The Influence of Sellers on Contract Choice: Evidence from Flood Insurance*

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Abstract

We examine the ability of insurers to influence the coverage limit decisions of 180,000 households in the National Flood Insurance Program. In this program, private insurers sell identical flood contracts at identical rates and bear no risk of paying claims. About 12% of new policyholders overinsure, selecting coverage limits that exceed their home's estimated replacement cost. Overinsuring is expensive relative to expected loss, making it difficult to explain with standard decision-making models. The rate of overinsuring differs substantially across insurers, ranging from zero to one-third of new policies. Insurer effects on the likelihood of overinsuring are statistically significant after controlling for the policyholder's characteristics. Additionally, some insurers seem to encourage households to overinsure in percentage terms (e.g., buy 110% of replacement cost) while others encourage rounding up in dollars (e.g., to the next $10,000). We find that insurers' distribution systems and commission rates influence whether their policyholders overinsure.

Keywords: Insurance Demand · Flood Insurance · Decision-Making Under Risk and Uncertainty · Insurer Operations · Financial Advice

JEL Classifications: D02 · D12 · D22 · D83 · G22

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1 Introduction

We examine whether insurers influence the contract choices of their policyholders. Economists model insurance decisions as a function of a consumer's risk exposure and risk preferences (e.g., Arrow, 1974; Cohen and Einav, 2007). For many insurance decisions, however, the consumer has incomplete information and must rely on the seller to understand the risk and the insurance contract. Thus, a consumer's contract decisions may depend on what its insurer recommends. Investigating potential seller effects in an insurance setting, however, often involves empirical challenges due to differences between insurers (e.g., credit rating) and the product features that they offer (e.g., coverage terms and pricing).

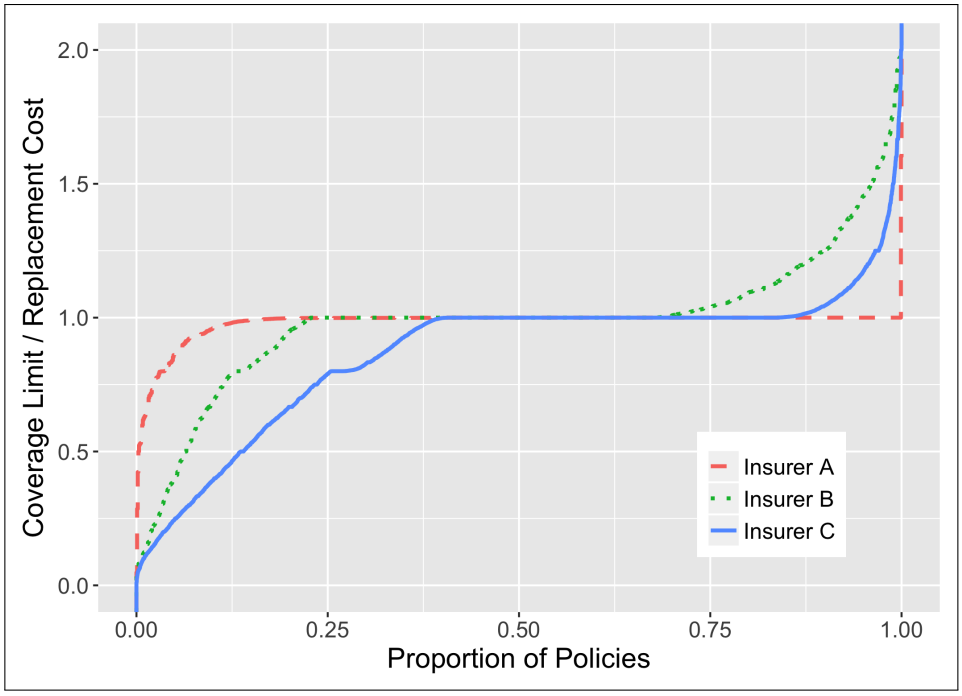
In this study, we examine a market setting that overcomes these empirical challenges—private insurers who sell residential flood insurance policies in the National Flood Insurance Program (NFIP). The U.S. federal government sets all terms of the insurance contract (e.g., premium rating, coverage options) and bears all claims risk. The NFIP incentivizes private insurers to sell these policies via commissions on the premium paid. Thus, the contracts in our study are identical in every sense except for the seller—an ideal setting to examine the ability of sellers to influence households' contract choices.

Our analyses focus on *overinsuring*, where consumers select a flood insurance coverage limit that is larger than their home's estimated replacement cost. About 12% of new policyholders overinsure. The replacement cost is the cost to rebuild the home with materials of like kind and quality, and is estimated by the seller at the time of purchase.[1] A household might overinsure for several reasons, which we discuss below. In our setting where insurers sell identical products, standard economic theory suggests that the selected coverage limit should not depend on the insurer. Yet we observe that overinsuring differs substantially across insurers. Figure 1 is a motivating illustration. It shows the distribution of selected coverage limits (relative to estimated replacement cost) for new policyholders of three large participating insurers. A ratio of 1 indicates full coverage, while a ratio above (below) 1 denotes overinsuring (underinsuring). The policyholders of Insurer A tend to purchase full coverage, and they never overinsure. The policyholders of Insurer B often overinsure, with more than 30% of policyholders purchasing excess coverage. Insurer C's policyholders are the most likely to partially insure (about 40%), though

[1] Throughout the paper, we refer to the seller's estimate of the cost at this point as the home's "replacement cost." Insurers use software to estimate replacement cost for the customer based on claims data and a home's characteristics (e.g., size, location, and construction materials). The NFIP instructs sellers to use "normal company practice" to provide the home's estimated replacement cost to the policyholder when the flood insurance contract is originated (NFIP, 2006, p. 4-175). Deriving an accurate estimate of the home's replacement cost is instrumental to the property insurance industry.

approximately 15% overinsure.

Figure 1: Policyholder Coverage Limits for Three Insurers



Note: Figure shows the distribution of selected building coverage limits (relative to estimated replacement cost) of new policyholders for three large insurers in the National Flood Insurance Program. We selected these three insurers for purposes of illustration. A ratio equal to 1 indicates full coverage, while a ratio greater than (less than) 1 indicates overinsurance (underinsurance). The policyholders of Insurer A tend to fully insure (i.e., choose a coverage limit equal to their home's replacement cost) and never overinsure. In contrast, more than 30% of Insurer B's policyholders overinsure. Finally, about 40% of the policyholders of Insurer C partially insure and approximately 15% overinsure.

Under an assumption of fully-informed consumers, overinsuring is difficult to explain with standard models of decision making (e.g., expected utility theory or prospect theory). The cost to overinsure appears large relative to the expected loss. Out of nearly 180,000 policies in our sample, assessed damages are greater than estimated replacement cost only 40 times—a rate of 0.02%. Six of these 40 policies with excess damage were overinsured. The mean amount of excess damage for the 40 policies is $6,872. This results in an expected loss per household of $1.53. Overinsuring households pay an average of $71.07 in additional premium for excess coverage, which is 4,645% of the expected loss. Paying such a large risk premium implies triple-digit levels of relative risk aversion.[2]

[2] A back-of-the-envelope calculation for a representative household in our data indicates that overinsuring would require a coefficient of relative risk aversion of at least 117. For this calculation, we assume that the representative household has initial wealth of the mean replacement cost for overinsuring households ($146,380), a 0.02% probability

Instead, insurance consumers may not be fully-informed, relying on the agent of the insurer to understand the underlying risk(s) and the terms of the contract. As the previous paragraph describes, it is possible (but rare) for a loss to exceed a home's estimated replacement cost. Such a situation may occur if the replacement cost is underestimated (e.g., due to software limitations), if post-loss costs are unexpectedly high (e.g., demand surge following a catastrophe, as in Döhrmann et al., 2017), or if additional expenses reduce the available limit (e.g., debris removal). Agents' training and experience would seem to give them an advantage at valuing these risks, relative to households. Because of this information asymmetry, a consumer's decision may be influenced by the seller's recommendation to purchase a higher limit.[3]

In our primary analysis, we examine whether the insurer selling the policy influences the likelihood that a household overinsures. Our baseline data include 179,917 new policies sold in 2010 by 48 insurers in all 50 states and 4 U.S. territories. While Figure 1 suggests notable insurer effects, the observed differences across insurers might be explained by characteristics of their policyholders or local markets. We strengthen our causal interpretation of insurer effects by modeling the likelihood that a household overinsures as a function of insurer fixed effects (i.e, an indicator variable for the insurer selling the policy), controlling for detailed policy-level characteristics and geographic fixed effects. Over a number of specifications, we find that the likelihood a household overinsures depends significantly on its insurer. Sorting the insurer fixed effects by quartile, we find that a household whose insurer is in the highest quartile is, on average, 12.3 percentage points more likely to overinsure than a household purchasing from an insurer in the lowest quartile.

We also examine the specific guidance that insurers appear to use in recommending excess coverage. For example, an insurer might suggest selecting coverage limits that are 10% higher than the estimated replacement cost. We identify a small set of possible "rules" and test the three most prevalent. These three rules ultimately explain more than 50% of excess limits selected. The

of \$6,872 possible excess damage, and must pay a \$71.07 premium to cover this risk. This household is assumed to be an expected utility maximizer with constant relative risk aversion, $1/(1-\rho)x^{(1-\rho)}$ with $x > 0$. We identify the minimum relative risk aversion for which the expected utility of overinsuring exceeds that of fully-insuring. A $\rho = 117$ is consistent with recent research showing the difficulty of explaining households' insurance decisions with expected utility. For example, households' homeowners deductibles (Sydnor, 2010) and their decision to fully insure rather than partially insure in the NFIP (Collier et al., 2017) each require triple-digit relative risk aversion. We conduct a similar calculation for cumulative prospect theory, using a reference point of no losses and no premiums paid and the parameters given by Tversky and Kahneman (1992). While Sydnor (2010) and Collier et al. (2017) find that cumulative prospect theory can explain households' deductible and coverage limits, we find that it *cannot* explain overinsuring for our representative household using this approach.

[3] Other insurance choices might also be influenced by the insurer, such as whether to partially insure. Identifying insurer effects on partially insuring is complicated by other factors that may also explain the decision to partially insure such as risk preferences, known variation in risk exposure, and institutional considerations (e.g., purchasing only the amount required by the mortgage). Identification of insurer effects on overinsuring appears relatively "clean" and motivates our focus on overinsuring. We briefly return to topic of insurer effects on partially insuring in Section 3.

most common overinsurance limit is choosing the program maximum of $250,000 regardless of the replacement cost, which describes 29% of excess limits. Half of overinsuring households choosing this limit have replacement costs below $200,000, so they buy at least $50,000 in excess coverage. The second most common excess limit rule is to set the limit at 110% of replacement cost, and the third most common is to select a coverage limit that equals the nearest $10,000 increment above the replacement cost. Of the 48 insurers in our dataset, 18 appear to follow a single rule, reinforcing the conclusion that overinsuring is an institutional recommendation.

Finally, we consider how market conditions and firm characteristics may influence each insurer's rate of overinsuring in a state. We find that insurers who primarily sell via "direct" agents (i.e., agents who are employed by the insurer) tend to have higher overinsuring rates than insurers who use "independent" agents (i.e., a third-party agency who may represent multiple insurers). We find that commission rates paid to direct agents are a significant driver of overinsuring. Overinsuring is positively related to flood insurance commissions—a 1 percentage point increase in an insurer's flood commission rate is associated with a 0.4 percentage point increase in the overinsuring rate. This relationship illustrates the conflict between agents and policyholders, with agents paid higher commissions more likely to sell excess coverage. We observe the opposite effect for non-flood commission rates (homeowners and auto), with a 1 percentage point increase in those commission rates associated with a 0.7 percentage point decrease in the flood overinsuring rate. One interpretation of this result is a substitution effect for an agent's effort, with an agent deploying sales effort to the line(s) of business paying the highest commission. We also find evidence that overinsuring is negatively related to competition, with overinsuring rates lower in states where many insurers sell federal flood policies.

Our paper contributes to the existing literature in several ways. Our main result shows that insurers help select households' flood insurance contracts. This finding creates questions regarding the extent to which a policyholder's insurance decisions reflect its risk preferences. Many of the foundational papers eliciting risk preferences from observed insurance choices (e.g., Barseghyan et al., 2013; Cohen and Einav, 2007; Sydnor, 2010) use data from a single insurer and so are unable to account for the insurer's influence. We add a new element to studies investigating demand for flood insurance (e.g. Botzen and van den Bergh, 2012; Browne and Hoyt, 2000; Kriesel and Landry, 2004; Landry and Jahan-Parvar, 2011) and catastrophe insurance (e.g. Grace et al., 2004; Kousky and Cooke, 2012). More generally, the paper adds to a behavioral literature on why consumer's insurance decisions differ from the predictions of standard models (which has already identified inertia, simplifying heuristics, information frictions, and other consumer-level factors, e.g., Abaluck and Gruber, 2011; Ericson and Starc, 2012; Handel and Kolstad, 2015).

Outside of an insurance context, our study provides additional evidence on the ability of sellers to influence demand. In an investigation of wholesale used car auctions, Lacetera et al. (2016) find that the latent ability of auctioneers significantly affected the probability of a sale, the sales price, and the speed of a sale. Our analysis complements theirs, in that we demonstrate the ability of sellers to influence the quantity demanded of a product which is sold at identical unit prices. Similarly, Foerster et al. (2017) show that financial advisors have a large influence on investment portfolio allocation, more than many investor-level attributes. Our study can be interpreted as evidence of similar effects on consumer choice and risk attitudes. We show such effects at the *institutional* level, in contrast to the influence of individual auctioneers or financial advisors.

We also add to the literature on intermediaries and agency conflicts. There is substantial empirical evidence of agency conflict in the investment advice literature (e.g., Christoffersen et al., 2013; Mullainathan et al., 2012), but evidence of biased advice in an insurance setting is mixed. Interviews and surveys with agents find no significant evidence of commissions inducing bias (Kurland, 1995; Cupach and Carson, 2002), while experiments show that consumers have a higher willingness to pay for insurance when purchasing from an agent paid on commission (Beyer et al., 2013). Anagol et al. (2017) conduct a field study to examine the selling behavior of life insurance agents in India. They find that agents recommend unsuitable products that confirm consumer biases to maximize their commission revenue. Their data are from "auditors" posing as Indian consumers, who recorded agents' recommendations. Thus, they do not observe choices made by individual consumers, but their findings explain observed trends in the Indian insurance market. Our study complements theirs, though differs in focus, as we study the actual choices of U.S. consumers, but do not directly observe the the actions of sellers.[4]

Finally, our findings are consistent with existing evidence of differences across insurance distribution channels. Insurers using direct agents have often been compared to insurers using independent agents (see Hilliard et al., 2013, and Regan and Tennyson, 2000, for reviews of the institutional differences), and we find that insurers selling via direct agents sell more excess coverage. Eckardt and Räthke-Döppner (2010) determine that independent agents provide higher quality information to consumers, and other studies find independent agents to provide higher levels of service and/or better customer satisfaction (e.g. Barrese et al., 1995; Eckardt, 2002; Trigo-Gamarra, 2008). Our finding that higher commission rates do not induce independent agents to sell excess coverage seems to align with the conclusions of these previous studies.

The remainder of this paper is arranged as follows. In Section 2, we provide background

[4] It is important to note that seller behavior in our study is not necessarily subversive. While the additional quantity purchased in our study has an extremely low probability of being needed (see Section 2.4), sellers may believe the purchase is worthwhile, as detailed claims data are not publicly available.

on the institutional setting and describe the data we use in our analysis. Section 3 outlines the methodology and result for our primary analysis, investigating differences in the likelihood of overinsuring between insurers. In Section 4, we consider a number of possible formulas insurers may use to suggest a limit relative to the estimated replacement cost. We offer a robustness check to potential selection issues in Section 5. We then investigate the ways in which insurers may incentivize agents to sell excess coverage in Section 6. Finally, we review our findings and discuss implications in Section 7.

2 Background

2.1 Institutional details

Standard U.S. homeowners insurance contracts exclude coverage for flood, so homeowners who wish to insure flood risk must purchase a standalone policy. More than 96% of residential flood insurance is underwritten by the NFIP (Dixon et al., 2006).[5] At the end of 2017, five million NFIP policies were in force for a total insured value of $1.3 trillion (FEMA, 2018).

Federal flood policies from the NFIP cover the home structure and contents with separate limits and deductibles. We focus our analysis on coverage for the home structure. The structure covered includes the dwelling, additions or extensions, a detached garage, and attached appliances and fixtures (e.g., dishwashers, water heaters, built-in microwave ovens, etc.). It also covers debris removal and loss avoidance expenses. Several exclusions apply, including (1) land, trees, and shrubs, (2) finished basements, and (3) walkways, decks, and driveways. Consumers select a coverage limit up to $250,000, in $100 increments, and choose a deductible of either $1,000, $2,000, $3,000, $4,000, or $5,000.[6]

Some homeowners are required to insure against flood, though this requirement has not been consistently enforced (Dixon et al., 2006). Homeowners with a mortgage from a federally-regulated lender are required to purchase flood insurance if their home is located in an area that federal flood maps estimate has more than a 1 percent annual flood probability (Zones A and V). The minimum limit for these households is the lowest of: (1) their home's replacement cost, (2) their outstanding

[5] While some insurers today offer flood coverage on a "nonadmitted" basis (not subject to state regulation), such coverage was rare in 2010 when our data were generated. In addition, entities such as Fannie Mae typically require that flood insurance be admitted.

[6] All contract details are from NFIP (2010). Coverages and exclusions are examples and are not a comprehensive list, details on pages POL 3-20. Limits and deductibles are outlined on pages RATE 1-2. Flood contracts also cover costs associated with updating damaged properties to comply with current flood management-related building requirements, subject to a $30,000 limit, at an additional charge (Coverage D, pages POL 8 and RATE 14).

mortgage balance, or (3) the $250,000 program maximum (NFIP, 2007, p.41). Thus, overinsuring is not necessary to satisfy mortgage requirements.

Private insurers sell NFIP policies by participating in the "Write Your Own" program. Participating insurers are responsible for selling and renewing policies, issuing contracts, and servicing flood claims. Compensation from the NFIP to participating insurers includes two allowances, an expense allowance and a commission allowance. The expense allowance averages 15.6% of collected premiums, and is based on the estimated costs of marketing, underwriting, and issuing the policy. The commission allowance, 15% of premiums, is intended to cover commissions paid to agents for selling activities. The NFIP also offers a 2% bonus for insurers who achieve an annual 5% growth in the number of policies written (allowance and bonus information from Michel-Kerjan, 2010, p. 409). The commission allowance is paid to the insurer regardless of the commissions paid to agents; the insurer may pay more or less to agents for selling the flood policies. This structure creates variation in sales incentives across insurers, which we employ in our analyses.

Insurance agents must complete training to sell flood insurance (U.S. Congress, 2004). Training courses educate agents on flood zones, policy wording, underwriting, rating, and claims settlement. The NFIP also provides an extensive manual to agents selling flood insurance policies, with guidelines for data collection and underwriting (e.g., NFIP, 2010). This flood training is in addition to insurance agent licensure requirements: in all U.S. states, agents selling *any* type of insurance must pass an exam to be licensed, participate in continuing education, and complete ethics training (see NAIC, 2013, for additional details).

The NFIP instructs agents to determine the replacement cost of the applicant's home using "normal company practice" during the application process (NFIP, 2006, p. 4-175). The insurance agent determines the home's replacement cost using estimation software with information on the home such as square footage, location, home age, foundation type, and basement characteristics. Insurers may develop their own software, though many use products from third-party vendors such as Marshall & Swift (part of CoreLogic) or E2Value.[7] Even though certain areas of the property are not covered by federal flood policies (such as finished basements), many replacement cost calculators include these items as input variables—so estimated replacement costs are a conservatively high estimate of the possible flood loss. Importantly, the policyholder may select any

[7] We contacted the 76 insurers in our data to ask how they estimated replacement cost. Eighteen insurers responded: eight were able to provide their replacement cost software vendor, four responding insurers no longer exist (e.g. were acquired and merged with another organization), two exist but no longer participate in the program, and the remaining four referred us to a person or organization that did not respond to follow-up. Out of the eight providing their replacement cost software, six currently use Marshall & Swift and two use E2Value. Two of the six using Marshall & Swift also use products from Verisk.

coverage limit up to $250,000, regardless of the calculated replacement cost. However, the flood insurance contract caps payments at the least of (1) the limit stated in the declarations, (2) the replacement cost of the damaged property estimated at the time of loss, or (3) the amount actually spent to repair or replace the damaged property (NFIP, 2010, p. POL 19).

2.2 Data

Our data include all NFIP policies written in 2010, but we narrow our sample to focus our analyses and to strengthen empirical identification. Table 1 outlines the number of observations kept with each data cleaning step. We are interested in a households' decision to (over)insure their home, so we exclude nonresidential policies and policies that only insure a home's contents (which is intended for renters). We also limit our analyses to single-family homes, as households living in multi-family dwellings (e.g., townhomes or condominiums) may have less freedom to choose the terms of their flood insurance policies. We keep only policies with the ability to overinsure within the $250,000 maximum program limit—the estimated replacement cost must be $249,900 or below. We wish to observe active choices by consumers, so we drop renewals of existing policies and examine only new issuances in 2010. This filter also avoids problems with "legacy" replacement cost calculations, which may be outdated or inconsistently updated by the agent. We examine only policies in areas designated "Zone A" on federal flood maps, which are homes with at least a 1% annual probability of flood, but are not exposed to storm surge. This zone is the largest in the flood program, comprising 55% of single-family unit policies with building coverage. We examine only this zone to ensure relatively homogeneous flood risk across policies, and our regressions include controls for property-specific risk factors within the zone. We also exclude policies with non-positive replacement costs. About 1.6% of policies are reported to have replacement costs of zero, which is a data error. We drop observations with insurers who sold fewer than 100 federal flood policies in 2010, as relatively few policies have a disproportionate influence on the estimated effects for those insurers.[8]

For 2010, the federal flood insurance program directly issued policies in three cases, and we add data filters to include only the third case. The program directly issued policies if the contract (1) insured a "severe repetitive loss property," (2) was a State Farm legacy contract, or (3) was originated by an independent agent that is not doing so on behalf of an insurer in the program. The NFIP designates a home a "severe repetitive loss property" if since 1978, it has (a) four claims

[8] Twenty-eight of the 76 insurers in our data issued fewer than 100 policies and so our baseline sample includes 48 insurers ($76 - 28 = 48$). The 100-policy threshold is an admittedly arbitrary cutoff, and we conduct robustness checks dropping insurers selling fewer than 300, 500, and 1,000 policies with no substantial difference in results.

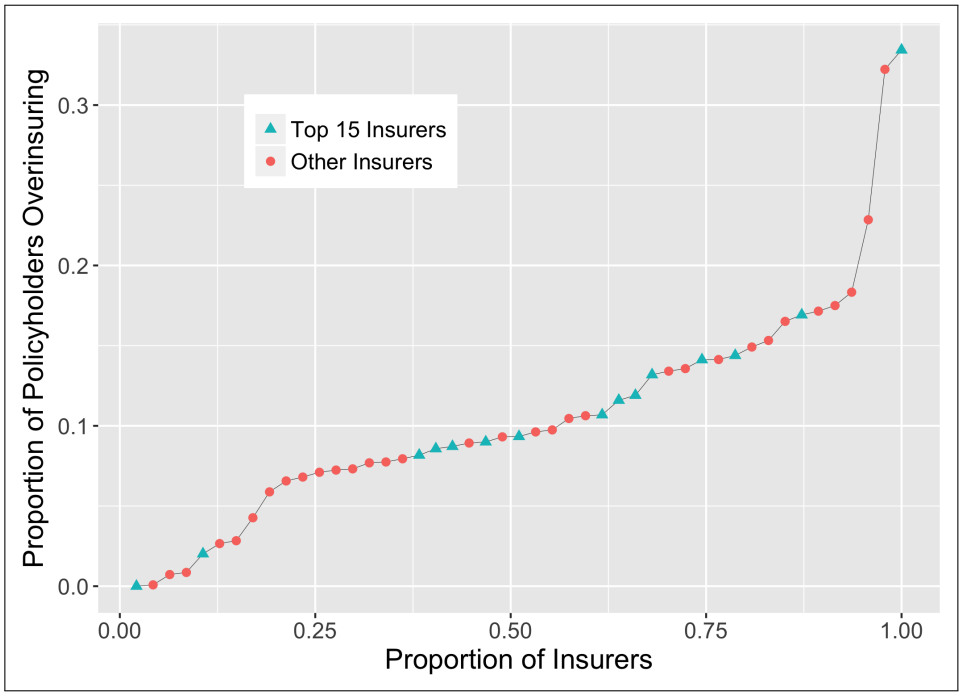
of at least $5,000 each or (b) total claims payments that exceed the value of the property (NFIP, 2011). If a flood causes an insured home to qualify as a repetitive loss property, the insurance renewal will be issued by the NFIP (rather than the original issuing insurer) and given a new policy number. Consequently, the policy appears as a new policy in our database even though it is likely considered a renewal from the household's perspective. State Farm officially left the flood insurance program on October 1, 2010, but its agents continued to service the existing flood insurance policies that it had originated. The renewals on these contracts were given a new policy number and coded as new, NFIP-direct business in our database. Thus, we add filters which exclude repetitive loss properties and contracts issued after October 1, ensuring that the remaining contracts coded as direct issuances from the NFIP are truly "new business" which are originated by independent agents. The resulting baseline sample includes 179,917 flood insurance policies.

Table 1: Data cleaning and filtering steps

Data step	**N remaining**
All policies in 2010	4,445,309
Keep if residential	4,174,842
Keep if purchased building coverage (omit contents only policies)	4,100,186
Keep if single-family units	3,727,896
Keep if flood zone A	1,963,393
Keep if new policy (omit renewals)	380,061
Keep if replacement cost $<$ $250,000	249,335
Keep if not a repetitive loss property	248,567
Keep if policy start date in January to September	183,992
Keep if replacement cost $>$ $0	180,982
Keep if insurance group sells $\geq$ 100 flood policies	179,917
Baseline Data	**179,917**

Figure 2 shows the distribution of overinsuring rates across the 48 insurers in the baseline data. Here and throughout the paper, we treat insurers in the same corporate group as a single insurer. Ten percent of insurers have overinsuring rates below 2%; half have rates below 10%; and at the 90th percentile, 10 percent have overinsuring rates above 17%. The mean overinsuring rate across insurers is 11%. The figure also denotes the 15 largest insurers (by number of flood policies) from the remaining 33 insurers. The top 15 insurers write 91% of policies and generate 90% of total premiums in our baseline data. As the figure shows, the distribution of overinsuring rates for the 15 largest insurers aligns with the distribution for smaller insurers. We include all 48 insurers in our regressions in Sections 3 and 4, but only show the results for the top 15 insurers in the interest of space.

Figure 2: Frequency of Overinsuring by Insurer



Note: Figure shows the distribution of overinsuring rates across the 48 insurers in the baseline data. The figure indicates the 15 largest insurers (by number of flood policies) with a triangle and the remaining 33 insurers with a circle. The top 15 insurers write 91% of policies and generate 90% of total premiums in our baseline data.

The variables in our dataset were populated by insurance agents selling the policies. The agent originating the contract completed a standard NFIP form, which required characteristics of the policy (e.g., deductibles, coverage limits, premiums) and of the insured home (e.g., replacement cost, location, flood zone, age, elevation). Each of these variables is included in our database except for personally identifiable information—we observe the home's ZIP code, but not its street address or the name of the policyholder.

2.3 Variables and descriptive statistics

Our data include characteristics of the home and its flood risk, which we use as control variables in our analysis. We define these variables in Table 2. Each of these is used by the NFIP in premium rating except for the home's age.

We compare households who overinsure to those who partially insure and fully insure in Table 3. Overinsuring and fully insuring households appear similar. They are comparable in terms

Table 2: Home Characteristics

Variable	Description
Basement	Describes the characteristics of the home's basement or crawlspace. It takes 5 values: none, finished basement, unfinished basement, crawlspace, and subgrade crawlspace.
CRS Score	The community's score on the Community Rating System (CRS). The CRS is a voluntary program that rewards communities for taking actions to mitigate flood risk beyond minimum NFIP requirements. Community actions reduce policyholder premiums by up to 45%. CRS score is the associated premium reduction, ranging from 0 (no mitigation) to 45 (maximum mitigation).
Elevation	An estimate of the elevation (in feet) of a policyholder's home relative to the 100-year floodplain. Elevation data are available on 56% of baseline policies.
Elevation Certificate	Home elevation is sometimes estimated by communities; however, homeowners can also contract an engineer or surveyor to evaluate their homes. This variable can take 12 values depending on who assessed the elevation and when.
Flood Zone	All households in the baseline survey are in flood Zone A. The A Zone is divided into 38 subcategories based on vulnerability (e.g., A1 to A30), which we include as dummy variables in our models.
Floors	Number of floors in the home, taking four possible values: 1, 2, 3 or more, or split-level.
Home Age	Age of the home, in years.
Mobile	Indicates whether the structure is a manufactured/mobile home.
Obstruction	Description for elevated buildings regarding the area and machinery attached to the building below the lowest floor. It takes 13 values, depending on the size of the area, whether it has permanent walls, and the presence/location of machinery (e.g., if it is elevated). We include dummy variables for these in our models.
Pre-FIRM	Indicates whether the home was built before federal flood risk maps were developed for its location.
Replacement Cost	The cost to replace property with the same kind of material and construction without deduction for depreciation.

Note: NFIP (2010) provides additional information on these variables. Each of these variables is included as a control in our regression models in Sections 3, 4, and 5.

of home age, elevation, deductible choice, and contents coverage. Overinsuring and fully insuring households are also similar regarding whether their homes were built before federal flood maps were developed (pre-FIRM) and actions taken by their community to reduce flood risk (CRS score). Pre-FIRM homes tend to have higher expected flood damage as they were built before building codes to reduce flood risk were in force. Partially insuring households tend to differ as they have lower valued, older homes that are at greater risk (lower elevation, lower CRS score, more frequently pre-FIRM). Households who partially insure have higher median premiums (though their average is lower) than those who fully insure despite having higher deductibles and insuring their contents less often.[9] Finally, households who overinsure have the highest aver-

[9] Collier et al. (2017) examine the decision to partially insure in the flood insurance program using data from 2003 to 2009. They provide a similar table (their Table 4) and reach similar conclusions regarding differences between partially,

age replacement cost, $146,380.

Table 3: Summary Statistics for Households who Partially Insure, Fully Insure, and Overinsure

		Partially Insure	Fully Insure	Overinsure
Observations		36,791	122,085	21,041
Home Characteristics				
Replacement Cost	Median	139,000	150,000	150,000
	Mean	137,548	144,889	146,380
	S.D.	54,921	58,457	59,930
Home Age	Median	40.06	34.46	32.69
	Mean	41.47	33.74	33.33
	S.D.	23.45	20.13	19.96
CRS Score	Median	0.00	10.00	10.00
	Mean	6.76	11.34	10.63
	S.D.	8.76	8.99	9.10
Elevation	Median	1.00	1.00	1.00
	Mean	1.29	1.76	1.71
	S.D.	2.36	1.97	2.15
Elevation Missing		0.70	0.37	0.35
Pre-FIRM		0.72	0.56	0.53
Mobile Home		0.03	0.04	0.02
Contract Characteristics				
Premium	Median	526	502	556
	Mean	618	658	750
	S.D.	395	436	520
Deductible = $1,000		0.62	0.71	0.70
Deductible = $2,000		0.16	0.16	0.15
Deductible = $5,000		0.21	0.12	0.14
Has Contents Coverage		0.41	0.63	0.66

Note: Table compares characteristics of partially insuring, fully insuring, and overinsuring households in our baseline data. The Community Rating System (CRS) is a voluntary program that rewards communities for taking actions to mitigate flood risk beyond minimum NFIP requirements; larger numbers indicate more actions taken. Pre-FIRM indicates that a home was built before federal flood risk maps were developed for its location.

2.4 The value of overinsuring

In this section, we use ex-post claims data for the policies in our sample to calculate the expected value of overinsurance. We then compare this expected value to the additional premium charged to determine the value of excess coverage. The 179,917 policies in our baseline data ultimately resulted in 1,434 claims—an overall claim rate of 0.79%. All claims occurred between January

fully, and overinsuring households.

2010 and September 2011, as these are annual flood insurance policies originated between January and September 2010. There were 40 claims in which damages exceeded the home's estimated replacement cost, so there was a 0.02% excess damage claim rate. Of these 40, six households had purchased excess coverage. Among households with claims, 2.8% incurred damage that exceeded the initially-estimated replacement cost.[10]

Table 4 shows characteristics of our baseline data, summarizing (1) all policies, (2) policies with claims of any amount, and (3) policies with claims incurring excess damage (i.e., damages that exceed the home's replacement cost value). Thus, Column 3 is a subset of Column 2, which is a subset of Column 1. Households who experienced excess damage were slightly more likely to have overinsured, 0.15 versus 0.12 for all baseline policies.[11] On average, policyholders who experienced excess damage selected higher coverage limits relative to their replacement costs.

Households with excess damage have much lower replacement costs than other households. The average replacement cost estimate for homes with excess damage is $49,179, compared to $143,562 for all baseline policies. Over 93% of baseline policies have a replacement cost greater than $49,179. Mobile homes disproportionately experience excess damage—mobile homes comprise 4% of policies and non-excess claims, but represent more than 23% of excess damage claims. Older homes have a higher overall claims probability, and a large portion of these homes were built before flood maps were developed. Homes with excess damage are newer than the average home with a claim but are about as likely to have been built before flood maps were developed. Homes with excess damage are located in communities that have taken fewer actions to reduce flood risk (CRS Score of 1.38 for claims with excess damage versus 10.32 for all policies). Homes with excess damage are more elevated than the average home in the data (2 feet versus 1.7 feet), but we make this observation with some caution since elevation data are often missing for homes with excess damage.

The average amount of damage above the home's replacement cost is $6,872. The sample of excess damage claims is right-skewed with five claims between $10,000 and $20,000, three claims between $20,000 and $30,000, and a maximum of $34,660. The median is $3,416, and seventeen of the 40 excess damage claims were $3,000 or less. We multiply the mean severity by the frequency of excess damage to calculate the expected value of damages in excess of a home's replacement

[10] Similar to homeowners insurance, a claims adjuster visits the affected home to assess damages. The adjuster's assessment of the home's value and total damages are independent of the contract's coverage limit and the replacement cost estimated by the insurer at origination of the policy (NFIP, 2006, pp. 4-202, 4-210).

[11] The difference in overinsuring rates between the 40 policyholders with excess damage (15%) and the other 179,877 policyholders (12%) is not statistically significant according to Fisher's exact test ($p = 0.47$). The difference in overinsuring rates between the 40 policyholders with excess damage (15%) and the other 1,394 claimants (11%) is also not statistically significant ($p = 0.44$).

Table 4: Summary Statistics for Policies, Claims, and Claims with Excess Damage

		All Policies	All Claims	Excess Damage Claims
Observations		179,917	1,434	40
Contract Characteristics				
Overinsurance Rate		0.12	0.11	0.15
Cov. Limit / Replacement Cost	Median	1.00	1.00	1.00
	Mean	0.95	0.88	1.01
	S.D.	0.23	0.29	0.23
Home Characteristics				
Replacement Cost	Median	149,000	125,500	37,500
	Mean	143,562	127,009	49,179
	S.D.	58,010	60,366	46,074
Home Age	Median	35.32	45.42	35.27
	Mean	35.27	46.37	35.24
	S.D.	21.07	22.86	18.54
CRS Score	Median	10.00	0.00	0.00
	Mean	10.32	3.23	1.38
	S.D.	9.14	5.80	4.53
Elevation	Median	1.00	1.00	2.00
	Mean	1.70	0.76	2.00
	S.D.	2.05	2.76	3.52
Elevation Missing		0.44	0.80	0.85
Pre-FIRM		0.59	0.84	0.80
Mobile Home		0.04	0.04	0.23

Note: Table compares characteristics of our baseline data, summarizing (1) policies, (2) policies with claims of any amount, and (3) policies with claims incurring damage greater than the home's estimated replacement cost. Thus, Column 3 is a subset of Column 2, which is a subset of Column 1. The Community Rating System (CRS) is a voluntary program that rewards communities for taking actions to mitigate flood risk beyond minimum NFIP requirements; larger numbers indicate more actions taken. Pre-FIRM indicates that a home was built before federal flood risk maps were developed for its location.

cost:

$$\begin{aligned} \mathrm{E}(Loss_{ExcessDamage}) &= \text{mean}(ExcessDamage) \times p(ExcessDamage) \\ &= \$6,871.55 \times 40/179,917 = \$1.53 \end{aligned} \tag{1}$$

where $p(\cdot)$ indicates the likelihood. Thus, a policyholder in our baseline sample has an expected loss from excess damage of \$1.53.[12]

[12] Expected loss might additionally be estimated at the policy level by conditioning on the home's characteristics (e.g., its replacement cost). We are reticent to pursue policy-level estimates in our data; however, because the observations of

We also calculate the amount that households pay for excess coverage. Our data include the insured home's characteristics used in the contract premium formula (NFIP, 2010, Chapter 5). This information allows us to price any contract available to the household. We calculate the premiums for excess coverage as the difference between the premium that each overinsuring household paid and what it would have paid had it purchased a coverage limit equal to the home's replacement cost.[13]

We find that overinsuring households pay a mean (median) additional premium of \$71.07 (\$24.00) for limits above replacement cost. Compared to selecting a coverage limit equal to the replacement cost, this additional coverage increases their premiums by a mean (median) of 14% (5%). Thus, the ratio of premiums to expected losses for the average overinsuring household is

$$\begin{aligned} Load &= \text{mean}(Premium_{ExcessCoverage})/\text{E}(Loss_{ExcessDamage}) \\ &= \$71.07/\$1.53 = 46.45 \end{aligned}$$

implying a premium loading for this excess coverage of 4,645%.[14]

excess damage are so few.

[13] To assess the accuracy of our calculations, we calculate each household's paid premiums given their contract choices such as building and contents coverage limits. We then compare our estimated premium to that actually paid by the policyholder. Our premium calculations are within \$1 of actual paid premiums for 92% of households (165,098 observations), and within \$10 for 98% of households. We limit the following analyses to the 165,098 households for which our premium calculations are within \$1.

[14] Our sample year of 2010 was a moderate year for floods—its claims were at the median for years 2000-2013. Households (and insurers) may instead be anticipating a year of severe storms when evaluating the price of excess coverage relative to expected loss. Thus, using policy data from 2010 may underestimate expected excess damage.

As a check, we also calculate $E(Loss_{ExcessDamage})$ using policy year 2012, which included losses from Superstorm Sandy. Sandy was the second-costliest recorded storm in the U.S. when it occurred. It also occurred shortly after our 2010 baseline sample, and so methods for determining the replacement cost in 2012 are likely similar to those in our baseline. Due to data availability in 2012, we must first calculate a baseline claim rate $p(Claim)$ and then multiply it by a conditional expectation of $p(ExcessDamage|Claim)$ to calculate the excess damage probability $p(ExcessDamage)$. We can then calculate the $E(Loss_{ExcessDamage})$ as follows:

$$\begin{aligned} E(Loss_{ExcessDamage}) &= p(Claim) \times p(ExcessDamage|Claim) \times mean(ExcessDamage) \\ &= \frac{\#\,claims_p}{\#\,policies} \times \frac{\#\,excess\,claims}{\#\,claims_c} \times \frac{\sum \$\,excess\,claims}{\#\,excess\,claims} \\ &= \frac{8,266}{221,369} \times \frac{118}{3,467} \times \frac{\$1,690,886}{118} \\ &= \$18.21 \end{aligned}$$

The first term above is calculated using the 2012 flood *policy* dataset, which is missing several of the filtering variables outlined in Table 1. Namely, we cannot exclude repetitive loss properties or replacement costs above \$250,000 from this term. This constraint inflates the baseline claim rate compared to using the 2010 sample, because it includes repetitive loss properties. The second and third terms, however, are calculated from the 2012 flood *claims* dataset, which does allow us to filter by repetitive loss properties and replacement cost (hence the lower claim count for $claims_c$, from the claims data, than for $claims_p$, from the policy data). Neither dataset in 2012 allows us to exclude insurers issuing fewer than 100 policies.

Evaluating 2010 premiums relative the large expected excess damage calculated with 2012 claims, we find the implied

Even when buying limits above replacement cost, there is still a possibility that these excess limits are insufficient. The average overinsuring household selects a coverage limit that exceeds their replacement cost by $33,000, but about 20% of overinsuring households select an amount of excess coverage that is less than the $6,872 average excess damage that we observe. Also, of the 40 claims with excess damage, only six households had purchased excess coverage. Of those six, three still experienced damages greater than their selected coverage limit.

In summary, we find that flood damage can exceed the home's estimated replacement cost; however, managing this risk by overinsuring appears to be an expensive way to address it relative to the risk. Moreover, while households with low replacement costs are at greatest risk of excess damage, households with above-average replacement costs tend to overinsure. The private insurance industry has developed ways to manage the risk of excess damage in other property insurance settings (e.g., an endorsement that guarantees the property's replacement cost, debris removal expenses as a separate limit), but these methods are not currently employed in the NFIP.

3 Insurer effects

3.1 Methodology

In this section, we examine whether the insurer selling the policy significantly affects the likelihood that a household overinsures. The empirical test for these insurer effects is a regression model of whether household i overinsures $\mathrm{I}(Over_i)$, as a function of insurer j fixed effects β_j and various policy-level controls $\mathbf{X_i}$. Our regression model for these primary results is the linear probability model:

$$\mathrm{I}(Over_i) = \alpha + \beta_j + \mathbf{X_i'}\gamma + \varepsilon_i \tag{2}$$

$$\begin{aligned}\mathrm{I}(Over_i) = \alpha + \beta_j &+ \gamma_1 \mathrm{D}(Basement_i) + \gamma_2 \mathrm{D}(CRSscore_i) + \gamma_3 \mathrm{D}(Elevation_i) \\ &+ \gamma_4 \mathrm{I}(ElevationCertificate_i) + \gamma_5 \mathrm{D}(FloodZone_i) + \gamma_6 \mathrm{D}(Floors_i) + \gamma_7 HomeAge_i \\ &+ \gamma_8 \mathrm{I}(HomeAge_i = Missing) + \gamma_9 \mathrm{I}(Mobile_i) + \gamma_{10} \mathrm{D}(Obstruction_i) \\ &+ \gamma_{11} \mathrm{I}(PreFIRM_i) + \gamma_{12} ReplacementCost_i + \delta_k + \lambda_t + \varepsilon_i\end{aligned}$$

where δ_k are location fixed effects (state or ZIP code) and λ_t are month fixed effects.[15]

premium load for excess coverage is 390% for the baseline sample ($71.07 ÷ $18.21 = 3.90). Thus, loads on overinsuring appear quite high even when using data exclusively from one of the costliest years in the program.

[15] For robustness, we also estimated our models using logit and obtained qualitatively similar results. Linear probability models (LPMs) offer several advantages over index models (e.g., logit or probit) in our setting. Interpreting the

In Equation (2), I($\cdot$) denotes an indicator variable and D($\cdot$) denotes a dummy set, which is a group of indicators representing discrete values of a variable. For example, D($Floors_i$) includes indicators for homes with one floor I($Floors_i = 1$), those with two floors I($Floors_i = 2$), etc. Table 2 in Section 2.3 describes each control variable. The home's age is missing for 0.3% of policies; in these cases, we record $HomeAge_i = 0$ and the indicator I($HomeAge_i = Missing$) $= 1$. Home elevation is measured to the nearest foot relative to the 100-year flood plain. The dummy set includes an indicator variable for each foot (e.g., I($Elevation_i = 1$)). It is bottom-coded at -5 such that all values below this are recorded as -5 and similarly top-coded at 10. It also includes an indicator if the home's elevation is unavailable.[16] In the regression models reported in Table 5, we begin with the insurer fixed effects alone. In the subsequent regressions we add month and location fixed effects and "Controls" where $Controls = \{Basement, CRSscore, Elevation, ElevationCertificate, HomeAge, Mobile, Obstruction, PreFIRM\}$. In the final regression, we also add replacement cost.

Estimates of $\hat{\beta}_j$ depend on which insurer is excluded from the set of insurer fixed effects in Equation (2) (i.e., which insurer is the reference group). To adjust for this, we transform the estimated insurer fixed effects by subtracting the estimate from the average effect across insurers.

$$\hat{\beta}_{norm,j} = \begin{cases} \hat{\beta}_j - \dfrac{1}{M}\displaystyle\sum_{m=2}^{M} \hat{\beta}_m & \text{for} \quad j = 2, ..., M \\ \\ -\dfrac{1}{M}\displaystyle\sum_{m=2}^{M} \hat{\beta}_m & \text{for} \quad j = 1 \end{cases} \tag{3}$$

where $j = 1$ denotes the omitted insurer

Our regression results in Table 5 report these transformed coefficients with standard errors adjusted accordingly. The interpretation of these coefficients is now slightly different—each $\hat{\beta}$ is now in reference to the average insurer effect rather than to the omitted insurer. Thus, a coeffi-

insurer effects in LPMs are more straightforward. LPMs facilitate normalization of beta coefficients. This normalization approach in our study of insurer effects follows methods used in examining auctioneer effects (Lacetera et al., 2016), hospital effects (e.g., Chandra et al., 2016), and teacher effects (e.g., Jacob and Lefgren, 2007). While index models have advantages in certain applications (e.g., examination of predicted values), econometric textbooks (e.g., Wooldridge, 2010; Angrist and Pischke, 2008) now frequently present the benefits of using LPMs for causal inference. For example, LPMs provide coefficients that minimize the mean squared error, and clustered, robust standard errors address concerns about heteroskedasticity.

[16] We include elevation as a control related to the flood risk of the home, but do not have a strong prior on how it may influence the choice to overinsure given our other model controls. Over 93% of homes for which the elevation is missing are pre-FIRM, as codes in identified flood zones tend to require building to a certain elevation. In our regression results, we find that the home's elevation and our indicator for missing elevation are not significant predictors of whether the policyholder overinsures.

cient of 0.1 for Insurer j would indicate that its policyholders are 10 percentage points more likely to overinsure than the policyholders of the average insurer in the data. We report robust standard errors clustered by state.[17]

3.2 Results

We provide our estimation results in Table 5. These models examine insurer effects on the likelihood that a household overinsures. We have randomized the order of insurers (e.g., Insurer 1 is not necessarily the largest insurer). The models include insurer fixed effects for all 48 insurers in the baseline data, but we only report the results for the 15 insurers originating the most policies in the baseline data in the interest of space. As we show in Figure 2, the distribution of overinsuring among the largest insurers appears similar to the distribution over all insurers. The estimated effects for the remaining 33 insurers are qualitatively similar to those of the top 15, and Figure 3 below shows the estimates for all insurers.

The results in Table 5 include four columns representing different specifications of our model. Column 1 only includes insurer fixed effects. Column 2 includes insurer fixed effects, state fixed effects, month fixed effects, and characteristics of the home as control variables. Column 3 replaces the state fixed effects in Column 2 with ZIP code fixed effects. Thus, in this model we compare insurer effects within a ZIP code, controlling for seasonal effects and features of the home that may affect its flood risk. Column 4 includes the same variables as Column 3, but adds replacement cost as an explanatory variable. Column 4 is our preferred model, but coefficient estimates do not appear to differ greatly between Columns 2, 3, and 4. The Pearson correlations of the coefficients for the model estimated in Column 4 with those in Columns 1 to 3 are 0.70, 0.99, and 1.00, respectively.

We prefer to include replacement cost as a control because insurers may pursue different income-based target markets within a ZIP code, which could influence our estimates of insurer effects. For example, suppose that higher income households tend to overinsure and Insurer 1 specializes in higher income households relative to the average insurer. We might erroneously attribute higher overinsuring rates for Insurer 1 to the insurer's influence on policy choices when, in fact, they are due to customer differences. Our ZIP code fixed effects likely control for a substan-

[17] Clustering intends to address possible correlations in model errors that would violate $i.i.d.$ assumptions (Cameron and Miller, 2015). Clustering by state or by insurer might be justified in our setting. Since our paper explores the possible influence of insurers, we prefer to avoid clustering standard errors by insurer because such clustering assumes *a priori* that model errors are correlated by the insurer. We examined clustering by insurer and found that it also leads to significant insurer effects and tends to result in smaller standard errors than clustering by state. Clustering by state gives more conservative results in this context and is our preferred approach.

Table 5: Insurer Effects on the Likelihood That a Household Overinsures, 15 Largest Insurers

	(1)	(2)	(3)	(4)
Insurer 1	−0.001	−0.018	−0.020*	−0.020*
	(0.015)	(0.012)	(0.012)	(0.012)
Insurer 2	0.226***	0.198***	0.193***	0.200***
	(0.022)	(0.023)	(0.024)	(0.023)
Insurer 3	−0.015*	−0.020***	−0.012	−0.012
	(0.008)	(0.007)	(0.008)	(0.008)
Insurer 4	−0.088***	−0.056***	−0.049***	−0.049***
	(0.003)	(0.006)	(0.007)	(0.007)
Insurer 5	0.008	−0.012***	−0.008*	−0.008*
	(0.008)	(0.004)	(0.004)	(0.004)
Insurer 6	0.061***	0.053***	0.052***	0.052***
	(0.017)	(0.011)	(0.012)	(0.011)
Insurer 7	−0.021**	−0.033***	−0.029**	−0.030**
	(0.010)	(0.010)	(0.013)	(0.013)
Insurer 8	0.011	−0.018**	−0.023**	−0.024***
	(0.014)	(0.008)	(0.009)	(0.009)
Insurer 9	0.033**	0.014	0.021**	0.019**
	(0.016)	(0.010)	(0.009)	(0.009)
Insurer 10	0.036***	0.013*	0.018**	0.020**
	(0.012)	(0.008)	(0.008)	(0.008)
Insurer 11	−0.018	−0.015	−0.009	−0.010
	(0.014)	(0.011)	(0.012)	(0.012)
Insurer 12	−0.022***	−0.026***	−0.022**	−0.024**
	(0.008)	(0.008)	(0.010)	(0.011)
Insurer 13	0.024	−0.003	−0.006	−0.006
	(0.018)	(0.025)	(0.024)	(0.024)
Insurer 14	−0.108***	−0.139***	−0.142***	−0.140***
	(0.003)	(0.006)	(0.007)	(0.007)
Insurer 15	−0.026***	−0.029***	−0.032***	−0.030***
	(0.006)	(0.006)	(0.005)	(0.005)
Replacement Cost	No	No	No	Yes
Controls	No	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes
Location FE	No	State	ZIP	ZIP
Clustered SE	State	State	State	State
N	179,917	179,917	179,917	179,917
R-Sq	0.017	0.034	0.109	0.112

Note: Dependent variable is whether a household overinsures (selects a coverage limit greater than the home's replacement cost). Regressions are linear probability models, follow Equation (2), and include insurer fixed effects for all 48 insurers in the baseline data. We normalize fixed effects following Equation (3). Table reports the results for the 15 insurers originating the most policies in the data in the interest of space. Column 1 only includes insurer fixed effects. Column 2 includes insurer fixed effects, state fixed effects, month fixed effects and characteristics of the home as control variables. Column 3 includes insurer fixed effects, ZIP code fixed effects, month fixed effects, and home characteristics. Column 4 includes the same variables as Column 3, but adds replacement cost as an explanatory variable. Standard errors are robust and clustered by state. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

tial amount of the variation in income and wealth across households; replacement cost is likely the best variable in our data to proxy variations in household income and wealth *within* a ZIP code.

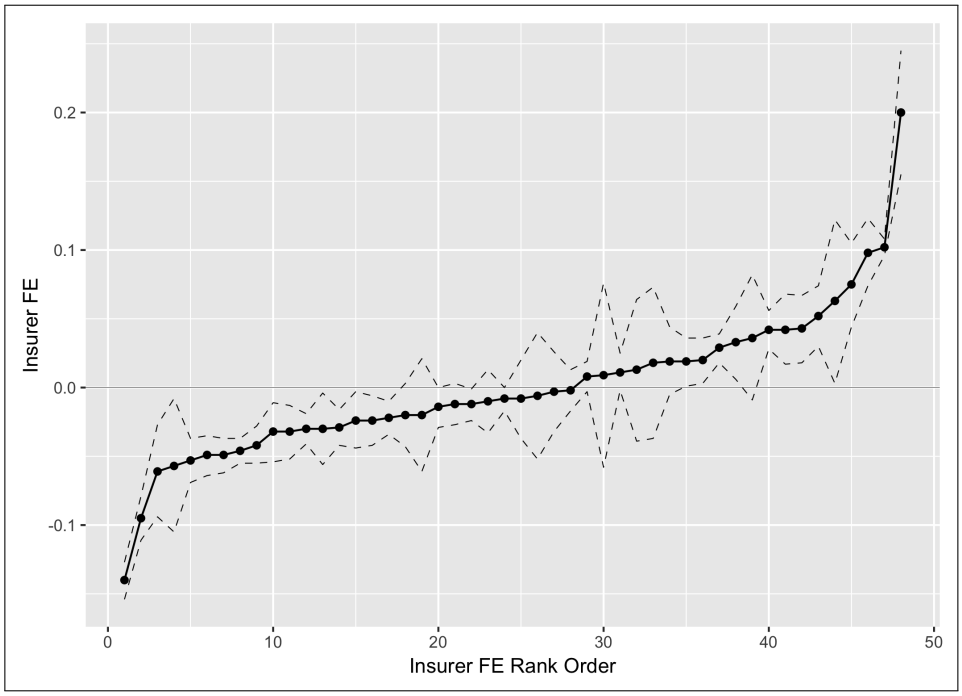
The results show that the insurer selling the policy significantly affects the likelihood that a household overinsures. We discuss the results from Column 4. The coefficients show the percentage point change in the likelihood of overinsuring if a household buys a policy from Insurer J relative to the average insurer in the baseline data. For example, suppose that a household decides to purchase flood insurance from Insurer 4. This household is 4.9 percentage points less likely to overinsure than if it bought a policy from the average insurer in the data. Instead, if the household purchases a policy from Insurer 2, it is 20 percentage points more likely to overinsure than purchasing from the average insurer and nearly 25 percentage points more likely to overinsure than if it used Insurer 4.

Figure 3 illustrates the results showing the insurer fixed effect coefficients for all 48 insurers using the results from Column 4. We rank the insurers from lowest to highest coefficient and plot the 95% confidence intervals as dotted lines. Zero on the vertical axis represents the average insurer effect. Of the 48 insurers, 31 insurers have fixed effects that significantly differ from from zero: 13 are positive and 18 are negative. Compared to the policyholders of the average insurer, the policyholders of the top five insurers, those with the largest fixed effects, are at least 5 percentage points more likely to overinsure while those of the bottom five insurers are at least 5 percentage points less likely to overinsure.[18]

We conduct two robustness tests considering the possibility that randomness might cause the insurer effects that we observe. First, we calculate an Empirical Bayes (EB) estimator (Morris, 1983) of the fixed effect coefficients. Natural heterogeneity in consumer preferences might lead to some observed differences across insurers due to sampling variation. Our large sample size should allow for precise estimation of insurer effects and mitigate this sampling concern, but the EB estimator explicitly adjusts for such sampling variation. This procedure has been used in studies of teacher effects (e.g., Jacob and Lefgren, 2007), hospital effects (e.g., Chandra et al., 2016), and auctioneer effects (Lacetera et al., 2016). We find that the EB-adjusted coefficients are almost identical to the results in this section. Second, we conduct a placebo test in which we randomly reorder the insurers in our dataset, arbitrarily matching a policyholder with a new insurer. We then repeat the above regressions using the "placebo" insurers. If our main analysis involved

[18] As an extension of this research, we use the same methods to examine whether a household's insurer affects the likelihood that it will partially insure or fully insure, with results in Online Appendix B. Because different decision processes may guide partially insuring and overinsuring, as discussed in Section 1, we consider this extension exploratory and beyond our core focus. Our results show statistically significant insurer effects for fully insuring and partially insuring. Thus, we find some initial evidence that insurer effects may extend beyond the decision to overinsure, and leave an in-depth analysis for future research.

Figure 3: Plot of insurer fixed effect estimates



Note: The rank of the fixed effect estimate is plotted on the x-axis, ranked from smallest to largest. The fixed effect estimate is plotted on the y-axis where zero equals the average insurer effect. Dotted lines represent a 95% confidence interval around the normalized estimate.

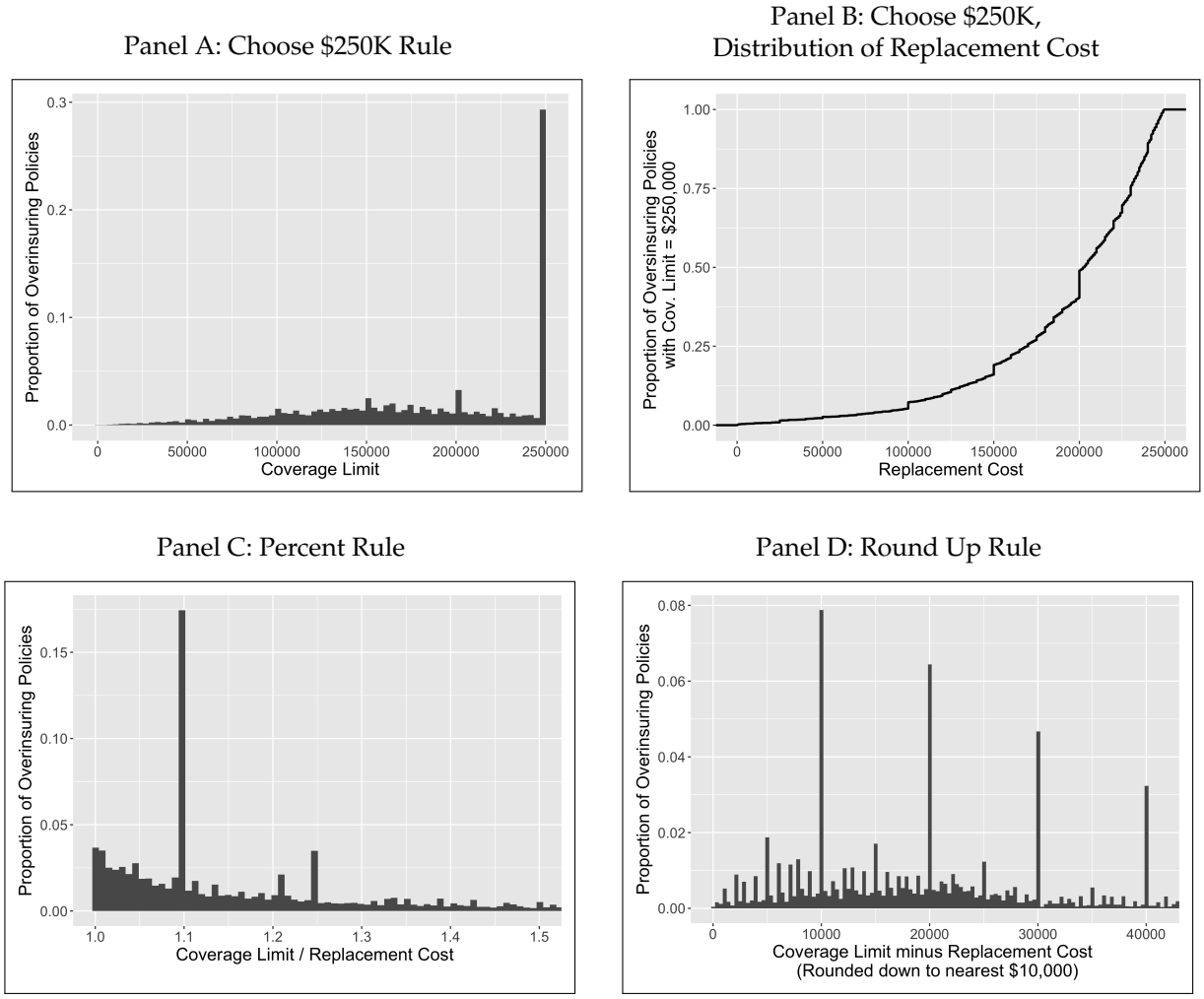
spurious effects, the analysis with placebo insurers would result in similar levels of significance for the insurer effects. Instead, the placebo insurer coefficients are not significantly different from zero. We discuss the methodology and provide tabular results in Online Appendix A.

4 Insurers' specific guidance for overinsuring

In this section, we examine insurer effects on the exact excess limit selected. Given that a household chooses to overinsure, what coverage limit should it choose? If consumers choose a limit based on their own preferences and beliefs, the selected excess coverage limits should be random across insures (after controlling for policyholder characteristics, location, etc.). Since insurers influence whether households overinsure (Section 3), they might also make specific limit recommendations to households.

Examining the distributions of absolute and relative excess limits, we identify three possible "rules" insurers might use to recommend limits. Figure 4 illustrates each. The most common rule

Figure 4: Coverage Limit Rules for Overinsuring Households



Note: Panel A is a histogram showing the coverage limits selected by overinsuring households. Panel B is the cumulative distribution of replacement costs for households who overinsure by selecting a $250,000 coverage limit. Panel C is a histogram showing the ratio of coverage limits to replacement cost for households who overinsure. Panel D is a histogram illustrating the "round up" rule for overinsuring households. The horizontal axis shows the selected coverage limit minus the home's replacement cost, rounded down to the nearest $10,000 increment (e.g., a home with a $201,000 replacement cost one with a $200,000 would each treated as $200,000). Thus, the highest peak in the histogram at $10,000 shows that households adopting this rule most often select a coverage limit by rounding their replacement cost to the next increment of $10,000.

is to purchase the program maximum of $250,000, which describes 29% of overinsuring households. This rule is the most costly; overinsuring households adopting this "choose $250K" rule pay an average additional premium of $100 for excess coverage. The large spike in Panel A of Figure 4 shows the prevalence of the $250,000 limit among households who overinsure and that some overinsuring households choose limits of $200,000 and $150,000. Panel B of Figure 4 shows

the replacement costs of overinsuring households with $250,000 coverage limits. Half of these households have replacement costs of $200,000 or less; one in five is buying at least $100,000 of excess coverage. The second most common rule is to purchase 110% of the replacement cost, which describes 18% of overinsuring households (Panel C). Households adopting this "increase 10% rule" spend $27 on average on excess coverage. The third most common rule is to purchase a coverage limit that equals the nearest $10,000 increment above the replacement cost. For example, a household with a $200,000 replacement cost and one with a $201,000 would each select a coverage limit of $210,000 using this rule. This rule explains the behavior of 8% of overinsuring households. Panel D shows that while rounding up by $10,000 is the most common version of this "round up" rule, households also commonly round up by $20,000, $30,000, or $40,000. Households adopting the "round up $10K" spend $13 on average on excess coverage. In total, the "choose $250K," "increase 10%," and "round up $10K" rules explain 50% of coverage limits of overinsuring households.[19]

We show the prevalence of each excess coverage rule for the top 15 insurers in the baseline data in Table 6. These insurers are numbered in the same order as our main results in Table 5. The table suggests that some insurers are especially likely to adopt certain rules. For example, 41% of overinsuring policyholders of Insurer 2 select the maximum allowable coverage limit of $250,000, while nearly half of the overinsuring policyholders of Insurer 13 purchase a coverage limit of 110% of their replacement cost.

The observed differences in Table 6 might be due to unobserved differences in policyholders and local markets, so as we do in Section 3.2, we control for these factors in our regression analysis. Our dependent variable is an indicator for whether policy i's limit is consistent with the rule, and we follow the methodology outlined in Section 3.1 and Equation (2). These regressions use our preferred model (shown in Column 4 of Table 5) and so include controls for a home's replacement cost, other characteristics of the home, ZIP fixed effects, and month fixed effects. We transform the insurer effect coefficients in each regression using Equation (3) so that each uses the average

[19] The "increase 10% rule" is a specific example of selecting some percentage point increase in the replacement cost. Excluding households who select the $250,000 maximum, 32% of remaining overinsuring households have a coverage limit that is some 5 percentage point increment (i.e., 105%, 110%, 115%, etc.) of their replacement cost ("percent rule").

The "round up $10K" rule is a specific example of purchasing some round value (e.g., $5,000) above the replacement cost ("round up rule"). Excluding households who select the "choose $250K" or "percent rule", 28% of remaining overinsuring households have a coverage limit that is rounded to some $5,000 increment above the replacement cost.

Some coverage limits could be explained by more than one rule, which is why the combination of the rules sum up to less than their parts, describing 50% of excess coverage limits rather than 55% ($29\% + 18\% + 8\% = 55\%$). For example, either the "increase 10%" or the "round up $10K" rules could lead an agent to recommend a household with a $100,000 replacement cost purchase a $110,000 coverage limit. Thus, this coverage limit would be coded for both rules; our regressions below identify which possible rule(s) each insurer uses. The "choose $250K" and broader "percent" and "round up" rules (beyond our selected 10% and $10,000 values) explains 66% of coverage limits for overinsuring households.

Table 6: Prevalence of Most Common Overinsuring Rules, 15 Largest Insurers.

		Overinsuring Households		
	Over Rate	Choose $250K	Increase 10%	Round up $10K
Insurer 1	0.11	0.22	0.03	0.08
Insurer 2	0.33	0.41	0.04	0.09
Insurer 3	0.09	0.25	0.04	0.07
Insurer 4	0.02	0.11	0.15	0.04
Insurer 5	0.12	0.21	0.05	0.09
Insurer 6	0.17	0.20	0.02	0.13
Insurer 7	0.09	0.30	0.07	0.14
Insurer 8	0.12	0.33	0.28	0.06
Insurer 9	0.14	0.26	0.21	0.07
Insurer 10	0.14	0.35	0.03	0.10
Insurer 11	0.09	0.15	0.02	0.14
Insurer 12	0.09	0.26	0.27	0.09
Insurer 13	0.13	0.14	0.48	0.06
Insurer 14	0.00	0.00	0.00	0.00
Insurer 15	0.08	0.21	0.04	0.11
Total Baseline	0.12	0.29	0.18	0.08

Note: The column "Over Rate" shows the percent of policyholders overinsuring for each insurer. Columns 3-5 show the proportion of overinsured policies using the given rule. "Choose $250K" indicates that overinsuring households select the program maximum of $250,000, "Increase 10%" indicates selecting a coverage limit that is 110% of the replacement cost, and "Round up $10K" indicates selecting a coverage limit by rounding up to the next $10,000 above the replacement cost (e.g., a household with a $200,000 and one with a $201,000 would each select a coverage limit of $210,000).

insurer as the reference group. While the incidence rates for the rules in Columns 3 to 5 of Table 6 only include overinsuring households, our regressions include the entire baseline sample.

We provide the regression results in Table 7. All 48 insurers in the baseline data are included in the regression, though we only report the top 15 insurers. The ordering of insurers corresponds to the previous results (i.e., Insurer 1 represents the same insurer here and in Tables 5 and 6). As with the previous results on insurer effects (Section 3.2), we find that a household's insurer significantly affects the likelihood that it adopts a specific level of excess coverage. For example, the policyholders of Insurer 2 are 9 percentage points more likely to choose the program maximum of $250,000 than the policyholders of the average insurer in the data. Also, the policyholders of Insurer 13 are significantly more likely than average to purchase 110% of their replacement cost (Column 2), but are significantly less likely to use one of the other rules relative to the average insurer's policyholders. This analysis provides further evidence that rather than consumers, in-

Table 7: Insurer Effects on Rules for Overinsuring, 15 Largest Insurers

	(1) I(Choose $250K)	(2) I(Increase 10%)	(3) I(Round up $10K)
Insurer 1	−0.003 (0.002)	−0.007 (0.005)	−0.003*** (0.001)
Insurer 2	0.090*** (0.020)	0.000 (0.003)	0.015*** (0.003)
Insurer 3	−0.004 (0.005)	−0.004** (0.002)	−0.003* (0.002)
Insurer 4	−0.007** (0.003)	−0.001 (0.002)	−0.005*** (0.001)
Insurer 5	−0.009*** (0.002)	−0.003 (0.002)	−0.001 (0.001)
Insurer 6	0.003 (0.003)	−0.008*** (0.002)	0.010*** (0.002)
Insurer 7	0.000 (0.004)	−0.005 (0.006)	−0.000 (0.003)
Insurer 8	−0.003 (0.002)	0.017*** (0.004)	−0.006*** (0.001)
Insurer 9	0.002 (0.004)	0.022** (0.011)	−0.000 (0.002)
Insurer 10	0.014*** (0.005)	−0.006** (0.003)	0.003 (0.003)
Insurer 11	−0.007*** (0.003)	−0.011*** (0.003)	0.003 (0.003)
Insurer 12	−0.007* (0.004)	0.016*** (0.005)	−0.002 (0.001)
Insurer 13	−0.024*** (0.004)	0.049*** (0.014)	−0.006*** (0.002)
Insurer 14	−0.049*** (0.005)	−0.015*** (0.002)	−0.014*** (0.001)
Insurer 15	−0.015*** (0.004)	−0.004* (0.002)	−0.004** (0.002)
Replacement Cost	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Location FE	ZIP	ZIP	ZIP
Clustered SE	State	State	State
N	179,917	167,808	179,917
R-Sq	0.126	0.061	0.077

Note: Dependent variables reported in column headers. "Choose $250K" indicates selecting the program maximum of $250,000, "Increase 10%" indicates selecting a coverage limit that is 110% of the replacement cost, and "Round up $10K" indicates selecting a coverage limit by rounding up to the next $10,000 above the replacement cost (e.g., a household with a $200,000 and one with a $201,000 would each select a coverage limit of $210,000). Models follow Equation (2), with the coefficients adjusted as in Equation (3) and include insurer fixed effects for all 48 insurers in the baseline data. Tables report the results for the 15 insurers originating the most policies in the data in the interest of space. In Column 2, we limit observations to households who can feasibly implement the "increase 10%" rule given the program maximum limit of $250,00—all households in that regression have replacement costs that do not exceed $227,000 (as $110\% \times \$227,000 = \$249,700$). Standard errors are robust and clustered at the insurer level. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

surers' institutional policies are directing these limit choices.

5 Are insurer effects explained by household selection?

Our identification strategy in Section 3 assumes that households are comparable across insurers, after controlling for features of the policyholder (e.g., location, home value, age of the home). However, suppose that households' risk preferences affect both their choice of insurer and their decision to overinsure. Because we do not account for risk preferences, we might incorrectly attribute their decision to overinsure to their insurer. In this context, a household might choose a homeowners or auto insurer for its risk-based characteristics (e.g., its credit score, capital reserves), and also purchase its federal flood insurance through this insurer because of economies of scope. In this section, we discuss two points which lead us to conclude that this household selection argument is an unlikely explanation for the large insurer effects that we observe.

First, our results in Section 4 indicate that the specific coverage limit that overinsuring households select varies by insurer. No standard model of decision making would predict that policyholders with a certain set of risk preferences would select into Insurer 9 and would also tend to choose a limit 10% above their replacement cost, while policyholders selecting Insurer 10 would prefer to round up by $10,000.

Second, as an additional analysis we examine markets where households may have less ability to choose the insurer originating their flood contract. About 3% of policies ($n = 5,207$) in our baseline sample are in a ZIP code in which a single insurer originated all the policies.[20] We re-estimate our regression of the likelihood that a household overinsures, using this restricted sample. Insurer effects should disappear if they are the result of a households' choice of insurer, since households in this sample may have limited choice of insurer. Persistent insurer effects in the restricted sample, however, would support our finding that insurers are guiding overinsuring.

We find that the insurer effects persist in our regressions using the restricted sample. Typically, the coefficients in the restricted sample are consistent in significance and sign and of similar magnitude to those in the baseline sample. The detailed regression results are in Online Appendix C. In sum, while households' preferences may influence their choice of insurer, this does not seem to explain the large insurer effects in our data.

[20] This analysis does not require that policyholders have access to only a single insurer—these policyholders could presumably travel to another ZIP code in the state to expand their choice of insurer. Rather, the argument is that if households sort into insurers based on their risk preferences, then the relationship between risk aversion and the selected insurer would be weaker in ZIP codes where fewer insurers are active. The median policyholder has 14 insurers selling federal flood insurance in its ZIP code.

6 Insurer characteristics and overinsuring

Thus far, we have shown that insurers influence whether households overinsure (Section 3) and that they appear to provide specific guidance for the excess coverage that they select (Section 4). Here, we examine insurers' characteristics to explain the variation in overinsuring rates (i.e., the proportion of policies overinsured) across insurers. We propose four mechanisms which may affect the likelihood that an insurer's policyholders overinsure. We evaluate the relationship between each mechanism and the insurer's rate of overinsuring in a given state (for state k, the proportion of insurer j's flood policies that are overinsured). We describe each mechanism briefly below and provide greater detail in Online Appendix D.

Managerial control: Insurers selling via "direct" agents (who represent a single insurer) often have more managerial control over their agents than those selling via "independent" agents (who may represent multiple insurers).[21] This control may take various forms, including setting sales goals and training or educating agents (Hilliard et al., 2013). Insurers using direct agents may thus induce their agents, who are their employees, to sell excess flood coverage without needing other incentives. We include an indicator variable for insurer j primarily selling via direct agents, $\mathrm{I}(Direct_j)$.

Commissions: Agents of insurers offering higher commission rates may be more likely to recommend that policyholders overinsure. We define commission rates as commissions and brokerage expenses divided by direct premiums written for insurer j in state k. We calculate commission rates for federal flood ($FloodCommRate_{jk}$) and non-flood personal lines ($OthCommRate_{jk}$, which includes auto and homeowners insurance). Direct agents generally receive lower commissions than independent agents (Regan and Tennyson, 2000), so we interact commission rates with dummies for the insurer's primary distribution system, $\mathrm{I}(Direct_j)$ and $\mathrm{I}(Indep_j) = 1 - \mathrm{I}(Direct_j)$.

Market share: The largest insurers in a particular market may have substantial influence over local agents, who may comply with the insurer's guidelines to maintain the relationship. In addition, consumers may be more receptive to recommendations from an insurer who dominates their local market. We define an insurer's market share in a particular line of business as the proportion of state k's total direct premiums written by insurer j. We calculate market share for federal flood

[21] Insurers use two general distribution systems to sell their policies, direct writing and independent agency. Direct writers are insurers whose agents are permitted to sell for a single insurance company. These agents include exclusive (or captive) agents, direct sales via phone or internet, managing general agents, or career agents. Independent agents represent multiple insurance companies. These include (non-exclusive) agents, brokers, and general agents. Insurers may use multiple systems to sell their policies, but report their "primary" system to A.M. Best (2010) during the rating process, which is the information that we use in our analysis. Hilliard et al. (2013) provide a detailed account of the similarities and differences between these distribution systems.

($FloodMktShare_{jk}$) and for non-flood personal lines (auto and homeowners, $OthMktShare_{jk}$) in our analysis.

Competition: Competitive markets may offer fewer opportunities for an insurer or agent to recommend excess limits, as competitors may claim that overinsuring is "bad advice" as a sales tactic (Bolton et al., 2007, makes a similar proposal regarding biased financial advice). Thus, we expect more competitive markets to have lower rates of overinsuring. We measure competition by the number of insurers selling federal flood insurance in state k, $NumFloodInsurers_k$, in the baseline sample.

To create the dataset for this analysis, we calculate the proportion of policies overinsured by insurer j in state k ($OverRate_{jk}$) from the baseline sample described in Section 2.2. This results in 975 insurer-state observations. We merge this NFIP data with financial data from the National Association of Insurance Commissioners (NAIC) financial statement database (NAIC, 2010) and from A.M. Best (2010). We treat insurers in the same corporate group (those sharing an NAIC group code) as a single insurer. A.M. Best provides the insurer's primary distribution system (direct or independent) and financial strength rating. Ten insurers in the NFIP data (46 observations) did not have a match in the NAIC database, resulting in 929 insurer-state observations. We also drop 58 observations with missing federal flood commissions, resulting in an overall sample of 871 observations of 35 insurers in 52 U.S. states and territories. Finally, we exclude observations in which insurer j in state k sold fewer than 20 NFIP baseline sample policies. Thus, the *Main Sample* in this section includes 437 observations of 35 insurers in 48 states issuing 164,512 policies, 91.4% of the NFIP baseline sample.[22]

We model insurer j's overinsuring rate in state k as a function of the mechanisms described

[22] We require a minimum number of policies because the overinsuring rate is imprecise when the number of new policies for insurer j in state k is very small. For example, suppose that an insurer sells one new policy in a state. The overinsuring rate would be 100% if the policyholder overinsured and 0% if it did not. Requiring at least 20 policies generates overinsuring rates in 5% increments or better. For robustness, we also report results for a *Restricted Sample* in which we increase the minimum number of policies from 20 to 50 ($N = 295$) and for *All Observations*, without instituting a policy minimum ($N = 871$). Our results hold for other minimum policy thresholds as well, though we do not report results in the interest of space. For example, using a 10-policy threshold or a 100-policy threshold generates significant results that are consistent with those using the main sample.

above and controls, as follows:

$$
\begin{aligned}
OverRate_{jk} = \alpha &+ \beta_1 \mathrm{I}(Direct_j) \\
&+ \beta_2 \mathrm{I}(Direct_j) \times FloodCommRate_{jk} + \beta_3 \mathrm{I}(Direct_j) \times OthCommRate_{jk} \\
&+ \beta_4 \mathrm{I}(Indep_j) \times FloodCommRate_{jk} + \beta_5 \mathrm{I}(Indep_j) \times OthCommRate_{jk} \\
&+ \beta_6 FloodMktShare_{jk} + \beta_7 OthMktShare_{jk} + \beta_8 NumFloodInsurers_k \\
&+ \mathbf{X'_{jk}}\gamma + \varepsilon_{jk}.
\end{aligned} \tag{4}
$$

The controls ($\mathbf{X_{jk}}$) include nine variables. Three of these variables are specific to flood insurance. First, we include insurer j's premiums written for federal flood in state k as a share of its total premiums across all lines nationally, to control for the importance of flood in the insurer's underwriting portfolio. Second, we include the natural log of the mean estimated replacement cost for insurer j's flood insurance policyholders in state k, to account for the insurer's appetite within the state. Third, we include a dummy variable for the 5% of insurers who report positive direct premiums written for flood insurance but no flood commissions.[23] The remaining six control variables are an indicator for publicly-traded, an indicator for mutual ownership, an indicator for reporting zero premiums written for homeowners or auto insurance in any state, a dummy set for A.M. Best financial strength rating, logged total assets, and logged firm age.

We report summary statistics for the raw values of all variables in Table 8. Direct writers comprise 49.7% of the sample, resulting in 217 observations of direct writers and 220 observations of insurers who sell through independent agents. We summarize commission rates by distribution system, since they are interacted in our regression analysis. Commission rates are lower for direct writing insurers, both in flood and non-flood lines of business. The mean (median) flood market share is approximately 8.2% (6.7%), which is skewed by certain insurers who capture a very large market share (up to 46.7%).[24] While approximately 6% of the insurer-state observations in our sample do not offer homeowners or auto insurance (and thus have 0% market share in non-flood lines), those insurers with a large market share in flood also tend to have a large share of the non-flood market (with a Pearson correlation of $\rho = 0.283$). The number of insurers selling new federal flood policies in a state ranges from 10 to 28, and the states with the fewest policies also tend to

[23] Two insurers comprise 20 of the 22 observations with zero flood commissions. It is not clear why these insurers report zero flood commissions. We include this control because paying zero flood commissions may have a substantially different implication than paying very small flood commissions. For example, the insurer may increase other commission rates when flood insurance is also sold. Excluding these insurers from our regressions does not qualitatively change the main results.

[24] The insurer with a 46.7% market share is in a state with only 210 total flood policies from our baseline data. In an examination including only states with at least 500 policies, the maximum flood market share is 32.5% with a mean (median) of 7.4% (6.1%).

Table 8: Summary Statistics for Insurer Characteristics, Main Sample

	Mean	Median	Min	Max	SD	N
Variables of interest						
Overinsurance rate	0.106	0.086	0.000	0.461	0.086	437
Direct	0.497	0.000	0.000	1.000	0.501	437
Commission rate - flood	0.144	0.159	0.000	0.272	0.078	217
Commission rate - home/auto	0.124	0.108	0.000	0.320	0.079	217
Independent	0.503	1.000	0.000	1.000	0.501	437
Commission rate - flood	0.180	0.174	0.000	0.522	0.057	220
Commission rate - home/auto	0.136	0.158	0.000	0.462	0.089	220
Market share - flood	0.082	0.067	0.000	0.467	0.065	437
Market share - home/auto	0.049	0.019	0.000	0.317	0.069	437
Number of flood insurers	19.059	19.000	10.000	28.000	3.508	437
Controls						
Flood ins share of total prems	0.330	0.122	0.002	1.000	0.380	437
Mean replacement cost ($100K)	1.341	1.350	0.351	1.880	0.256	437
No flood commissions reported	0.050	0.000	0.000	1.000	0.219	437
No home/auto prems	0.059	0.000	0.000	1.000	0.237	437
Public	0.602	1.000	0.000	1.000	0.490	437
Mutual	0.343	0.000	0.000	1.000	0.475	437
Rating (N=0, A+=6)	5.293	5.000	0.000	6.000	0.884	437
Firm total assets ($B)	85.8	64.2	0.1	285.3	90.6	437
Firm age	116.2	106.0	13.0	216.0	51.3	437

Note: Summary statistics by insurer-state observation. Commission rates are broken out by Direct and Independent because we interact commission rates with distribution system in the regression. Direct, public, mutual, rating, firm age, and firm total assets are measured at the national level. Rating is scaled from 0 to 6, with 0 being a rating of "Not rated" and 6 being a rating of "A+." Number of flood insurers takes the same value for all insurers in a state. We report firm age, firm total assets, and mean replacement cost as raw values for summary purposes but include the logged values in our regression.

have fewer insurers competing in the market. Replacement cost is reported as the mean for each insurer-state observation, with an overall mean of $134,100.

We report the results of our regression analysis in Table 9. We show results for the main sample in Columns 1-3, which requires that insurer j sells at least 20 policies in state k. Column 1 includes only our variables of interest, with no controls. We add the controls described above to the model in Column 2. Column 3 includes controls and state fixed effects, and we omit our competition measure ($NumFloodInsurers$) from this model as it takes the same value for all insurers in a state. The model without fixed effects allows us to compare market conditions across states, while the fixed effects model compares insurers within a state. Our restricted sample in Column 4 replicates Column 2, including only insurer-state observations with at least 50 new flood policies sold. We

Table 9: Insurer Characteristics Associated with Overinsuring

	Main Sample			Restricted	All
	(1)	(2)	(3)	(4)	(5)
$Direct$	0.037***	0.046***	0.046***	0.056***	0.030*
	(0.007)	(0.010)	(0.011)	(0.010)	(0.017)
$Indep \times FloodCommRate$	0.062	0.020	0.068	0.110	−0.107
	(0.064)	(0.068)	(0.072)	(0.096)	(0.155)
$Direct \times FloodCommRate$	0.479***	0.432***	0.490***	0.534***	0.345***
	(0.074)	(0.068)	(0.067)	(0.063)	(0.084)
$Indep \times OthCommRate$	−0.062	−0.049	−0.083	−0.016	−0.057
	(0.052)	(0.060)	(0.066)	(0.057)	(0.116)
$Direct \times OthCommRate$	−0.668***	−0.702***	−0.717***	−0.776***	−0.721***
	(0.078)	(0.119)	(0.131)	(0.123)	(0.141)
$FloodMktShare$	0.086	−0.057	0.015	−0.048	−0.182**
	(0.068)	(0.060)	(0.063)	(0.049)	(0.087)
$OthMktShare$	−0.017	0.156*	0.168*	0.082	0.289***
	(0.055)	(0.085)	(0.093)	(0.082)	(0.105)
$NumFloodInsurers$	−0.002	−0.003***		−0.004***	−0.003**
	(0.002)	(0.001)		(0.001)	(0.002)
Controls	No	Yes	Yes	Yes	Yes
FE	None	None	State	None	None
Clustered SE	State	State	State	State	State
N	437	437	437	295	871
R-Sq	0.304	0.508	0.596	0.624	0.143

Note: The dependent variable is insurer j's overinsuring rate in state k. Regressions follow Equation (4). Columns 1-3 are our main sample, excluding insurers writing fewer than 20 new federal flood policies in the state. Our restricted sample in Column 4 replicates Column 2, excluding insurers writing fewer than 50 new flood policies in the state. Column 5 also replicates Column 2, but includes all insurer-state observations (with no policy minimums). Column 1 includes our variables of interest only, with no controls. Controls in Columns 2-5 include the proportion of insurer j's total premiums attributed to federal flood in state k, A.M. Best financial strength rating, log of net total assets, log of firm age, log of mean replacement cost in the state, and dummies for publicly-traded insurers, mutual insurers, flood-only insurers, and insurers who report zero flood commissions. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

also replicate the model in Column 2 without a policy minimum, reporting results in Column 5. In all models, continuous variables are mean-centered to address collinearity between flood and non-flood lines of business. We cluster standard errors by state.

The model in Column 2 is our preferred model, as it allows us to examine the effect of competition while still controlling for other factors. In this model, direct writers have overinsuring rates approximately 4.6 percentage points higher than insurers selling via independent agents, suggesting that managerial control is one mechanism associated with overinsuring. Commissions to these

direct agents also help explain the variation in overinsuring rates. Flood commission rates are positive and significant for insurers who sell through direct agents ($Direct \times FloodCommRate$), but not for those selling via independent agents. Increasing direct agent flood commissions by one percentage point increases the overinsuring rate by 0.43 percentage points. Non-flood commission rates are negative and significant, again for direct writers only ($Direct \times OthCommRate$). Increasing home and auto commissions decreases the overinsuring rate by 0.70 percentage points. This may be a substitution effect between flood and other personal lines, where high commissions for home and auto insurance will lead agents to dedicate more effort to those lines and expend less effort on selling excess flood coverage. We also find evidence that overinsuring is negatively related to competition in our preferred model; increasing the number of insurers selling federal flood insurance in the state by one reduces the overinsuring rate by 0.3 percentage points.

7 Conclusion

Households face a complex, high-stakes problem in selecting an insurance contract, and we believe that this complexity leads to the contract decisions that we observe. Households must weigh premiums paid today against conditional future payments in rare states of the world. Often, the household has never experienced these rare states and may know little about their likelihood. Insurers and their agents offer guidance in the sales process, but this advice may differ substantially across sellers. Households may be unable to evaluate this advice and purchase contract features that are of low value or that are inconsistent with their risk preferences.

We examine the ability of insurance companies to influence households' flood insurance decisions. Specifically, we investigate overinsuring—choosing a flood insurance limit in excess of the structure's estimated replacement cost. We show that the likelihood of purchasing excess flood coverage varies significantly based on the insurer selling the policy, even when controlling for policyholder characteristics. Further, a households' insurer affects the likelihood that it adopts a specific excess coverage limit. Some insurers appear to systematically advise purchasing the maximum program limit ($250,000), others suggest rounding up from the replacement cost in percentage terms (e.g., 110%), and others recommend rounding up in dollar amounts (e.g., to the next $10,000). Households purchasing from insurers who use "direct" agents are more likely to overinsure, and this is compounded by the flood commission rates paid to those direct agents. We also observe a substitution effect for those same insurers—overinsuring rates are lower when non-flood commissions are high. There is also some evidence of a competition effect, in that overinsuring rates tend to be lower when more insurers participate in the flood insurance market.

Our findings are economically significant and have implications for the broader market. For about 165,000 new flood insurance policies in our baseline data, consumers paid total additional premiums of $1,187,149 for $561 million in total excess coverage limits.[25] We selected our sample in the interest of empirical identification in our analysis; these 165,000 policies represent only 3.7% of the total federal flood insurance policies in force in 2010. Thus, the amount paid for excess coverage each year is likely several orders of magnitude greater than what we observe in our baseline sample. A household's initial decision to overinsure likely will affect its flood insurance premiums for years to come.[26] While our study focuses on federal flood insurance for robust comparisons across insurers, other lines of insurance (such as auto and homeowners) may also be subject to sellers recommending relatively expensive coverages.

Our results have important policy implications. First, we highlight households' susceptibility to guidance in making complex financial decisions. Insurance choices are one of many consequential household financial decisions, and research in other complex domains suggests a similar susceptibility (e.g., in financial planning, Christoffersen et al., 2013; Foerster et al., 2017). Improved risk communication and decision making guidelines, from independent public or private organizations (e.g., the Consumer Financial Protection Bureau or the Insurance Information Institute), may help households evaluate the quality of advice and identify suboptimal recommendations.

Second, sellers providing advice also may benefit from better information. In our setting, agents may not be aware of the seemingly low value of excess coverage. Intermediaries face a number of competing motivations, including to (1) add value to their customers, (2) maximize their compensation, (3) minimize the risks of errors and omissions lawsuits, and (4) properly represent their contracted insurer.[27] When the optimal contract is unclear because the underlying risk is not well understood, an intermediary may rely more on motivations (2), (3), or (4) to make a recommendation. Educating sellers about the underlying risk and ensuring they have the tools to provide high-quality advice may improve households' insurance decisions.

Managing flood risk is a complex, economically significant problem, and one that is projected to increase due to rising sea levels, more frequent severe storms, and urbanization. Only a third of

[25] We base this calculation on the 92% of policies in our sample for which we can accurately calculate their premiums using the program's premium rating equations.

[26] Using the filters described in Section 2.2, we examine policies from 2009 that were renewed in 2010. About 1% of renewals reduced their coverage limit and 70% retained the same coverage limit. Looking only at renewals in 2010 with coverage limits below the program maximum of $250,000, we find that 22% of these renewals increased their coverage limit by 10% relative to their 2009 coverage limit.

[27] Even though (1) and (2) are the source of agency conflict between agents and policyholders, these motivations are not necessarily mutually exclusive. Insurers and agents often manage a multi-year, multi-product business relationship with consumers. The structure of this repeated game encourages cooperation (e.g., providing good advice to customers). Cooperation with a long-term focus may benefit all parties in the transaction.

residential properties in the "100 year" flood plain (with a 1% annual flood probability) currently insure (Wright, 2017). How to communicate information about evolving flood risks and provide effective guidance to households and intermediaries remains an open question and a critical topic for future research.

References

Abaluck, J. and J. Gruber (2011, June). Choice Inconsistencies Among the Elderly: Evidence from Plan Choice in the Medicare Part D Program. American Economic Review 101(4), 1180–1210.

A.M. Best (2010). Best's Key Ratings Guide: Property-Casualty. Oldwick, NJ: A.M. Best Co.

Anagol, S., S. Cole, and S. Sarkar (2017, March). Understanding the Advice of Commissions-Motivated Agents: Evidence from the Indian Life Insurance Market. Review of Economics and Statistics 99(1), 1–15.

Angrist, J. D. and J.-S. Pischke (2008). Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press.

Arrow, K. (1974). Essays in the Theory of Risk-Bearing. New York: American Elsevier Pub. Co.

Barrese, J., H. I. Doerpinghaus, and J. M. Nelson (1995, June). Do Independent Agent Insurers Provide Superior Service? The Insurance Marketing Puzzle. The Journal of Risk and Insurance 62(2), 297–308.

Barseghyan, L., F. Molinari, T. O'Donoghue, and J. C. Teitelbaum (2013, October). The Nature of Risk Preferences: Evidence from Insurance Choices. The American Economic Review 103(6), 2499–2529.

Beyer, M., D. de Meza, and D. Reyniers (2013). Do Financial Advisor Commissions Distort Client Choice? Economics Letters 119, 117–119.

Bolton, P., X. Freixas, and J. Shapiro (2007, August). Conflicts of Interest, Information Provision, and Competition in the Financial Services Industry. Journal of Financial Economics 85(2), 297–330.

Botzen, W. and J. van den Bergh (2012, April). Risk Attitudes to Low-Probability Climate Change Risks: WTP for Flood Insurance. Journal of Economic Behavior & Organization 82(1), 151–166.

Browne, M. J. and R. E. Hoyt (2000). The Demand for Flood Insurance: Empirical Evidence. Journal of Risk and Uncertainty 20(3), 291–306.

Cameron, A. C. and D. L. Miller (2015). A Practitioner's Guide to Cluster-Robust Inference. Journal of Human Resources 50(2), 317–372.

Chandra, A., A. Finkelstein, A. Sacarny, and C. Syverson (2016). Healthcare Exceptionalism? Performance and Allocation in the U.S. Healthcare Sector. American Economic Review 106(8), 2110–2144.

Christoffersen, S. E., R. Evans, and D. K. Musto (2013). What Do Consumers' Fund Flows Maximize? Evidence from Their Brokers' Incentives. The Journal of Finance 68(1), 201–235.

Cohen, A. and L. Einav (2007). Estimating Risk Preferences from Deductible Choice. American Economic Review 97(3), 745–788.

Collier, B., D. Schwartz, H. Kunreuther, and E. Michel-Kerjan (2017). Risk Preferences in Small and Large Stakes: Evidence from Insurance Contract Decisions. National Bureau of Economic Research Working Paper 23579, 1–60.

Cupach, W. R. and J. M. Carson (2002). The Influence of Compensation on Product Recommendations Made by Insurance Agents. Journal of Business Ethics 40(2), 167–176.

Dixon, L., N. Clancy, S. Seabury, and A. Overton (2006). The National Flood Insurance Program's Market Penetration Rate: Estimates and Policy Implications. Technical report, American Institutes for Research.

Döhrmann, D., M. Gürtler, and M. Hibbeln (2017, September). Insured Loss Inflation: How Natural Catastrophes Affect Reconstruction Costs: Insured Loss Inflation. The Journal of Risk and Insurance 84(3),

851–879.

Eckardt, M. (2002). Agent and Broker Intermediaries in Insurance Markets-An Empirical Analysis of Market Outcomes. Thunen-Series of Applied Economic Theory Working Paper 34, 1–32.

Eckardt, M. and S. Räthke-Döppner (2010, April). The Quality of Insurance Intermediary Services-Empirical Evidence for Germany. The Journal of Risk and Insurance 77(3), 667–701.

Ericson, K. M. and A. Starc (2012). Heuristics and Heterogeneity in Health Insurance Exchanges: Evidence from the Massachusetts Connector. American Economic Review 102(3), 493–497.

FEMA (2018). Policy statistics. Federal Emergency Management Agency, https://bsa.nfipstat.fema.gov/reports/1011.htm.

Foerster, S., J. T. Linnainmaa, B. T. Melzer, and A. Previtero (2017, August). Retail Financial Advice: Does One Size Fit All? The Journal of Finance 72(4), 1441–1482.

Grace, M., R. W. Klein, and P. Kleindorfer (2004). Homeowners Insurance with Bundled Catastrophe Coverage. The Journal of Risk and Insurance 71(3), 351–379.

Handel, B. R. and J. T. Kolstad (2015). Health Insurance for "'Humans": Information Frictions, Plan Choice, and Consumer Welfare. American Economic Review 105(8), 2449–2500.

Hilliard, J. I., L. Regan, and S. Tennyson (2013). Insurance Distribution. In G. Dionne (Ed.), Handbook of Insurance. New York, NY: Springer New York.

Jacob, B. A. and L. Lefgren (2007). What Do Parents Value in Education? An Empirical Investigation of Parents' Revealed Preferences for Teachers. The Quarterly Journal of Economics 122(4), 1603–1637.

Kousky, C. and R. Cooke (2012, April). Explaining the Failure to Insure Catastrophic Risks. The Geneva Papers on Risk and Insurance–Issues and Practice 37(2), 206–227.

Kriesel, W. and C. Landry (2004). Participation in the National Flood Insurance Program:an Empirical Analysis for Coastal Properties. The Journal of Risk and Insurance 71(3), 405–420.

Kurland, N. B. (1995). Ethics, Incentives, and Conflicts of Interest: A Practical Solution. Journal of Business Ethics 14(6), 465–475.

Lacetera, N., B. J. Larsen, D. G. Pope, and J. R. Sydnor (2016, November). Bid Takers or Market Makers? The Effect of Auctioneers on Auction Outcome. American Economic Journal: Microeconomics 8(4), 195–229.

Landry, C. E. and M. R. Jahan-Parvar (2011, June). Flood Insurance Coverage in the Coastal Zone. The Journal of Risk and Insurance 78(2), 361–388.

Michel-Kerjan, E. O. (2010). Catastrophe Economics: The National Flood Insurance Program. Journal of Economic Perspectives 24(4), 165–186.

Morris, C. N. (1983, March). Parametric Empirical Bayes Inference: Theory and Applications. Journal of the American Statistical Association 78(381), 47–55.

Mullainathan, S., M. Noeth, and A. Schoar (2012). The Market for Financial Advice: An Audit Study. National Bureau of Economic Research Working Paper 17929, 1–34.

NAIC (2010). Property-Casualty Insurer Financial Statement Filings. National Association of Insurance Commissioners, Item type: Dataset.

NAIC (2013). State licensing handbook. National Association of Insurance Commissioners, http://www.naic.org/prod_serv/STL-HB-13.pdf.

NFIP (2006). Transaction record reporting and processing plan for the Write Your Own Program. National Flood Insurance Program, http://bsa.nfipstat.fema.gov/manuals/manuals.html.

NFIP (2007). Mandatory purchase of flood insurance guidelines. National Flood Insurance Program, https://www.fema.gov/faq-details/Mandatory-Purchase-of-NFIP-Coverage.

NFIP (2010). Flood insurance manual. National Flood Insurance Program, https://www.fema.gov/flood-insurance-manual-effective-may-1-2010.

NFIP (2011). Giudance for severe repetitive loss properties. National Flood Insurance Program, https:

//www.fema.gov/pdf/nfip/manual201205/content/20_srl.pdf.

Regan, L. and S. Tennyson (2000). Insurance Distribution Systems. In G. Dionne (Ed.), Handbook of Insurance, pp. 709–748. Springer Netherlands.

Sydnor, J. (2010). (Over)insuring Modest Risks. American Economic Journal: Applied Economics 2(4), 177–199.

Trigo-Gamarra, L. (2008, July). Reasons for the Coexistence of Different Distribution Channels: An Empirical Test for the German Insurance Market. The Geneva Papers on Risk and Insurance–Issues and Practice 33(3), 389–407.

Tversky, A. and D. Kahneman (1992). Advances in Prospect Theory: Cumulative Representation of Uncertainty. Journal of Risk and Uncertainty 5(4), 297–323.

U.S. Congress (2004). Bunning-Bereuter-Blumenauer Flood Insurance Reform Act of 2004. https://www.fema.gov/media-library-data/20130726-1748-25045-4942/fira2004.pdf.

Wooldridge, J. M. (2010). Econometric Analysis of Cross Section and Panel Data. MIT press.

Wright, R. (2017, January). Keynote Remarks: National Flood Conference.

Online Appendix A Bayesian Shrinkage and Placebo Tests

Natural variation in consumer preferences might lead to some observed differences across insurers due to sampling variation, which could be incorrectly interpreted as insurer effects. Our large sample size should allow for precise estimation of insurer effects and mitigate this sampling concern. However, as an additional precaution, we examine our results using the Empirical Bayes (EB) "shrinkage" estimation procedure of Morris (1983), which adjusts for sampling variation. This procedure has been used in studies of teacher effects (e.g., Jacob and Lefgren, 2007), hospital effects (e.g., Chandra et al., 2016), and auctioneer effects (Lacetera et al., 2016). We calculate the EB coefficients ($\hat{\beta}_j^{EB}$) by "shrinking" each fixed effect estimate ($\hat{\beta}_j$) closer to the approximate mean of the true effects ($\bar{\beta}$):

$$\hat{\beta}_j^{EB} = (1 - \lambda_j)\bar{\beta} + (\lambda_j)\hat{\beta}_j$$

where

$$\lambda_j = \frac{\sigma^2}{\sigma^2 + \sigma_j^2}.$$

In the above, σ^2 is the variance of all insurer effects and σ_j^2 is the square of insurer j's fixed effect standard error. The weight λ_j effectively shrinks each insurer effect based on the reliability (i.e. variance) of the estimate. Since we have normalized $\hat{\beta}$ in our regression results to be relative to the average, $\bar{\beta} = 0$ and the first term disappears. The adjusted EB estimator is thus:

$$\hat{\beta}_j^{EB} = (\lambda_j)\hat{\beta}_j$$

Table A1 summarizes our results using this adjustment. The first column repeats our preferred model from Table 5 for comparison. The second column applies the Bayesian shrinkage adjustment. The adjustment has almost no effects on the results. For example, the largest effect among the top 15 insurers is on Insurer 2; the shrinkage adjustment reduces the coefficient estimate from $\beta = 0.200$ to 0.198.

We conduct a placebo test in which we randomly assign an insurer from our dataset to each policyholder. This test also examines the possibility that the observed differences across insurers are due to random sampling variation. For this test, we randomly reorder the insurers, arbitrarily matching a policyholder with a new insurer, which we call its "placebo insurer," and reestimate our models to examine the effect of the placebo insurer. If our main results are due to random sampling, then we would expect to observe coefficients for our placebo insurers that are similar in magnitude and statistical significance as our main results. Instead, we find coefficients that are very close to zero and statistically insignificant, shown in Table A2. The results of this placebo test provide additional evidence that sampling variation does not explain the insurer effects that we observe.

Table A1: Bayesian Shrinkage Adjustment

	(1) Primary Model	(2) Bayesian Shrinkage Adjustment
Insurer 1	−0.020*	−0.019
	(0.012)	(0.012)
Insurer 2	0.200***	0.170***
	(0.023)	(0.023)
Insurer 3	−0.012	−0.012
	(0.008)	(0.008)
Insurer 4	−0.049***	−0.048***
	(0.007)	(0.007)
Insurer 5	−0.008*	−0.008*
	(0.004)	(0.004)
Insurer 6	0.052***	0.050***
	(0.011)	(0.011)
Insurer 7	−0.030**	−0.028**
	(0.013)	(0.013)
Insurer 8	−0.024***	−0.024**
	(0.009)	(0.009)
Insurer 9	0.019**	0.018**
	(0.009)	(0.009)
Insurer 10	0.020**	0.019**
	(0.008)	(0.008)
Insurer 11	−0.010	−0.009
	(0.012)	(0.012)
Insurer 12	−0.024**	−0.023**
	(0.011)	(0.011)
Insurer 13	−0.006	−0.005
	(0.024)	(0.024)
Insurer 14	−0.140***	−0.138***
	(0.007)	(0.007)
Insurer 15	−0.030***	−0.030***
	(0.005)	(0.005)
Replacement Cost	Yes	Yes
Controls	Yes	Yes
Month FE	Yes	Yes
Location FE	ZIP	ZIP
Clustered SE	State	State
N	179,917	179,917
R-Sq	0.112	0.112

Note: Dependent variable is whether a household overinsures. Models follow Equation (2) and include insurer fixed effects for all insurers in the sample, though we only report the results for the 15 insurers originating the most policies in the interest of space. The models include insurer fixed effects, state fixed effects, month fixed effects and characteristics of the home as control variables. Column 1 shows the results from our preferred model, as described in Table 5; Column 2 shows the adjusted coefficients using the Bayesian shrinkage estimator. Regressions report robust standard errors clustered by state. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table A2: Placebo Test, Repeating Regressions with a Randomly Assigned Insurer

	(1)	(2)	(3)	(4)
Placebo Insurer 1	0.001	0.001	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Placebo Insurer 2	0.008	0.006	0.006	0.006
	(0.006)	(0.006)	(0.007)	(0.007)
Placebo Insurer 3	0.003	0.002	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Placebo Insurer 4	−0.000	0.000	0.005	0.005
	(0.012)	(0.011)	(0.010)	(0.010)
Placebo Insurer 5	0.001	0.001	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Placebo Insurer 6	−0.004*	−0.004	−0.003	−0.003
	(0.003)	(0.003)	(0.002)	(0.002)
Placebo Insurer 7	−0.004	−0.004	−0.001	−0.001
	(0.008)	(0.007)	(0.008)	(0.008)
Placebo Insurer 8	−0.000	0.000	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Placebo Insurer 9	0.002	0.002	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Placebo Insurer 10	0.001	0.002	0.003	0.003
	(0.006)	(0.006)	(0.006)	(0.006)
Placebo Insurer 11	0.000	−0.001	−0.002	−0.002
	(0.004)	(0.005)	(0.005)	(0.005)
Placebo Insurer 12	−0.003	−0.002	−0.003	−0.003
	(0.005)	(0.005)	(0.005)	(0.005)
Placebo Insurer 13	0.005	0.003	0.005	0.005
	(0.005)	(0.005)	(0.005)	(0.004)
Placebo Insurer 14	−0.003	−0.003	−0.002	−0.002
	(0.007)	(0.007)	(0.007)	(0.007)
Placebo Insurer 15	0.002	0.002	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Replacement Cost	No	No	No	No
Controls	No	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes
Location FE	No	State	ZIP	ZIP
Clustered SE	State	State	State	State
N	179,917	179,917	179,917	179,917
R-Sq	0.000	0.021	0.097	0.100

Note: Dependent variable is whether a household overinsures (selects a coverage limit greater than the home's replacement cost). The placebo insurer is the randomly-assigned insurer from our dataset. Regressions are linear probability models, follow Equation (2), and include insurer fixed effects for all 48 insurers in the baseline data. We normalize fixed effects following Equation (3). Table reports the results for the 15 insurers originating the most policies in the data in the interest of space. Column 1 only includes insurer fixed effects. Column 2 includes insurer fixed effects, state fixed effects, month fixed effects and characteristics of the home as control variables. Column 3 includes insurer fixed effects, ZIP code fixed effects, month fixed effects, and home characteristics. Column 4 includes the same variables as Column 3, but adds replacement cost as an explanatory variable. Standard errors are robust and clustered by state. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Online Appendix B Modeling partially and fully insuring

This section supports the analysis in Section 3. While we focus on households who overinsure, our approach also allows us to examine other coverage limit choices. We compare three related outcomes, partially insuring (selecting a coverage below the home's replacement cost), fully insuring, and overinsuring. About 20% of policyholders partially insure, 68% fully insure, and 12% overinsure. We use our preferred model, which includes ZIP code fixed effects, month fixed effects, and policy-level control variables including the home's replacement cost, as described in Section 3.1. We also transform the beta coefficients using Equation (3) so that the insurer effects in each regression are relative to the average insurer.

Table B1 shows the results. The outcome variable in the first column is an indicator for whether the household partially insures. The model shows that compared to other policyholders in the same ZIP code with similar home characteristics, the policyholders of certain insurers are more likely to partially insure. For example, the policyholders of Insurer 6 are 15 percentage points more likely to partially insure than those of the average insurer. Certain insurers also appear more likely to influence their customers to fully insure (Column 2). For example, the policyholders of Insurer 14 are 13 percentage points more likely to fully insure than those of the average insurer. Column 3 repeats the overinsuring results presented in Table 5 for comparison.

The combination of the three columns also illustrates differences across insurers. For example, Insurer 8 may specifically encourage fully insuring as its policyholders are significantly more likely to fully insure but significantly less likely to partially insure or overinsure than the average insurer. In contrast, Insurer 6 may not encourage fully insuring as its policyholders demonstrate the opposite pattern.

Table B1: Insurer Effects on Partially Insuring, Fully Insuring, and Overinsuring

	(1) I(Partial)	(2) I(Full)	(3) I(Over)
Insurer 1	0.044***	−0.024	−0.020*
	(0.008)	(0.015)	(0.012)
Insurer 2	0.012	−0.211***	0.200***
	(0.012)	(0.031)	(0.023)
Insurer 3	0.060***	−0.047***	−0.012
	(0.009)	(0.008)	(0.008)
Insurer 4	0.053***	−0.004	−0.049***
	(0.016)	(0.020)	(0.007)
Insurer 5	0.043***	−0.035***	−0.008*
	(0.010)	(0.012)	(0.004)
Insurer 6	0.146***	−0.198***	0.052***
	(0.016)	(0.012)	(0.011)
Insurer 7	0.069***	−0.039	−0.030**
	(0.021)	(0.030)	(0.013)
Insurer 8	−0.040***	0.064***	−0.024***
	(0.005)	(0.008)	(0.009)
Insurer 9	0.039	−0.058***	0.019**
	(0.024)	(0.017)	(0.009)
Insurer 10	0.054***	−0.073***	0.020**
	(0.017)	(0.014)	(0.008)
Insurer 11	0.120***	−0.110***	−0.010
	(0.031)	(0.027)	(0.012)
Insurer 12	0.041***	−0.017	−0.024**
	(0.014)	(0.021)	(0.011)
Insurer 13	−0.028	0.034**	−0.006
	(0.023)	(0.015)	(0.024)
Insurer 14	0.011	0.129***	−0.140***
	(0.010)	(0.008)	(0.007)
Insurer 15	0.089***	−0.059***	−0.030***
	(0.021)	(0.022)	(0.005)
Replacement Cost	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Location FE	ZIP	ZIP	ZIP
Clustered SE	State	State	State
N	179,917	179,917	179,917
R-Sq	0.281	0.202	0.112

Note: Dependent variables are whether households partially insure (select a coverage limit below the home's replacement cost, Column 1), fully insure (coverage limit equals replacement cost, Column 2), or overinsure (coverage limit exceeds replacement cost). Models follow Equation (2), with the coefficients adjusted as in Equation (3) and include insurer fixed effects for all 48 insurers in the baseline data. Tables report the results for the 15 insurers originating the most policies in the data in the interest of space. Standard errors are robust and clustered at the insurer level. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Online Appendix C Supporting analysis on household selection

This section provides additional details on the analysis in Section 5 regarding whether the insurer effects that we observe are a result of household selection—that a household's risk preferences affect both its choice of insurer and its decision to overinsure. Because we do not account for risk preferences, we might incorrectly attribute a household's decision to overinsure to its insurer.

We re-estimate our regression of the likelihood that a household overinsures, restricting the sample to policies in ZIP codes in which all policies are written by a single insurer. We assume that households have few or no choices regarding their flood insurer in this restricted sample, reducing the potential influence of a household's choice of insurer on the analysis. About 3% of policies in the baseline sample are in this restricted sample ($n = 5,254$). The most-represented ZIP code in the restricted sample has 15 policies. In 75% of cases, there is only one policy in the ZIP code. This structure challenges the use of our preferred model, which includes ZIP code fixed effects; instead, we use state fixed effects (which are shown for the baseline sample in Column 2 of Table 5). Five insurers in the baseline sample are not included in the restricted sample as they are never the only seller of flood insurance in a ZIP code.

We are interested in two aspects of the results. First, we examine whether insurer effects exist in the restricted sample. Insurer effects should disappear if they are the result of a households' choice of insurer, since households have limited choice of insurer in the restricted sample. Second, we examine whether the insurer effects are similar in sign and magnitude in the restricted sample to those in the baseline sample. We do not expect the same level of significance since the sample is much smaller. To facilitate comparisons, we select Insurer 8 as the reference insurer because it has the same rate of overinsuring (12%) in the baseline and restricted samples.[28] Homes in the restricted sample may differ from those in the baseline sample. For example, these homes may be in less densely populated areas. Thus, similar insurer effects in the two regressions would add to evidence that insurers are guiding overinsuring.

Table C1 shows the results for the largest 15 insurers, which are representative of the remaining insurers. Our discussion here is in reference to all insurers in the regressions. Column 1 shows the coefficient estimates for the baseline sample; Column 2 shows the estimates for the restricted sample. Typically, the estimates in the restricted sample are consistent in significance and sign and of similar magnitude to those in the baseline sample. For example, among the top 15 insurers, the policyholders of Insurer 2 are the most likely to overinsure in both samples. The insurer effects also rank similarly across samples, with a Spearman rank correlation of 0.46 ($p < 0.01$, and a Pearson correlation of 0.56, $p < 0.01$).

We do observe some differences in the insurer effects across regressions. The insurer effects are significantly different across the two models for 13 insurers (out of the 43 in both regressions). For example, Insurer 13 has a positive but statistically insignificant coefficient in the baseline sample, a negative, significant coefficient in the restricted sample, and these coefficients significantly differ from each other ($\chi^2 = 29, p < 0.01$). Such differences might emerge from households' preferences

[28] The purpose of our main analyses (e.g., in Section 3.2) is to compare insurer effects in a single regression, leading us to normalize the insurer effects so that they are in reference to the average insurer (Section 3.1). Instead, in this analysis we compare coefficients across regressions and so use a single insurer as a reference group, as the average insurer effect might change across regressions.

or other unobserved characteristics in these models (e.g., differences in risk between the restricted and unrestricted samples). We conclude that households' preferences may influence their choice of insurer, but do not seem to explain the large insurer effects in our data.

Table C1: Insurer Effects, Policies from ZIP Codes with a Single Insurer

Reference Group: Insurer 8	(1) Baseline Sample	(2) Restricted Sample
Insurer 1	−0.000	0.010
	(0.019)	(0.027)
Insurer 2	0.222***	0.157***
	(0.025)	(0.053)
Insurer 3	−0.001	−0.016
	(0.012)	(0.024)
Insurer 4	−0.038***	−0.047***
	(0.010)	(0.016)
Insurer 5	0.007	−0.013
	(0.009)	(0.027)
Insurer 6	0.071***	0.064**
	(0.015)	(0.024)
Insurer 7	−0.016	−0.029
	(0.017)	(0.030)
Insurer 9	0.031**	0.022
	(0.012)	(0.030)
Insurer 10	0.034***	0.018
	(0.012)	(0.023)
Insurer 11	0.002	−0.028
	(0.012)	(0.017)
Insurer 12	−0.009	−0.022
	(0.011)	(0.022)
Insurer 13	0.016	−0.125***
	(0.025)	(0.046)
Insurer 14	−0.119***	−0.124***
	(0.008)	(0.029)
Insurer 15	−0.009	0.039
	(0.009)	(0.028)
Replacement Cost	Yes	Yes
Controls	Yes	Yes
Month FE	Yes	Yes
Location FE	State	State
Clustered SE	State	State
N	179,917	5,254
R-Sq	0.036	0.086

Note: Dependent variable is whether a household overinsures. Models follow Equation (2) and include insurer fixed effects for all insurers in the sample, though we only report the results for the 15 insurers originating the most policies in the interest of space. The models include insurer fixed effects, state fixed effects, month fixed effects and characteristics of the home as control variables. Column 1 shows the results from our baseline sample; the "Restricted Simple" in Column 2 only includes policies from ZIP codes in which a single insurer originated all the policies. We use Insurer 8 as the reference group as its policyholders have a similar rate of overinsuring in the baseline sample and restricted sample, 12% in both cases, facilitating comparisons across the columns. Regressions report robust standard errors clustered by state. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Online Appendix D Variable definitions

Here, we provide further details on our variables of interest in the Section 6 analysis. Insurer financial data are from annual statements insurers report to state regulators, which are aggregated by the National Association of Insurance Commissioners (NAIC). We collect state-level data from "Page 14" of the annual statement. Commission rates and market share are both calculated using Direct Premiums Written (DPW), which is the gross revenue generated from selling a policy, without subtracting premiums ceded to a reinsurance company (the NFIP, in the case of federal flood insurance). Commission rates are based on Commissions and Brokerage Expenses ($Comms$), which is defined by the 2010 NAIC instruction manual to include:

all payments, reimbursements and allowances, on direct writings, computed as a percentage of premiums for production, management, or other services to:

- *Managers*
- *Supervising General Agents*
- *General Agents*
- *Regional and District Agents*
- *Local Agents*
- *Office Agents*
- *Brokers*
- *Solicitors*
- *Other producers and agents*

This specifically excludes salaries, allowances and payments not computed as a percentage of premiums, contingent commissions, premium taxes, commissions received for special services such as loss adjustment and inspection, and a number of other items. Thus, we believe that our measure of commission rates accurately represents the premium-based compensation insurers pay to their agents for selling policies.

We examine commission rates and market share separately for each insurer's federal flood and non-flood lines of business. The NAIC defines "Federal Flood" as, "coverage provided by the Federal Insurance Administration (FIA) of the Federal Emergency Management Agency (FEMA) through insurers participating in the National Flood Insurance Program's (NFIP) Write Your Own (WYO) program." No other products or programs are included in this definition, so this should accurately represent the amount of flood written by WYO insurers.[29] We define non-flood personal lines as Homeowners Multiple Peril, Personal Auto Physical Damage, and Personal Auto Liability

[29] We observed a few instances of insurers who issued flood policies according to our NFIP dataset reported zero DPW from Federal Flood. We investigated this extensively, finding circumstantial evidence that affiliated insurers accounted for the policies via a different subsidiary or shifted the income to a different year. Because we cannot be certain why, we excluded policies sold by those insurers from our analysis in Section 6.

lines of business. These were the largest non-flood personal lines in property-casualty insurance in 2010, comprising 14.6%, 14.6%, and 20.9% of total property-casualty premiums, respectively.

We explicitly define our variables of interest in Table D1.

Table D1: Insurer Characteristic Variable Construction

Variable	**Name**	**Calculation**	**Exp. sign**
Overinsurance rate	$OverRate_{jk}$	$= \frac{\sum_l I(Over_{ijk})}{\sum_l NumFloodPols_{jk}}$	Dependent var
Managerial control	$Direct_j$	$= 1$ for direct response $= 0$ otherwise	$(+)$
Commissions (flood)	$FloodCommRate_{jk}$	$= \frac{\sum_l Comms_{jkl}}{\sum_l DPW_{jkl}}$ where $l \in$ {Federal Flood}	$(+)$
Commissions (other)	$OthCommRate_{jk}$	$= \frac{\sum_l Comms_{jkl}}{\sum_l DPW_{jkl}}$ where $l \in$ {Auto, HO}	$(+)$
Market share (flood)	$FloodMktShare_{jk}$	$= \frac{DPW_{jkl}}{\sum_j DPW_{jkl}}$ where $l \in$ {Federal Flood}	$(+)$
Market share (other)	$OthMktShare_{jk}$	$= \frac{\sum_l DPW_{jkl}}{\sum_{jl} DPW_{jkl}}$ where $l \in$ {Auto, HO}	$(+)$
Competition	$NumFloodInsurers_k$	$= \sum_j I(NumFloodPols_{jk} > 0)$	$(-)$

Note: The subscripts indicate insurer j in state k writing line of business l. $Comms$ is direct Commissions and Brokerage Expenses and DPW is Direct Premiums Written. The "Auto" line of business above includes personal auto liability, property damage, and no-fault. The homeowners multiple-peril line of business is abbreviated "HO." $Direct$ is determined from the primary distribution system listed in A.M. Best's 2010 *Key Rating Guide* (self-reported by insurers). $OverRate$ and $NumFloodInsurers$ are based on policy data from the NFIP. All other data are from the NAIC annual financial statements.