \alpha, \phi)$ indicates adverse selection: at higher prices, marginal individuals are more costly to insure. The marginal cost curve therefore lies below the average cost curve, $AC(p, \alpha, \phi)$. The insurer sets a subsidized price p' below marginal cost.[12]

The efficient equilibrium occurs at the intersection of the willingness to pay curve that is not distorted by frictions in uptake, $D(p, \alpha, 1)$, and the marginal cost curve. This is point A in the graph. It is efficient for homeowners to purchase insurance if their expected payout plus their risk premium exceeds their cost to the insurer. However, frictions $\phi_i > 1$ distorts demand so that homeowners may not purchase insurance even when their expected benefit exceeds the price. The figure shows the observed willingness to pay curve as a level downward shift of the frictionless willingness to pay curve for illustration.[13]

The presence of a wedge between observed and frictionless willingness to pay has important implications for optimal policy. The intersection of the observed willingness to pay curve $D(p, \alpha, \phi)$ and the marginal cost curve, at point B, occurs at the price p^{mc} above the subsidized price p'. If observed demand is used as the welfare-relevant metric, the insurer would conclude that increasing prices from p' to p^{mc} would lead to a welfare gain equal to the area between the marginal cost and observed willingness to pay curves, shown in light grey. However, the frictionless willingness to pay curve implies that it is efficient to insure all homeowners with $D(p, \alpha, 1) > p'$. If behavioral frictions lower willingness to pay, then increasing prices from p' to p^{mc} actually *reduces* welfare because the benefit of insurance is greater than the cost for all homeowners who become uninsured as a result of the price increase. The reduction in welfare is given by the dark grey area between the frictionless willingness to pay and marginal cost curves.

Implementing the efficient equilibrium at point A actually increases the share of insured homeowners, from $s(p', \alpha, \phi)$ to $s(p^*, \alpha, \phi)$. Figure 1.a illustrates the case where it is optimal for all homeowners to purchase insurance. Since homeowners' purchase decisions are based on $D(p, \alpha, \phi)$, achieving 100% take-up requires either further subsidizing prices to p^*, or enforcing a mandatory purchase requirement.[14] The mandate makes it possible to sustain prices at a level above p^* with

[12] Since the insurer does not observe marginal costs, subsidies are based on average cost. I illustrate the case here where prices are also below marginal cost, consistent with my empirical evidence for flood insurance.

[13] The frictionless willingness to pay curve may be more or less steep than the observed demand curve. Appendix B shows that if the frictionless willingness to pay curve is a level shift of the observed willingness to pay curve, then any individual differences in frictions, marginal utility, and expected utility when uninsured offset on average.

[14] Two other ways to achieve the efficient equilibrium are imposing a tax on uninsured homeowners equal to $MC(p^*, \alpha, \phi) - D(p^*, \alpha, \phi)$ or implementing policies that target the removal of any frictions directly. The second alternative requires more information on the form of any frictions. Identifying which possible frictions play important roles in low uptake is an important area for future research.

the same welfare gain, shown in black.

3 Data

This paper uses three administrative data sets on flood insurance policies, flood insurance claims, and residential houses. I supplement these data with spatial data on flood risk. Additional details are in Appendix C.

Flood Insurance Policies and Claims – I obtained the flood insurance policies and claims data through five Freedom of Information Act (FOIA) requests from the Federal Emergency Management Agency (FEMA). The flood insurance data are the universe of NFIP policies and claims for 2001 to 2017 in the 20 Atlantic and Gulf Coast states shown in Figure 2. Each observation includes standard variables, such as premium and coverage, for individual contracts. The claims data include the depth of the flood water that entered the home and the event number that FEMA assigns to catastrophes such as Hurricane Katrina, to distinguish them from localized "nuisance" floods.

I impose several sample restrictions. First, I restrict the analysis to houses in high-risk flood zones because the minimum elevation requirements and the variation in flood insurance prices from Congressional reform target houses in these areas. Second, I limit the analysis to single-family primary residences. Price increases differentially affect business owners, multi-unit property managers, and owners of vacation homes, who may have different incentives and risk aversion than homeowners.[15] Appendix C.1 describes additional restrictions imposed during the data cleaning, such as excluding houses that have negative coverage totals or that are missing key variables. The final sample includes 11,983,183 policies. Throughout, all monetary values are deflated to 2017 dollars using the consumer price index for housing, unless otherwise stated.

Spatial Data on Flood Zones – I use geographic information system data on flood zone designations from the National Flood Hazard Layer (NFHL). The NFHL is a digital map layer that covers 90% of the U.S. surface area and delineates NFIP flood zones and communities. It also includes georeferenced information such as community identification numbers and initial flood map years.

Housing – The housing data set is from the Zillow Transaction and Assessment Database (ZTRAX). It comprises parcel-level tax assessment data on the universe of residential properties in the 20 Atlantic and Gulf Coast states. Using the latitude and longitude coordinates for each property, I determine the flood zone for each house in the entire eastern U.S. by spatially linking the housing data with the NFHL. I also match each house to its NFIP community to determine if it was built before or after its community's initial flood map, i.e., whether it is an adapted house. I impose the same sample restrictions as for the insurance data. I exclude houses built during the time period of the analysis so that the composition of the adapted control group does not change.

[15] High-risk properties account for around 80% of policies and two-thirds of claims (Kousky et al., 2016). Single-family primary residences account for about 70% of policies (NRC, 2015).

The main analysis focuses on a panel of 13,433,549 observations of houses in high-risk flood zones built within a 30-year window centered on the year of their community's first map.

Federal FOIA disclosure laws prohibit the release of addresses in the insurance data. However, the policy variation that I exploit differentially affects houses depending on their flood zone and when they were constructed relative to the community's first flood map. This means that I need to know only the average payouts and insured shares of adapted and non-adapted houses in high-risk flood zones. Therefore, I link individual policies to houses based on construction year, zip code, community identification number, and flood zone. Appendix C.1 discusses possible sources of measurement error in these variables, such as flood map updates, and Appendix C.2 describes the matching procedure in detail.

4 Stylized Facts

This section presents descriptive evidence on flood insurance purchasing behavior from merging the microdata on houses, insurance contracts, and claims throughout the Atlantic and Gulf Coast states. The stylized facts are based on Table 1, which shows comparative summary statistics for adapted and non-adapted houses in high-risk flood zones for the years 2001 to 2017. Panel A summarizes demand; Panel B summarizes insurer costs conditional on the purchase of a policy. Panel B includes all policies written for high-risk houses to provide a complete picture of insurer costs. Some county tax assessment offices do not collect house construction year, and so approximately 70% of these policies are matched to houses.[16]

First, homeowners' purchased coverage amounts provide full insurance against realized damages from most floods. Purchased coverage exceeds \$200,000, but the average claim is made for \$60,000. In general, coverage purchased is non-binding for 93% of claims, and damages are fully reimbursed. This fact reduces concern about the empirical relevance of intensive margin selection, which arises when homeowners who purchase more generous coverage make higher claims (Einav et al., 2010). This also provides an empirical foundation for modeling flood insurance policies as full insurance contracts.

Second, the average subsidy to homeowners in high-risk flood zones is about 30% (\$1.85 per \$1,000 of coverage, or \$450 total) during the 17 years of this study.[17] This *ex post* subsidy is heterogeneous across both space and time. Figure 2 shows that high-risk homeowners in some counties receive more payouts than they pay in premia during the time period of this study, but

[16]Appendix Table A.1 shows comparative summary statistics for matched and unmatched policies. The main difference is that payouts are lower in the matched subsample. This is because Louisiana does not collect house construction year for 88% of tax assessment records, and so the matched subsample excludes Hurricane Katrina. Louisiana accounts for almost 40% of the unmatched policies.

[17]Model-based estimates of subsidies vary (CBO, 2017; GAO, 2014; Kunreuther et al., 2017), while estimates based on statutory discounts are similar or larger (Bakkensen and Ma, 2019). The fact that the NFIP includes statutory subsidies in the rate schedule suggests that flood insurance is subsidized relative to both the *ex post* costs that I observe and *ex ante* expected costs.

many do not. Figure 3 shows that the time series of payouts to high-risk homeowners is highly variable. In years with relative little flooding, prices exceed payouts on average. Hurricane Katrina in 2005 is both an expensive loss year for the NFIP and a large subsidy to Louisiana residents.[18]

Third, insurance take-up rates are low. Fewer than 60% of homeowners in high-risk flood zones purchase flood insurance. This finding corroborates take-up rates based on smaller geographies or aggregate data (NRC, 2015). This low take-up rate is surprising given subsidies of about 30% of realized average cost. Appendix Figure A.5 shows that average take-up rates are higher in communities that are subsidized during this time period, but are still well below 100%.[19] However, insurance purchase decisions are based on a household's own costs, and not on the average cost of the insured population. A finding that marginal homeowners are 30% less costly to insure than average could rationalize this stylized fact. The following section tests for selection on private information to assess whether such selection can explain this low take-up through willingness to pay and costs alone. Section 7.1 carefully considers other possible explanations.

5 Econometric Model

5.1 Effects of Price and Adaptation on Demand and Cost

I estimate homeowners' willingness to pay and cost curves and test for selection by exploiting the price changes mandated by the Biggert-Waters and HFIAA reforms and the differences in the minimum elevation requirements for adapted and non-adapted houses. Biggert-Waters and the HFIAA increased flood insurance prices only for non-adapted houses beginning in 2013, and I use this exogenous policy variation to construct an instrument for prices. The main estimating equation is:

$$y_{it} = \rho p_{it} + \beta 1[adapted_i = 1] + \lambda_{zt} + \nu_{zdf} + \tau_{fdt} + \epsilon_{it} \tag{2}$$

In this equation, the variable y_{it} is a demand outcome (i.e., a purchased coverage amount or an indicator for purchasing an insurance contract) or a cost outcome (i.e., a payout amount per \$1,000 of insurance coverage or an indicator for making a claim) in year t for house i. The variable p_{it} is the price per \$1,000 of insurance coverage and the variable $1[adapted_i = 1]$ equals 1 for houses that are subject to the adaptation policy (i.e., minimum elevation requirements). The first parameter of interest, ρ, measures the average effect of a \$1 increase in the price of flood insurance on the demand and cost outcomes. If there is adverse selection on residual information that is uncorrelated with the model covariates, increasing prices leads to higher average costs of

[18] Figure 3 is consistent with aggregate FEMA payouts. Total NFIP claims during Hurricane Katrina exceeded the total amount paid out in all years before 2005 (AIR, 2005).

[19] A positive correlation between average take-up and subsidies is expected because many homeowners purchase insurance after floods (Gallagher, 2014). Appendix Figure A.5 compares subsidies and take-up for the same sample, while the overall subsidy is calculated based on matched and unmatched high-risk policies. Back-of-the envelope calculations using the total number of houses and policies suggest that overall take-up may be around 5% higher.

homeowners who remain insured, and so ρ will be positive in the regressions where payout is the dependent variable; ρ negative is advantageous selection. The second parameter of interest is β, which measures the mean effect of the adaptation policy on demand and cost. Adapted houses pay lower prices for insurance even before the price reform; this specification estimates the effect of the adaptation policy holding prices constant. If selection on adaptation is important, adapted houses are less likely to be insured and less costly to insure, and so β will be negative in regressions where demand or cost are the dependent variables. The error term ϵ_{it} captures unobserved influences on a homeowners' demand and cost in a given year. Throughout the paper, standard errors are clustered at the community level to allow arbitrary correlation in the error terms of neighboring houses that are mapped in the same year.

I use three sets of important covariates to control for temporal and geographic variation in flood severity that could drive changes in demand or cost that are unrelated to prices or adaptation. Unlike other types of insurance such as health, where total annual costs are smooth on average, floods vary in magnitude depending on the severity of the hurricane year, are highly spatially correlated, and may strike areas with concentrations of houses built in different years. The first set of covariates used to address these distinguishing market feastures are zip code×year fixed effects λ_{zt}, which control for the average flood experience of each zip code in each year. These fixed effects are important because houses built in high-risk flood zones before construction code changes are concentrated in different parts of the country from houses built after, as shown in Appendix Figure A.4.

I also include decade built×flood severity linear time trends τ_{fdt}. Table 1 shows that adapted houses purchase more coverage, which could reflect higher value of newer construction. Decade built time trends control for differential appreciation of newer and older houses between calendar years 2001 and 2017; I allow for differential appreciation of houses of the same vintage that are struck by floods of different severity.[20]

Zip code×decade built×flood severity fixed effects ν_{zdf} control for the high variance of flood severity across years and for determinants of the rate schedule (i.e., house vintage and local flood zone). These controls are important for two main reasons. First, Figure 3 shows that the variation in flood severity between years is much larger than the variation in prices; in the extreme case where no flood occurs, costs for adapted and non-adapted houses are mechanically identical and equal to zero, regardless of prices. Therefore, to identify the effect of panel variation in prices on insurer costs in equation (2), we want to compare outcomes for houses that experience similar floods before and after the reform. Second, the cost reduction provided by adaptation increases in flood severity, as I show below. Hence, the difference in costs between adapted and non-adapted houses

[20] If decade built time trends are excluded, intensive margin demand slopes upward. Deflating total coverage to $2017 makes it appear that adapted houses purchase more insurance in the early years of the sample because nominal coverage is about 15% higher for these houses, in all years. This effect vanishes when controlling for differential trends in the value of new and old construction using decade built time trends or estimating the effect on nominal coverage, as shown in Appendix Table A.5.

increases for more severe floods and for newer construction subject to more stringent construction standards. The inclusion of these controls helps to ensure that differences in costs in each year are unrelated to idiosyncratic differences in how severe floods are that year or which houses are flooded.[21]

I construct two proxies for annual flood severity in each zip code. The first are indicator variables for the quintile of the depth of flood water that enters homes in the zip code, measured from the claims data. The second are indicator variables for FEMA's classification of the worst flood event to strike each zip code in a given year (i.e., no flood, nuisance flood, or catastrophe). I interact the zip code×decade built fixed effects with both flood severity proxy variables.[22]

Conditional on the three sets of covariates, the effects of prices and adaptation in equation (2) are identified from annual differences between adapted and non-adapted houses built in the same zip code and the same decade that are struck by floods of similar severity. The test for selection on the adaptation policy is based on the correlation of the minimum elevation requirements with demand and cost, and therefore does not require exogenous variation in house characteristics.

The test for selection on unobservable determinants of natural disaster risk requires price variation that is uncorrelated with unobserved shocks to insurance demand and cost. For example, OLS estimates of the effects of prices on demand and cost in equation (2) would be biased upward (i.e., less negative) if a costly flood event, such as Hurricane Katrina, causes the NFIP to raise prices and also causes homeowners to purchase more insurance. I isolate price variation that is uncorrelated with other determinants of demand or cost by instrumenting price in equation (2) with an indicator for whether a house is treated by the Biggert-Waters and HFIAA price reforms. Specifically, the instrument is $1[t \geq 2013] \times 1[adapted_i = 1]$, where the indicator $1[t \geq 2013]$ equals 1 if an observation is from after calendar year 2012 and $1[adapted_i = 1]$ is defined above. The identifying assumption is that the price reform is the only factor that differentially affects adapted and non-adapted houses in 2013, conditional on the model covariates:

$$\mathbb{E}[(1[t \geq 2013] \times 1[adapted_i = 1]) \times \epsilon_{it} | 1[adapted_i = 1], \lambda_{zt}, \nu_{zdf}, \tau_{fdt}] = 0 \tag{3}$$

This assumption holds if no other contemporaneous factor generates different trends in demand and costs for the two types of houses. For example, controlling for flood severity addresses any unobserved trends in extreme weather that could differentially affect places with more new or old construction. I implement an indirect test of the identifying assumption by examining whether prices, demand, and costs for adapted and non-adapted houses have similar trends in the years before the reform. I estimate the coefficients ψ_t in these event study graphs from the following

[21] Consider, for example, the extreme case where there are only two zip codes, one with mostly non-adapted houses and one with mostly adapted houses. One flood event strikes the adapted houses in 2007. Prices increase for non-adapted houses beginning in 2013, but no other floods occur. Without controlling for flood severity, the market would look advantageously selected.

[22] Appendix Tables A.4, A.5, and A.6 show almost identical estimates of equation (2) for all outcomes using each flood severity proxy separately.

regression equation:

$$y_{it} = \sum_{t=2001}^{2017} \psi_t 1[year = t] \times 1[adapted_i = 1] + \Psi_{2012} 1[adapted_i = 1] + \lambda_{zt} + \nu_{zdf} + \tau_{fdt} + \epsilon_{it} \quad (4)$$

I also report the corresponding reduced form estimates of the reform using the differences-in-differences regression equation:

$$y_{it} = \theta_1 1[t \geq 2013] \times 1[adapted_i = 1] + \theta_2 1[adapted_i = 1] + \lambda_{zt} + \nu_{zdf} + \tau_{fdt} + \epsilon_{it} \quad (5)$$

Here, the parameter θ_1 measures the average effect of the price reform on adapted houses in the post-2012 period shown in the event study graphs. The parameter θ_2 measures initial differences in prices, demand, and costs for adapted houses relative to non-adapted houses. When price enters this equation as the outcome variable, this regression is the first stage of the instrumental variables model (2).

The price and demand models use 13,433,549 observations on approximately 746,308 houses in high-risk flood zones in the 20 Atlantic and Gulf Coast states between 2001 and 2017. The cost models are estimated on 11,983,183 matched and unmatched high-risk policies in these states. The cost estimates using the subsample of matched policies are similar, though less precise due to the smaller sample size. Appendix D.1 discusses the matched sample estimates, along with alternative specifications of equation (2) that include different sets of covariates.

5.2 Heterogeneous Effects by Flood Severity

The high variance of flood severity across years could drive differences in *ex post* average flood insurance costs independently of any price changes. The effect of adaptation could also vary depending on the severity of a flood and whether one occurs at all. I therefore examine heterogeneous effects of prices and adaptation for adapted houses relative to non-adapted houses that experience similar flood events before and after the reform. I estimate the following equation:

$$\begin{aligned} y_{it} = &\sum_{q=1}^{6} \alpha_{1,q} 1[t \geq 2013] \times 1[adapted_i = 1] \times 1[Q_{zt} = q] + \sum_{q=1}^{6} \alpha_{2,q} 1[adapted_i = 1] \times 1[Q_{zt} = q] \\ &+ \sum_{q=1}^{6} \alpha_{3,q} 1[t \geq 2013] \times 1[Q_{zt} = q] + \lambda_{zt} + \nu_{df} + \tau_{fdt} + \epsilon_{it} \quad (6) \end{aligned}$$

In this equation, $1[Q_{zt} = q]$ is an indicator for flood severity in zip code z and year t. The parameters $\alpha_{1,q}$ measure the effects of the price changes from Biggert-Waters and the HFIAA on the outcomes y_{it} for adapted houses relative to non-adapted houses, conditional on experiencing similar floods. The parameters $\alpha_{2,q}$ measure the importance of adaptation in increasingly severe floods. I measure flood severity using six categories of monotonically increasing water depth, defined using the water depth quintile and FEMA's classification of the flood event type as above and described in detail in Appendix C.1.[23] Appendix Table A.8 shows that the results are invariant if flood severity is defined using fewer water depth categories or only using the flood event type.

To examine the average effect of adaptation on demand and cost across all flood categories, I also plot the share of insured homeowners and average payout by year of construction of the house relative to the year that its community is mapped. The coefficients γ_Δ are estimated from the regression equation:

$$y_{it} = \Sigma_{\Delta=-10}^{\Delta=10}\gamma_\Delta 1[year\,built_i - year\,map_c = \Delta] + \lambda_{zt} + \nu_{df} + \tau_{fdt} + \epsilon_{it} \tag{7}$$

In this equation, Δ measures the number of years between the year of construction of house i and the year of the initial flood map in the house's community c. The figures plot γ_Δ plus the mean for adapted houses built in the year after the community is mapped (i.e., $\Delta = 1$). I focus on the instrumental variables estimates of equation (2) that control for both prices and adaptation, rather than regression discontinuity-type estimates of the differences in demand and cost shown in these graphs. I do so because adapted and non-adapted houses face both different construction codes and different prices.[24] Appendix Figure A.8 shows that these differences are large.

6 Results

6.1 Demand

Figure 4.a shows clearly that the HFIAA and Biggert-Waters reform decreased insurance prices for adapted houses relative to non-adapted house as of 2013. By 2017, relative prices for adapted houses have fallen by \$1 per \$1,000 of coverage. The estimated average effect of the reform is an 18% decline in the relative price of insurance (Table 2). This provides a strong first stage for the subsequent instrumental variables analysis (Stock and Yogo, 2005). The lack of a pre-trend in the years before the reform supports the idea that any changes in demand and cost after 2012 can be attributed to this price change.

How does this price change affect demand? After the reform, adapted homeowners are on average 1.9 percentage points more likely to purchase insurance (Table 3, Panel A). Figure 4.b shows that, beginning in 2013, there is a statistically significant increase in the relative share of adapted houses that are insured, and demand increases as relative prices continue to decline. Five years after the reform, adapted houses are about four percentage points more likely to be insured. This is a significant seven percent change in demand because uptake is low even before

[23]Equation (6) is a triple-difference regression that overlays the water depth indicators on the differences-in-differences regression (5). The water depth categories are defined at the zip code×year level, and so these do not enter (6) separately from the zip code×year fixed effects. The other covariates are interacted with the flood severity proxies, which are co-linear with the water depth indicators.

[24]Appendix Figure A.9 provides some evidence that the elevation requirement binds: adapted houses that purchase insurance are built 1 foot above the minimum requirement on average. Approximately 93% of adapted houses that purchase insurance at built at or above the minimum requirement.

the price change. Demand in the years before the reform is statistically indistinguishable from demand in 2012. There is also no reaction to the announcement of the price increases in 2012, which suggests that the change in demand is due to the price changes in 2013, rather than salience or information effects that could be correlated with the reform. The event study graphs that separately examine the shares of houses purchasing any building coverage or any contents coverage have similar patterns as the graph for the share of houses purchasing any policy (Appendix Figure A.11).

Insurance demand depends on adaptation as well as on prices. Figure 5.a summarizes demand by year of house construction relative to the year the house's community is mapped, and shows that, despite their lower insurance prices, adapted houses are significantly less likely to be insured. The instrumental variables estimates separately identify the effects of both prices and adaptation on demand (Table 3, Panel B). The price effect is consistent with the event study graphs in time: a $1 increase in the price of $1,000 of insurance coverage reduces the probability of purchasing any insurance by 2.7 percentage points. This estimate is the slope of the observed demand curve, s_p, and implies a price elasticity of about -0.25 (i.e., relatively inelastic).[25]

As Figure 5.a suggests, the adaptation effect is substantial: houses that are required to be elevated are about 25% less likely to be insured, conditional on prices. The coefficients on adaptation are larger in the instrumental variables regressions than in the differences-in-differences regressions because the instrumental variables models control for prices; the mean effect of adaptation in the differences-in-differences regressions combines the shift inward of the demand curve from the reduction in risk with the offsetting movement along the demand curve from the lower prices paid by elevated houses. The instrumental variables estimates of the adaptation effect isolate the large inward shift of the demand curve. This result suggests that homeowners treat adaptation policy as a substitute to formal insurance. One possible explanation is that the average house elevation of 10 feet conveys a strong visible signal that adapted houses are safer and that the expected benefit from flood insurance is lower.

Conversely, Table 4 shows that the intensive margin price response is small, conditional on purchase. The relative amount of total coverage purchased by adapted houses in the post-reform period increases by a marginally statistically significant 1% (Panel A).[26] There is some evidence that the Biggert-Waters reform had a similar, marginally statistically significant effect on house prices (Gibson et al., 2019). This small intensive margin elasticity and the descriptive evidence of full insurance on the intensive margin discussed previously suggests that homeowners may generally

[25] There are few existing estimates against which to compare this natural disaster insurance price elasticity. Model-derived estimates and case studies that use panel regressions without any quasi-experimental variation estimate price elasticities for flood insurance in the range of -0.49 to -0.06 (NRC, 2015). My estimate is close to health insurance price elasticities (e.g., Hackmann et al., 2015).

[26] The limited intensive margin response emphasizes that average price changes are due to changes in the list price, and not purchased coverage. Appendix Table A.4 also shows that the demand elasticity is robust to using predicted prices based only on elements of the NFIP rate schedule.

insure the value of their house, and purchase less coverage in response to declining property value. The limited house price effect also suggests that resorting of homeowners plays a relatively small role in the response to the reform. Consistent with the higher value of newer construction, coverage purchased for adapted houses is about 10% higher than for older, non-adapted houses.

The instrumental variables estimates are robust to many sensitivity analyses, but differ substantially from the OLS estimates. Appendix Table A.4 shows that instrumenting for prices is important because the OLS estimate of the effect of prices on extensive margin demand is biased upward, consistent with both prices and take-up responding positively to floods. Appendix Tables A.4 and A.7 also show instrumental variables estimates of the effects of prices and adaptation on extensive margin demand are similar to the main estimates in sign, magnitude, and precision using different covariates, restricting to subsamples of the data, and estimating using probit. Appendix Table A.5 shows sensitivity analyses for intensive margin demand, which are generally qualitatively similar but are more sensitive to the inclusion of decade built time trends due to plausible differences in the trends in value of new and old construction. The OLS results of the effect of prices on intensive margin demand are biased downward. The direction of this bias is consistent with both price increases after floods and coverage choices that reflect declining house value after floods. Appendix D.1 discusses all of these results in detail.

6.2 Insurer Costs

I now turn to discuss the effects of prices and adaptation on insurer costs. Since both prices and adaptation affect demand, there is the possibility for selection on both unobservable and observable determinants of natural disaster risk. If adverse (advantageous) selection on unobserved variables is important, the relatively lower prices for adapted houses will attract lower (higher) risk homeowners, and so relative average costs will fall (rise) for adapted houses after the price reform. If adverse selection on adaptation is present, houses that are subject to the adaptation policy and that are less likely to be insured will also be less costly to insure, conditional on prices.

Two main pieces of evidence suggest that selection on unobserved variables in this market is limited. First, Figure 4.c shows that the time series of relative average costs for adapted houses has no significant trend either before or after the reform; the differences in average cost after the reform are neither consistently positive or negative. Second, Figure 6 shows that the effect of price on cost is statistically indistinguishable from zero comparing houses that experience floods of similar severity before and after the reform. This figure shows the differences in outcomes for adapted and non-adapted houses for six increasing water depths (in blue), and the effect of the price reform on these differences (in red). Consistent with the demand results from the previous section, relative prices fall for adapted houses after the reform, and demand increases. The NFIP does not price on location-specific risk, and so the decline in prices is the same regardless of flood severity, with no effect on cost (Figure 6.c). Appendix Tables A.8 and A.9, which use different flood severity metrics or exclude Hurricane Katrina, all show that the effect of price on cost is statistically indistinguishable from zero, small in magnitude, and neither consistently positive or negative.[27]

Consistent with these event study graphs, Table 5 suggests that there is no systematic selection on unobservables. Both the reduced form and the instrumental variables estimates show that prices have no significant effect on either claim probability or average cost. The effect of price on cost is generally a precisely estimated zero except when comparing houses that experience the worst flooding (i.e., "depth 6", which includes highly variable hurricanes). Figure 6.c indicates that the variance of the average cost elasticity estimate is driven by the most catastrophic floods: the cost elasticity estimate is a much less precisely estimated zero effect for the flood category that includes these extremely variable events, compared with the estimates for less severe floods. Pooling floods of all severity, the high cost variance across years that characterizes this setting reduces the precision of the estimated average effect of price on cost. The estimate in Table 5 and those in Appendix Table A.6 that use similar flood severity controls are all noisier than the demand elasticity estimates, and the most precise of these only allows us to reject cost elasticity estimates in excess of 0.19 with 95% confdence—about half of cost elasticity estimates in the health insurance setting (Hackmann et al., 2015). However, the time series of relative average costs excluding the 13% of houses in zip codes experiencing highly variable hurricanes shows a very precise zero effect of the reform (Appendix Figure A.10 and Appendix Table A.6), which is consistent with the separate cost elasticity estimates by flood severity (Figure 6.c and Table 6).[28] Excluding the variability of these catastrophes, cost elasticity estimates in excess of 0.04 (i.e., 25% of the elasticity needed to explain low uptake, or 10% of health cost elasticity estimates) can be rejected with 95% confidence.

By contrast, the event study graphs and regression estimates suggest that selection on observable house characteristics is important. Figures 5 and 6 show that adapted houses are both less likely to purchase insurance and less costly to insure. Costs are about one-third lower for adapted houses on average (Figure 5.b), but there is significant heterogeneity in the cost reduction from the adaptation policy depending on the severity of the flood (Figure 6.c). The difference in costs between adapted and non-adapted houses is mechanically equal to zero if no flood occurs, but is statistically and economically important during more severe floods. Costs for adapted houses are almost 40% lower during the most catastrophic floods. These results help explain why the coefficients in the aggregate time series of costs in Figure 4.c vary around zero depending on whether a given year involves catastrophic losses (e.g., Hurricane Katrina in 2005) or little flooding (e.g., 2009-2010).

Table 5 also underscores the reduction in claim probability and average payout from adaptation

[27] The graphs for claim probability show the same patterns (Appendix Figures A.11.f and A.12.b).

[28] It seems plausible that homeowners may be less able to predict their costs during tail events than during smaller floods, and hence we might expect homeowners to have *less* private information about their costs during hurricanes relative to insurance models.

(Panel B). Specifically, adapted houses are 18% less likely to make a claim and are 31% less costly to insure on average.[29] I emphasize that the instrumental variables regressions control for prices and isolate the inward shift of the cost curve from the adaptation policy. Since these results are based on *ex ante* differences in house characteristics rather than varying the elevation of houses, these estimates measure the long-run effect of the adaptation policy on homeowners' joint decisions over whether to purchase insurance and adapted houses.[30]

Overall, this evidence suggests that there is adverse selection on house elevation, but that there is limited private information that is correlated with willingness to pay. Despite the NFIP's coarse rate schedule, homeowners seem to have less private information about natural disaster risk than about their risks of poor health (Einav et al., 2010), unemployment (Landais et al., 2018), death (Finkelstein and Poterba, 2014), and disability (Hendren, 2013). The lack of evidence of selection on private information in this market can perhaps be attributed to infrequent risk realizations and out-of-date flood maps (DHS, 2017). Though I find no systematic evidence of asymmetric information, whether houses are subject to elevation requirements is an example of "asymmetrically used" information by insurers because adapted houses are still less costly conditional on the differential rate schedule (Finkelstein and Poterba, 2014). These results suggest that price adjustments that account for house elevation are efficient and seem unlikely to lead to substantial changes in average costs.

Appendix Table A.6 presents OLS estimates and sensitivity analyses of the effects of prices and adaptation on average costs, and Appendix D.1 discusses these other results. The OLS estimates are biased upward substantially in a way that is consistent with the NFIP increasing prices in response to costly flood events. Importantly, without instrumenting for prices, the market looks adversely selected. The sensitivity analyses estimate the instrumental variables models controlling for different sets of covariates, restricting to subsamples of the data, and excluding Louisiana and the effects of Hurricane Katrina. Most of these estimates are similar to the main estimates in sign, magnitude, and precision, though some estimates on smaller data samples are less precise.

[29] I do not estimate log specifications because only 2% of policies have non-zero claims. Appendix Table A.6 shows estimates with inverse hyperbolic sine transformations.

[30] To calculate the welfare effect of subsidizing adaptation, the cost curves should be net of the cost of implementing the adaptation policy. Depending on the foundation type, elevating an existing house costs between $15,000 and $150,000, but elevating during construction costs only $5,000 (Hurley, 2017). Comparing Table 6 and Appendix Table A.2 suggests that adapted houses are about $3,000 less costly to insure during floods that average 0.33-ft in the zip code. This back-of-the-envelope calculation suggests that adding an elevated foundation during construction pays for itself in two 0.33-ft floods and elevating an existing house requires at least five 0.33-ft floods to be worthwhile. In practice, very few homeowners elevate their houses after construction.

7 Discussion and Implications for Welfare and Policy

7.1 Interpreting Low Willingness To Pay

An important implication of the results in the previous section is that adverse selection appears unable rationalize low levels of flood insurance uptake: observed willingness to pay is 30% below *own* costs at current prices. Figure 1.b shows the empirical marginal cost curve $MC(p, \alpha, \phi)$ and observed willingness to pay curve $D(p, \alpha, \phi)$ for non-adapted houses; Appendix Figure A.3 shows the graph for the pooled market. The pre-reform levels of price, average cost, and share insured are the initial equilibrium at p'. I estimate a slope of $s_p = -0.03$ ($s.e. = 0.01$) for demand (Table 3). Neither the event study graphs or the regression estimates provide evidence of selection on unobservables after controlling for differences in house elevation. This has two implications for the graphical representation of the market. First, the marginal cost curve is locally flat, rather than downward-sloping, in the price-share insured space. Second, average and marginal costs are equal across the range of the willingness to pay distribution that I observe, which means that current prices are below homeowners' expected benefit from insurance.[31] Though marginal and average costs may look different in the tails of the willingness to pay distribution, extrapolating outside the range of observed prices suggests that willingness to pay is below cost for approximately 50% of homeowners.

Several standard explanations, other than adverse selection, may contribute to low take-up, though many seem unable to substantially explain the wedge between observed willingness to pay and own cost for uninsured homeowners. The first possible explanation is that public bail-outs depress insurance demand. Finkelstein et al. (2019b) suggest that the fact that uninsured individuals typically do not pay their full medical costs could explain much of the similar wedge between willingness to pay and cost in the low-income Affordable Care Act exchange in Massachussetts. Such "uncompensated care" exists in flood insurance markets as well: uninsured homeowners have three public funding options if they are flooded and they are uninsured. First, they can apply for a grant from FEMA's Individuals and Households Program. These grants are capped at \$33,000, though the average payout over the program's lifetime is \$4,500. A second funding option is a low-interest Small Business Administration loan, which must be repaid. Finally, homeowners can apply for Community Development Block Grant Recovery assistance, which is administered by state and local officials and capped at an amount specific to each disaster event. Homeowners can apply to receive both block grants and flood insurance, and carrying flood insurance can increase the maximum available grant (Horn, 2018).

Unlike in health insurance markets, however, the magnitudes of these public bail-out options seem unable to rationalize much of the wedge between own cost and willingness to pay for natu-

[31] I estimate the slopes of the demand and cost curves across adapted and non-adapted houses, which implicitly assumes that adaptation shifts the levels of demand and cost but not the slopes. Appendix E.1 relaxes the assumption of linearity.

ral disaster insurance. The average payout from the Individuals and Households Program is less than 10% of the average flood insurance payout, and closes less than 15% of the wedge.[32] While public assistance in low-income health insurance exchanges could explain the wedge in those markets, public post-natural disaster assistance would have to be more than ten times actual average receipts in order to close the corresponding wedge in natural disaster insurance markets. The $54,000 average bail-out required to fully explain the extent of uninsurance actually exceeds the program's grant limit by more than $20,000, or 66%. By contrast, homeowners report expecting federal assistance to cover more or less what they actually receive (i.e., around 10% of damages) (Bakkensen and Barrage, 2019), though mistaken expectations could be one of several possible behavioral frictions in this setting. Small Business Administration loans and Community Development Block Grants appear unable to rationalize any of the wedge because homeowners must repay them or can apply for them regardless of whether they have flood insurance, respectively. Overall, while these bail-outs provide homeowners with much-needed sources of post-disaster funds, their relative contribution to low uptake seems to be smaller than in other settings where willingness to pay for insurance is puzzlingly low.

A second possible explanation for low uptake is moral hazard, which may play some role but which also seems to fall short of rationalizing why willingness to pay is so low. Homeowners' value of insurance would fall if they would have avoided some of their flood damages if they were uninsured. However, I estimate that an elevated foundation reduces cost by $2.64 per $1,000 of insurance. Therefore, even in the extreme case where purchasing insurance substitutes for elevating one's house, such moral hazard would explain at most 25% of the wedge between willingness to pay and expected payouts for uninsured homeowners.

Third, observed patterns of homeowner behavior suggest that hassle costs are not the primary barrier to take-up. The initial purchase of a flood insurance policy seems to involve some hassle to acquire purchase information, arrange for an assessor to visit the house and measure its elevation, and file paperwork. However, homeowners are most likely to buy flood insurance shortly after purchasing their house, when any mandatory purchase requirement is most likely to bind, but often let their policy lapse the following year (NRC, 2015). This evidence suggests that the contribution of hassle costs to low take-up is small because the time and information costs associated with the initial purchase of the policy are greater than the costs of remaining enrolled. Renewal simply involves mailing a check or paying online.[33]

Fourth, some homeowners may be uninsured because the net benefit from insurance is smaller than their home equity and the costs of walking away from their mortgage (i.e., credit score penalties and moving costs). Such limited liability may be important for some low-income homeowners,

[32] For example, the average Individual and Households Program grant after Hurricane Harvey in 2017 was $4,400. The average flood insurance payout was $117,000 (Horn and Webel, 2019). FEMA states that these grants do not replace flood insurance, but rather "return the primary home to a safe and sanitary or functioning condition" (FEMA, 2019a).

[33] This pattern of take-up and subsequent non-renewal also suggests that inertia is unlikely to explain low uptake.

but seems unlikely to be the primary explanation. Using American Community Survey data, I calculate that about 45% of homeowners in the zip codes in the analysis own 100% of their homes. Over 75% of homeowners have at least 20% equity, which is roughly equal to the average flood insurance payout if a claim is made. Almost all homeowners have some equity from their down payment (Li and Goodman, 2016). More concretely, Ouazad and Kahn (2019) estimate that hurricanes increase the probability of foreclosure by only 1.6 percentage points, which seems too small to explain why over 40% of homeowners are uninsured. This study does not find any heterogeneity in the riskiness of loans inside and outside of high-risk flood zones after floods. Moreover, Gallagher and Hartley (2017) find that homeowners *with* flood insurance are more likely to move after floods because they use claims receipts to pay off their mortgages.

Fifth, credit constraints more generally could contribute to low willingness to pay, though also seem unlikely to explain the extent of uninsurance. Gallagher (2014) documents that insurance take-up increases after flood events, which suggests that many uninsured homeowners can afford flood insurance, but choose not to purchase it. Though there is likely important income heterogeneity in high-risk flood zones, these areas are also characterized by highly desirable coastal amenities, and this amenity value is not offset by flood zone designations (Bin et al., 2008). As a result, income in high-risk flood zones is generally above average, and flood insurance premia are only about 1% of median household income (CBO, 2017).

A sixth explanation for low willingness to pay is misperception of risk, which could play an important role. My results seem to be consistent with existing research that shows that homeowners underestimate the probability of experiencing a flood. For example, Bakkensen and Barrage (2019) find survey evidence that about 40% of high-risk flood zone residents report being "not at all worried about flooding in the next decade", which suggests a low perceived benefit of insurance. More generally, this survey and others find that 60-70% of coastal homeowners underestimate their flood risk relative to FEMA's models, which are conservative, and independent property-specific assessments (Bakkensen and Barrage, 2019; Royal and Walls, 2019). These studies also find that homeowners update their flood risk beliefs after being flooded, which is consistent with observed increases in insurance take-up after floods (Gallagher, 2014). Homeowners' lack of understanding of their own risk, driven perhaps by infrequency of floods, may help explain the lack of evidence of selection on private information in this market.[34]

Housing markets provide additional support for the hypothesis that homeowners could underestimate their true flood risk in important ways. The weak capitalization of flood zone designations into home values supports incomplete internalization of risk (Beltran et al., 2018). Gibson et al. (2019) also show that flood map updates decrease property values, and that a recent flood strongly attenuates the effect of this new information on house prices. If homeowners accurately perceive

[34] Models of insurance demand that assume that willingness to pay is observed after the individual receives information about their risk profile seem less applicable to natural disaster insurance markets, which lack such informative signals (Hendren, 2019).

their risk, we would not expect such belief updating, nor differences between houses that have and have not flooded.

There is also some uncertainty around the magnitude of expected costs in the tail of the willingness to pay distribution. Estimating the full distribution of *ex ante* expected costs is of particular interest for natural disaster insurance markets, where claims are typically driven by loss events that are more extreme and infrequent than most other insurance markets. For example, Florida did not receive a major hurricane during the 17 years of this study, though it is reasonable to expect that they may do so in the future. By contrast, Appendix Table A.1 shows that if the most catastrophic flood during the study time period (Hurricane Katrina) is excluded, average cost and price are approximately equal. A significant wedge remains for the 40% of homeowners with lower willingness to pay than the marginal homeowner, but discounting this one catastrophe can explain about 45% of the overall wedge. The statutory discounts in the NFIP rate tables support that many homeowners receive substantial subsidies relative to actuarial cost estimates (Bakkensen and Ma, 2019; CBO, 2017). Discounting of the tail events that characterize this market may therefore be yet another factor contributing to low uptake.

Overall, several explanations appear to be important for rationalizing remarkably low willingness to pay for natural disaster insurance, and there is significant uncertainty regarding the contribution of many. However, it seems plausible that behavioral frictions, such as risk misperception, are a key part of this puzzle. Ericson and Snydor (2017) discuss other behavioral biases, such as inertia, inattention, and myopia, that have been shown to be consequential in other insurance markets. Many of these biases have not been explored in natural disaster insurance markets and may also depress demand. Such frictions have important implications for the welfare effects of proposed natural disaster insurance reforms, which I turn now to discuss.

7.2 Welfare Implications

The plausible importance of frictions in take-up in this setting suggests that caution is advisable in interpreting homeowners' revealed preference demand as their true valuation of insurance and using it as the basis for evaluating proposed reforms. Figure 1.b shows the empirical observed willingness to pay curve as well as the marginal cost curve for non-adapted houses based on the results from the previous section. Since this observed willingness to pay curve seems to reflect decisions that exclude some of the benefit of insurance, welfare analysis requires information on the frictionless willingness to pay curve.

The extent to which expected payouts exceed observed willingness to pay underestimates the possible distortion in demand because homeowners should be willing to pay a risk premium above marginal cost. Appendix B shows that calculating the risk premium requires information on two additional parameters: a coefficient of absolute risk aversion and the effect of insurance on the variance of consumption.[35] These parameters have not yet been estimated for natural disaster

[35] Some consumption data sets, such as the Panel Study of Income Dynamics, include information on other

insurance, but estimates from the health and property insurance literatures suggest that the magnitude of the risk premium in this setting may be large.[36]

Natural disaster insurance appears to provide a valuable consumption smoothing mechanism against low-probability, high-cost extreme weather events. For example, calibrating the coefficient of absolute risk aversion using estimates from the literature and the effect of insurance on the consumption variance using the observed variance of payouts combined with estimates of the effects of floods on household finance yields an average risk premium of approximately \$90 per \$1000 of insurance coverage. Appendix E provides the details of this calibration. Though these estimates of the risk premia require simplifying assumptions, they suggest overall that many homeowners would benefit in expectation from purchasing natural disaster insurance. These risk premia also exclude the value of insurance against correlated shocks to land and labor income.

Accounting for the potential for optimization frictions to distort demand significantly changes policy recommendations in this setting. First, if willingness to pay is low because of behavioral frictions, increasing prices to be actuarially fair decreases social welfare—the opposite sign of the welfare effect based on revealed preference demand. Figure 1.b shows that in this case it is efficient to insure the 15% of homeowners who cease to purchase insurance after increasing prices to equal expected cost. The welfare loss from the price increase, shown as the dark grey area between the frictionless willingness to pay and cost curves, appears to be large: for example, the calibration in Appendix E yields a welfare loss of \$1,770 per high-risk homeowner, per year, or \$3.7 billion total. By contrast, using revealed preference demand to calculate the welfare effect of actuarially fair prices leads to a perceived welfare gain of about \$30 per high-risk homeowner, per year (\$60 million total), shown in light grey. The welfare effect has the opposite sign because the wedge between frictionless and observed willingness to pay is large enough to drive observed willingness to pay *below* marginal cost, so that increasing prices looks efficient.[37]

Second, expanding requirements to purchase flood insurance is welfare-improving in the presence of frictions. In the textbook setting of an adversely selected market, government mandates are beneficial because average cost pricing by private insurers leads to inefficient underinsurance. Here, a mandate is useful even in the absence of private information because it appears to correct distortions in demand from any frictions in uptake.[38] Appendix E estimates that this welfare gain

insurance types such as health, but not floods (Gruber, 1997; Finkelstein et al., 2019a). Other insurance valuation methods require either assuming that envelope conditions hold (i.e., no optimization frictions) or completely specifying the effect of insurance on all arguments of the utility function (Finkelstein et al., 2019a).

[36] Risk aversion may differ from these other settings if other natural disaster risks are correlated with financial risk (Einav et al., 2012). The effect of natural disaster insurance on the variance of consumption, which requires information on the conditional distribution of consumption for individuals with and without flood insurance, is also unobserved. Appendix E discusses how to use the observed overall variance of payouts to bound the risk premium.

[37] These qualitative conclusions also apply to local price changes that are less reliant on functional form assumptions outside the range of observed prices; Figure 1.b shows that the realized price increase from Biggert-Waters and the HFIAA, which closed about one-third of the gap between initial and actuarially fair prices, appears to cause a welfare decline.

[38] The intuition for a natural disaster insurance mandate parallels the motivation for Corporate Average Full

may be as large as \$3,500 to \$8,000 per high-risk homeowner, per year.

If behavioral frictions are important, then actuarially fair prices combined with a mandate seem likely to lead homeowners to make more efficient decisions than either policy in isolation. Unlike other types of insurance, natural disaster insurance subsidies encourage homeowners to move to at-risk areas, and so prices below actuarially fair levels have a social welfare cost. However, in the absence of a mandate, frictions dampen such price signals by causing homeowners to decrease insurance demand, rather than paying higher prices that more accurately reflect risk; such uninternalized flood risk inflates property values by 10% in coastal areas (Bakkensen and Barrage, 2019). Insurance price changes alone are insufficient to address both spatial distortions and frictions in uptake, and flood insurance price reform on its own has had small effects on house prices thus far (Gibson et al., 2019).

Actuarially fair prices and an insurance mandate are efficient, but raise important equity concerns. Congress reduced the 25% annual growth rate of prices implemented by Biggert-Waters partially on the grounds that low-income homeowners could not afford such price increases. To address heterogeneity in ability to pay, targeted subsidies modeled after the Affordable Care Act may be welfare-improving and could make price reform more politically feasible. Homeowners for whom credit constraints and low home equity could contribute to low willingness to pay are individuals with the highest marginal utility of consumption. It is likely efficient to insure these homeowners for distributional reasons.

8 Conclusion

This paper develops a model of natural disaster insurance markets and compiles new data in order to quantify homeowners' willingness to pay for natural disaster insurance, the costs of providing insurance to them, and the social welfare effects of proposed reforms. In so doing, this paper demonstrates three ways in which natural disaster insurance differs from more commonly studied insurance types, such as health, unemployment, and long-term care. First, frictions in uptake appear to be significant in this setting. I find that only about half of high-risk homeowners in the Atlantic and Gulf Coast U.S. are willing to pay an amount equal to their expected payout for a flood insurance contract. In comparison with other types of insurable risk, natural disasters are infrequent and catastrophic. Homeowners may be more likely to misperceive loss probabilities when informative risk realizations are lacking, which provides one plausible explanation for the wedge between observed willingness to pay for natural disaster insurance and the expected benefit that insurance provides. The extent of underinsurance against flood risk raises questions about homeowners' willingness to pay to insure against climate change risks more broadly. People are

Economy standards and subsidies for energy-intensive durable goods. Such policies are intended to correct "internalities" that consumers impose on themselves by making purchase decisions without fully accounting for lifetime energy costs (Allcott et al., 2014). Such a mandate does not require information on the precise form of the frictions, which have yet to be thoroughly explored in the literature.

gradually accepting that climate change is occurring (Leiserowitz et al., 2019), but this paper's findings suggest that they may only insure themselves after the realization of these risks.

Second, unlike other insurance types such as health or unemployment, I find no systematic evidence of adverse selection on unobservables in natural disaster insurance markets. Homeowners' lack of private information about their own risk is consistent with their overall misperception of natural disaster probabilities or with insurers' natural hazard models surpassing homeowners' ability to predict future extreme weather events. However, I show that adverse selection on observable determinants of natural disaster risk is important. Adaptation policies (i.e., minimum elevation requirements) provide salient signals about risk, and so greater adjustment of insurance prices to account for these differences would be efficient.

Third, mispricing of natural disaster insurance is particularly complex. Recent attempts to raise flood insurance prices toward actuarially fair levels have traded off political interests, fiscal solvency, and affordability. The link between property values and location-specific insurance prices adds tension to this debate. These pricing issues threaten the future of public flood insurance, with 10 short-term re-authorization bills in the last two years keeping the U.S. government in the business of backing flood risk (Horn and Webel, 2019). This paper quantifies key parameters relevant for this policy debate and suggests that the welfare loss from proposed price increases is much larger than revealed preference demand suggests. Without complementary reforms that target distortions in demand, proposed price changes could lead to substantial social welfare losses. Since adaptation reduces the financial burden on insurers by decreasing both demand and cost, subsidizing adaptation should perhaps be considered as a complement or alternative to price increases. However, government intervention in natural disaster insurance markets, through either the direct provision of insurance or in the form of policies to encourage enrollment, may be required: private insurers cannot break even if homeowners are unwilling to pay their own costs.

Additional research is needed on consumer behavior in natural disaster insurance markets to guide implementing information-based policies and modeling the primitives underlying homeowners' choices. This paper provides a framework for analyzing welfare in natural disaster insurance markets that requires few assumptions on the source of any frictions. However, this generality comes at the expense of stronger assumptions for out-of-sample predictions. Carefully designed surveys could measure the causes and correlates of frictions in uptake to microfound consumers' choices. Such information would also permit analysis of policies designed to reduce these frictions directly (Handel et al., 2019).

Overall, this paper highlights how optimal policy in natural disaster insurance markets is complicated by frictions in uptake, selection on observables, spatial distortions, and affordability concerns. Insurance against floods, wildfires, windstorms, and earthquakes all similarly reduce the impacts of high cost, low probability, and spatially correlated natural hazards. However, the public flood insurance market in the U.S. differs from many other natural disaster insurance markets, which are mostly private and often bundle natural disaster coverage with other perils.

Important questions about the design of these private markets remain unanswered. The potential welfare effects that hinge on the choice of policy instruments in all of these markets are large because of the high cost of extreme weather events. Natural disasters that already cause hundreds of billions of dollars of damage are intensifying (IPCC, 2018). In light of the amount at stake, optimal natural disaster insurance market design should be an academic and policy priority.

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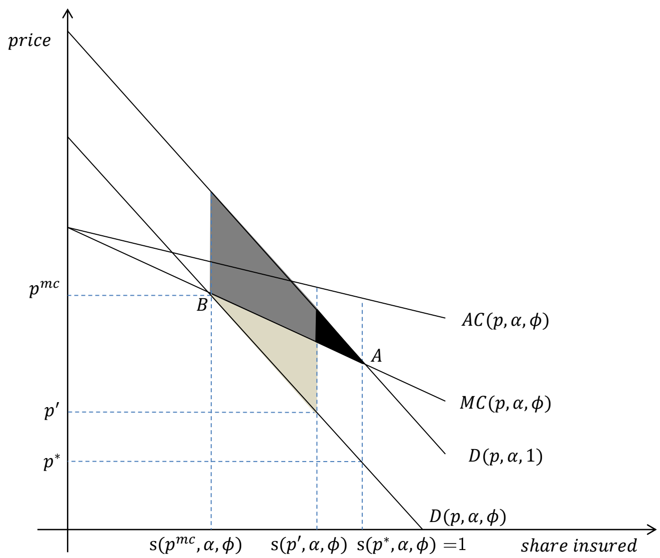
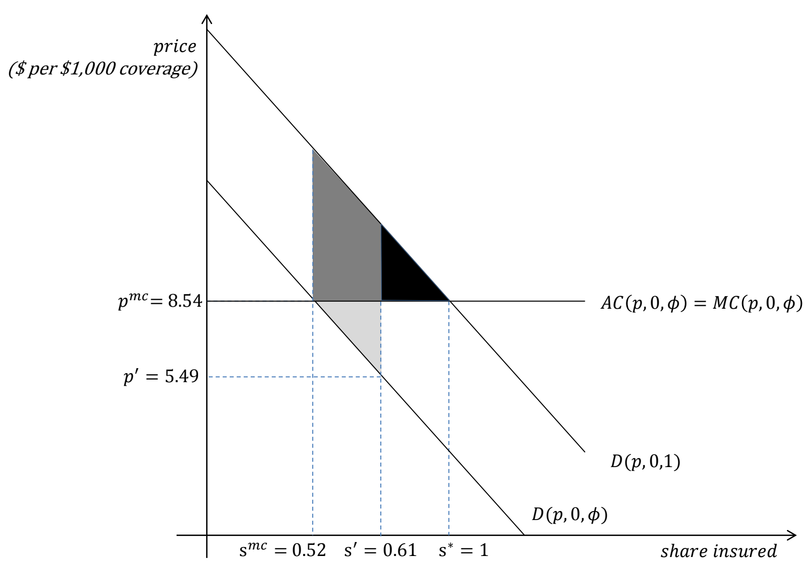
Figures and Tables

Figure 1: Graphical Approach to Selection

Panel A: Theoretical Natural Disaster Insurance Market Equilibrium

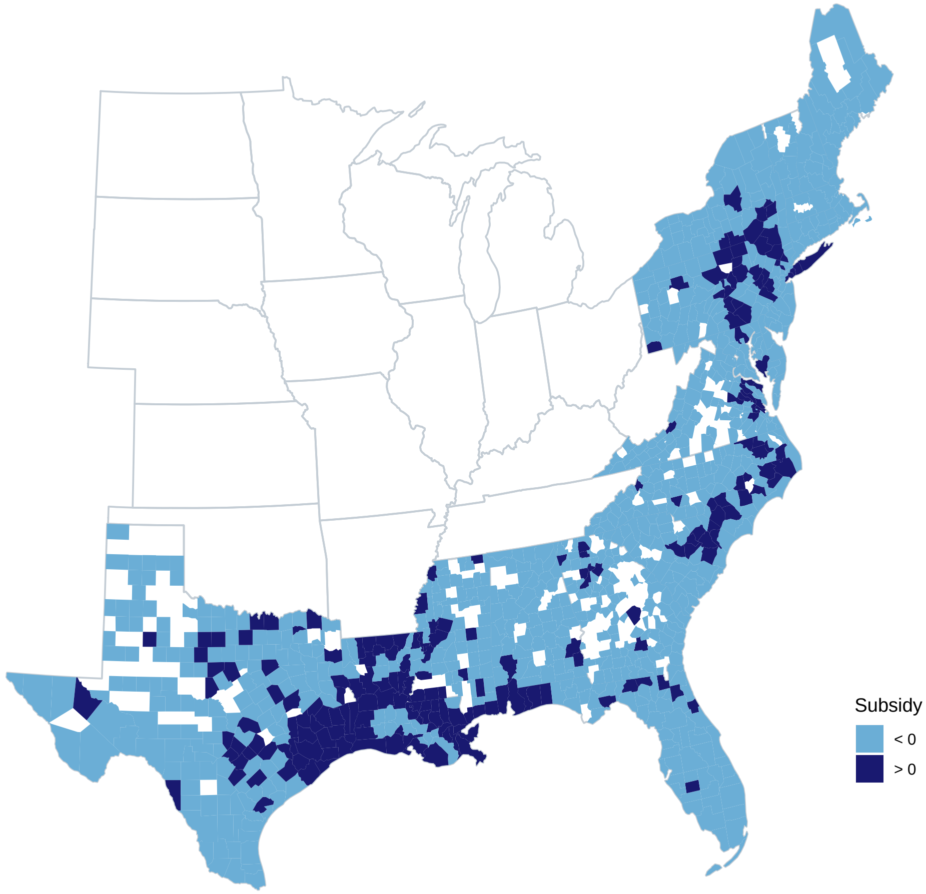


Panel B: Empirical Natural Disaster Insurance Market Equilibrium



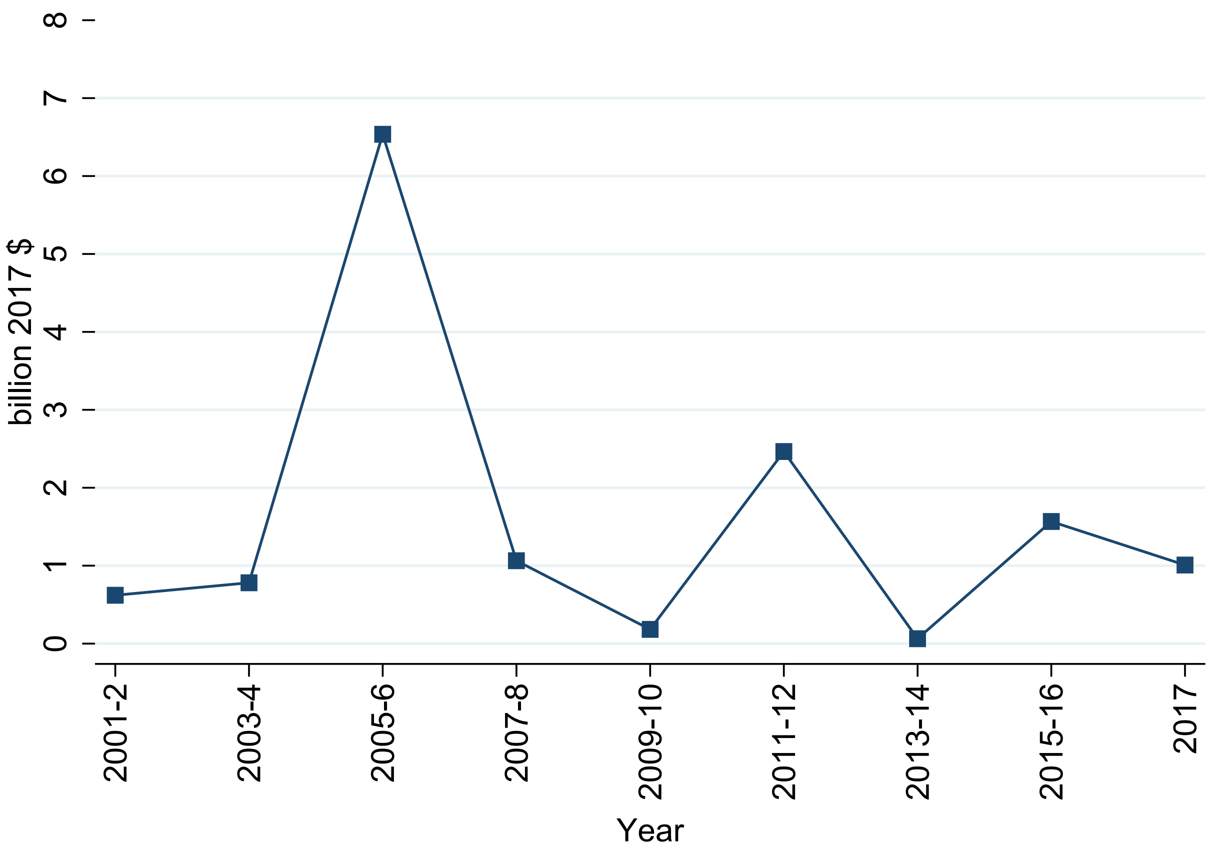
Notes: Panel A shows a theoretical equilibrium in the natural disaster insurance market in the presence of adverse selection, price subsidies, and frictions in uptake. The figure depicts the average cost curve $AC(p, \alpha, \phi)$, the marginal cost curve $MC(p, \alpha, \phi)$, the observed willingness to pay curve $D(p, \alpha, \phi)$, and the frictionless willingness to pay curve $D(p, \alpha, \phi = 1)$ for a given level of adaptation α and frictions ϕ. Panel B shows the empirical willingness to pay and cost curves for non-adapted houses (i.e., $\alpha = 0$). See text for a detailed description.

Figure 2: Average Realized Flood Insurance Subsidy to High-Risk Houses, By County



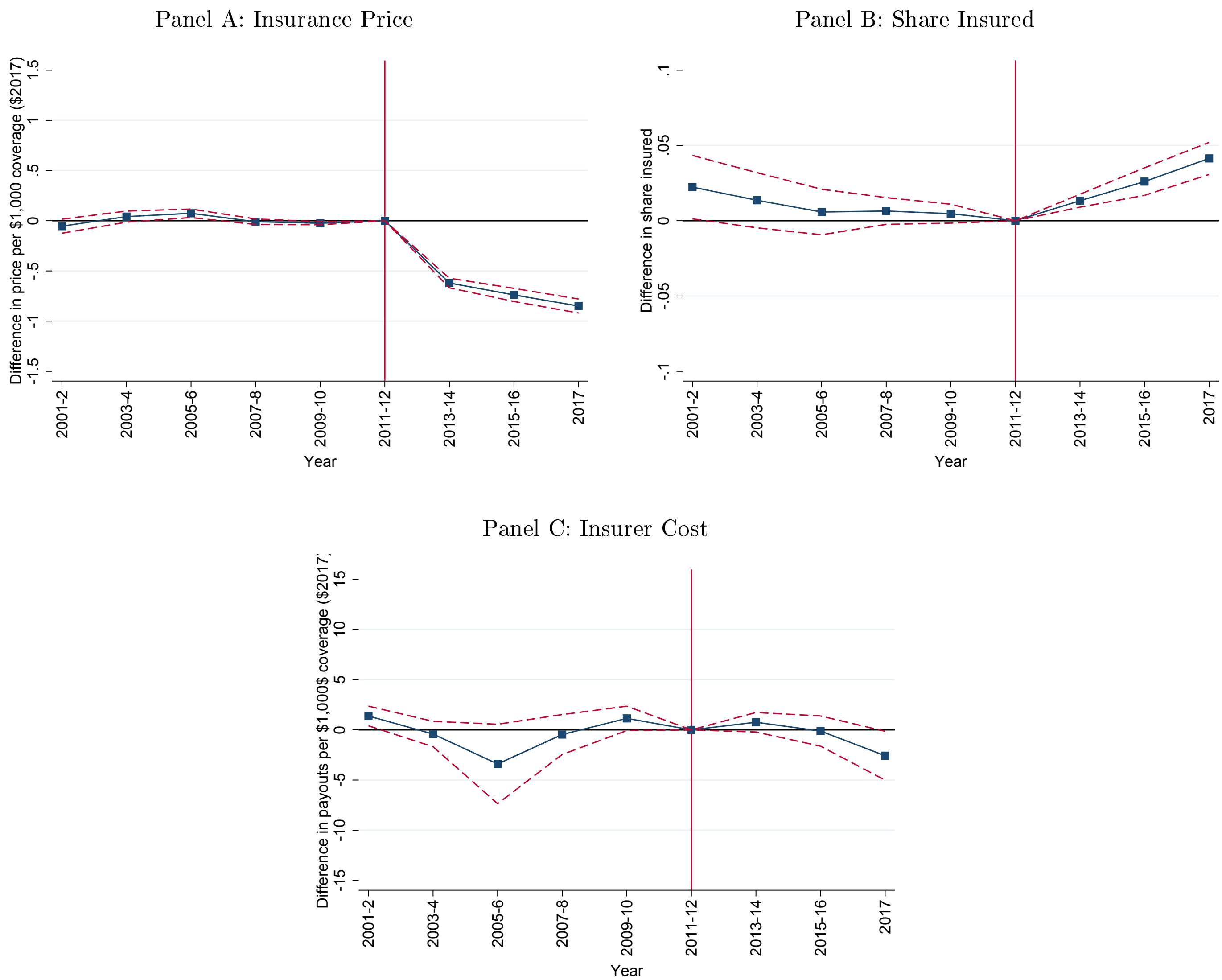
Notes: This map shows counties included in the analysis where flood insurance in high-risk flood zones is and is not subsidized between 2001 and 2017. The subsidy is calculated as the county-average payout minus price per $1,000 insurance coverage. The 20 states included in the analysis are Alabama, Connecticut, Delaware, Florida, Georgia, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Texas, Vermont, and Virginia. These 20 states account for 83% of total flood insurance policies written nationwide (NRC, 2015). Counties shown in white in these states have no high-risk flood insurance policies.

Figure 3: Total Flood Insurance Payouts to High-Risk, Single-Family, Primary Residences



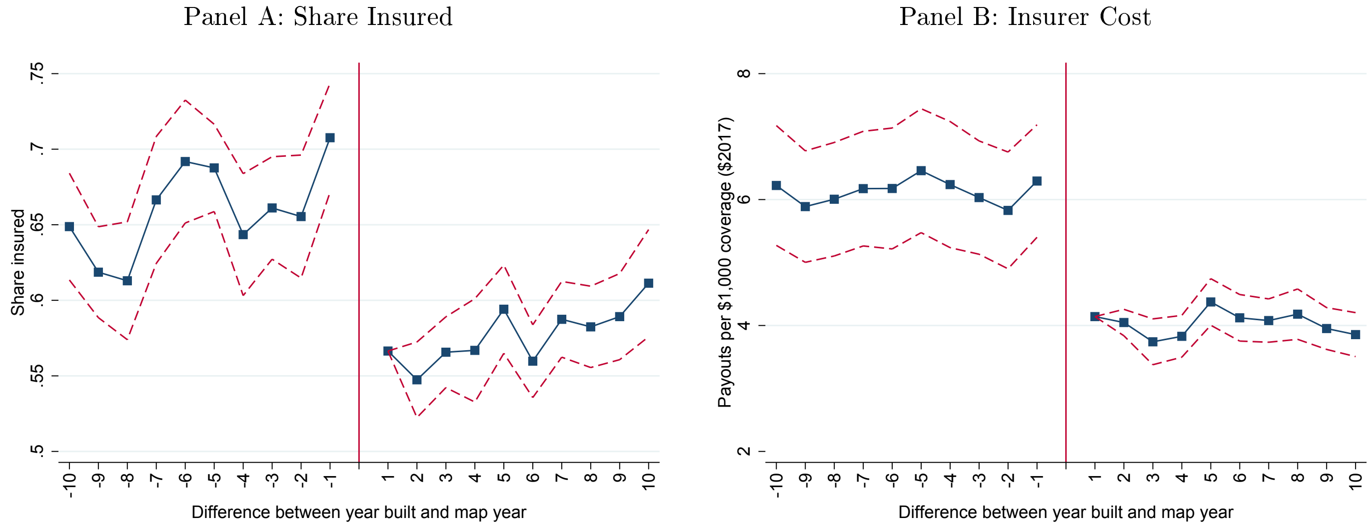
Notes: This graph shows total flood insurance payouts to homeowners in high-risk flood zones in the 20 Atlantic and Gulf Coast states included in the analysis. The sample includes single-family primary residences built within 15 years of their community's initial flood map.

Figure 4: Effects of Flood Insurance Reform on Relative Price, Demand, and Cost for Adapted Houses



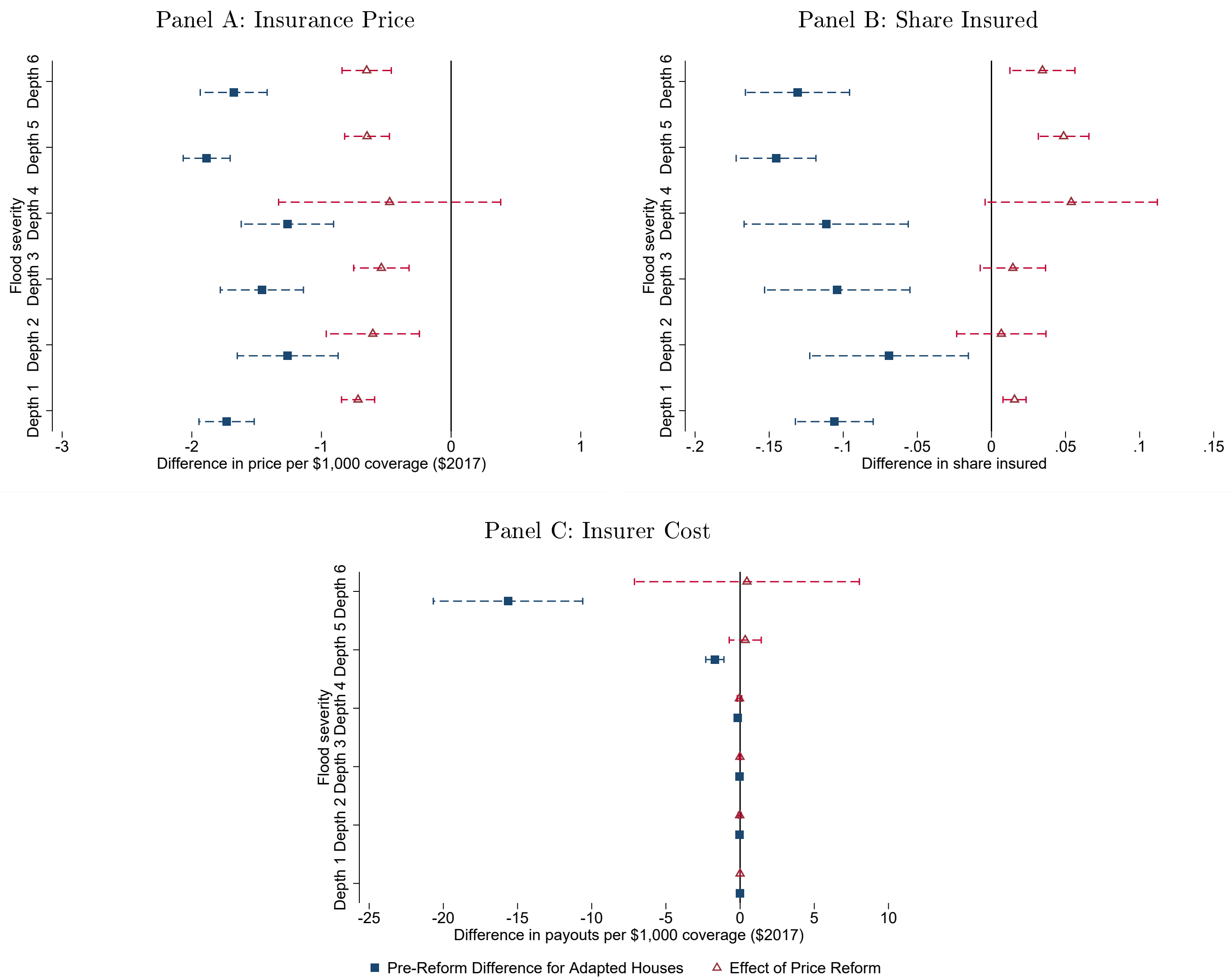
Notes: These graphs show the average price of flood insurance, share insured, and cost for adapted houses relative to non-adapted houses in high-risk flood zones. Adapted houses are built after communities are mapped and are required to be elevated. The coefficients are estimated from equation (4) in 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 5: Differences in Demand and Cost for Adapted and Non-Adapted Houses, By Construction Year



Notes: These graphs show the share of insured homeowners and average insurer payouts, 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. Houses built in the year that a community is mapped are excluded from the analysis since they cannot be classified as adapted or non-adapted. The coefficients are estimated from equation (7) in the text. Data are from the years 2001-2012, before Congress increased prices in 2013. Solid lines show average outcomes. Dashed lines are 95% confidence intervals. Standard errors are clustered by community.

Figure 6: Effects of Flood Insurance Reform on Relative Price, Demand, and Cost for Adapted Houses, By Flood Severity



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, for floods of different depths. Adapted houses are built after communities are mapped and are required to be elevated. 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.

Table 1: Summary Statistics, All Years

	All Houses (1)	Adapted Houses (2)	Non-Adapted Houses (3)
Panel A: Demand			
N	13,433,549	6,921,152	6,512,397
Year Built	1978.7	1985.4	1971.5
	(8.9)	(5.2)	(6.0)
Premium per $1,000 Cov.	4.38	3.11	5.73
	(2.79)	(2.09)	(2.80)
Elevation Requirement (ft)	5.33	10.40	0.00
	(6.80)	(6.15)	(0.00)
Prob. of Purchase			
Any Policy	0.58	0.56	0.59
	(0.49)	(0.50)	(0.49)
Building	0.57	0.56	0.58
	(0.50)	(0.50)	(0.49)
Contents	0.41	0.43	0.40
	(0.49)	(0.49)	(0.49)
Coverage ($1,000s, if purchase)			
Total	240.7	267.6	217.1
	(111.5)	(107.0)	(107.4)
Building	194.9	213.9	176.8
	(84.0)	(78.8)	(82.8)
Contents	45.8	53.7	40.3
	(42.4)	(44.1)	(40.5)
Panel B: Costs			
N	11,983,183	5,317,675	6,665,508
Payout per $1,000 Cov.	6.23	3.79	8.18
	(61.06)	(47.47)	(69.99)
Total Payout ($)	1,216.8	859.5	1,501.8
	(12,736.6)	(11,272.9)	(13,786.7)
Total Payout ($1,000s, if claim)	62.5	60.8	63.3
	(65.6)	(71.8)	(62.5)
Claim Probability	0.019	0.014	0.023
	(0.136)	(0.117)	(0.150)

Notes: Summary statistics are presented for houses in the 20 Atlantic and Gulf Coast states 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. Panel A shows summary statistics for all single-family primary residences in high-risk flood zones for which year of construction is available; Panel B is all high-risk policies written. Data are from the years 2001-2017. All monetary values are in $2017. Standard errors are in parentheses.

Table 2: First Stage Effect of Congressional Reform on Flood Insurance Prices

	Price	
	(1)	(2)
Adapted × $1[t \geq 2013]$	-0.810***	-0.701***
	(0.033)	(0.032)
Adapted	-2.099***	-1.525***
	(0.098)	(0.100)
Non-Adapted Dep. Var. Mean	5.491	
N	13,433,549	
Zip code × Year FE	✓	✓
Decade Built × Flood Severity Controls		✓

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

Notes: The dependent variable is the price per $1,000 of flood insurance coverage ($2017). The coefficients are estimated using equation (5) in the text. 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. 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). Standard errors clustered by community are in parentheses.

Table 3: Effect of Prices and Adaptation on Extensive Margin Demand

	Any Policy (1)	Building Policy (2)	Contents Policy (3)
Panel A: Differences-in-Differences			
Adapted × $1[t \geq 2013]$	0.019***	0.018***	0.008**
	(0.005)	(0.005)	(0.004)
Adapted	-0.108***	-0.106***	-0.051***
	(0.016)	(0.015)	(0.013)
Panel B: Instrumental Variables			
Price	-0.027***	-0.025***	-0.012**
	(0.006)	(0.006)	(0.006)
Adapted	-0.148***	-0.144***	-0.069***
	(0.022)	(0.022)	(0.020)
Non-Adapted Dep. Var. Mean	0.619	0.615	0.423
K-P F−stat	487	487	487
N		13,433,549	
Zip code × Year FE	✓	✓	✓
Decade Built × Flood Severity Controls	✓	✓	✓

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

Notes: The dependent variables are indicators for purchasing any policy, a policy that includes building coverage, and a policy that includes contents coverage. The coefficients in Panels A and B are estimated using equations (5) and (2) in the text, respectively. In Panel B, price is instrumented using the interaction of indicators for adapted and post-2012. 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. 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). Standard errors clustered by community are in parentheses.

Table 4: Effect of Prices and Adaptation on Intensive Margin Demand

	Total Coverage (1)	Building Coverage (2)	Contents Coverage (3)
Panel A: Differences-in-Differences			
Adapted × $1[t \geq 2013]$	1.35*	0.62	0.72**
	(0.80)	(0.60)	(0.35)
Adapted	26.32***	18.23***	8.10***
	(3.86)	(3.11)	(0.92)
Panel B: Instrumental Variables			
Price	-1.87*	-0.87	-1.01**
	(1.11)	(0.84)	(0.46)
Adapted	23.85***	17.08***	6.77***
	(4.38)	(3.76)	(1.12)
Non-Adapted Dep. Var. Mean	217.14	176.81	40.33
K-P $F-$stat	332	332	332
N		11,983,183	
Zip code × Year FE	✓	✓	✓
Decade Built × Flood Severity Controls	✓	✓	✓

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

Notes: The dependent variables are total amounts of coverage purchased and separate amounts for building and contents, in 1,000s ($2017). The coefficients in Panels A and B are estimated using equations (5) and (2) in the text, respectively. In Panel B, price is instrumented using the interaction of indicators for adapted and post-2012. 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. 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). Standard errors clustered by community are in parentheses.

Table 5: Effects of Prices and Adaptation on Insurer Costs

	Any Claim (1)	Average Cost (2)
Panel A: Differences-in-Differences		
Adapted $\times$ $1[t \geq 2013]$	0.020	0.234
	(0.073)	(0.469)
Adapted	-0.418***	-2.211***
	(0.067)	(0.470)
Panel B: Instrumental Variables		
Price	-0.028	-0.326
	(0.101)	(0.652)
Adapted	-0.455**	-2.641**
	(0.179)	(1.224)
Non-Adapted Dep. Var. Mean	2.481	8.535
K-P $F-$stat	332	332
N	11,983,183	
Zip code $\times$ Year FE	✓	✓
Decade Built $\times$ Flood Severity Controls	✓	✓

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

Notes: The dependent variables are an indicator for making a claim and the average insurer payout per $1,000 insurance ($2017). Claim probabilities are multiplied by 100. The coefficients in Panels A and B are estimated using equations (5) and (2) in the text, respectively. In Panel B, price is instrumented using the interaction of indicators for adapted and post-2012. 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. 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). Standard errors clustered by community are in parentheses.

Table 6: Effects of Prices and Adaptation on Demand and Cost, By Flood Severity

	Prices (1)	Any Policy (2)	Total Cov. (3)	Any Claim (4)	Average Cost (5)
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	-1.46***	-0.104***	25.18***	-0.055***	-0.038***
	(0.16)	(0.025)	(5.01)	(0.014)	(0.014)
Depth 4 × Adapted	-1.26***	-0.112***	30.13***	-0.151***	-0.156***
	(0.18)	(0.028)	(4.01)	(0.033)	(0.031)
Depth 5 × Adapted	-1.89***	-0.145***	31.26***	-0.850***	-1.702***
	(0.09)	(0.014)	(1.99)	(0.158)	(0.313)
Depth 6 × Adapted	-1.68***	-0.131***	29.46***	-2.610***	-15.642***
	(0.13)	(0.018)	(3.60)	(0.347)	(2.569)
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 × $1[t \geq 2013]$	-0.54***	0.014	4.83***	0.017	-0.013
	(0.11)	(0.011)	(1.55)	(0.021)	(0.029)
Depth 4 × Adapted × $1[t \geq 2013]$	-0.47	0.054*	-0.59	0.017	-0.042
	(0.44)	(0.030)	(6.79)	(0.056)	(0.078)
Depth 5 × Adapted × $1[t \geq 2013]$	-0.65***	0.049***	-3.26*	0.316	0.344
	(0.09)	(0.009)	(1.85)	(0.192)	(0.551)
Depth 6 × Adapted × $1[t \geq 2013]$	-0.65***	0.034***	-1.74	-0.287	0.458
	(0.10)	(0.011)	(2.38)	(0.552)	(3.867)
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=13,433,549); 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.

Appendix – For Online Publication

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.[39] 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

[39] 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.

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.

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:

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

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:

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

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 $\tilde{D}(s(p, \alpha, \phi, \delta), \phi, \alpha, \delta) = p$.[40]

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.

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

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

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

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.[41] 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.

[41]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.

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, Mississippi, 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.[42] 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

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

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 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.[43]

I conduct several analyses to verify that the flood water depths that I measure using the claims

[43] 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.

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.[44] The National Oceanic 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.

[44] 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.

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.[45] 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

[45] 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.

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 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:

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

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.[46]

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.[47] 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:

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

[46]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.

[47]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.

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 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:

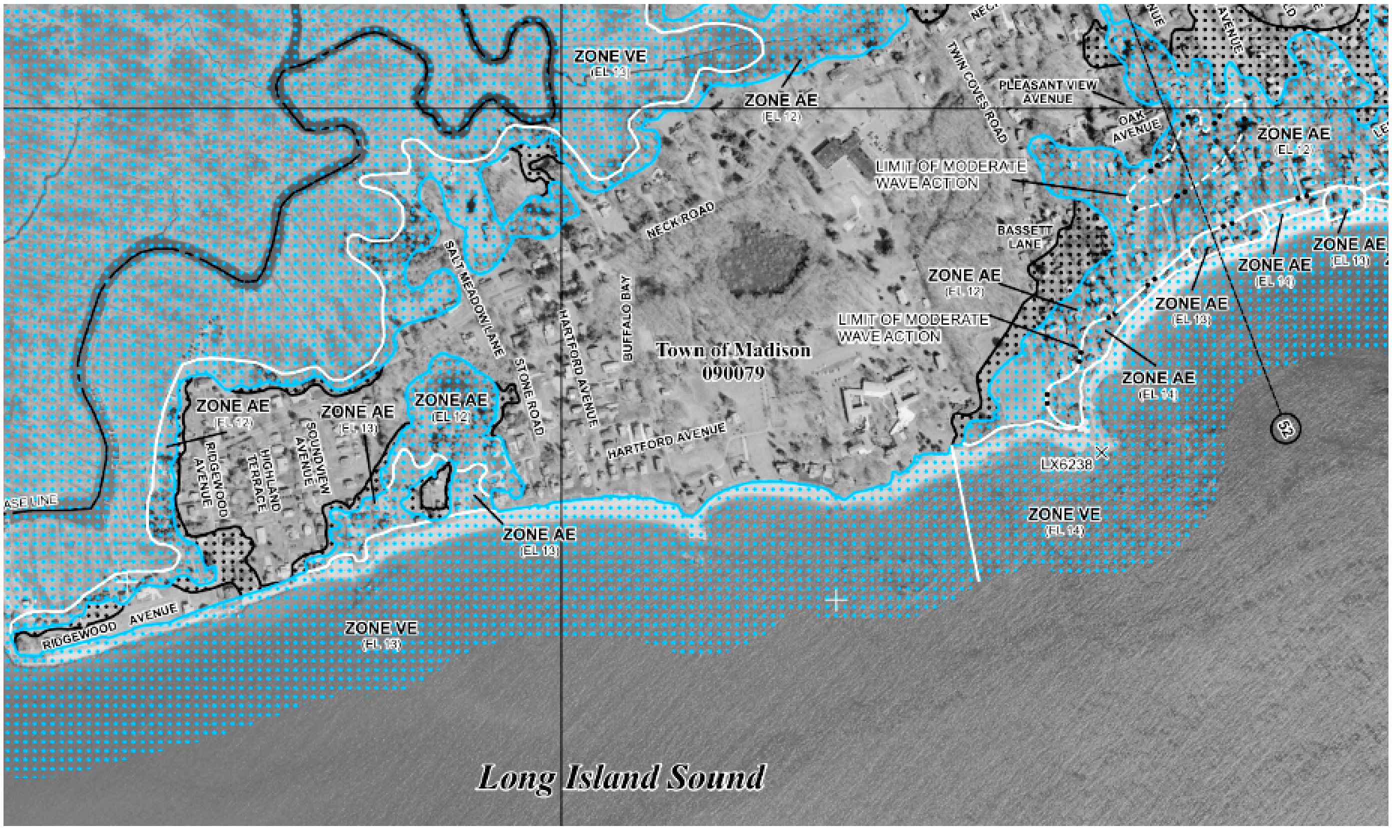
$$\Delta W = (D(p', 1, 1) - MC(p', 1, 1) + D(p^{full}, 1, 1) - MC(p^{full}, 1, 1)) \times$$
$$(1 - (s' + \theta_s^s)) \times \frac{1}{2} \times (217.1 + \theta_2^i) \times 1,043,345$$
$$= (92.67 - 8.54 + 2.21 + 76.00 - 8.54 + 2.21) \times (1 - (0.61 - 0.11)) \times \frac{1}{2} \times (217.1 + 26.3) \times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

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

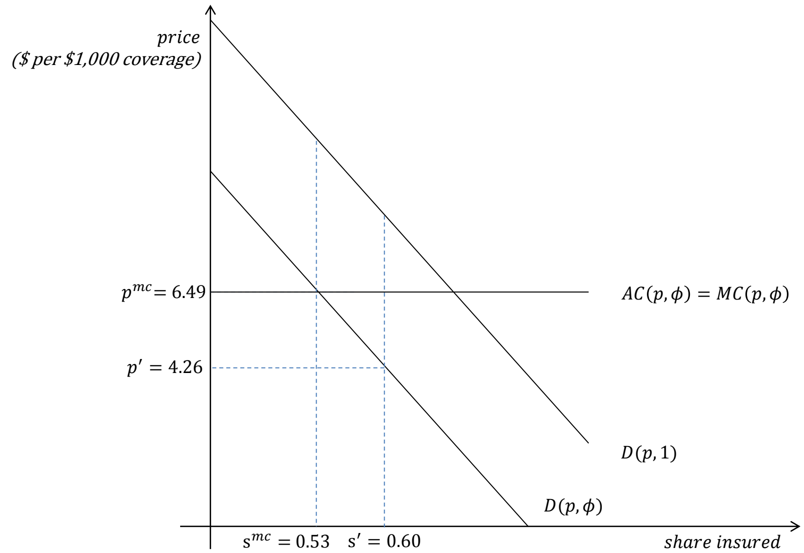


Notes: This map shows the Flood Insurance Rate Map (FIRM) for the town of Madison, CT (NFIP, 2018b). Dotted areas are high-risk flood zones. Minimum elevation requirements (in feet) for new construction are in parentheses for each detailed zone.

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).

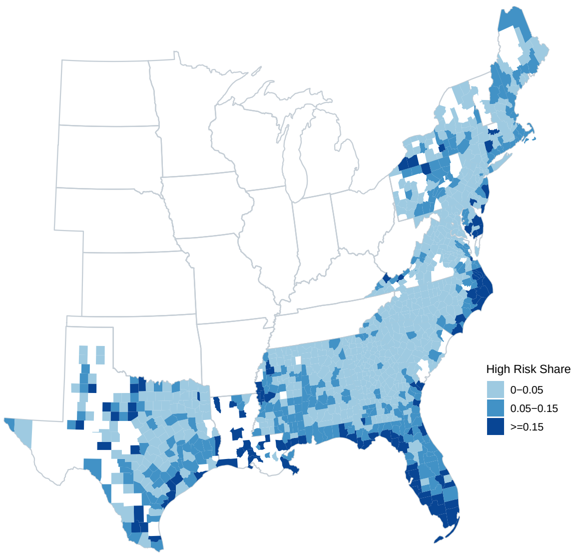
Figure A.3: Empirical Willingness to Pay and Cost Curves for Adapted and Non-adapted Houses



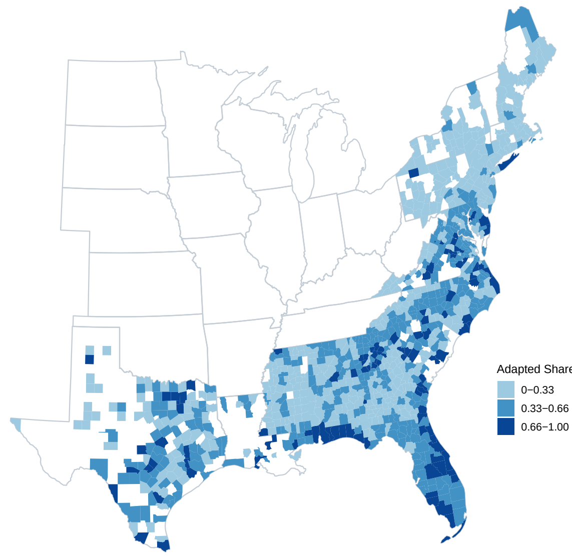
Notes: This figure shows the empirical average cost curve $AC(p, \phi)$, the empirical marginal cost curve $MC(p, \phi)$, the empirical observed willingness to pay curve $D(p, \phi)$, and the frictionless willingness to pay curve $D(p, \phi = 1)$ for the pooled market of adapted and non-adapted houses,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

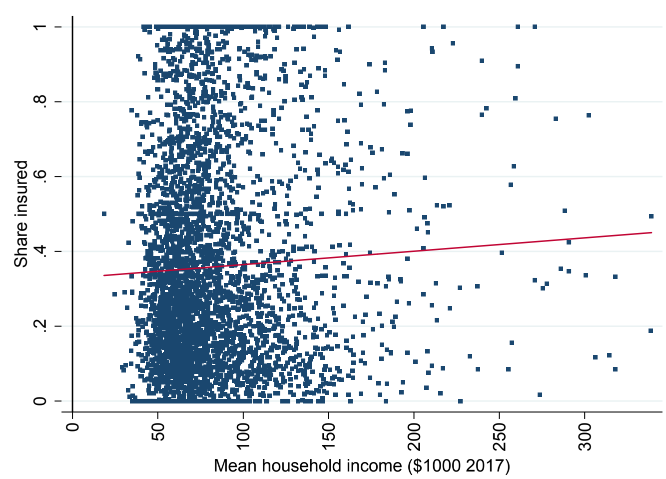


Notes: This map shows the share of the residential housing stock in high-risk flood zones (Panel A) and the share of high-risk houses that is adapted (Panel B), by county. Adapted houses are built after a community is formally mapped by the National Flood Insurance Program and are required to meet minimum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

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

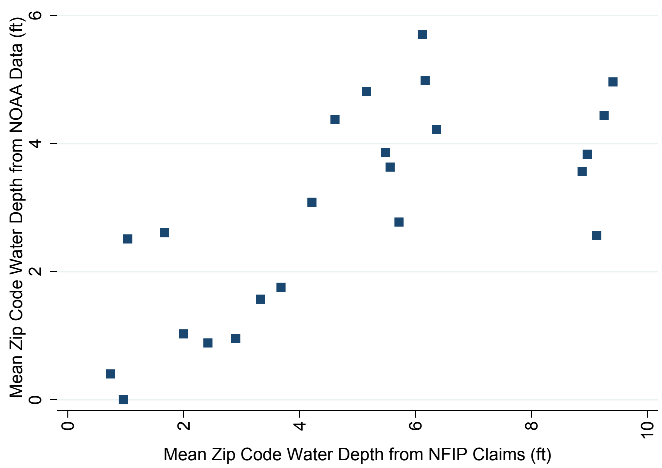
Notes: These graphs show the correlation between the average flood insurance subsidy and average take-up rate in high-risk flood zones by community, for non-adapted houses (Panel A) and adapted houses (Panel B). The subsidy is calculated as average payout minus average premium per $1,000 of coverage ($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



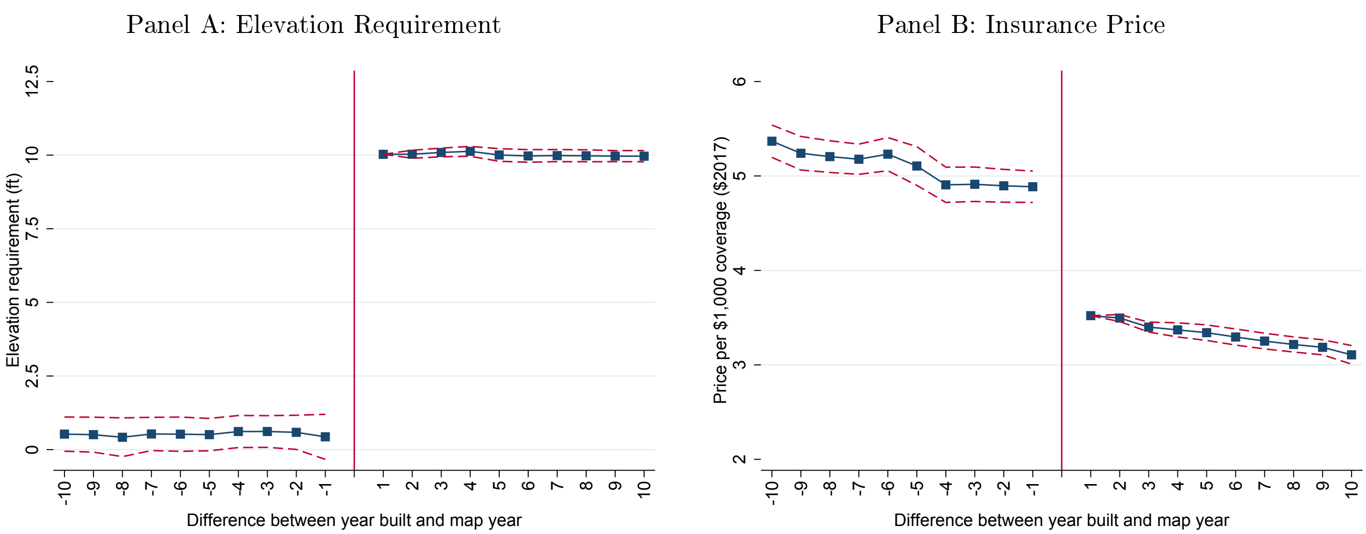
Notes: This graph shows the correlation between average household income and average take-up rate in high-risk flood zones by community. Take-up increases by 0.4 percentage points for every $10,000 increase in mean household income. Each point shows a community's average income and take-up rate for the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

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



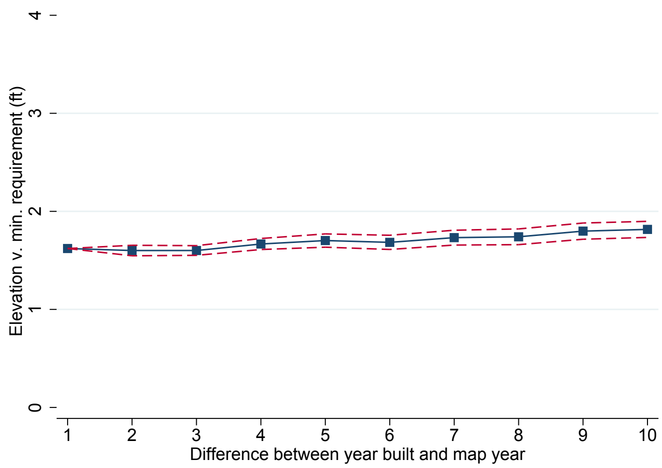
Notes: This graph shows the correlation between the reported average water depth in high-risk flood zones in the claims data and the measured average flood water depth from the National Oceanic and Atmospheric Administration (NOAA) in zip codes affected by Hurricane Katrina.

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



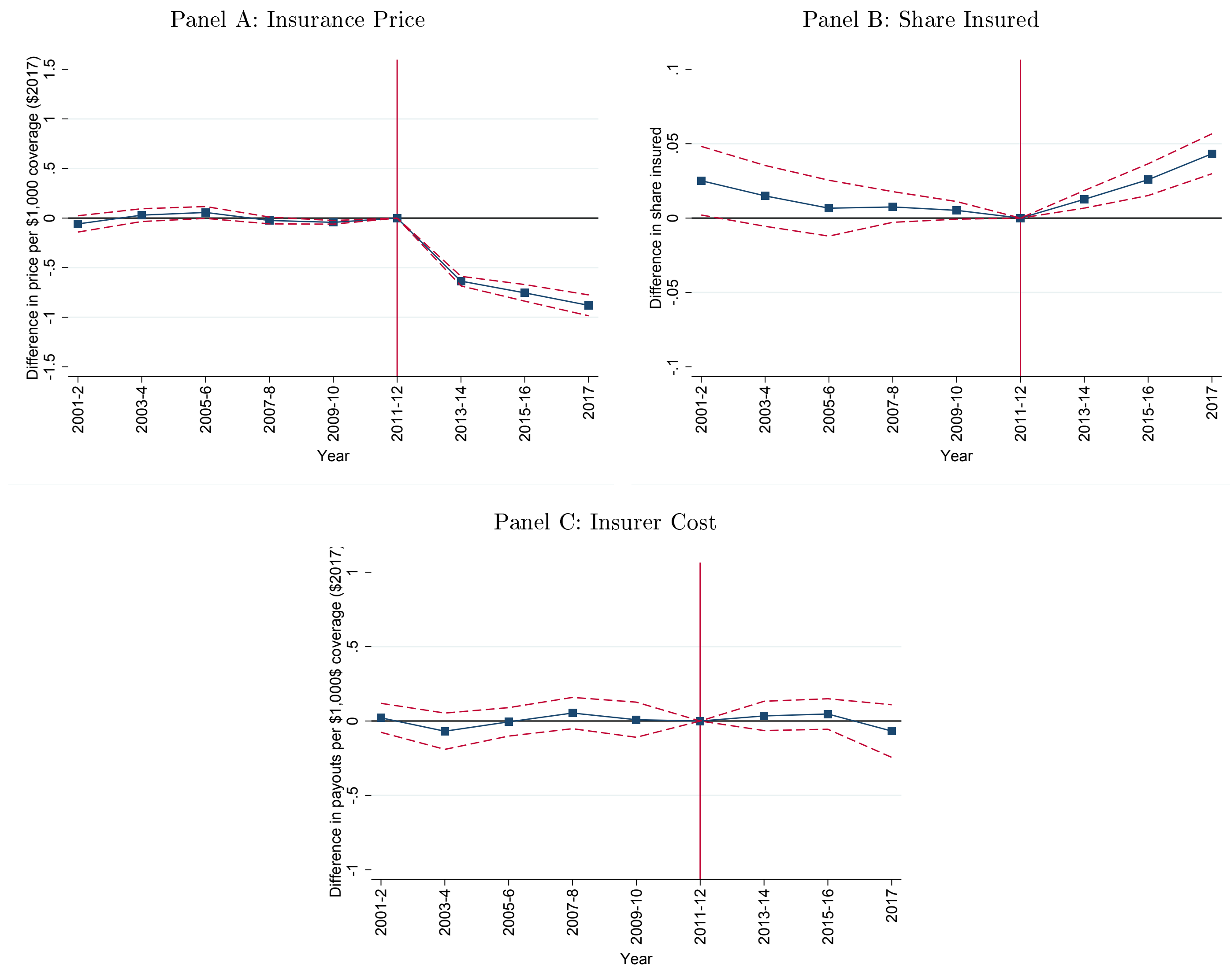
Notes: These graphs show the minimum elevation requirement for new construction (Panel A) and prices (Panel B), by year of house construction relative to the year of the initial flood map in the community in which the house is located. Adapted houses are built after communities are mapped and are required 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



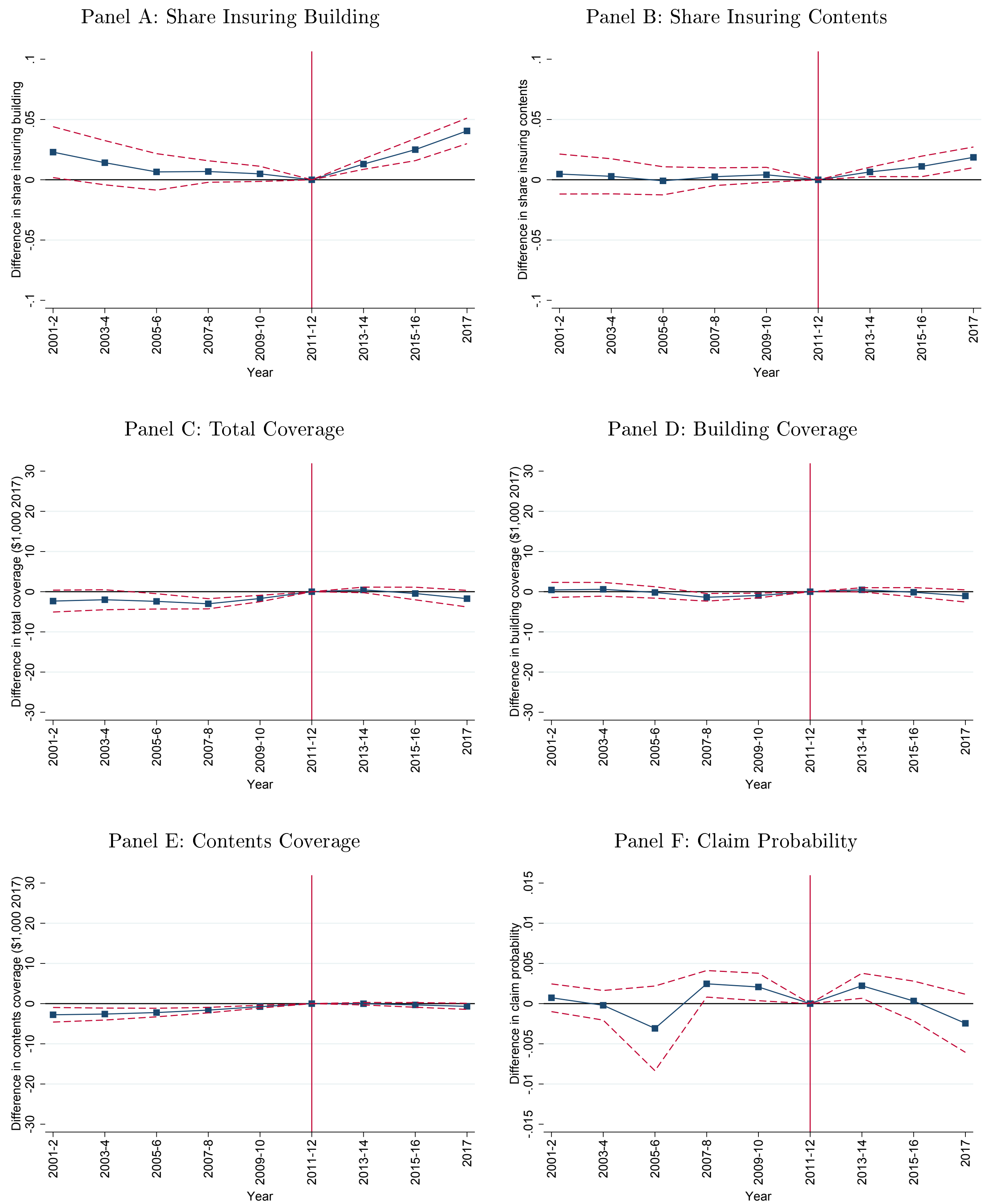
Notes: This graph shows the difference between the height of a house's foundation and the minimum construction requirement, measured from the flood insurance policy data set. The coefficients are estimated from equation (7) in the text, excluding non-adapted policies that are not subject to minimum elevation 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.

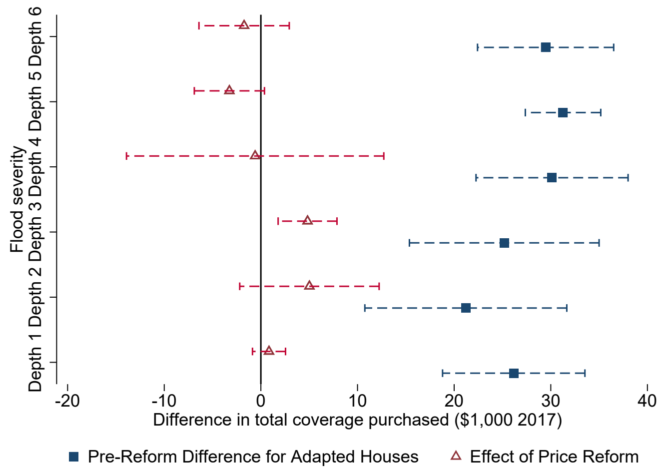
Figure A.11: Effects of Flood Insurance Reform on Demand and Cost Outcomes for Adapted Houses



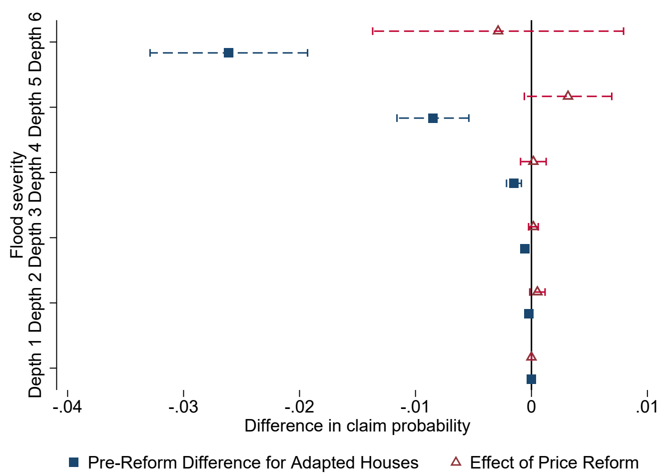
Notes: These graphs show the time series of demand and cost outcomes for adapted houses relative to non-adapted houses in high-risk flood zones. The coefficients are estimated from equation (4) in the text. Solid lines show differences in outcomes between adapted and non-adapted houses relative to the 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

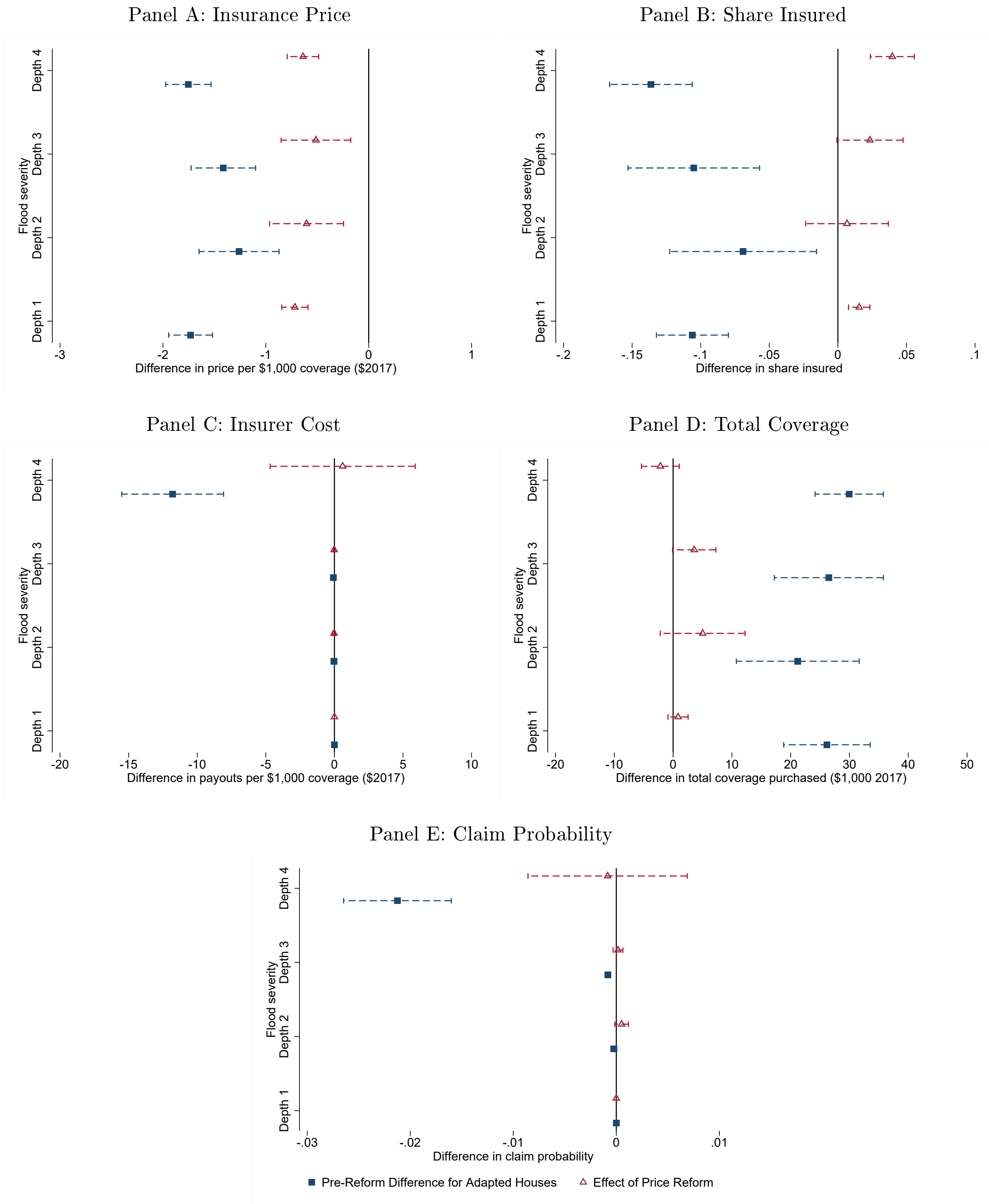


Panel B: Claim Probability



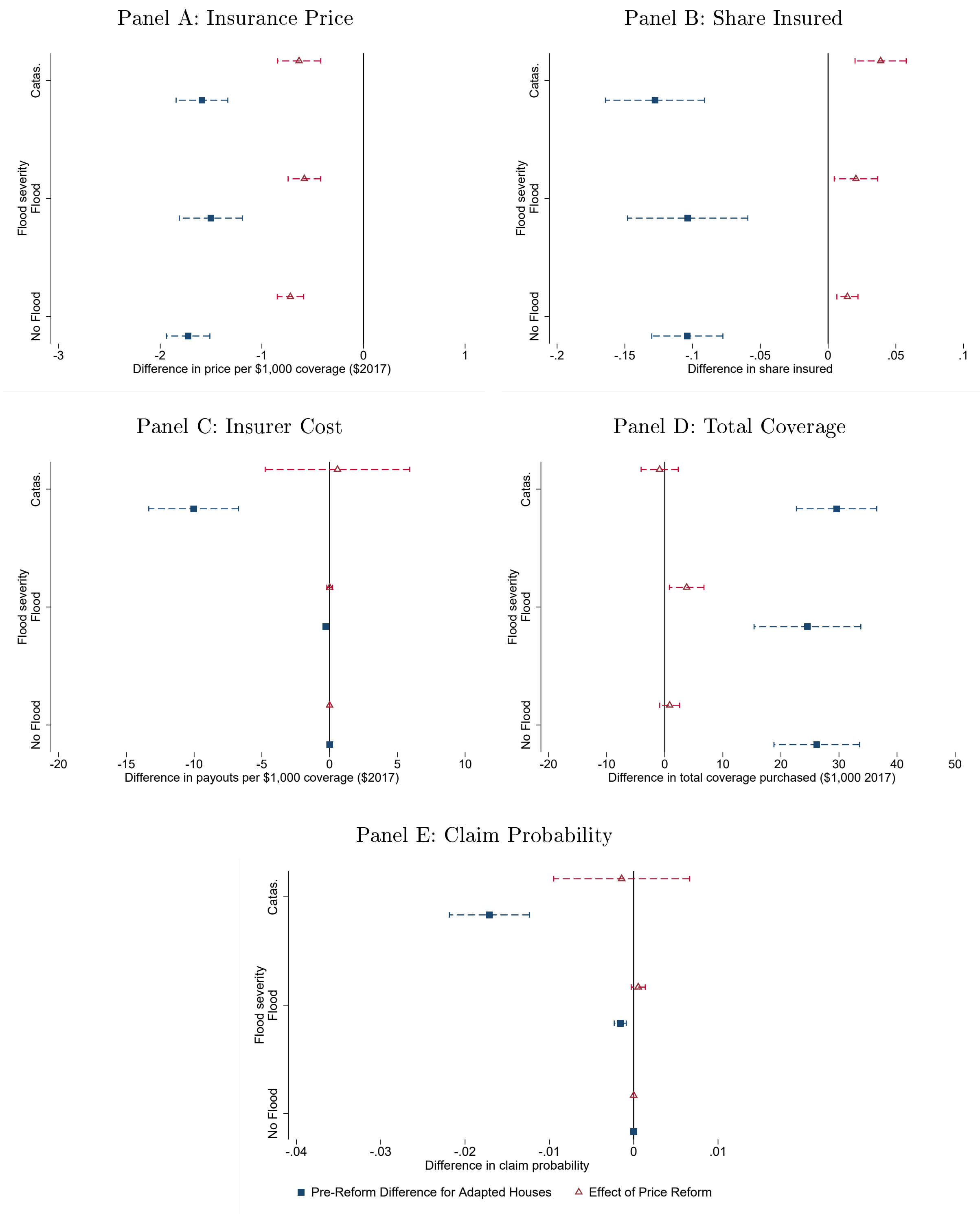
Notes: These graphs show total coverage purchased and claim probability for adapted houses relative to non-adapted houses in high-risk flood zones, by flood severity. The coefficients are estimated from equation (6) in the text. Squares are the difference between adapted and non-adapted houses in the 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



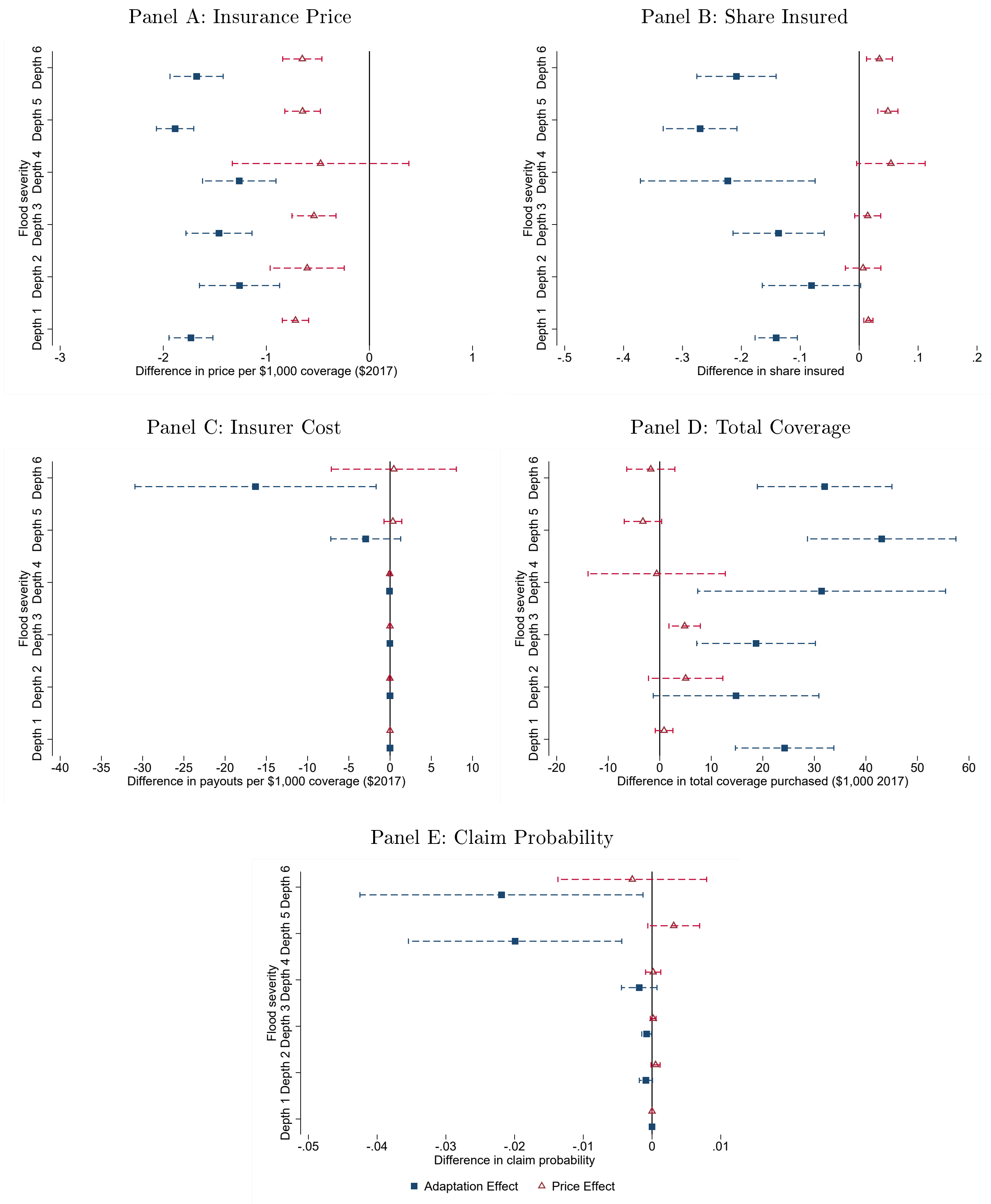
Notes: These graphs show price, demand, and cost outcomes for adapted houses relative to non-adapted houses in high-risk flood zones, by water depth quintile. The coefficients are estimated from equation (6) in the text using four categories for flood severity (no flood, three increasing water depths). 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 $\times$ $1[t \geq 2013]$	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 $\times$ $1[t \geq 2013]$	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 $\times$ 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$\times$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.