The Journal of Risk and Insurance

DOI: 10.1111/jori.12280

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 percent of new policyholders overinsure, selecting a coverage limit that exceeds 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 percent 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.

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

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We thank David Eckles, Jed Frees, Rob Hoyt, Kenneth Klein, Joan Schmit, Roxane Steinacker, Justin Sydnor, and seminar participants at University of Wisconsin-Madison, Temple University, the American Risk and Insurance Association, and the Southern Risk and Insurance Association for helpful comments. We also thank Jianing Yao and Juan Zhang for their research assistance.
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differences between insurers (e.g., credit rating) and the product features that they offer (e.g., coverage terms and pricing).

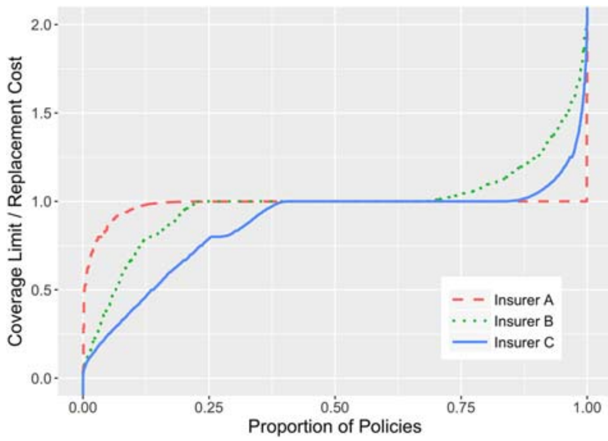
In this study, we examine a market setting that overcomes these empirical challenges—private insurers who sell residential flood insurance policies in the National Flood Insurance Program (NFIP). The U.S. federal government sets all terms of the insurance contract (e.g., premium rating, coverage options) 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 percent 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 one indicates full coverage, while a ratio above (below) one 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 percent of policyholders purchasing excess coverage. Insurer C's policyholders are the most likely to partially insure (about 40 percent), though approximately 15 percent 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 percent. 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

[1]Throughout the article, 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). Insurers are required to report the home's replacement cost to the NFIP for the policies that we study. 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.

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 percent of Insurer B's policyholders overinsure. Finally, about 40 percent of the policyholders of Insurer C partially insure and approximately 15 percent overinsure.

is 4,645 percent 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 percent probability 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.

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, Gürtler, and Hibbeln, 2017), or if additional expenses reduce the available limit (e.g., debris removal).[3] Agents' training and experience would seem to give them an advantage in 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.[4]

In our primary analysis, we examine whether the insurer selling the policy influences the likelihood that a household overinsures. From a dataset of the 4.4 million active flood policies in 2010, we apply a number of filters to more cleanly examine households' decisions of whether to overinsure. For example, we examine only new residential policies (the "Data" subsection describes our data in detail). 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 percent 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 percent of excess limits selected. The most common overinsurance limit is choosing the program maximum of $250,000 regardless of the replacement cost, which

[3]Insurers and their agents may have additional reasons to recommend overinsuring, including generating larger commission revenue, guarding against annual inflation in construction costs, and managing professional liability or reputation risk. For example, overinsuring may reduce the risk that policyholders are dissatisfied with their claims settlement because they believed that they deserved a larger payment.

[4]Other insurance choices might also be influenced by the insurer, such as whether to partially insure or what deductible to choose. Identifying insurer effects in these domains is complicated by other factors. For example, the decision to partially insure may also depend on 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 the topic of insurer effects on partially insuring and deductible decisions in the "Insurer Effects" section.

describes 29 percent of excess limits (6,072 out of the 21,041 overinsuring households in our data). 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 percent 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 being more likely to sell excess coverage. We observe the opposite effect for nonflood 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.

Our results indicate that the sales process meaningfully affects households' insurance choices. We find that the likelihood of overinsuring depends on the insurer selling the policy, and our results on the limit-setting "rules" further support this finding. Other participants in the insurance supply chain also may exhibit an influence. For example, individual agents have direct contact with the consumer and often provide customized advice on insurance coverage. Agents wear several hats—they represent an insurer (a point that we leverage in our data), they are individuals with their own views, they represent a local agency, etc.[5] Systematic effects of the agent, agency, or other party on households' contract choices also may exist; however, our data only allow us to analyze insurer-level effects. We speculate that individual agent effects may even eclipse insurer effects, and we hope that our findings motivate additional research to identify and measure the influence of the various individuals and organizations in the insurance distribution system on households' choices.

Our article contributes to the existing literature in several ways. Our main result shows that insurers help select households' flood insurance contracts. This finding creates

[5]Third-party administrators (e.g., Marsh's Torrent Technologies) are another example of organizations in the insurance supply chain that might affect the recommendations of agents (Kousky et al., 2018). These organizations offer "back office" services related to regulatory compliance, training, technology development, transaction processing, customer relationship management, and claims handling.

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., Cohen and Einav, 2007; Sydnor, 2010; Barseghyan et al., 2013) 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., Browne and Hoyt, 2000; Kriesel and Landry, 2004; Landry and Jahan-Parvar, 2011; Botzen and van den Bergh, 2012) and catastrophe insurance (e.g., Grace et al., 2004; Kousky and Cooke, 2012). More generally, the article adds to a behavioral literature on why consumer 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; Dumm et al., 2017).

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 affect 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., Mullainathan et al., 2012; Christoffersen, Evans, and Musto, 2013), 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, de Meza, and Reyniers, 2013). Anagol, Cole, and Sarkar (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 actions of sellers.[6]

Finally, our findings are consistent with existing evidence of differences across insurance distribution channels. Insurers using direct agents have often been compared

[6]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 Online Appendix A for a detailed analysis), sellers may believe the purchase is worthwhile, as detailed claims data are not publicly available.

to insurers using independent agents (see Regan and Tennyson, 2000, and Hilliard, Regan, and Tennyson, 2013, 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 article is arranged as follows. In the "Background" section, we provide background on the institutional setting and describe the data we use in our analysis. The "Insurer Effects" section outlines the methodology and result for our primary analysis, investigating differences in the likelihood of overinsuring between insurers. In the "Insurers' Specific Guidance for Overinsuring" section, we consider a number of possible formulas insurers may use to suggest a limit relative to the estimated replacement cost. We then investigate the ways in which insurers may incentivize agents to sell excess coverage in the "Insurer Characteristics and Overinsuring" section. We offer a number of robustness checks considering potential selection issues and insurer motivations to recommend overinsuring in the "Robustness Tests" section. Finally, we review our findings and discuss implications in the "Conclusion" section.

Background

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 95 percent of residential flood insurance is underwritten by the NFIP (Dixon et al., 2006; Kousky et al., 2018).[7] 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. Limits and deductibles for the building and contents are not related in any way (i.e., contents coverage is not a percentage of building coverage, as is common for homeowners insurance). We focus our analysis on coverage for the home structure, as there is a calculated and reported replacement cost of the structure on which we base our definition of "overinsuring." 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. In 2010 when the policies in our data were sold, consumers could select a

[7]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.

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.[8]

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). These households must purchase flood insurance with a limit at least as large as "the lowest of [1] 100 percent of the replacement cost of the insurable value of the improvements; [2] the maximum insurance available from the NFIP, which is currently $250,000 per dwelling; or [3] the unpaid principal balance of the mortgage" (Fannie Mae B7-3-07; see NFIP, 2007, for more details). Thus, overinsuring is not necessary to satisfy federal mortgage requirements as fully insuring to replacement cost would satisfy requirement [1].

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. Michel-Kerjan (2010) estimates that private insurers receive "more than one-third of the premiums collected by the program" (p. 409). Compensation from the NFIP to participating insurers includes an expense allowance (12.5–13.5 percent of premiums, based on the estimated costs of marketing, underwriting, and issuing the policy), state premium tax payments (2.3 percent of premiums), and a 15 percent allowance for commissions paid to agents for selling activities (Kousky, 2018). The NFIP also offers a 2 percent bonus for insurers who achieve an annual 5 percent growth in the number of policies written (Michel-Kerjan, 2010). 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. State-level departments of insurance are involved in training agents to sell flood insurance and they report the details of their training requirements to FEMA (FEMA, 2018). 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, in order to be licensed, agents selling any type of insurance

[8]These limits and deductibles are available to households located in an area that federal flood maps estimate has more than a 1 percent annual flood probability, which is the focus of our analysis. Households in lower-risk areas have a different set of deductible and limit choices, but those are excluded from our sample. 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).

must pass at least one exam, 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. The agent selling the policy reports this replacement cost estimate to the NFIP, and this reported value comprises the "Replacement Cost" variable in our dataset. Insurers may develop their own estimation software, though many use products from third-party vendors such as Marshall & Swift (part of CoreLogic) or E2Value.[9] 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 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).[10]

In examining the claims experience of the policies in our data, it is possible (but rare) for flood damage to exceed the home's estimated replacement cost. Out of nearly 180,000 policies, 1,434 (0.79 percent) filed a flood claim on their 2010 policy, and 40 (0.02 percent) experienced a claim in excess of the estimated replacement cost. The average excess damage was $6,872 above the estimated replacement cost. In Online Appendix A, we provide a detailed analysis of costs and benefits of overinsuring, showing that the average overinsuring household paid an additional premium of $71.07 to insure an expected loss of $1.53, which implies a premium loading of 4,645 percent. Ultimately, the risk of excess loss is nonzero, but overinsuring appears to be an expensive way to address it relative to the risk.

[9]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.

[10]Claims settlements can be made on either an actual cash value or a replacement cost basis. The NFIP (2010) manual notes that "Replacement cost coverage applies only if the building is the principal residence of the insured and the building coverage chosen is at least 80 percent of the replacement cost of the building at the time of the loss" (p. PRP 2, see p. POL 18 for more details).

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 ≥100 flood policies	179,917
Baseline data	179,917

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 household's 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 percent annual probability of flood, but are not exposed to storm surge. This zone is the largest in the flood program, comprising 55 percent 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 nonpositive replacement costs: about 1.6 percent 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.[11]

[11]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.

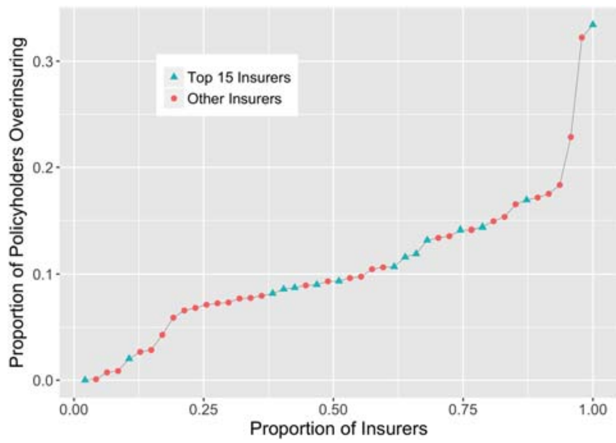
For 2010, the federal flood insurance program directly issued policies in three cases, and we add data filters to include only the third case. The program directly issued policies if the contract (1) insured a "severe repetitive loss property," (2) was a State Farm legacy contract, or (3) was originated 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 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.[12] The resulting baseline sample includes 179,917 flood insurance policies.

Figure 2 shows the distribution of overinsuring rates across the 48 insurers in the baseline data. Here and throughout the article, we treat insurers in the same corporate group as a single insurer.[13] Ten percent of insurers have overinsuring rates below 2 percent; half have rates below 10 percent; and at the 90th percentile, 10 percent have overinsuring rates above 17 percent. The mean overinsuring rate across insurers is 11 percent. The figure also denotes the 15 largest insurers (by number of flood policies) from the remaining 33 insurers. The top 15 insurers write 91 percent of policies and generate 90 percent 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 the "Insurer Effects" and "Insurers' Specific Guidance for Overinsuring" sections, but only show the results for the top 15 insurers in the interest of space.

[12] About 0.9 percent of our sample are "NFIP direct" policies. They are sold by private insurance agents to households, and the NFIP (rather than a private WYO company) is listed as the "insurer" in our data. Much of the administrative work (e.g., training, claims processing, etc.) is conducted by the NFIP's third-party administrator (Kousky, 2018). We treat the NFIP direct as one of the insurers in our regressions.

[13] Multiple subsidiaries within the same insurance group may participate in the WYO program. We observe 9 groups (out of 48) with multiple WYO subsidiaries. These subsidiaries may participate in different states, target different consumer markets, or be the result of prior acquisitions by the group and exist to maintain the acquired company's agent network. For example, State Auto Mutual Group participated in 2010 and included Patrons Mutual Insurance Company of CT (in CT, MA, and RI) and State Auto Property and Casualty Insurance Company (in 24 other states). As subsidiaries within groups are likely to share some central resources (such as accounting, claims processing, etc.) and are often branded as a single insurer, we believe it is appropriate to examine insurers at the group level.

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 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.

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 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

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 percent. 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 percent 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 the "Insurer Effects", "Insurers' Specific Guidance for Overinsuring" and "Are Insurer Effects Explained by Household Selection?" subsections.

higher deductibles and insuring their contents less often.[14] Finally, households who overinsure have the highest average replacement cost, $146,380.

Insurer Effects

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

[14]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, fully, and overinsuring households.

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.

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:

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

$$\begin{aligned}\mathrm{I}(Over_i) = \alpha + \beta_j &+ \gamma_1 \mathrm{D}(Basement_i) + \gamma_2 \mathrm{D}(CRSscore_i) + \gamma_3 \mathrm{D}(Elevation_i) \\ &+ \gamma_4 \mathrm{I}(ElevationCertificate_i) + \gamma_5 \mathrm{D}(FloodZone_i) + \gamma_6 \mathrm{D}(Floors_i) + \gamma_7 HomeAge_i \\ &+ \gamma_8 \mathrm{I}(HomeAge_i = Missing) + \gamma_9 \mathrm{I}(Mobile_i) + \gamma_{10} \mathrm{D}(Obstruction_i) \\ &+ \gamma_{11} \mathrm{I}(PreFIRM_i) + \gamma_{12} ReplacementCost_i + \delta_k + \lambda_t + \varepsilon_i \qquad (1)\end{aligned}$$

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

In Equation (1), 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 the "Data" subsection describes each control variable. The home's age is missing for 0.3 percent 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 floodplain. 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] The controls for flood zone, pre-FIRM properties, and elevation are intended to address heterogeneity in risk and cross-subsidization between households in our sample.[17] The risk of excess damage varies on whether the insured structure is a mobile home (see Online Appendix A), so we include I($Mobile_i$) as a control. In the regression models reported in Table 4, 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.

[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 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., Angrist and Pischke, 2008; Wooldridge, 2010) 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 percent 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.

[17]Flood insurance in the NFIP is known for cross-subsidization (Michel-Kerjan, 2010; Kousky, 2018), and overinsuring may be less expensive for policyholders who benefit from this cross-subsidization. Our sample includes only households in Zone A, but there may still be differences in risk within the zone. Using 2003 data, Hayes, Spafford, and Boone (2007) report that, on average, pre-FIRM properties paid premiums 60 percent below actuarially fair rates and comprised nearly 90 percent of the subsidized policies. These subsidized properties do not appear more likely to overinsure in our data—53 percent of overinsured policies are pre-FIRM, while 56 percent (72 percent) of fully (partially) insuring households are pre-FIRM. See Kousky and Shabman (2014) for additional details on the NFIP's pricing.

Table 4
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 (1), and include insurer fixed effects for all 48 insurers in the baseline data. We normalize fixed effects following Equation (2). 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.

Estimates of $\hat{\beta}_j$ depend on which insurer is excluded from the set of insurer fixed effects in Equation (1) (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.

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

$$\text{where } j = 1 \text{ denotes the omitted insurer} \tag{2}$$

Our regression results in Table 4 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 coefficient 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.[18]

Results

We provide our estimation results in Table 4. 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 4 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.

[18]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. As our article 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.

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 percent confidence interval around the normalized estimate.

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 substantial 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 percent 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.[19]

We include several robustness tests of these results in the "Robustness Tests" section. Namely, we conduct additional analyses considering possible unobserved selection effects on which insurer a household chooses, differences across insurers regarding whether they recommend a "small" versus "large" level of overinsuring that may clarify the insurer's motivations, a coefficient adjustment (the Bayesian shrinkage estimation), and a placebo test to examine whether our findings are an anomaly of our estimation strategy. Throughout, we find qualitatively consistent results with those presented here.

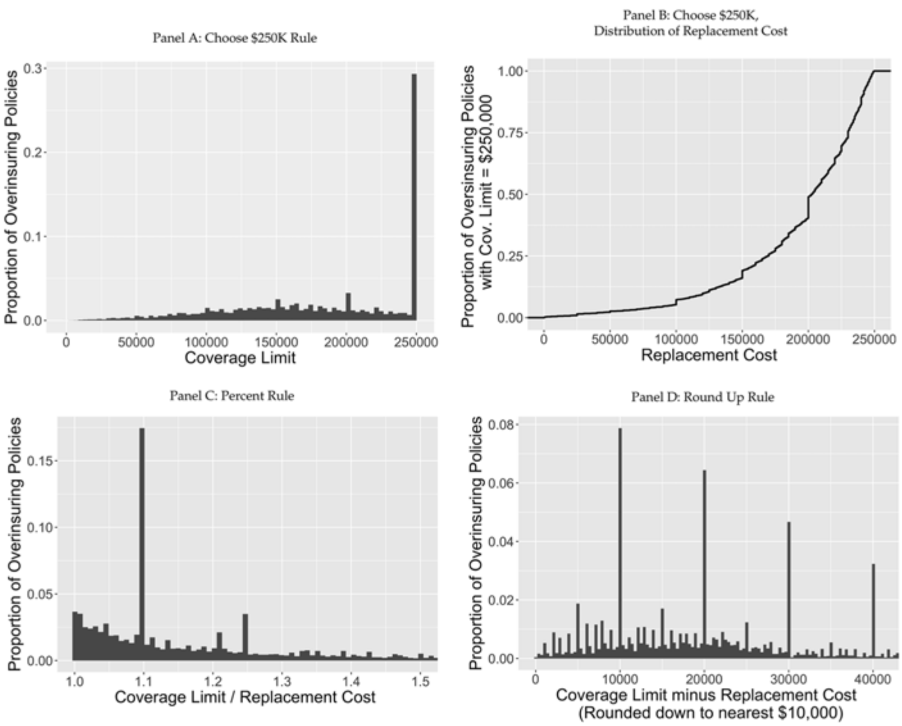
Insurers' Specific Guidance for Overinsuring

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.). As insurers influence whether households overinsure (the "Insurer Effects" section), 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 is to purchase the program maximum of $250,000, which describes 29 percent of overinsuring households. This rule is the most costly; overinsuring households adopting this "choose $250K" rule pay an average additional premium of

[19] 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, fully insure, or select the lowest deductible, with results in Online Appendix C. Because different decision processes may guide partially insuring, deductible decisions, and overinsuring, as discussed in the "Introduction" section, we consider this extension exploratory and beyond our core focus. Our results show statistically significant insurer effects in each case: fully insuring, partially insuring, and selecting the lowest deductible. Interestingly, different insurers seem to recommend the lowest deductible than those who recommend overinsuring (Pearson correlation of 0.32, $p = 0.03$). 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 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 and one with a $200,000 would each be 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.

$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 percent of the replacement cost, which describes 18 percent of overinsuring households (Panel C). Households adopting this "increase 10 percent 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 percent 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" rule spend \$13 on average on excess coverage. In total, the "choose \$250K," "increase 10 percent," and "round up \$10K" rules explain 50 percent of coverage limits of overinsuring households.[20]

The coverage limit rules illustrated in Figure 4 might be due to unobserved differences in policyholders and local markets, so as we do in the "Results" subsection, 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 the "Methodology" subsection and Equation (1). These regressions use our preferred model (Column 4 of Table 4) 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 (2) so that each uses the average insurer as the reference group. Our regressions include the entire baseline sample.[21]

[20]The "increase 10 percent" rule is a specific example of selecting some percentage point increase in the replacement cost. Excluding households who select the \$250,000 maximum, 32 percent of remaining overinsuring households have a coverage limit that is some 5 percentage point increment (i.e., 105 percent, 110 percent, 115 percent, etc.) of their replacement cost ("percent rule").
Similarly, 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 percent 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 percent of excess coverage limits rather than 55 percent ($0.29 + 0.18 + 0.08 = 0.55$). For example, either the "increase 10 percent" or the "round up \$10K" rules could lead an agent to recommend a household with a \$100,000 replacement cost purchase a \$110,000 limit. Thus, this 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 percent and \$10,000 values) explain 66 percent of coverage limits for overinsuring households.

[21]Regression analyses of the specific rules could be conducted with either the full sample or only the subsample of policies that are overinsured. The former examines households who follow a specific rule (e.g., "round up \$10K") relative to all other households, while the latter would compare these households to others who overinsure. We prefer using the full sample for two reasons. First, doing so imposes fewer assumptions on the analysis. To model the subsample only, we would use a two-part model (such as a Tobit) in which the first part models the decision to overinsure or not and the second models the specific excess limit selected. Such an estimation strategy implicitly assumes that households and agents approach the decision in this way—first deciding to overinsure, and then selecting a limit. In addition, standard

We provide the regression results in Table 5. 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 Table 4). As with the previous results on insurer effects (the "Results" subsection), 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 percent 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, insurers' institutional policies are directing these limit choices.

INSURER CHARACTERISTICS AND OVERINSURING

Thus far, we have shown that insurers influence whether households overinsure (the "Insurer Effects" section) and that they appear to provide specific guidance for the excess coverage that they select (the "Insurers' Specific Guidance for Overinsuring" section). Here, we examine insurers' observable characteristics to explain the variation in overinsuring rates (i.e., the proportion of policies overinsured) across insurers. We propose three 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.1.

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).[22] This control may take various forms, including setting sales goals and training or educating agents (Hilliard, Regan, and Tennyson, 2013). Insurers using direct agents may thus induce

Tobit models assume that the latent variable in the first part is normally distributed. Thus, this subsample approach places an additional modeling structure regarding how the decision to overinsure is made and the distribution of the data, which is not required if we use the full sample. Second, using the full sample facilitates comparisons between the specific rules in this section and our other regression analyses, as we use the same model to examine several outcome variables, including whether households overinsure (Table 4) and whether households select the lowest deductible (Table C1 in the Online Appendix).

[22]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 (nonexclusive) 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, Regan, and Tennyson (2013) provide a detailed account of the similarities and differences between these distribution systems.

TABLE 5
Insurer Effects on Rules for Overinsuring, 15 Largest Insurers

	(1) I(Choose $250K)	(2) I(Increase 10 percent)	(3) I(Round up $10K)
Insurer 1	−0.003	−0.007	−0.003***
	(0.002)	(0.005)	(0.001)
Insurer 2	0.090***	0.000	0.015***
	(0.020)	(0.003)	(0.003)
Insurer 3	−0.004	−0.004**	−0.003*
	(0.005)	(0.002)	(0.002)
Insurer 4	−0.007**	−0.001	−0.005***
	(0.003)	(0.002)	(0.001)
Insurer 5	−0.009***	−0.003	−0.001
	(0.002)	(0.002)	(0.001)
Insurer 6	0.003	−0.008***	0.010***
	(0.003)	(0.002)	(0.002)
Insurer 7	0.000	−0.005	−0.000
	(0.004)	(0.006)	(0.003)
Insurer 8	−0.003	0.017***	−0.006***
	(0.002)	(0.004)	(0.001)
Insurer 9	0.002	0.022**	−0.000
	(0.004)	(0.011)	(0.002)
Insurer 10	0.014***	−0.006**	0.003
	(0.005)	(0.003)	(0.003)
Insurer 11	−0.007***	−0.011***	0.003
	(0.003)	(0.003)	(0.003)
Insurer 12	−0.007*	0.016***	−0.002
	(0.004)	(0.005)	(0.001)
Insurer 13	−0.024***	0.049***	−0.006***
	(0.004)	(0.014)	(0.002)
Insurer 14	−0.049***	−0.015***	−0.014***
	(0.005)	(0.002)	(0.001)
Insurer 15	−0.015***	−0.004*	−0.004**
	(0.004)	(0.002)	(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 percent” indicates selecting a coverage limit that is 110 percent 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 (1), with the coefficients adjusted as in Equation (2) 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 percent” rule given the program maximum limit of $250,00—all households in that regression have replacement costs that do not exceed $227,000 (as $1.10 \times \$227,000 = \$249,700$). Standard errors are robust and clustered at the insurer level.

their agents, who are their employees, to sell excess flood coverage without needing other incentives. We include an indicator 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 insurer j's commission rate in state k as "Commissions and Brokerage Expenses" divided by "Direct Premiums Written" using the state-level NAIC financial statement data. We calculate commission rates for federal flood ($FloodCommRate_{jk}$) and nonflood personal lines ($OthCommRate_{jk}$). Nonflood personal lines includes both homeowners and auto lines of business, and we include both to capture a larger component of nonflood commissions an insurer might pay its agents. 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 ($FloodMktShare_{jk}$) and for nonflood personal lines (auto and homeowners, $OthMktShare_{jk}$) in our analysis.[23]

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 the "Data" subsection. 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 in-

[23]There are likely additional mechanisms an insurer may use to motivate an agent to recommend overinsuring, but we are limited to mechanisms which can be inferred from financial statement and similar data. Agent training, estimation software, informal networks, etc., each may have an effect on overinsuring, but we do not observe these factors. For example, we find that policyholders of insurers using direct distribution systems are more likely to overinsure; however, our data does not clarify whether specific guidance to overinsure is transmitted through the insurer to agents via training, corporate policy, memos, etc. State and federal governments appear well-positioned to create more uniform guidance as they have the ability to provide information via training and other resources. We return to a discussion of improving the information available to insurers and their agents in the conclusion.

TABLE 6
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
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+." 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. Data on whether an insurer uses a Direct or Independent Agent distribution system and the insurer's financial strength are from A.M. Best (2010), the overinsuring rate is from the NFIP data, and the remaining data are from NAIC (2010).

cludes 437 observations of 35 insurers in 48 states issuing 164,512 policies, 91.4 percent of the NFIP baseline sample.[24]

[24]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 percent if the policyholder overinsured and 0 percent if it did not. Requiring at least 20 policies generates overinsuring rates in 5 percent 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.

We model insurer j's overinsuring rate in state k as a function of the mechanisms described above and controls, as follows:

$$\begin{aligned} OverRate_{jk} = \alpha &+ \beta_1 \mathrm{I}(Direct_j) \\ &+ \beta_2 \mathrm{I}(Direct_j) \times FloodCommRate_{jk} + \beta_3 \mathrm{I}(Direct_j) \times OthCommRate_{jk} \\ &+ \beta_4 \mathrm{I}(Indep_j) \times FloodCommRate_{jk} + \beta_5 \mathrm{I}(Indep_j) \times OthCommRate_{jk} \\ &+ \beta_6 FloodMktShare_{jk} + \beta_7 OthMktShare_{jk} + \mathbf{X}'_{\mathbf{jk}}\gamma + \varepsilon_{jk}. \end{aligned} \tag{3}$$

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 product mix. 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 percent of insurers who report positive direct premiums written for flood insurance but no flood commissions.[25] 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 6. Direct writers comprise 49.7 percent 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, as they are interacted in our regression analysis. Commission rates are lower for direct writing insurers, both in flood and nonflood lines of business.[26] The mean (median) flood market share is approximately 8.2 percent (6.7 percent), which is skewed by certain insurers who capture a very large market share (up to 46.7 percent).[27] While approximately 6 percent

[25]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.

[26]The median flood commission for direct writers is 15.9 percent and is 17.4 percent for insurers using independent agents. Total compensation from the NFIP to private WYO insurers is approximately one-third of premiums (Michel-Kerjan, 2010). Insurers appear to be increasing agents' commissions beyond the commission allowance (15 percent of premiums), perhaps using the funds from the expense allowances and/or bonuses that the insurers receive in the program (see more details on NFIP payments to insurers in the "Institutional Details" subsection).

[27]The insurer with a 46.7 percent 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 percent with a mean (median) of 7.4 percent (6.1 percent).

Table 7
Insurer Characteristics Associated with Overinsuring

	Main Sample			Restricted	All
	(1)	(2)	(3)	(4)	(5)
Direct	0.037***	0.047***	0.046***	0.056***	0.038**
	(0.007)	(0.010)	(0.011)	(0.011)	(0.018)
Indep × FloodCommRate	0.058	0.016	0.068	0.130	−0.111
	(0.067)	(0.071)	(0.072)	(0.108)	(0.160)
Direct × FloodCommRate	0.478***	0.441***	0.490***	0.568***	0.366***
	(0.073)	(0.068)	(0.067)	(0.067)	(0.085)
Indep × OthCommRate	−0.063	−0.048	−0.083	−0.040	−0.080
	(0.053)	(0.061)	(0.066)	(0.069)	(0.115)
Direct × OthCommRate	−0.675***	−0.699***	−0.717***	−0.815***	−0.686***
	(0.078)	(0.117)	(0.131)	(0.137)	(0.139)
FloodMktShare	0.121*	0.006	0.015	0.040	−0.073
	(0.069)	(0.058)	(0.063)	(0.074)	(0.097)
OthMktShare	−0.013	0.171**	0.168*	0.068	0.275**
	(0.057)	(0.085)	(0.093)	(0.086)	(0.106)
Controls	No	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes	Yes
Clustered SE	State	State	State	State	State
N	437	437	437	295	871
R-Sq	0.298	0.494	0.596	0.690	0.229

Note: The dependent variable is insurer *j*'s overinsuring rate in state *k*. Regressions follow Equation (3). 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 3, excluding insurers writing fewer than 50 new flood policies in the state. Column 5 also replicates Column 3, but includes all insurer-state observations (with no policy minimums).

of the insurer-state observations in our sample do not offer homeowners or auto insurance (and thus have 0 percent market share in nonflood lines), those insurers with a large market share in flood also tend to have a large share of the nonflood market (with a Pearson correlation of $\rho = 0.283$). 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 7. Only the estimated coefficients for our variables of interest are included in this table due to space constraints, but we report the full results in Online Appendix D. We show results for the main sample in Columns 1–3, which requires that insurer *j* sells at least 20 policies in state

The sales of flood insurance appear to be related to those of homeowners insurance (market shares have a Pearson correlation of $\rho = 0.30$). While an agent may sell homeowners insurance and flood insurance at the same time, it is possible that the policies have different limits. For example, some insurers may endorse their homeowners policy with ISO's "extended replacement cost coverage" endorsement (HO 04 11) to address the risk of insufficient limits. Such an endorsement is not available for NFIP flood insurance, and so the policy limit would need to be set higher to address the risk of an excess loss.

k. Column 1 includes only our variables of interest, with no controls. Column 2 adds controls described above to the model in Column 1. Column 3 adds state fixed effects to the model in Column 2. Our restricted sample in Column 4 replicates Column 3, including only insurer-state observations with at least 50 new flood policies sold. We also replicate the model in Column 3 without a minimum number of policies, reporting results in Column 5. In all models, continuous variables are mean-centered to address collinearity between flood and nonflood lines of business. We cluster standard errors by state.

The model in Column 3 is our preferred model, as it controls for unobserved differences between states. 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* × *FloodCommRate*), but not for those selling via independent agents. Increasing direct agent flood commissions by one percentage point increases the overinsuring rate by 0.49 percentage points. Nonflood commission rates are negative and significant, again for direct writers only (*Direct* × *OthCommRate*). Increasing home and auto commissions decreases the overinsuring rate by 0.72 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.

ROBUSTNESS TESTS

Are Insurer Effects Explained by Household Selection?

Our identification strategy in the "Insurer Effects" section 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 the "Insurers' Specific Guidance for Overinsuring" section 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 percent 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 percent of policies ($n = 5,207$) in our baseline sample are in a ZIP code in which a single insurer originated all the policies.[28] We reestimate our regression of the likelihood that a household overinsures, using this restricted sample. Insurer effects should disappear if they are the result of a household's choice of insurer, as 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 B.1. In sum, while households' preferences may influence their choice of insurer, this does not seem to explain the large insurer effects in our data.

Comparing "Small" and "Large" Overinsuring

Our data does not allow us to directly observe insurers' motivations to recommend overinsuring, but here we extend our analysis of insurers' specific guidance (the "Insurers' Specific Guidance for Overinsuring" section) to consider possible motivations. Insurers' recommendations to overinsure by a "small" amount (relatively close to replacement cost) might be motivated by different considerations than insurers who recommend overinsuring by a large amount (e.g., selecting a \$250,000 coverage limit on a home with a \$150,000 replacement cost). For example, some insurers might recommend overinsuring out of concern for inflation risk and demand surge, which previous research shows can increase the cost to repair or rebuild a damaged property (e.g., Hallegatte, 2008; Döhrmann, Gürtler, and Hibbeln, 2017). Based on our reading of this literature, we consider overinsuring up to 115 percent of the replacement cost as possibly motivated by concerns related to inflation risk and demand surge.[29] Fifty-four percent of overinsuring households select a coverage limit at or below 115 percent of the replacement cost.

[28]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.

[29]Hallegatte (2008) calculates a demand surge of 13 percent due to Katrina. Döhrmann, Gürtler, and Hibbeln (2017) estimate the 95th percentile of demand surge is 7–10 percent for catastrophes greater than \$100 million. They also find that demand surge is higher when the construction sector has limited capacity, which was not likely the case in 2010. Regarding "normal" inflation, the 3-year average price change for residential construction goods was 2.33 percent in 2009 (U.S. Bureau of Labor Statistics).

Overinsuring appears expensive from our estimates, whether choosing a limit below or above 115 percent of the replacement cost (Online Appendix A). While overinsuring by the former is less costly than the latter, we do not intend for this analysis to convey an endorsement for either overinsuring strategy.

We divide overinsuring into two categories, up to 115 percent of the replacement cost (i.e., "small" amounts, where $RC < Limit \leq RC \times 1.15$) and above 115 percent (i.e., "large" amounts, where $RC \times 1.15 < Limit$), and regress an indicator for each category on the explanatory variables from our preferred model. We discuss the main findings here and report the detailed results in Online Appendix B.2. We find that most insurers who recommend overinsuring engage in some combination of recommending limits below and above the 115 percent threshold. For example, the policyholders of Insurer 2 are 8 percentage points more likely to overinsure at the lower level (up to 115 percent of the replacement cost) than the average insurer and are 12 percentage points more likely to overinsure at the higher level than the average insurer. We conclude that the insurers in our data who recommend overinsuring do not cleanly divide into those recommending "small" amounts and those recommending "large" amounts, at least as we have defined them. If insurers encourage overinsuring to address inflation risk and demand surge, it appears that these concerns are not their only motivation, or that they perceive policyholders' exposures to those risks to be greater than the "small" amounts that we have modeled here.

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. In this estimation, we calculate the EB coefficients by "shrinking" each fixed effect estimate closer to the approximate mean of the true effects. The adjustment has almost no effects on the results. For example, the largest effect among the top 15 insurers is on Insurer 2 in the main results (Table 4); the shrinkage adjustment reduces the coefficient estimate from $\hat{\beta}_2 = 0.200$ to 0.198. We report the detailed results of our estimation in Online Appendix B.3.

As a further check on sampling variation, we conduct a placebo test in which we randomly assign an insurer from our dataset to each policyholder. 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 Online Appendix B.4. The results of this placebo test provide additional evidence that sampling variation does not explain the insurer effects that we observe.

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 household's 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 percent), 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 nonflood commissions are high.

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.[30] We selected our sample in the interest of empirical identification in our analysis; these 165,000 policies represent only 3.7 percent 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.[31] 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, Evans, and Musto, 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

[30] 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.

[31] Using the filters described in the "Data" subsection, we examine policies from 2009 that were renewed in 2010. About 1 percent of renewals reduced their coverage limit and 70 percent 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 percent of these renewals increased their coverage limit by 10 percent relative to their 2009 coverage limit.

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.[32] 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 residential properties in the "100 year" flood plain (with a 1 percent 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.

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[32] 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.

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