Expecting Climate Change: A Nationwide Field Experiment in the Housing Market

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Abstract

Climate change presents new risks for property in the United States. Due to the high cost and sometimes unavailability of location-specific property risk data, home buyers can greatly benefit from acquiring knowledge about these risks. To explore this, a large-scale nationwide natural field experiment was conducted through Redfin to estimate the causal impact of providing home-specific flood risk information on the behavior of home buyers in terms of their search, bidding, and purchasing decisions. Redfin randomly assigned 17.5 million users to receive information detailing the flood risk associated with the properties they searched for on the platform. Our analysis reveals several key findings: (1) the flood risk information influences every stage of the house buying process, including the initial search, bidding activities, and final purchase; (2) individuals are willing to make trade-offs concerning property amenities in order to own a property with a lower flood risk; (3) the impact of the flood risk information on behavior is more pronounced for users conducting searches in high flood risk areas, but does not differ significantly between buyers in Republican and Democrat Counties; and (4) the information resulted in changes to property prices and altered the market's hedonic equilibrium, providing a new finding that climate adaptation can be forward-thinking and proactive.

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1 Introduction

Climate change endangers both economies and human well-being across the globe. The ways in which people adjust their actions in light of new climate change-related information ("new news") will play an increasingly crucial role in determining the societal consequences of carbon emissions (Nordhaus, 1993; Hinkel et al., 2014; Auffhammer, 2018; Kahn, 2020; IPCC, 2021). Adaptation to climate change can take place through various means. For instance, both businesses and individuals have the option to relocate to areas that offer greater protection from climate change-related disasters; this is often referred to as a "higher ground" approach. Once a location is chosen, they can further safeguard themselves by investing capital in defensive measures (Barreca et al., 2016; Deschenes, Greenstone and Shapiro, 2017; Ito and Zhang, 2020).

Adaptation behaviors like these are predicated upon individuals' awareness of high-stakes climate risks associated with properties in the housing market, like flooding. However, an increasing body of evidence suggests that individuals in the United States are largely unaware of these risks (Bakkensen and Barrage, 2022; Wagner, 2022). This lack of awareness implies that properties located in high-flood risk areas in the U.S. may be overvalued, with some estimates around \$200 billion in aggregate (Gourevitch et al., 2023), which is expected to worsen over time as the population's exposure to climate change risk intensifies (Marcoux and Wagner, 2023).

The lack of flood risk awareness could be highly meaningful given that flood-related events have caused more direct economic damage than any other type of natural disaster worldwide (Miller, Muir-Wood and Boissonnade, 2008). In the United States alone, these damages have exceeded \$1 trillion since 1980 (NOAA, 2018; Wing et al., 2022), and some argue that the indirect economic damages could be greater than the direct effects (Hallegatte, 2008; Koks et al., 2015). These direct and indirect economic consequences are expected to escalate over time and might not be mitigated, even if society were to dramatically and immediately reduce carbon dioxide emissions (Dottori et al., 2018; Wobus et al., 2019).

The human costs associated with flooding may be mitigable if people become aware of current and future risks and actively engage in adaptive behavioral changes (offsetting measures). By increasing understanding of the risks involved and taking appropriate action, individuals can potentially reduce the impact of flooding on their lives and livelihoods. However, we do not yet know how individuals react to information about specific climate change-related risks associated with their investments. There is no causal evidence suggesting that climate change risk information impacts on people's search and house buying decisions and ultimately where people live. To explore this, we conducted a rigorous assessment to measure the causal impact of climate change information on searching and buying decisions within the United States national housing market. We present the first large-scale field experimental evidence offering insights into how precise flood risk information influences the behavior of home buyers across the United States. Our nationwide natural field experiment was conducted in late 2020 utilizing the Redfin website and application ("app"), involving the participation of a substantial user base (17.5 million individuals in total). For home buying in the U.S., using an online search brokerage such as Redfin is extremely common; according to the National Association of Realtors, 97% of U.S. home buyers use the internet for their search.

In an unexpected and unannounced manner, Redfin randomized the assignment of complete property-level flood information at the individual customer level. Randomization took place either at the device level or, if the user was registered with Redfin and logged in, at the individual level (so all devices would definitely have the same experimental group). For each property that a treated user searched for, they were provided with two key pieces of information: a flood risk score ranging from 1 (minimal risk) to 10 (extreme risk), and the predicted likelihood of flooding over a 30-year period.[1] Customers were not able to filter their search results based on the flood score, and sellers were blind to the information.[2]

Apart from the flood risk information, all other features of the Redfin search experience remained consistent for both the treated and control groups. The flood risk information had no direct bearing on any search or pricing algorithms. Considering the significant market share held by Redfin during the experiment, our study generated variation in flood information within approximately 20% of the entire U.S. internet property market throughout the experiment's duration, resulting in nearly 400 million property views. This widespread participation allowed for robust analysis of the effects of flood information on searching and buying behavior within the housing market, and whether the information affected the hedonic equilibrium.

In our natural field experiment, the detailed new flood risk information displayed on Redfin for every property in the United States was generated by First Street Foundation (FSF) (Bates et al., 2021). FSF is a registered 501(c)(3) non-profit organization that embraces an open science perspective and continuously updates and enhances its predictive model (although this model and output are relatively recent). The FSF model can predict flood risk for the whole of the U.S. and it has been argued that the FSF model and output are more reliable and valid than those provided by FEMA for a number of reasons; indeed, considerable literature has highlighted the limitations of FEMA's mapping technology (Wing et al., 2018, 2022). Unlike

[1] This flood risk information was positioned approximately two-thirds of the way down the viewing page for each property, regardless of whether the individual was using their phone or computer.

[2] During the experiment, no seller or agent complained to or questioned Redfin about the flood risk information.

FEMA's flood maps, which primarily serve the requirements of the National Flood Insurance Program and thus do not measure flood risk for the whole of the US, the FSF flood score is generated by a predictive model that incorporates not only past flood risks but also considers future climate change trends and pluvial and fluvial risks.[3] The FSF predictive model has undergone peer review (Armal et al., 2020; First Street Foundation, 2020; Flavelle et al., 2020; Porter et al., 2021), and ongoing research efforts aim to validate its model predictions by leveraging recent natural disasters as natural experiments.

Our main hypothesis is that the presence of property-level flood risk information will affect consumer behavior and the housing market. We posit that the availability of this new flood risk information will lead to a reduced likelihood of individuals searching for, engaging with, and purchasing high flood risk homes. We develop and build on the closed form hedonic models presented in Epple (1987) and Giannias (1999). We show that moving from partial to full information on the distribution of flood risk on properties can affect demand. Our emphasis is on one's belief updating about a property based on the asset's attributes draws on previous research on expectations and decision-making (Manski, 2004; Glaeser and Nathanson, 2017; Kuchler, Piazzesi and Stroebel, 2023). We are precise on the populations in our data that would be exposed to the new flood risk news to test this "new news" hypothesis– these are individuals who are searching for properties that were previously seen as previously safe (in a state of the world before FSF model and outputs) but now are high risk for flood (because of the FSF output and predictions). By testing how information shapes individuals' expectations, we aim to shed light on the role of information in facilitating forward-looking adaptation to climate change.

The Redfin data allows us to observe the entire search process for both treated and control customers, as well as their interactions with the Redfin app for each property they visit, both before and during the field experiment. Our partnership with Redfin provides us with

[3] Several notable distinctions exist between FEMA's flood maps and FSF's maps. Firstly, FEMA's flood maps do not provide universal coverage across the United States, whereas the FSF flood score offers national coverage. Secondly, FSF's national model incorporates pluvial (precipitation) and fluvial (rivers, creeks) flooding simulation, which FEMA's maps do not include. Thirdly, FSF's model employs a Regionalized Flood Frequency Analysis (RFFA) approach that utilizes traditional statistical propensity matching techniques to model ungauged streams, river reaches, and regions with known gauged characteristics, thereby producing flow parameters with high confidence. Additionally, FSF's model incorporates environmental factors to assess recent and future changes in flood risk over a 30-year period. Fourthly, every local FEMA map must be agreed on by local politicians, businesses, and other organizations; in other words, the maps consider flood risks as defined by FEMA, but also political and business interests (which means real flood risk is not presented accurately to the public and markets). In contrast, FSF models are not affected by local lobbying concerns. Lastly, the flood score data provided by FSF varies for each property in the United States, therefore providing more granular information than FEMA's version. FSF's hazard layer for a 1-in-100-year event (representing a 1% annual risk of occurrence) identifies approximately 1.7 times as many properties at risk compared to FEMA's Special Flood Hazard Area designation (First Street Foundation, 2020). These problems have been previously discussed as FEMA's flood maps are currently outdated for policymaker and consumer use (Mulder and Kousky, 2023), emphasizing the need for improved mapping technologies and updated flood risk information.

comprehensive insights into user behavior without the need to impose much structure on the search process–we observe it directly through eyeballs on the app where treatment is orthogonal to everything related to searching and buying a property. Another measurement and identification benefit of the partnership with Redfin is that they employ real estate agents, an organizational practice that grants us access to detailed information on bidding behavior for all users who engage the services of a Redfin agent, both before and during the experiment, both for control and treated users. This vertical arrangement throughout the home searching and buying process enables a comprehensive analysis of how trusted information about the future, specifically related to flood risk, influences sorting and market outcomes in the real estate sector. Throughout the duration of the experiment, Redfin had an average of 1,757 lead agents per month across the country (Redfin, 2021). This wealth of agent data is instrumental in enhancing our understanding of bidding patterns and buying behavior, but also how search behavior maps onto bidding and buying behavior, which has not been previously linked in the literature.

Additionally, we augment our analysis by linking the Redfin data with market data on all U.S. property transactions and listings during our experimental period. This linking allows us to examine the impact of treatment information disclosure on the hedonic equilibrium of the housing market. By incorporating transaction data, we can assess how the availability of randomized flood risk information influences the overall market dynamics and pricing. All of these data sources provide a novel and comprehensive foundation for our project, enabling us to accurately measure search dynamics, bidding behavior, and the impact of information disclosure on individuals' climate-risk adaptive behavior.

1.1 Primary Findings

We report three main sets of results. First, we show how the randomized flood risk information changes people's search and property engagement behavior, and how they learn and develop strategies to trade-off the flood disamenity in their search behavior. Second, we show how the randomized flood risk information changes people's bidding and buying behavior. Third, we show how the randomized flood risk information shifts the resulting hedonic housing price distribution.

First, our analysis revealed that the randomized flood risk information had a significant and meaningful impact on users' search behavior. Specifically, individuals who randomly received the flood risk information were more inclined to search and browse properties with lower flood risk compared to the control group. Among those who initially searched for homes with high flood risk, the treatment led to a 12% reduction in the flood risk of their searched homes after two months. We found that consumers learned which properties and locations had high flood risk and created a sense of which properties were to be avoided (these homes make up 4% of US housing stock). The information had little impact on the flood score for searched homes for those searching for relatively lower risk homes before the treatment started.

The availability of detailed search data allowed us to gain precise insights into the trade-offs consumers make when searching for lower flood risk properties. We found that treated individuals were willing to trade-off certain property characteristics, such as neighborhood amenities (bike and walk score), and their consideration set of properties became more spatially concentrated. We found that treated individuals did not adjust the price, size, number of bedrooms, or number of bathrooms of their search.[4] These results suggest a process of spatial elimination in the search behavior, which is consistent with the elimination by aspects model (Tversky, 1972; Payne, Bettman and Johnson, 1988). People kept the same search parameters for the number of bedrooms and bathrooms, price, and square foot, but traded off flood risk for neighborhood characteristics.

We also found that when the flood score was very variable in a defined location (i.e., high standard deviation of flood scores within a zip code), the impact of the randomized flood information was significantly large, but the information had no impact when the flood score was very uniform within a zip code. Together with the above result, this suggests that the impact of the information led people to search geographically narrower and overall more efficiently (see the time-to-offer results below). We also found that the spatially further away that people are searching for a home from where they live, the treatment effects are larger, suggesting that this information substituted somewhat for local experience. Finally, we also found that the flood risk information did not push people to search for homes with other climate risky attributes that were not observable to the individual user (such as heat, wind, and wildfire).[5]

All of these results suggest that individuals actively and organically adjusted their search parameters and strategies in response to the flood risk information provided by Redfin. Users in the treatment group could not filter flood score on their search on the app, so they discovered the flood score by learning by searching. While there might be several mechanisms as to why the information led to a change in behavior (that we cannot estimate because we had no exogenous variation), such as larger anticipated flood damage costs, larger insurance costs, or even public shame about buying a high flood risk home, our results and these mechanisms are most consistent with and can be rolled into our new news hypothesis. That is, we predicted

[4]Our data allows us to observe the consideration set for all consumers, which is usually unobserved in studies (Honka, Hortaçsu and Wildenbeest, 2019).

[5]At the time of the experiment, only flood risk was available to treated users, although we had information on the heat, wind, and wildfire risk of each property.

that treatment effects from the information should be for the homes that were not previously identified as high risk but now are due to climate change and better modeling (from FSF). In fact, roughly 2.5% of U.S homes fall into this category and this is where we see the largest treatment effects of the flood risk information on search behavior.

However, it is important to note that we failed to reject several null hypotheses. For instance, individuals across all income levels exhibited similar behaviors in response to the flood risk information. Furthermore, we examined whether users browsing from counties impacted by a recent flood event showed different treatment effects. However, our analysis revealed no significant difference in treatment effects for individuals browsing from these counties compared to others.

We also investigated whether there was a divide in responsiveness to the risk information based on political affiliation, using county-level Presidential voting patterns as a proxy (Dunlap, McCright and Yarosh, 2016). Interestingly, we found that Democrats and Republicans responded similarly to the flood risk information, both in terms of search behavior, engagement, and bidding behavior. In real estate markets, all buyers are confronted with tradeoffs, and our results suggest that across the political spectrum, flood risk information induces, on average, the same behavioral response.

Second, our analysis of the impact of flood risk information on physical engagement with homes and overall bidding behavior revealed several interesting findings. While the randomized flood risk information did not significantly change the overall probability of touring a property, placing an offer, or closing a bid through Redfin (the extensive margin behaviors),[6] it did have an effect on the bidding behavior at the intensive margin. Specifically, we observed that treated individuals who were initially browsing high flood risk properties were more likely to make offers on properties with approximately 57% lower flood scores compared to their control counterparts. We show that this is not a selection effect but a change in where the user makes an offer. In line with our theoretical model, when we examine those properties that are in-land and have a medium or high flood risk, we find a reduction in offers by 35% and 58%. These results suggest that even medium-risk homes in-land (which is approximately 11% of U.S. housing stock) are negatively impacted by the full information on flood risk.

We also find that all treated consumers (irrespective of their baseline risk) make an offer quicker than the control group, and this is larger for those that are searching for high flood risk homes at baseline—-a 7% reduction in time finding their home and making an offer. This result suggests that this flood risk information increased allocative efficiency in the housing

[6]The information also did not change what type of customer was likely to tour and place an offer through Redfin, so we do not find selection on observables as we move down the funnel.

market across all flood risk types. Both of these results are consistent with the elimination by aspects model found in the search data above and are driven by the homes that are part of the "new news" hypothesis–those properties that are classed as high flood risk by FSF but not by FEMA.

Overall, these findings indicate that the flood risk information influenced what properties people chose to make offers on, as they sought to strike a balance between flood risk and other property attributes. The information also affected what properties the treated users ended up living in–i.e., lower flood risk properties.[7] Altogether, the information affected the behaviors of those searching and bidding for medium and high risk homes which overs 15% of the US housing stock.

Third, our analysis of the impact of the flood risk information on the hedonic equilibrium pricing of properties revealed significant findings. We leveraged the exogenous variation created by our randomization, which resulted in some homes having a higher percentage of treated users and others having a lower percentage just through random chance.[8] We found that when all Redfin looking (eyeballing) a property are treated (in comparison to no Redfin users treated for that property), property prices dropped by $7,000 (1.7% of the property price) for homes with high flood risk across the United States. Because 100% of Redfin market share was only 8% of the total housing market share,[9] if we extrapolate and scale-up these results linearly, the effect of property prices would be around a 21% reduction ($85,000). Given that FEMA estimates that the average cost for flood damage in the NFIP in the U.S. from 2016 to 2022 was $66,000, these numbers are quite aligned, especially given that the average price for properties for sale on the MLS is higher than the price for properties insured through the NFIP.

The flood risk information had a tangible effect on property prices, with homes in high flood risk areas experiencing a decrease in value. This value can be construed as the value of the best information available on the expectations of climate change impacting high-risk homes. The ex-ante losses posed by climate change are lower if risk lovers (and maybe those with an edge in upgrading risky homes) are more likely to live in these homes. While we cannot directly observe these attributes of people, our evidence supports the claim of some "reshuffling." Due to the high risk homes having less competition, we find that that prices for less risky homes increased by around $4,000. Overall, the information cause less competition on the high risk homes (4% of the homes in the U.S.) and more competition on the medium

[7]The observed behavior can be interpreted as individuals "voting" with their actions, making choices that optimize their desired bundles of flood risk, other amenities, and tax considerations (Banzhaf and Walsh, 2008).

[8]One can think of this design as akin to Crépon et al. (2013), but where homes (as opposed to areas) randomly receive from 0 to 100% of the searchers as treatment users.

[9]Only 40% of the total Redfin customers were placed into the field experiment.

risk homes (15% of the homes in the U.S.).

Notably, these results suggest that the flood risk information provided by FSF revealed previously unrecognized flood risks that were not captured in the property market by FEMA's maps. We found no heterogeneity in terms of the initial property price, suggesting that the impact of the flood risk information was consistent across different price ranges. This supports our earlier search results, which showed that consumers of all income levels and from different geographic locations were affected by the flood risk information. We also find some evidence that investors (which are an increasing share of the US housing market[10]) are also affected by the information.

Overall, our findings from analyzing how the flood risk information impacted search, engagement, offers, and the housing market all the search provide evidence that the flood risk information through the "new news" mechanism. This mechanism influenced the hedonic equilibrium pricing of properties, with homes in high flood risk areas experiencing a reduction in value due to the newly revealed flood risks provided by FSF's predictive model.

1.2 Relationship to Existing Literature

Our research addresses a crucial gap in the literature by conducting a field experiment that examines the impact of climate change information on the process of searching for and buying a home with no selection into the field experiment with complete covertness. While previous studies have used observational data or simulations to analyze climate change adaptation (Massetti and Mendelsohn, 2020),[11] our experiment leverages a unique opportunity to study the causal effects of flood risk information on consumer behavior and provide the first evidence that climate change adaptation can be forward-looking without the role of physically experiencing climate change.

Existing empirical literature has explored how climate risk is capitalized into local home

[10]See DeFusco et al. (2018); Bayer, Mangum and Roberts (2021); Favilukis and Van Nieuwerburgh (2021).

[11]Despite the limitations of identification in previous research, there have been several notable papers that have highlighted the possibility that adaptation can be an important mechanism for reducing the marginal costs of climate change (Lemoine, 2018; Biardeau et al., 2020; Bento et al., 2020; Dundas and von Haefen, 2020; Aragón, Oteiza and Rud, 2021; Cruz Álvarez and Rossi-Hansberg, 2021; Davis et al., 2021; Heutel, Miller and Molitor, 2021; Kahn et al., 2021; Carleton et al., 2022). While there are non-experimental papers suggesting that flood maps (Hino and Burke, 2021; Weill, 2022) or flood disclosure requirements (Lee, 2021) may cause a change in property prices, these maps and disclosures are based on the inferior FEMA maps that exclude the new flood-risk science and are not forward looking. We would not find any treatment effects in our experiment if previous information sets were complete, available, and accessible, hence our new news interpretation would not exist.

prices, with mixed findings regarding the extent of capitalization.[12] In addition, such studies often assume that market participants are fully aware of the actual risk faced by properties.[13] In contrast, our research challenges this assumption by demonstrating that individuals are averse to high flood risk properties once they are exposed to new information, leading to our new news hypothesis. The fact that the flood risk information influenced search behavior, bidding behavior, and hedonic equilibrium pricing suggests that the information was not previously known or fully incorporated into market outcomes prior to the experiment.

Our findings align with the growing body of literature that shows individuals have difficulty evaluating probabilities of infrequent hazards and may lack adequate information about risk (Slovic, 1987; Siegrist and Gutscher, 2006; Botzen, Aerts and van den Bergh, 2009; Bubeck, Botzen and Aerts, 2012; Wachinger et al., 2013; Mulder, 2021; Bakkensen and Barrage, 2022; Wagner, 2022). It also contributes to the understanding that incomplete information in hedonic models can hinder the estimation of the value of non-market amenities (Barwick et al., 2019; Bergman, Chan and Kapor, 2020; Myers, Puller and West, 2022; Ainsworth et al., 2023; Gao, Song and Timmins, 2023). Our research contributes to this field by providing empirical evidence on the role of readily-available, accurate flood risk information in shaping consumer behavior and market outcomes. In so doing, we shed light on the limitations of individuals' risk perception, and emphasize the need for improved information dissemination to facilitate better decision-making in the housing market.

Our research is also related to important papers that have estimated the adaptation costs of coastal flooding, hurricanes, and storms (Seetharam, 2018; Balboni, 2019; Hong, Wang and Yang, 2020; Desmet et al., 2021; Fried, 2022; Jia, Ma and Xie, 2022; Bilal and Rossi-Hansberg,

[12] There are a range of studies suggesting weak or partial capitalization of flood risk into property values (Harrison, T. Smersh and Schwartz, 2001; Hallstrom and Smith, 2005; Bin et al., 2008; Daniel, Florax and Rietveld, 2009; Kousky, 2010; McKenzie and Levendis, 2010; Bin and Landry, 2013; Beltrán, Maddison and Elliott, 2018; Ortega and Taṣpınar, 2018; Bernstein, Gustafson and Lewis, 2019; Eichholtz, Steiner and Yönder, 2019; Muller and Hopkins, 2019; Murfin and Spiegel, 2020; Baldauf, Garlappi and Yannelis, 2020; Gibson and Mullins, 2020; Keys and Mulder, 2020; Giglio et al., 2021; Hino and Burke, 2021). Some other studies often fail to detect significant negative effects, or may even find positive premiums (Bin and Kruse, 2006; Atreya and Czajkowski, 2019). The size of these capitalization effects partially depend on the mortgage lender and insurer behavior (Gallagher, 2014; Garbarino and Guin, 2021; Ouazad and Kahn, 2022), but also on the research design as it is unlikely that these studies thoroughly control for unobservables (Kurlat and Stroebel, 2015; Piazzesi, Schneider and Stroebel, 2020; Giglio, Kelly and Stroebel, 2021).

[13] Recent research has documented that the majority of households in high risk flood zones do not even have basic flooding insurance (Kousky et al., 2020; Wagner, 2022) and that many people are not flood insurance literate and do not understand their level of risk (Botzen, Kunreuther and Michel-Kerjan, 2015; Royal and Walls, 2019; Kousky and Netusil, 2023). Moreover, any adaptation measures that are taken, such as home elevation, are under-invested because benefits accrue too far into the future (Hovekamp and Wagner, 2023). Conell-Price and Mulder (2024) conducted a survey experiment with homeowners in a Qualtrics online panel, and found that owners who underestimate their own flood risk showed no belief updating when provided the true risk (using the FSF model). This result suggests some entrenched motivated reasoning due to the bad news effect with these homeowners on the supply side, and further supports information interventions on the demand side, which might be more effective as the bad-news motivated reasoning would be absent.

2023; Castro-Vincenzi, 2023; Hsiao, 2023). Our paper complements their work by adopting a microeconomic perspective focused on the assignment of heterogeneous home buyers to different homes. This matching process is more likely to feature less ex-post regret if home buyers are better informed about the emerging risks that specific homes face. Since a home purchase is typically considered a longer-term investment, expectations of emerging risks should play a key role in the search process.[14] The results from our natural field experiment suggest that anticipating such risks is important for assessing the general equilibrium welfare effect of increased flooding.[15]

We believe that the forward-looking element of climate change is important, yet many existing large climate adaptation models do not allow for such expectations' impact on behavior and welfare (they only examine the costs of experienced extreme events). Additionally, by studying how consumers trade off current and future climate risks against other housing attributes, our research contributes to the understanding of decision-making processes in the housing market, which we know little about.[16]

Our paper builds on an emerging literature that seeks to improve the locational investment decisions made by those assigned to a treatment group. For example, Chetty, Hendren and Katz (2016), Chetty and Hendren (2018), and Bergman et al. (2019) attempt to steer people to neighborhoods based on a model of upward mobility to help such individuals anticipate what their child will gain from growing up there. Bottan and Perez-Truglia (2020) has a model to illustrate what individuals could gain from selling their homes and test such information on selling their property. The FSF flood risk information in our treatment should be thought of as a similar model-based information intervention.[17]

We also build on the literature on housing search. There are not many papers that observe and analyze the individual search behavior of home buyers because it is usually difficult to observe home buyers' behavior or ascertain the data from search companies. And there are none that tie search data to bidding and transaction data like we have. The only paper

[14]The treatment in our field experiment does not reference any changes in government policy, thereby maintaining fixed expectations about potential future government interventions in flood risk. These expectations are important, as they significantly influence decisions related to investment and migration (Hsiao, 2023).

[15]This result is consistent with the other work on the climate change adaptation benefits of better weather forecasts (Molina and Rudik, 2022; Cole, Harigaya and Surendra, 2023; Downey, Lind and Shrader, 2023; Shrader, 2023; Shrader, Bakkensen and Lemoine, 2023; Burlig et al., 2024).

[16]According to Greenstone (2017) "*(t)here is currently tremendous interest in randomized control trial experiments in economics, but I am not aware of any field experiment applications of Rosen's hedonic model to date (although they would be an incredible addition both substantively and methodologically.*" That is what we do in this paper.

[17]Our main results are also consistent with other papers showing that it is possible to change location choices and welfare using information in a field experiment (Bergman, Chan and Kapor, 2020; Ainsworth et al., 2023). These two papers focus on school choice and find that even in the presence of public information on school value add, consumers still have biased beliefs on location choice. In our case of flooding, there was no public information on flooding at the property level in the U.S., so our consumers were not necessarily biased given their information sets. What we estimate is the effect of new flooding news on location choice.

approaching the level of data we have is Piazzesi, Schneider and Stroebel (2020), but on a much smaller scale with no exogenous variation in the level of amenity for users and no information on bidding/buying behavior of the demand side.[18]

We also add to the general literature on housing search and dynamics. We find that the results of our field experiment are consistent with an elimination-by-aspects search model, which suggests that information frictions are very important to understanding the housing market. In comparison to the papers in this literature (Piazzesi and Schneider, 2009; Genesove and Han, 2012; Head, Lloyd-Ellis and Sun, 2014; Ngai and Tenreyro, 2014; Burnside, Eichenbaum and Rebelo, 2016; Guren, 2018), we show experimentally that search frictions can be reduced by the right information that alters their search, bidding, and buying behaviors. Finally, the flood information causes home buyers to bid and buy their homes earlier, and thus affects the time-to-sell value. In comparison to the papers in the time-to-sell literature that primarily focus on price (Genesove and Mayer, 1997; Ngai and Sheedy, 2020; Gabrovski and Ortego-Marti, 2021), we show experimentally that reducing information frictions with respect to flooding can reduce time-to-sell by 7% and that such demand-side information can impact on overall allocative efficiency.

Overall, we view our field experiment estimates to be important because they convey how home investors respond to low cost yet salient "new news" information about emerging risks.[19] We view our research as a first step in an ambitious research agenda that examines the welfare effects of societal learning about emerging climate risks. Investors are not passive agents in the climate change adaptation debate; they are forward-looking and can anticipate climate change without having to experience it. Since the field experiment was conducted in 2020-2021, a significant portion of the U.S. housing market now makes this information readily available to both buyers and sellers. Platforms like Redfin.com, Zillow.com, Homes.com, and CoStar, among others, currently provide access to this data. As a result, future research on the U.S. housing market must consider the findings of this paper, particularly in light of the fact that consumers now have comprehensive information on climate-related risks.

The paper is structured as follows: Section 2 describes the background and the natural field experiment, and section 3 states the data used and the empirical design. Section 4 analyzes the field experiment, section 5 analyzes the impact of the information on the housing market, and finally, section 6 concludes.

[18] There are other papers that use Google search/trends data, but they do not observe individuals and their search strategies (Wu and Brynjolfsson, 2015; Møller et al., 2023), or a set of selected consumers are surveyed (Genesove and Han, 2012).

[19] Since the field experiment was completed, the flood risk information has been rolled out to all consumers on Redfin and other online property marketplaces due to its success (e.g., Realtor, Estately, homes.com, apartments.com). Redfin now also provides this information on other risks that have been known to have incomplete markets, such as wildfire risk (Baylis and Boomhower, 2023; Boomhower, Fowlie and Plantinga, 2023).

2 The Field Experiment

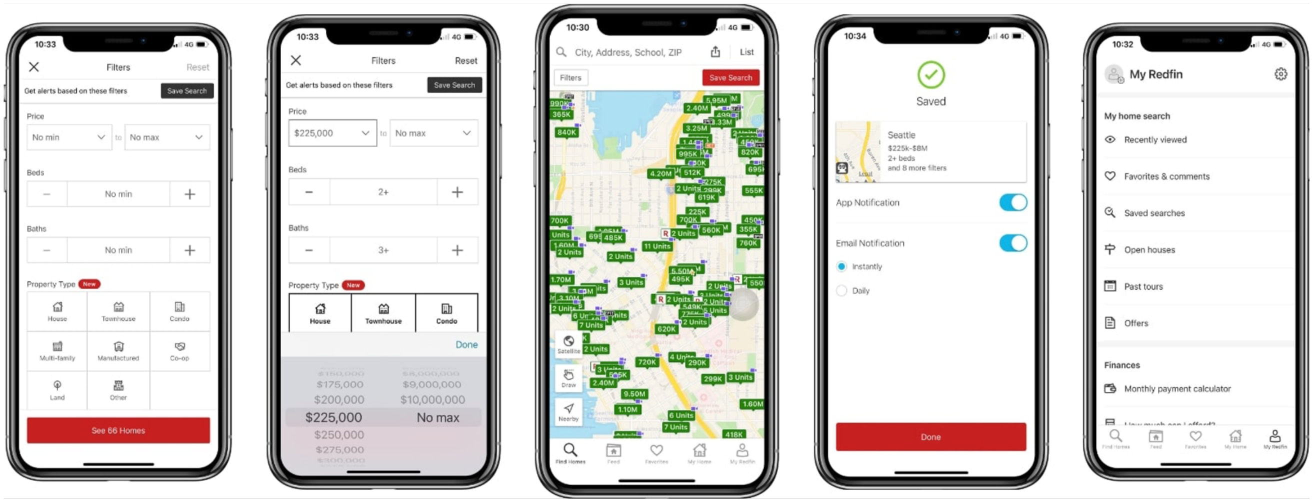
In this section, we describe the background to the field experiment in 2.1, the design of the field experiment in 2.2, the implementation of the field experiment in 2.3, and the theoretical model that guides our field experiment and its interpretation in 2.4.

2.1 Background

The field experiment was conducted through one of the largest full-service real estate brokerages in the United States, i.e., Redfin, that had more than 47 million average monthly users in 2021. Redfin acts as a full-service real estate brokerage that pairs agents with people to sell their current homes or buy new ones. We will first provide the background to the treatment and then describe the design of the field experiment.

Redfin allows users to search for properties to buy in any part of the United States. The search process is as follows: (1) the user opens the app and a map pops up with all of the homes for sale around their current location (see center screen in Figure 1–a green price label box corresponds to a property for sale); (2) the user can start to move the map around or change the location to see what properties are in a give location; and (3) the user can filter their search, based on price ranges, number of bedrooms, number of bathrooms, home type (e.g., house, townhouse, condo, etc.), size of property and lot, time on Redfin, and then basic home features (e.g., garage, pool, etc.). At the time of the field experiment, the user could not filter on flood score or walk/transit score (see left two screens in Figure 1). Also, for those in the treatment group, they could not filter on flood score. For registered users, they can like and save a property, see their search history, and re-start any saved searches (see right two screens in Figure 1) (in addition to receiving emails). By clicking on the green price label box, the user gets to see the full property listing. In our data we can observe what properties they are seeing on the app.

Figure 1: The Redfin app



For the flood score information, Redfin had contracted with the non-profit organization First Street Foundation (FSF), who created the Flood Factor Score as a tool to predict a property's current and future risk of flooding.[20] FSF models flooding from fluvial, pluvial, and coastal sources (tidal and surge) while also integrating current and future environmental considerations, all at a property level (Bates et al., 2021). Notably, the model provides the ability to capture flooding in areas of the country that do not have a gauge, are under-gauged, or are outside of typical flood risk models' purview. The method used to create that flood risk relies on a novel Regionalized Flood Frequency Analysis (RFFA) approach that makes use of traditional statistical propensity matching techniques to model the characteristics of ungauged streams, river reaches, and country with known gauged characteristics to produce likely flow parameters with high confidence. Additionally, a core component of the model is the ability to also include pluvial (rainfall) events as probabilistic flood risks with depths and associated return periods (First Street Foundation, 2020). The model has undergone peer review, is open sourced, and the flood models are perceived as being one of the best in the United States.[21]

[20] It is currently selling its prediction model's forecasts to several agencies in the U.S. government and to the GSEs, but also now makes the flood risk data for every U.S. residential property freely and publicly available. FSF has received funding from donors such as 2040 Foundation, Hightide, and Grantham.

[21] An open science process has led to the creation of this FSF model. Many scientists have contributed to the model, and they are part of an iterative scientific process refining the model and testing its accuracy. The risk scores are reported to the public without confidence intervals. The scientific community continues to debate the merits of educating the public about current and future risks without overloading the public with nuances regarding model uncertainty regarding the veracity of key assumptions (Cooper et al., 2022). Any predictive model of flood risk will induce both Type 1 and Type 2 errors. There will be some locations where the model will over-state the risk, and there will be other areas where the model will under-state the true risk (Bates, 2023), although the model attempts to reduce false positives by using the conservative climate scenario SSP2-4.5 instead of the extreme scenario of SSP5-8.5.

The Flood Factor Score is a 1 to 10 score presented as (a) minimal (1), (b) minor (2), (c) moderate (3-4), (d) major (5-6), (e) severe (7-8), and (f) extreme (9-10) flood risk. It notifies the individual about a property's potential of risk flooding at least once over a life of a 30-year mortgage signed today. The flood risk score is two-dimensional, where a high flood score implies that a property has a larger likelihood and severity of flooding over the next 30 years (see Figure A1). The score incorporates the current and future risk of all major types of flooding (and their combinations), including high-intensity rainfall, overflowing rivers and streams, high tides, and coastal storm surges. The score can vary considerably for properties in the same neighborhood due to local flood dynamics, such as property differences in elevation, proximity to water bodies, and proximity to flood risk reduction projects (First Street Foundation, 2020). This information is the most objective the individual can receive on the flood risk of a property.[22]

2.2 The Design of the Field Experiment

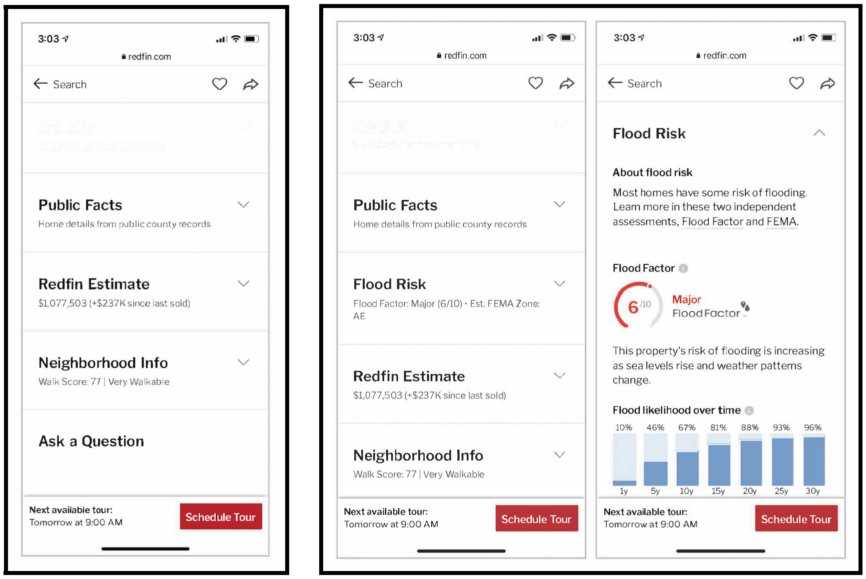
The overall design was a natural field experiment since users were not aware of the experiment, and there was no selection in or out of the experiment (Harrison and List, 2004). In this natural field experiment, Redfin randomly assigned new and existing Redfin users to either the treatment group, in which they were shown a Flood Factor Score section on every on-the-market and off-the-market property listing page they visited, or to a control group without a Flood Score section. Figure 2 presents the experiment experience using a mobile device for both the control and treatment groups within a property page with a flood score of 6 (i.e., major flood risk). The control group (Figure 2(a)) did not see the flood risk section while scrolling a property page, whereas the treatment group (Figure 2(b)) had full access to it.[23]

[22]We do not test whether the individuals in our experiment fully update their beliefs as a result of receiving the treatment information, nor do we examine whether there are other mechanisms as to why this information might work in changing behavior, e.g., attention. We provide some indicative evidence that the results below that show that the results information changed behavior more over time, which goes against the attention mechanisms.

[23]Figure A2 shows the color and labels Redfin used to show a property's flood score within the flood risk section, ranging from 1 to 10.

Figure 2: The Visual Experience for the Treatment Group and the Control Groups

(a) Control *(b) Treatment*



The flood risk section was placed after the property's public facts and neighborhood information. When a user clicks on the flood risk section, they view an "about flood risk" paragraph, the colored (i.e., from light green to dark red depending on the risk) Flood Factor Score, and the flood likelihood of the property over time (i.e., 1, 5, 10, 15, 20, 25, and 30 years).[24]

The Redfin users in the treatment group always see the main flood risk number as they scroll down the page for every property that they search for, but they can ignore the more in-depth flood risk probabilities over time by not clicking on the tab (that unfolds the full 30 year flood risk information). They choose their own intensity of engagement with the provided information. Redfin did not nudge the home searchers to focus on this information or advertise the new information feature to consumers (they had to organically discover it on their own with no help in learning about the flood risk). It is included as an additional piece of information about the home. Throughout the searcher's web page experience, we observe their full organic search activity (for all those in both treatment and control groups). The flood risk information covered 99.9% of the U.S. housing market (First Street Foundation, 2020).

[24]Research by Keller, Siegrist and Gutscher (2006) suggests that providing flood risk probabilities over 30 years as opposed to one year helps individuals more make informed decisions.

2.3 Implementation of the Field Experiment

The nationwide natural experiment enrolled 17,455,506 unique users (8,730,329 users in the treatment group and 8,725,177 in the control arm) for 12 weeks between October 1st, 2020 and January 3rd, 2021.[25] The number of unique users in the field experiment represented approximately 41% of average monthly unique Redfin users in 2020 (Redfin, 2020). The experiment enrolled both new users (5,827,406 in the control group and 5,832,461 in the treatment group) browsing the website and app and existing ones (2,877,250 in the control arm and 2,876,760 in the treatment arm) who have been browsing the website and app before entering to an experiment arm. Of these individuals, we have 1,328,785 (664,352 in the control arm and 664,433 in the treatment arm) individuals who are registered Redfin users. We focus on this registered sample because: (i) they have a higher likelihood of actually purchasing a home; (ii) we observe their behavior for a longer time frame (usually from before the experiment so we know their flood risk type); and (iii) we can guarantee compliance with the assignment mechanism (see below).

Randomization Architecture. Redfin sets up randomized experiments by creating independent cohorts of equal size. Its cohort assignment is random, independent, and sticky. The randomness element ensures that users have an equal probability of being assigned to any cohort. The independence criterion ensures that a user's cohort assignment in one experiment does not influence their assignment in subsequent experiments. Stickiness guarantees that once a user has been allocated to a specific cohort, they remain within that group throughout the experiment.

Redfin assigns users to treatment and control cohorts through a hashing algorithm, considering both the unique experiment ID and the unique user ID (i.e., an HTTP cookie). The algorithm begins by first hashing the experiment ID using the SHA-1 algorithm. Following this, the hashed experiment ID is combined with the user's unique ID, which is then hashed via the MD5 algorithm. The assignment of users to a specific cohort is then conducted by dividing the MD5 hashed identifier by the total number of cohorts (two in our case) and using the remainder from this operation to determine the user's assignment (i.e., treatment and control).

Given the cohort assignment, Redfin employs a system known as "Bouncer flags" to further control the enrollment of users into experiments. Bouncer flags can be activated for any proportion of public users (approximately 40% for our experiment), and the users under these flags are designated as enrolled users. Whenever a user browses Redfin, the bouncer flag first identifies a user's cohort and quickly decides the specific experience a user will view

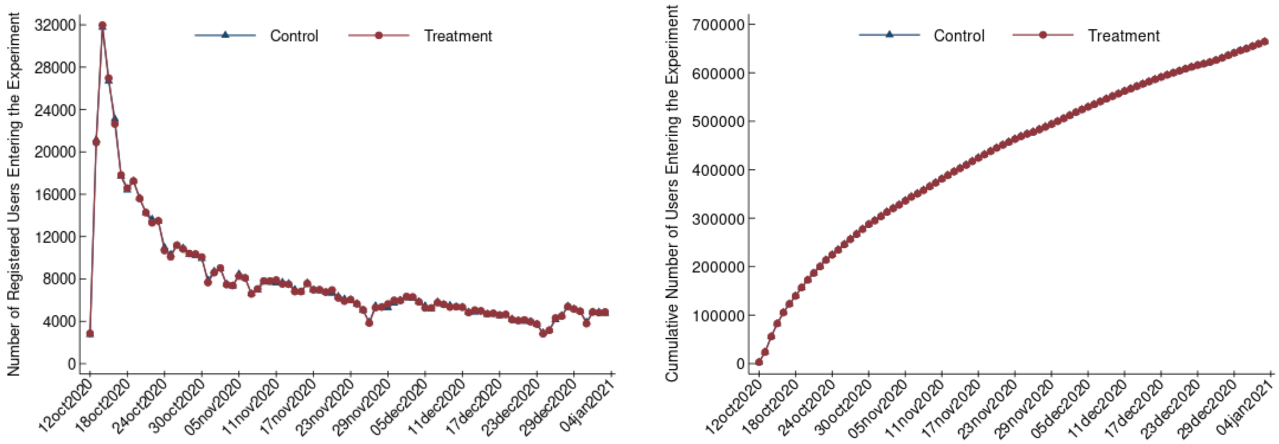
[25] At this point in time, the macroeconomic environment was between the COVID-19 peaks and a stable economy. We had full access to the data from Redfin for one week before the first day of the experiment.

while browsing listings. This stage ensures the stickiness of users within each experiment.

Individuals entered the experiment sequentially through time (see Figure 3)[26] by first checking whether an individual's HTTP cookie (i.e., the user identifier) has been assigned to the experiment and, if not, randomly assigning the user to a treatment arm until the target number of daily experiment assignments was reached. A variable number of individuals entered the experiment each day; on average, 103,902 individuals per group entered each day. Once an individual entered the experiment, they remained in the same group until the end of the experiment. After the experiment finished, Redfin scaled up the treatment to everyone so every user had access to the Flood Factor section for each property they viewed.

Figure 3: Number of Registered Users Entering the Experiment

(a) By Day (b) Cumulative



2.4 The Unbiasedness of the Treatment Effect Due to Randomization

The nature of the randomization and its implementation allows us to be precise about internal validity of our study. More specifically, how our study satisfies the three assignment mechanism restrictions and the four exclusion restrictions to be able to identify an unbiased treatment effect. For the three assignment mechanism restrictions, we comply with the non-zero probability condition (every Redfin user has a probability of being assigned to treatment and we controlled the functional form of the assignment), individualism (assignment of each Redfin users to treatment was orthogonal to the outcomes and assignments of other Redfin users), and unconfoundedness: (the assignment of each Redfin user to treatment is perfectly orthogonal to potential outcomes).

We also satisfy the four exclusion restrictions. First, we have SUTVA. In our experiment,

[26]See Figure A3 for a visual representation of how the 17.5 million Redfin customers entered the experiment.

any Reffin user's potential outcomes do not vary with the assigned treatment or to that undertaken by any other Redfin user. That means that there is no variation in the form or version of the treatment that leads to different potential outcomes.[27] Second is observability, and in our experiment, we have to observe a user on the platform to be assigned to treatment or control. In this case, we will always observe the control and treatment's first potential outcome in the experiment period. We might have differential attrition over time (throughout searching or from searching to moving to bidding and buying a property), however we test this and do not find that the assignment to treatment affects whose potential outcomes we observe over time.

Third, we have complete compliance. As mentioned in the randomization architecture section, for those Redfin users who are registered, we can guarantee complete compliance over the course of the experiment. For those that are not registered users, we cannot guarantee full compliance to our assignment, so that is the reason we focus on those users for the search, although we will examine the impact for all users too. Forth, given these three assumptions are not violated, we can therefore state that we have statistical independence, meaning that the assignment mechanism governing who is treated and who is not treated is independent of all potential outcomes. This allows us to recover an internally valid unbiased estimator of the impact of flood risk information on behavior.

2.5 Demand Side Hypotheses Through the Lens of a Hedonic Housing Assignment Model

A parametric closed form hedonic assignment model allows us to concisely state our paper's core hypotheses. At any point in time, there is a hedonic equilibrium real estate pricing gradient that maps each home's attributes into a market price. In equilibrium, every home is occupied and given market prices nobody wants to trade homes.

To simplify the exposition, we model climate change as a one time change in the distribution of risk across geographic locations. There is a "before" and an "after" period. The assumption that "climate change" is a one time surprise allows us to sidestep the modeling challenge of incorporating expectations into a closed form hedonic assignment model.[28]

If climate change increases the risk that a given home faces and if a buyer is unaware of this shift, then the buyer may subsequently regret her investment. If climate increases the risk

[27] For example, a treated Redfin user searching for a home has no impact on the search or potential outcomes of other Redfin users.

[28] We recognize that different people will have different baseline beliefs about emerging climate risks. Some may believe the FEMA risk maps as delineating risks. Others may rely on their past experience in the areas they have lived. Some may be skeptical about whether the risk of extreme events is rising. Those who are most surprised by the "new news" of the FSF nudge and those who become aware of now "known unknowns" are likely to value this forecast information the most. Future hedonic research can follow Severen, Costello and Deschenes (2018) by integrating the "forward-looking Ricardian approach" into closed form hedonic assignment models.

that different homes face and if this knowledge is common knowledge, then in the hedonic equilibrium, those who choose to live in riskier homes will be compensated through lower prices. In our empirical work below, only a subset of buyers are informed about the new risks.

To simplify the algebra below, we focus on one attribute of housing namely flood safety (f). We assume that consumers purchase one property and the numeraire good X. Properties are assumed to vary only with respect to the local flood safety level.[29] Consumers only differ by their preference for flood safety (γ). It is assumed to be normally distributed with mean $\bar{\gamma}$ and standard deviation σ_γ.

We assume the supply of properties is exogenous, and their safety follows the distribution $N(\bar{h}, \sigma_h^2)$. We consider a quadratic hedonic pricing function $P(f) = \pi_0 + \pi_1 f + \pi_2 f^2$. Each home buyer's utility is given by:

$$U_i = Y - P(f) + \gamma_i f := C - \pi_1 f - \pi_2 f^2 + \gamma_i f \tag{1}$$

where Y denotes income, and we collect all constant terms into C. The home buyer chooses the safety level that maximizes their utility. By setting the FOC to 0, each home buyer's chosen safety level is:

$$f_i = \frac{\gamma_i - \pi_1}{2\pi_2} \tag{2}$$

We aggregate f_i to obtain the aggregate demand density for the safety level. Based on our assumption on γ, the demand density follows $N(\frac{\bar{\gamma}-\pi_1}{2\pi_2}, \frac{\sigma_\gamma^2}{4\pi_2^2})$. In equilibrium, the demand density must match the supply density at each safety level. We match the first two moments of the demand density with those of the supply density to solve for π_1 and π_2, given as follows:

$$\pi_1 = \bar{\gamma} + \frac{\bar{h}\sigma_\gamma}{\sigma_h} \text{ and } \pi_2 = -\frac{\sigma_\gamma}{2\sigma_h} \tag{3}$$

Then the gradient of the hedonic function is $\frac{\partial P}{\partial f} = \bar{\gamma} + \frac{\bar{h}\sigma_\gamma}{\sigma_h} - \frac{\sigma_\gamma}{\sigma_h} f$. The function is concave as consumers have a diminishing marginal willingness to pay for safety.

[29] We assume higher flood risk lowers utility but do not parse out the reasons as to why it causes a loss. There are at least five reasons why higher flood risk could cause a utility loss: (1) people think they will die or be physically hurt in the flood; (2) people think that flooding will destroy their home; (3) people think that flood areas will experience rising insurance prices over time; (4) people think they will lose time and resources cleaning up after flood after flood; (5) people think they will spend more money offsetting flood risk to reduce flood damage in high FSF score areas.

Proposition 1: Due to climate change, the distribution of flood safety shifts such that; $\bar{h}$ decreases to $\bar{h}'$ and σ_h^2 increases to $\sigma_h'^2$. When home buyers have full information about this new distribution, the price gradient becomes steeper at higher safety levels, in comparison to the pre-climate change world.[30]

Consumers reevaluate the safety level of each property based on their new information on climate change. In this case, the gradient of the new hedonic function is $\frac{\partial P_{new}}{\partial f} = \bar{\gamma} + \frac{\bar{h}'\sigma_\gamma}{\sigma_h'} - \frac{\sigma_\gamma}{\sigma_h'} f$. Consider a given safety level f_0. We can calculate the difference in price gradient before and after climate change: $\frac{\partial P_{new}}{\partial f} - \frac{\partial P_{old}}{\partial f} = (\frac{\bar{h}'}{\sigma_h'} - \frac{\bar{h}}{\sigma_h})\sigma_\gamma + (\frac{1}{\sigma_h'} - \frac{1}{\sigma_h})\sigma_\gamma f_0$. Because $\frac{1}{\sigma_h'} - \frac{1}{\sigma_h} > 0$, the difference is an increasing function of f_0. Note that the first term is negative, which suggests that consumers may be willing to pay less for properties with low safety levels in the full information scenario.

Now suppose only k% of the population (randomly selected) know the true distribution of safety levels after climate change. We assume the z-score of each property is constant before and after climate change.[31] That is, for a property with safety f in the post-climate change world, its pre-climate change safety level is $\bar{h} + \frac{f-\bar{h}'}{\sigma_h'}\sigma_h$. For home buyers without information on the new distribution of safety, their utility is given by:

$$U_i = C' - \pi_1' f - \pi_2' f^2 + \gamma_i(\bar{h} + \frac{f - \bar{h}'}{\sigma_h'}\sigma_h) \tag{4}$$

That is, they are likely to overestimate the safety of a property and derive more utility from living in a riskier place. This implies the following proposition.

Proposition 2: Consider two consumers with the same risk preference, and only consumer A knows the true climate change induced distribution of the safety of properties. Then consumer A bids higher for properties that are safer under climate change and bids lower for the riskier properties.

We now study the equilibrium in the partial information scenario. For consumers with true information, their chosen safety is $f_i^{\text{treat}} = \frac{\gamma_i - \pi_1'}{2\pi_2'}$. For those without true information, by setting the FOC of their utility function to zero, we solve for their choice $f_i^{\text{control}} = \frac{\gamma_i \frac{\sigma_h}{\sigma_h'} - \pi_1'}{2\pi_2'}$. The demand density is the density of $k f_i^{\text{treat}} + (1-k) f_i^{\text{control}}$. To find the equilibrium, we again match the moments of the demand density with the moments of the supply density $N(\bar{h}', \sigma_h'^2)$. The new hedonic coefficients are given by:

[30] To simplify the discussion, we assume that climate change leads to a one time shift in the distribution of safety.

[31] This assumption can be relaxed. In general, we need a one-to-one mapping function from pre-climate change safety to post-climate change safety. We choose the function that preserves the z-score for algebraic simplicity.

$$\pi_2' = -\frac{\sigma_\gamma}{2\sigma_h'}\sqrt{k^2 + (1-k)^2(\frac{\sigma_h}{\sigma_h'})^2} \text{ and } \pi_1' = k\bar{\gamma} + (1-k)\bar{\gamma}\frac{\sigma_h}{\sigma_h'}^2 - 2\pi_2\bar{h}' \tag{5}$$

We can compare the price gradient with respect to safety in the partial information post-climate change world with that in the pre-climate change world.

Proposition 3: When a larger fraction of home buyers receive the new information, the increase in the price gradient is larger, especially at high safety levels.

Proposition 1 is a special case of this proposition (i.e. when $k = 1$). Intuitively, when more people know the true risk, more of them are willing to buy safer properties. The price function becomes steeper at high safety levels due to the rising demand.

Our three propositions suggest that safety is currently undervalued due to a lack of information on risk, but once that information on risk becomes available (i.e., new news), people act on it and value it, and those with a higher preference for safety will act on it even more.[32]

This "new news" hypothesis allows us to be a bit more precise about who is expected to change their behavior as a result of this information. This hypothesis predicts that the following consumers will be affected by the new information:

(a) consumers searching for properties that are in-land (i.e., not coastal) but have high flood risk defined by FSF;

(b) consumers searching for properties that are in-land (i.e., not coastal) but close to a waterfront (e.g., river, lake) and have high flood risk defined by FSF; and

(c) consumers searching for properties that are not defined risky by FEMA by are on the coast.

For populations (a), (b), and (c), the information will revise their flood risk beliefs upward and will search and buy lower flood risk homes, as per propositions 1 and 2. We believe that the central tenet and test of this new news hypothesis is the following two groups of consumers will be less affected by the FSF flood risk information:

(d) consumers searching for properties in already FEMA designated as high risk; and

(e) consumers searching for properties with zero to low risk.

[32]We have considered the case where everyone knows the true distribution of property safety, respectively, under two states: without and with climate change. However, we also predict what will happen if there are some people who do not believe in climate change. In Appendix A.1, we discuss this case.

Population (d) should already be informed about the flood risks because of current information dissemination and because you need flood insurance to obtain a mortgage in these FEMA areas.[33] These are the predictions for the new news hypothesis on search and offers.

Based on our propositions and predictions, property prices will change their gradient w.r.t. flood risk. The prices on FSF high flood risk but FEMA low/no risk properties will decrease through a lack of demand (either a lower willingness to pay by consumers or a lack of offers overall that will reduce competition and reduce prices) and that the prices on FSF low risk properties will go up because of an increase in demand (either a higher willingness to pay by consumers or an increase in competition for the property that will drive up prices).

3 Data and Empirical Strategy

In this section, we describe the data and its sources (3.1), the estimation strategy (3.2), and show the randomization balance tests (3.3).

3.1 Data

The datasets used in this paper come from multiple sources, arising either from browsing, touring, and bidding data generated by Redfin, multiple listing service and county records, or publicly available data sets, such as census estimates. The web data-generating process was the following.[34] Every time an individual clicks on a home, the website collects the following information about the individual's home session activity.

Property views data. Once a user clicks and opens a new property, a single data point is generated with the following columns: the user's anonymized unique ID and an anonymized login ID;[35] the timestamp when the property view began; whether the action was conducted by a *bot*; whether the action was conducted via a cellphone or a desktop; the zip code and its accuracy (in *kms.*) from where the user conducted the search; the flood risk score of the property; the list price of the property at that point in time; the number of bedrooms and bathrooms of the property; the approximate square feet of the property; the zip code where the property is located; whether the property is new construction; whether the property is a

[33] We recognize that there still might not be full information from the FEMA high flood risk ratings, but there should be less of an effect for this population than populations (a) to (c).

[34] An individual accessing the website through a computer, phone, or tablet can browse property listings on the market and the entire stock of homes.

[35] The "unique ID" follows each individual across time, and it is created the first time a browser visits our partner's webpage. The "login ID" is created when an individual decides to register to the platform.

short sale;[36] the year when the property was built; and the walking, transit, and bike scores where the property is located.[37] We organize this dataset as a panel where our observation unit is the user at the day level.

Engagement data. This data section provides information about the actions a user conducted within a property page. That is, whenever a user scrolled or clicked a feature within a property page, a single data point was generated with the following information: the user's anonymized unique ID and an anonymized login ID; the timestamp of the action; whether the action was conducted by a *bot*; whether the action was conducted via a cellphone or a desktop; and the engaged action conducted (e.g., clicked on the pictures, "favorited" a house, conducted a tour, etc.). This data also contains the seconds spent per session, the number of sessions, and the number of total and unique listing views, among other variables. In this sense, we have multiple single data points for every property view that a user conducts. As mentioned above, we organize this dataset as a panel where our observation unit is the individual at the day level.

Touring, bidding, and closing data. A unique feature of our study is that we can follow individuals through each step of the home-buying experience: the search, the property tour, the bid, and the closing process for a property. A single data point is generated every time a user tours a house, places a bid, or closes a deal. These observations contain the user's anonymized unique ID and an anonymized login ID; the day on which action was done (i.e., either touring the property, placing an offer to a property, or closing the deal); the property ID that allows knowing characteristics of the property; the offer price and characteristics of the offer and close; and characteristics of the tour. We organize this dataset as a panel where our observation unit is the user at the touring, bidding, or closing level.

Multiple Listings Service Data. Multiple Listing Service (MLS) data comes from Redfin and covers those regions where the brokerage operates.[38] Each listing contains unique listing and property identifiers, sale date, sale price, listing added and end date, listing price, number of bedrooms, year built of the property, approximate square feet of the property, number of bedrooms, whether the listing is new construction, geographic characteristics of the property, among other variables.

[36] A short sale is a sale that takes place when a financially distressed homeowner sells their property for less than the amount due on the mortgage. The buyer of the property is a third party (not the bank), and all proceeds from the sale go to the lender.

[37] These scores are supplied by Walk Score, and they range from 0 - 100. Walk Score measures the walkability of any address, Transit Score measures access to public transit, and Bike Score measures whether a location is good for biking. A higher score represents a better measure for each category.

[38] Redfin currently operates in every state in the United States except for North Dakota. For a complete list of the local markets where Redfin operates, see the following link.

3.2 The Empirical Strategy

Our objective is to estimate whether the randomized disclosure of flood risk information about a property affects the behavior of individuals throughout the home buying search process. To do this, we rely on three estimators.

Average Treatment Effect (ATE) across post-treatment time points. We estimate the ATE of disclosing a property's flood risk information on the behavior of individuals throughout the home buying process. In our dataset, our unit of observation is the user at the day level. Users are organized as a panel, where every row of the data set is the average value of a user in a given day. We implement an estimator with the following functional form:

$$y_{it} = \beta_0 + \beta_1 I_{it} + \beta_2 D_i + \beta_3 (I_{it} * D_i) + u_{it} \tag{6}$$

Where, y_{it} is the average outcome of individual, i, during day, t. We will focus on the flood risk score of the property as the outcome variable. I_{it} is an indicator that takes 1 if the observation occurs after the individual, i, was first treated. The binary treatment indicator for individual, i, is $D \in \{0;1\}$. This estimator takes the form of a classic difference-in-differences to take advantage of the experiment design and deal with a potential regression to the mean situation commonly observed in longitudinal experiments (Twisk et al., 2018). β_3 in equation 6 provides an unbiased estimate of the ATE, and randomization provides internal validity of the estimate. Standard errors are clustered at the individual level.

Conditional Average Treatment Effect (CATE) across post-treatment time points. We use a similar estimator as in equation 6 with an interaction term on an observed covariate, $X \in \mathbb{R}$, in the following way:

$$y_{it} = \beta_0 + \beta_1 (I_{it} * X_i) + \beta_2 (D_i * X_i) + \beta_3 (I_{it} * D_i * X_i) + u_{it} \tag{7}$$

Where, X_i, represents the covariate of individual, i. For this estimator, we focus our attention on using the baseline average flood risk of all the houses viewed before the experiment begins for individual, i, as a covariate, X_i. This estimator differs from equation (6) above, since the information might have a very different impact across the different types of flood risk that an individual is exposed to. This specification is going to be our main specification to understand how the effects of the information impact people who are searching and buying low, medium, and high risk flood properties, and to test our new news hypothesis.

To account for multiple hypotheses, we used the Romano-Wolf procedure to adjust for the familywise error rate Romano and Wolf (2010). This procedure employs a step-down approach that progressively adjusts p-values based on their significance, using bootstrap resampling to account for dependencies between tests. We applied this procedure to equation 7 with three subgroups (i.e., low, medium, and high-risk search at baseline) and six subsets of registered users: (1) all registered users, (2) those without a waterfront search at baseline, (3) those with a waterfront search at baseline, (4) those without a FEMA search at baseline, (5) those with a FEMA search at baseline, and (6) those with a waterfront search but no coastal search at baseline. We conducted 1,000 resamples for the search regressions and 3,000 resamples for the offer regressions, clustering standard errors at the user level.

Our approach here is conservative, since we are using the CATEs for testing one main hypothesis of new news, i.e., the response to treatment for those searching for high flood risk homes is likely to be different than those searching for low flood risk homes, especially when the high flood risk is a surprise (i.e., not previously been defined as high flood risk due to FEMA biases). We have two different sub-populations that receive the treatment, but the treatment is different for each of the sub-populations. As per List, Shaikh and Vayalinkal (2023), one could argue that we are testing one hypothesis, but we try to be conservative in our multiple hypotheses testing.[39]

Average Treatment Effect at any post-treatment time point. We use the following estimator to obtain an estimate of the average treatment effect of disclosing a property's flood risk information on the behavior of individuals at *any* point throughout the home buying process, and it allows us to understand whether treated users kept adjusting their search patterns as time passed. Relative to the estimator of equation 6, this estimator provides a flexible, dynamic functional form across time to understand how the treatment changes over time:

$$y_{it} = \beta_0 + \sum_{k \neq -1} \beta_k \left(T_{ik} \cdot D_i \right) + u_{it} \tag{8}$$

Where T_{ik}, is an indicator variable for individual, i, in the period, $k \neq 1$, since the treatment was implemented to that specific individual. This indicator variable remains zero for all the control units, and as before, $D \in \{0;1\}$, is a binary treatment indicator for individual, i. The coefficient that estimates the estimand during period, t, in equation 8 is β_k. To provide further evidence that randomization ensured a balance between the treatment and control units, we conducted a joint test of the null hypothesis: $\sum_{t<T_0} \beta_k = 0$. Standard errors are clustered at the individual level.

[39]Moreover, we test this new news hypothesis for different outcome variables (e.g., search, engagement, and offers). We do not need to adjust for multiple hypothesis testing for these three outcome variables because of two reasons. First, the population of interest changes between search to engage to offer (think of it as a funnel), so we are not fixing the sample and changing the outcome variable. Second, as argued by Viviano, Wuthrich and Niehaus (2021) and List, Shaikh and Vayalinkal (2023), even if we had the same sample throughout, it is not clear whether the null hypotheses corresponding to all such outcomes should be included in the family of testing. In our case, it is of interest to determine, with some confidence, which outcomes are affected by the flood risk treatment, especially as there is not a clear way for us to aggregate search, engagement, and offer data.

3.3 Pre-Experiment Balance

We check the balance in the observable covariates between treatment and control to ensure the randomization worked. Each column of tables A1 and A2 provide estimates of regressing outcomes of interest before the experiment began against a treatment dummy variable for registered users.[40] We cannot statistically reject the null hypothesis for the coefficient of interest for every regression, providing evidence that randomization worked by creating balanced treatment and control groups before the experiment began. Figures A4 (a) through (f) present the estimates generated by the event-time study estimator for individuals at any given *pre-treatment* time point, aiming to assess differences in pre-trends. The results further suggest that the randomization process was effective, indicating the likelihood of parallel pre-trends between treatment and control units. Tables A5 to A10 present balancing tests in the observable covariates between treatment and control stratified by average flood risk category (i.e., low, medium, and high) at baseline. We cannot reject the null between treated and control users at baseline. Finally, Table A11 presents the number of registered users within each flood risk category before the experiment began, stratified by treatment assignment for the registered individuals.[41] One cannot reject that treatment and control distributions are different (Pearson $\chi^2(5) = 5.1$, p-value = 0.398), suggesting a balance between the number of treatment and control users within flood risk categories.

Registered vs. Non-Registered Users. Given that most of our results have as sample users that "registered" on the website, tables A13 and A14 present the results of regressing outcomes of interest at baseline against a "registered" dummy variable. Registered and non-registered users have different browsing patterns. On average, registered users browsed 31% more properties, and their zip code concentration index was 19%–i.e., registered users concentrated their browsing patterns in a higher number of zip codes. Regarding the characteristics of the houses, registered users browsed properties with 0.9% fewer bedrooms, 0.3% fewer bathrooms, 0.7% fewer square feet, 0.1% lower year of built, 6.3% higher flood scores, and 6.3% higher list prices.[42] They also had a 0.2% less probability of browsing a new construction and a 0.3% less probability of browsing short sales. Finally, they browsed properties with 4.2% more, 1.1% less, and 2.7% more walk, transit, and bike scores, respectively.

Given that registered users are more typical of the average individual who is going to buy

[40]Tables A3 and A4 provide estimates for all users.

[41]Table A12 presents the results for all users.

[42]The states of California (27.11% of all the registered users with pre-experiment information), Washington (9.07%), Illinois (7.63%), Maryland (5.25%), New York (5.19%), Massachusetts (4.49%), Texas (3.80%), Virginia (3.04%), Florida (3.52%), and Pennsylvania (3.85%) had the top 10 highest number of registered users participating in our experiment. The states of Florida (22.62%), California (13.01%), New York (8.98%), Washington (6.95%), and Illinois (4.94%) had the highest percentage of registered users browsing, on average, extremely risky properties pre-experiment.

properties in the market in 2020, we will conduct the empirical analysis on search, engagement, and bidding with registered individuals in the experiment. We will leverage the whole dataset to examine general equilibrium effects on the housing market.

4 Results

In this section, we provide evidence of how the randomized treatment flood risk information affected (i) home search behavior over time (4.1); (ii) engagement with the homes (4.2); and (iii) tours, offers, and closes (4.3). We will then analyze whether the treatment effects differ by political partisan alignment and recent flooding events (4.4).

4.1 Home Search Behavior Dynamics

In searching for a home using the Redfin Platform, the buyer knows their preferences and their budget constraint. The search process allows the searcher to learn about the heterogeneous differentiated products available for purchase. While it is easy to quickly learn an area's day-to-day weather conditions, it has not been easy to acquire information about property-specific environmental risks. As the cost of acquiring such information is effectively lowered to zero for a randomized subset of Redfin users, we study how they respond to this access to information.

First, we estimate equation (6) for the whole sample, not segmenting by flood risk. Tables A15 (i.e., for all Redfin users) and A16 (i.e., for registered Redfin users) present the average treatment effects of having access to the flood factor on the number of properties browsed per day (column 1), the average characteristics of the browsed properties per day (columns 2 to 5), the average flood score of the properties browsed per day (column 6), and the Herfindahl–Hirschman zip code location index (HHI) of a user by day (column 7).[43] On average, without stratifying users by their average flood score of all the houses viewed before the experiment began, the treatment had no significant effect on the daily browsing behavior of users. Specifically, it did not alter the average number of properties viewed, nor did it affect the typical characteristics of these properties, such as the number of bathrooms, bedrooms, square footage, list price, or the HHI zip code associated with the properties browsed.

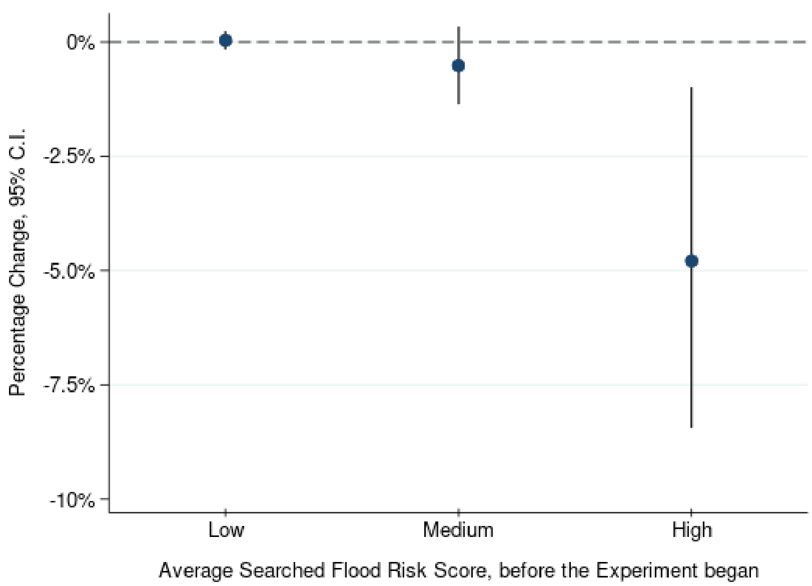
When categorizing users based on the average flood risk score of all properties they viewed prior to the experiment (as determined by the CATE in equation (7)), registered treated users had a meaningful and significant change in their search behavior, marked by a steady decline in the flood risk profile of properties they investigated before the start of the experiment.

[43] Tables A17 and A18 present estimates for those users with information pre-experiment.

Figure 4 presents estimates of β_3 from equation (7) by baseline average flood score search category. The most significant shift was observed among users who, before the experiment, browsed on average properties with high (severe or extreme) flood risk. Specifically, treated registered users in this category showed a 4.7% reduction in the flood risk score of the properties they browsed compared to their counterparts in the control group, with a statistical significance of $p<0.01$. This reduction in flood risk score, equivalent to a 0.5-point decrease on a ten-point scale, represents a substantial change. To put the magnitude of this effect into perspective, it equates to average reductions in long-term flood risk of 8.0%, 10.6%, 6.2%, 4.1%, 3.4%, 2.9%, and 2.7% over timeframes of 1, 2, 5, 10, 20, and 30 years, respectively.

However, for users browsing in areas with relatively low initial flood risk, the potential for significant reduction was naturally limited, prompting an analysis of the standard deviation effect size. For the high-risk treated group, the standardized effect size was -10.8%. In contrast, the effect sizes for users focusing on low and medium flood risk properties were 0.03% (standard error = 0.10) and -0.54% (standard error = 0.43), respectively, highlighting the nuanced impact of the intervention across different levels of initial flood risk.[44]

Figure 4: CATE on the Average Flood Score of a Daily Search for Registered Users
% Change relative to Control



Note: Coefficients are in the form of $((e^{\beta_3}-1)\cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

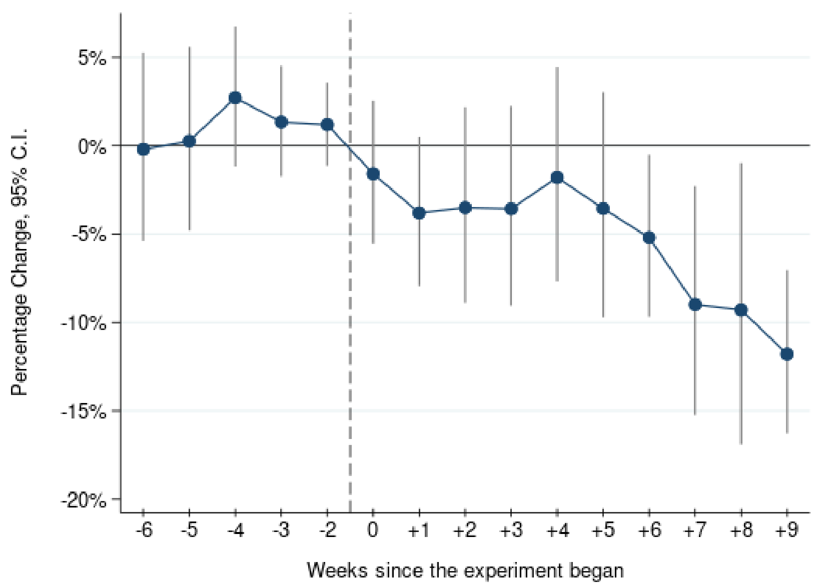
[44]When expanding the analysis to include all users, not just those registered, we found that users browsing on average low, medium, and high flood-risk areas prior to the experiment demonstrated changes in the flood risk scores of 0.00% (standard error = 0.03), -0.78% (standard error = 0.17), and -1.73% (standard error = 0.95), respectively, compared to their counterparts in the control group.

In Figure 5, we present estimates of β_k from estimator 8 (i.e., an event-time study) for registered users browsing, on average, high risk properties before the experiment. The results show that, on average, there was no statistically significant difference between treatment and control groups before the experiment, suggesting that randomization was properly conducted. However, as time progressed, treated users began browsing properties with progressively lower flood scores than the control group. By the ninth week, treated users were browsing properties with a -11.8% ($p < 0.01$) lower flood score compared to a week before the experiment, whereas after the sixth week, the reduction was -5.2% ($p < 0.01$) less flood risk score, relative to control users.

Our analysis revealed no statistically significant impacts in event-time studies of registered users who browsed properties with low and medium risk levels before the experiment commenced. Specifically, Figures A5 (a) and A5 (b) display the outcomes for users who, on average, were looking at properties with low and medium levels of risk prior to the start of the experiment, respectively.

Figure 5: Event-time Study on the Average Daily Flood Score of Properties Searched for Registered Users

High-risk cohort, % Change relative to Control



Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 8. Coefficients are relative to the week before a user entered the experiment. Vertical lines crossing the estimates are confidence intervals at the 95% level. The vertical dashed line represents the beginning of the experiment for a user. The x-axis represents each user's baseline average flood score search category before the experiment began. Pre-trends p-value = 0.66, leveling of coefficients p-value = 0.000

Place-based factors may also influence the impact of flood information. For instance, differences in information access and local knowledge between homeowners and non-local buyers can create a situation where the latter may unwittingly purchase properties with higher environmental risks. In addition, the relative place-based risks associated with flood-prone areas could further affect the effectiveness of our treatment. For example, people residing in safe areas may be more likely to adjust their home search when looking for properties in high-risk areas, whereas those already in flood-prone areas may not be as responsive to our treatment. In this sense, we calculated the difference in the mean, standard deviation, and coefficient of variation of the zip code's flood score between an individual's origin and most search destinations at baseline, and we interacted it with the treatment and the average flood score search at baseline to test our previous hypothesis.

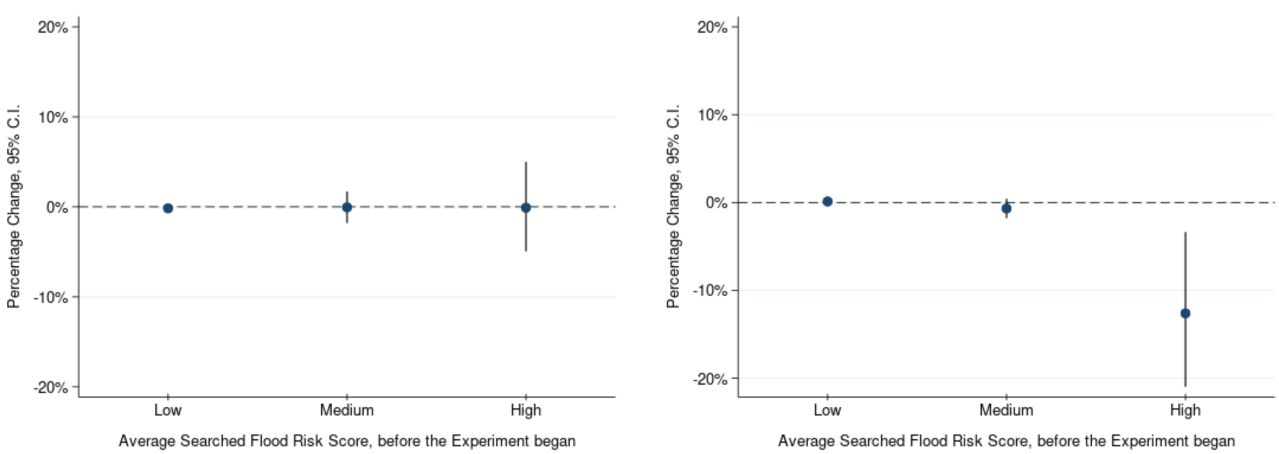
Our findings revealed a decrease of 12.77% in the average flood risk for individuals who, before the experiment, primarily searched for homes in high flood risk areas and whose search areas had a higher coefficient of variation (CV) in flood risk than their origin. This decrease, observed after receiving flood risk information, is depicted in Figure 6 (b) and could stem from two adjustments: either the treated individuals shifted their searches to zip codes with a lower average flood risk or to those with a greater standard deviation in flood risk. When we analyzed the effect of combining the treatment with the difference in flood risk scores (mean and standard deviation) between the destination and origin zip codes, we found no significant or meaningful impact, as shown in Figures A6 and A7.

Figure 6: CATE on the Average Flood Score of a Daily Search for Registered Users, by Characteristics of Most Searched Destination and Origin Zip Code at Baseline

% Change relative to Control

(a) **Lower Coefficient of Variation** Flood Score at Destination Zip Code than Origin

(b) **Higher Coefficient of Variation** Flood Score at Destination Zip Code than Origin

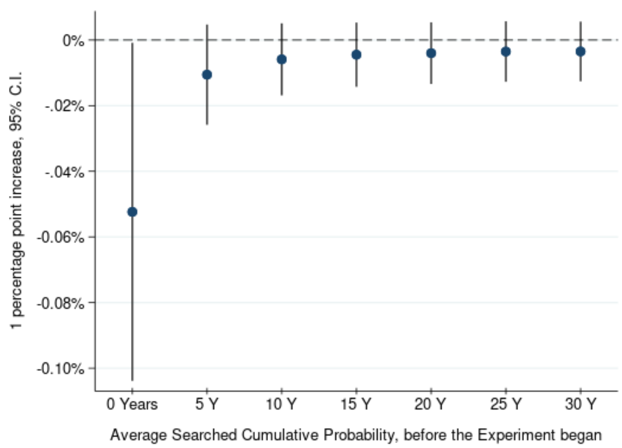


Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's average flood score search category before the experiment began.

Besides showing flood risk categories, our study provided a detailed view of flood risk via a quinquennial cumulative flood probability for properties, as visually detailed in Figure 2. Keeping users' pre-experiment flood score search categories constant, a one percentage point increase in the baseline cumulative flood probability for 2020 resulted in a 0.052% decrease in the average flood score search, with no statistically significant effects observed for cumulative probabilities in subsequent 5-year increments up to 30 years.

Figure 7: CATE on the Average Flood Score of a Daily Search for Registered Users, by Cumulative Flood Probability at Baseline

% Change relative to Control

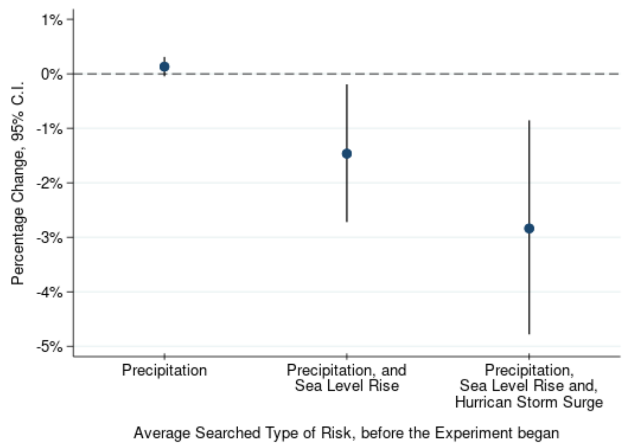


Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's average flood probability search before the experiment began.

Our data partner also classifies the type of flood risk each property faces. FSF classified environmental risks into three categories: "Precipitation," "Precipitation and Sea Level Rise," and "Precipitation, Sea Level Rise, and Hurricane Storm Surge." Holding each user's average flood score search category before the experiment constant, we found that individuals who searched at baseline for properties with "Precipitation, Sea Level Rise, and Hurricane Storm Surge" risks experienced a 2.8% reduction in their flood score exposure. In contrast, those who searched for properties with "Precipitation and Sea Level Rise" risks reduced their exposure by 1.4%. However, browsing for properties with only "Precipitation" risk at baseline did not yield a statistically significant effect (Figure 8).

Figure 8: CATE on the Average Flood Score of a Daily Search for Registered Users, by Type of Risk at Baseline

% Change relative to Control



Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average type of environmental risk search before the experiment began. Coastal areas on the East Coast and Hawaii are referred as "Precipitation, Sea Level Rise, and Hurricane Storm Surge", other coastal areas are "Precipitation, and Sea Level Rise" and all other locations are "Precipitation".

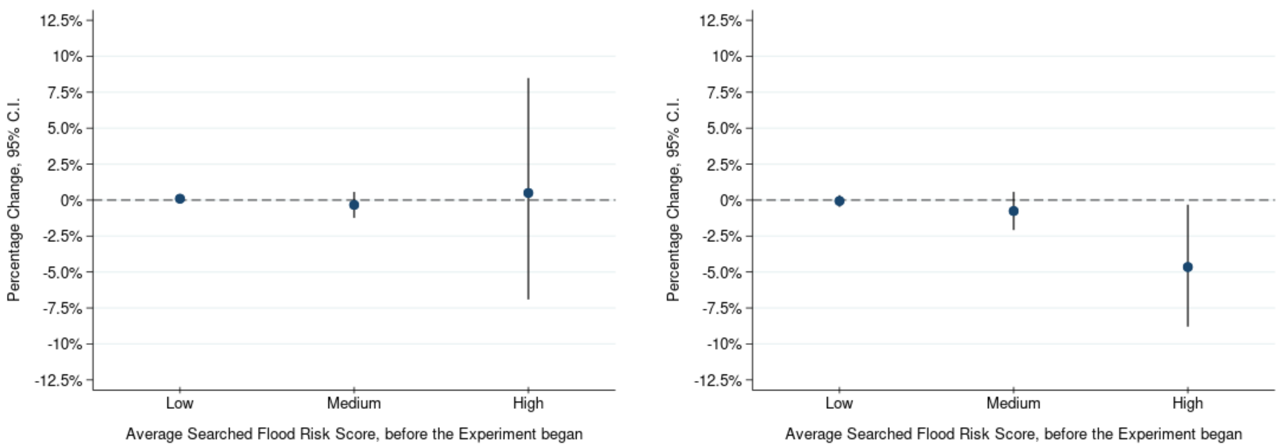
Our analysis extends to the treatment's impact on diverse groups searching for homes based on specific criteria: (a) waterfront location (seas/coastal, rivers, lakes) or not; (b) within FEMA high-risk zones or not; (c) coastal proximity or not; and (d) combinations of these factors. We classified individuals into different categories based on whether their pre-experiment searches included homes with these characteristics.

Figures 9 (a) and (b) illustrate that flood risk information mostly influenced customers searching for waterfront properties before the experiment. Figures 10 (a) and (b) reveal a similar effect on those searching for FEMA high-risk properties, with a greater impact on those without FEMA high-risk properties in their initial search. Figure 11 indicates the information's effect on customers considering the waterfront comes from properties not situated on the coast. These findings collectively support the "new news" hypothesis, demonstrating the treatment's effectiveness, particularly for individuals interested in waterfront properties not classified as coastal and, thus, not included in the NFIP or marked as risky by FEMA.

Figure 9: CATE on the Average Flood Score of a Daily Search for Registered Users

% Change relative to Control

(a) Without Waterfront Search at Baseline (b) With Waterfront Search at Baseline

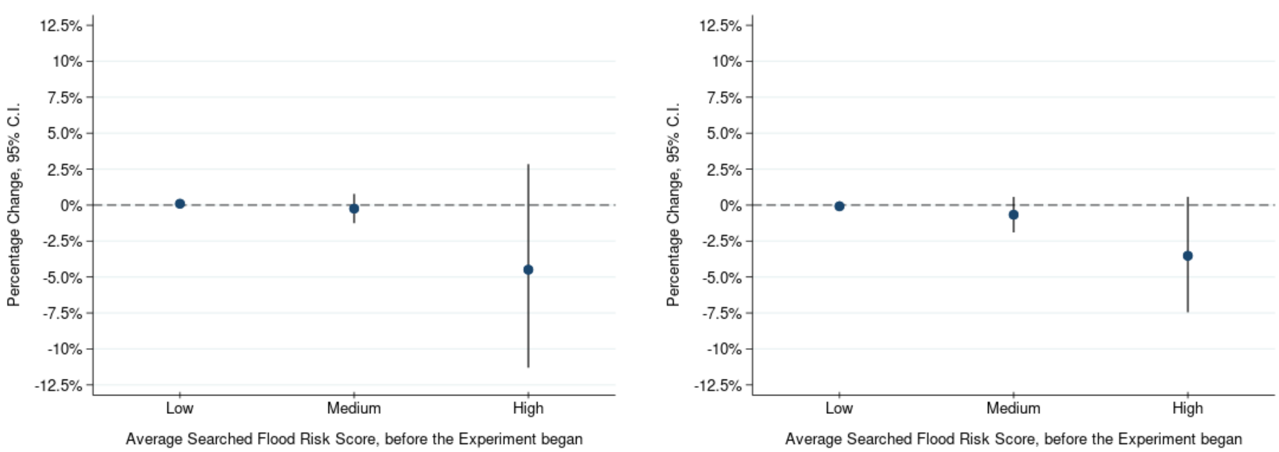


Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who did not browse any waterfront property before the experiment are classified as "without" waterfront search at baseline. On the other hand, users who browsed at least one waterfront property before the experiment are classified as "with" waterfront search at baseline.

Figure 10: CATE on the Average Flood Score of a Daily Search for Registered Users

% Change relative to Control

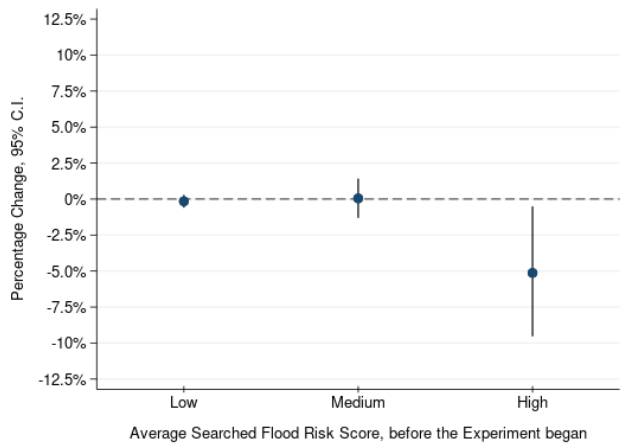
(a) Without FEMA Risk Search at Baseline (b) With FEMA Risk Search at Baseline



Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who did not browse any property considered risky by FEMA before the experiment are classified as "without" FEMA risk search at baseline. On the other hand, users who browsed at least one property considered risky by FEMA before the experiment are classified as "with" FEMA risk search at baseline.

Figure 11: CATE on the Average Flood Score of a Daily Search for Registered Users, With Waterfront and Without Coastal Search at Baseline

% Change relative to Control



Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who browsed at least one waterfront property before the experiment are classified as "with" waterfront search at baseline. A property is classified as being located on the coast when its geographic coordinates (latitude and longitude) are 200 meters or less from the nearest shoreline. Users who did not browse any coastal property before the experiment are classified as "without" coastal search at baseline. On the other hand, users who browsed at least one coastal property before the experiment are classified as "with" coastal search at baseline.

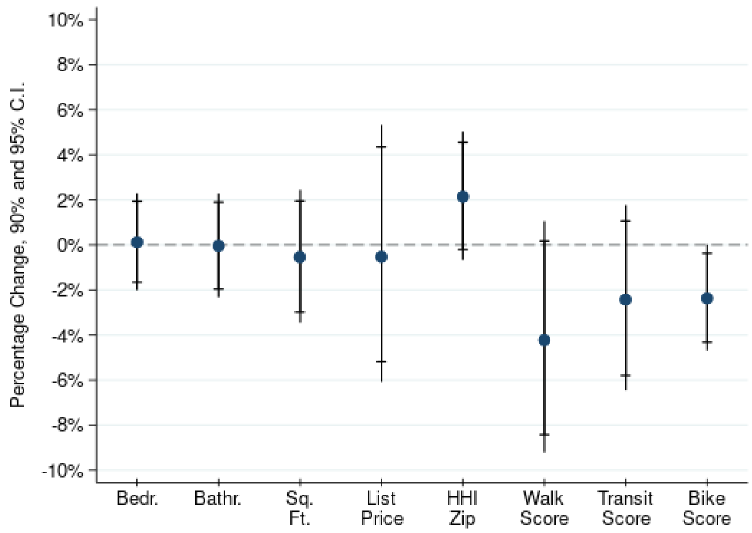
We now test what property attributes users are willing to trade off for a reduction in the flood score of property. As seen in Figure 12, users browsing high flood risk properties pre-experiment appear not to trade-off in the number of bedrooms, bathrooms, square footage, or list price a property has for a lower flood score. However, we observed an uptick in the Herfindahl-Hirschman Index (HHI), indicating a more focused search pattern and efficient search among consumers within particular zip codes, although a confidence level of 90% supports this finding.

We observed a decrease in bike score, with similarly sized reductions in walk and transit scores, though the latter two showed greater variability. Bike scores assess infrastructure like lanes and trails, topography, destinations, road connectivity, and biking prevalence. Walk scores evaluate proximity to amenities like grocery stores, schools, and restaurants, awarding points based on distance, and consider pedestrian friendliness through population density and road metrics like block length and intersection density. We hypothesize that both walk and bike scores may reflect the availability of public funds for infrastructure improvements and the area's business climate, suggesting that while highly valued, users may compromise on these aspects.

Figures A8 and A9 in the Appendix show that users who initially searched for properties with low and medium flood risk, respectively, did not significantly change how they valued property attributes, suggesting no notable trade-offs were made.

Figure 12: CATE on the Average Outcomes of a Daily Search for Registered Users Browsing High Risk Properties at Baseline

% Change relative to Control

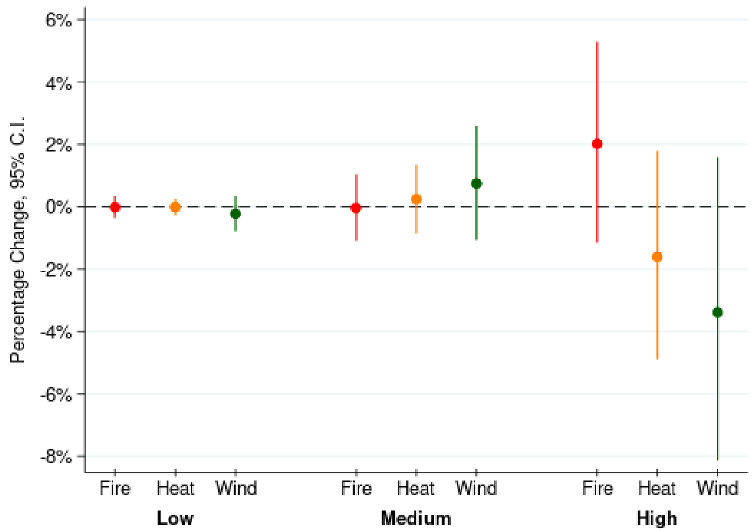


Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 90% and 95% levels. The x-axis represents treatment effects for users browsing high flood risk properties, on average, before the experiment began.

To investigate if users were open to higher fire, heat, and wind risks for lesser flood risk, we examined changes in these scores for viewed properties. Note that neither treated nor control groups had access to fire, heat, or wind scores during the experiment. Results in Figure 13 show no statistically significant differences in scores between the groups. Nonetheless, an increase in fire scores was observed for users initially viewing high flood risk properties, though this rise was not statistically significant.

Figure 13: CATE on the Average Fire, Heat, and Wind Outcomes of a Daily Search for Registered Users

% Change relative to Control



Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents treatment effects for users browsing low, medium, and high flood risk properties, on average, before the experiment began.

4.1.1 Nonparametric Conditional Average Treatment Effects

The impact of flood information on users may vary based on individual characteristics. We recognize that Redfin customers could vary with respect to their risk aversion, and they can vary with respect to their incomes and their local social capital, and family ties to an area where they are searching. Such searchers may also vary with respect to whether they trust the data that Redfin is supplying.

In the previous section, we demonstrated heterogeneity in treatment effects by analyzing how these effects differed depending on users' pre-experiment flood risk search behavior. However, the impact of our treatment could also vary based on other individual characteristics, in addition to baseline flood risk search behavior. Moreover, the estimator used to calculate the previous CATE, i.e., the estimator presented in equation 7 relies on the linearity assumption of the effect that covariates, X_i, have on the treatment. If these effects were nonlinear, our calculated estimates would be biased or would not cover the entire distribution of heterogeneous treatment effects.

To account for the possibility of nonlinearity and to incorporate the influence of other baseline characteristics on treatment effects, we utilize a Generalized Random Forest algorithm known as causal forests (Athey, Tibshirani and Wager, 2019; Athey and Wager, 2021). We further describe this algorithm in section A.4. Figures A21 to A23 show the predicted conditional average treatment effects through causal forests stratified by baseline flood risk categories.

Several results are worth highlighting. Figure A21 shows how the algorithm identified that 80%[45] of the conditional average treatment effects were negative for those users browsing extremely risky properties before the experiment began—albeit only 25% of them were statistically significant at the 90% level. The largest reduction for this group was a reduction of -20% in the average flood risk score. Moreover, Figure A22 also plots how causal forests found that about 60% of the treatment effects were negative for those users browsing medium risky properties before the experiment began. The most significant reduction was -15% relative to the control group.

Finally, for those in the low pre-experiment risk groups, we did not find *negative* statistically significant treatment effects (Figure A23). Nevertheless, we found positive statistically significant effects at the right end of the treatment effects distribution.

4.2 Engagement

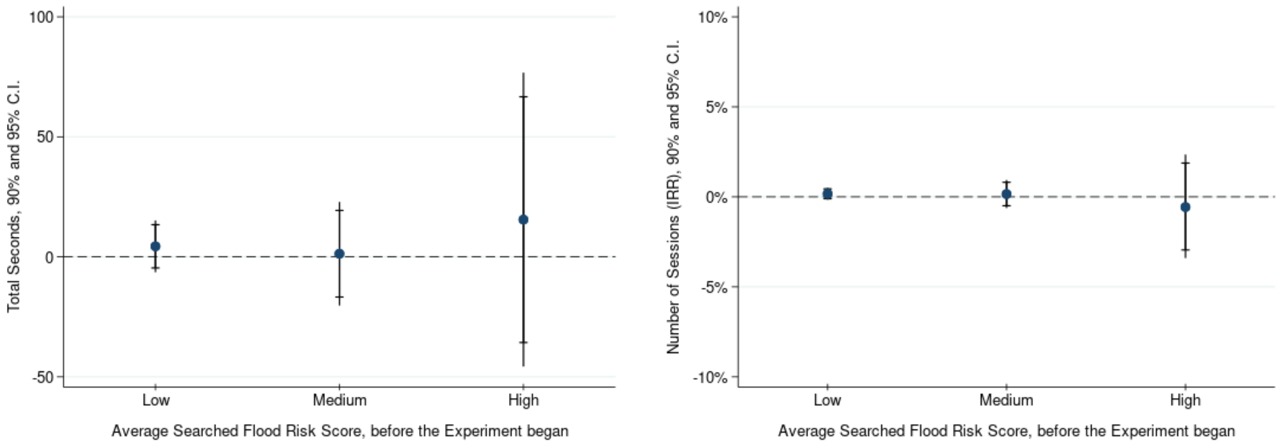
The Redfin experiment represents an "intention to treat." Each searcher must decide whether she keeps engaging with this information. Everyone has a time budget constraint and individual home buyers know their home purchase priorities. It is conceivable that a home buyer would spend relatively little time engaging with the flood risk data, given that there are many other dimensions of a home's quality to consider. In this section, we test this hypothesis.

Figure A11 reveals that the treatment had no statistically significant effect on website registration likelihood. Similarly, Tables A19 (for all users) and A20 (for registered users) indicate no significant differences in daily website usage—measured by seconds spent, sessions per day, unique home views, or total home views—between treatment and control groups. Further analysis based on pre-experiment flood score searches showed individuals interested in high-risk properties did not spend more time but engage in fewer sessions on Redfin's website, as detailed in Figures 14 (a) and (b). Similarly, Figures 15 (a) and (b) indicate that these users did not viewed more unique and total homes daily.

[45]When focusing on the population regardless of their pre-experiment average flood search, we found that 62.1% were affected by the flood risk information.

Figure 14: CATE on the Time Spent on the Website per Day for Registered Users

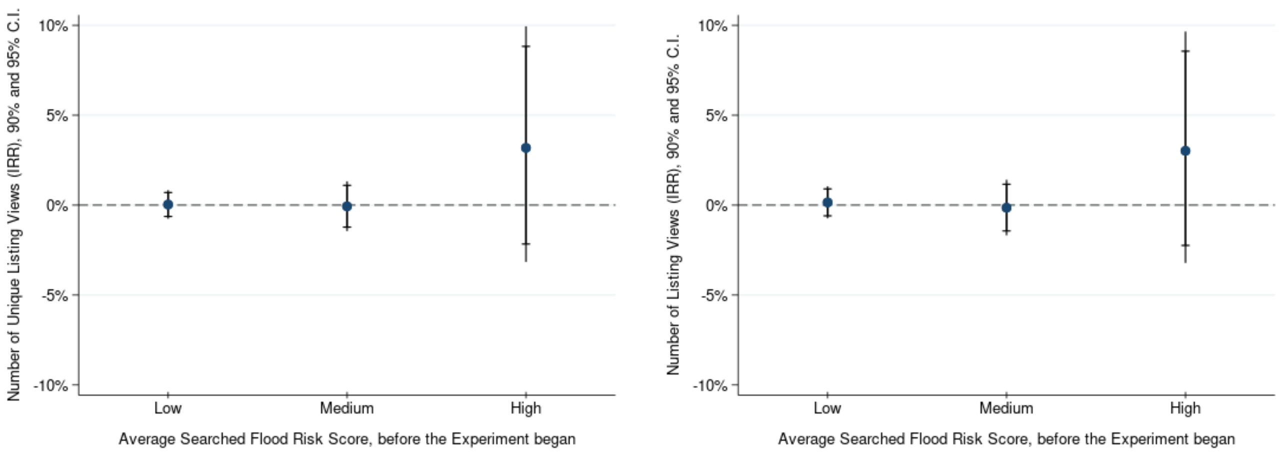
(a) Seconds Spent (b) Number of Sessions



Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Figure (b) estimates were calculated using a Poisson regression and transformed to incidence rate ratios.

Figure 15: CATE on the Number of Homes Viewed per Day for Registered Users

(a) Unique Home Views (b) Total Home Views



Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Both figure estimates were calculated using a Poisson regression and transformed into incidence rate ratios.

However, we do find that the treatment had an impact on some engagement with the listings. Figure 16 shows how the treatment (stratified by the baseline average flood score search category) affected the times a user engaged with (a) the flood risk section[46], (b) "favorite" a

[46]Engaging with the flood risk refers to reaching the flood risk section for the treated individuals and reaching the section where the flood risk should be for the control individuals.

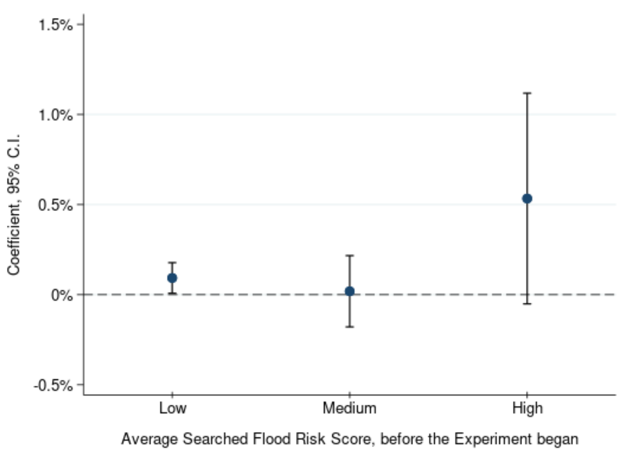
property, (c) next photo, and (d) active similar properties, as a percentage of all the properties a user browsed per day. Both groups of users, those browsing, on average, low risk and high risk properties at baseline, exhibited increased engagement with the flood risk section once they entered the experiment, compared to the control users (Figure 16 (a)). As well, users browsing, on average, properties with low flood risk pre-experiment "favorited" more properties once the flood score became available, whereas those browsing, on average, high risk properties pre-experiment, "favorited" fewer properties (Figure 16 (b)) and clicked fewer times "next photo" (Figure 16 (c)).

Our findings presented above suggest that users previously browsing high risky properties adjust their search behavior once they learn about the flood risk (which we have already seen from the average flood score search results in the previous section). This finding has important economic content because we reject the hypothesis that informed, risk-loving individuals seek out risky homes. If such "complete information" matching was taking place, then we would not expect to observe the facts we reported above.

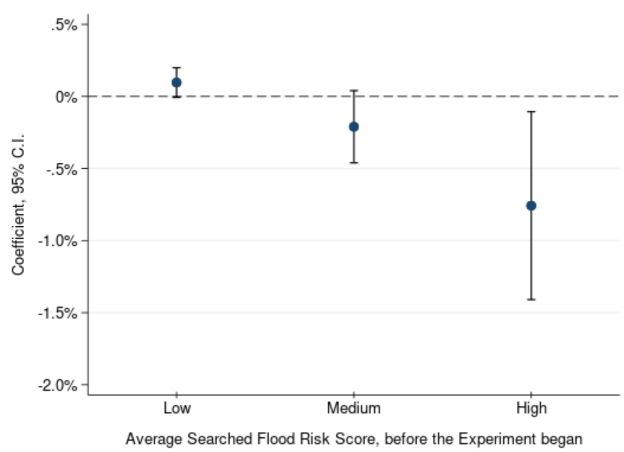
Figure 16: CATE on the Percentage of Times Registered Users Engaged with a Specific Property's Features per Day

% Times User Engaged with Feature for Listings Viewed per Day

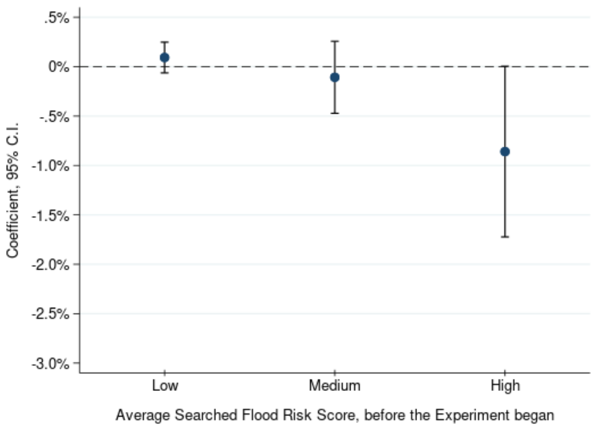
(a) Engaged with the Flood Risk Section



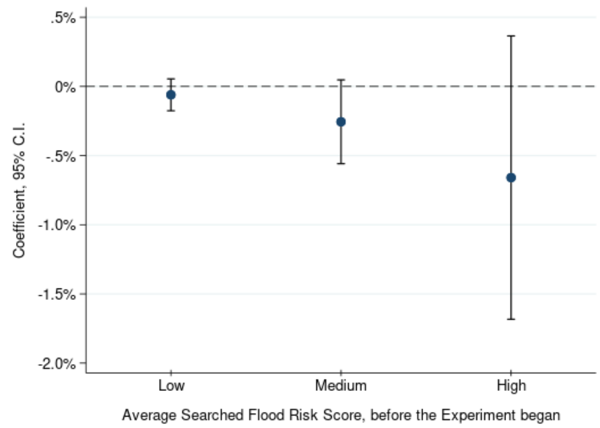
(b) Clicked "Favorite" a Property



(c) Clicked Next Photo



(d) Clicked Active Similar Properties



Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

We also examine some of these engagement metrics for different types of properties (based on the user's pre-experiment search history). Figures A12 and A13 in the Appendix show the average treatment effect on the engagement with the flood risk section for users browsing waterfront and FEMA-risky properties at baseline. Consistent with the search results, we found that treated users looking at the waterfront and FEMA-risky areas are more likely to spend more time searching for the flood risk section. Lastly, Figures A14 and A15 in the Appendix illustrate that the treatment influenced the frequency of treated users marking properties as "favorite," mirroring the trend observed in Figure 16 (b).

4.3 Tours, Offers, and Closes

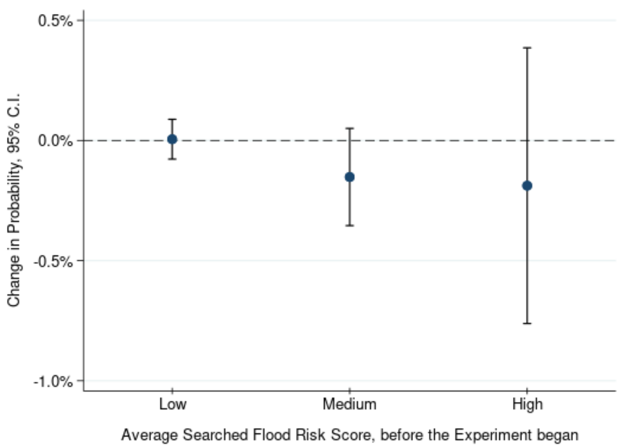
Redfin provides customers with an integrated house purchase process such that home buyers can search for a specific home and then work with a Redfin directed brokerage service. It gives its users the option to tour properties, place a bid on a particular property, and close a deal. In our experiment for all users who search for a given property and then choose to tour the property and then place a bid for that property, we observe each of these steps play out in the housing purchasing process. Based on revealed preference logic, we view touring and bidding on a home as important (and costly) evidence that one is responding to information. In this section, we will analyze whether the treatment information affected the extensive margin decision to tour and make an offer, as well as conditional on touring and making an offer, do they change the type of home they tour and make an offer on.

Tours. As seen in Figures 16 (a) and (b), having access to the flood risk score of the properties doesn't affect the likelihood of booking a tour or canceling a home tour, irrespective of their baseline flood score search or the flood score of the property; that is, we do not find a statistically significant difference on the probability of booking or canceling a home tour for the treatment group. We also found that providing flood score information influenced the timing of property tours, as illustrated in Figure A16. Users who initially browsed properties with low, medium, and high flood risk experienced a change in the days to tour a property, +.9%, -2%, and -.8%, respectively, compared to the control group.

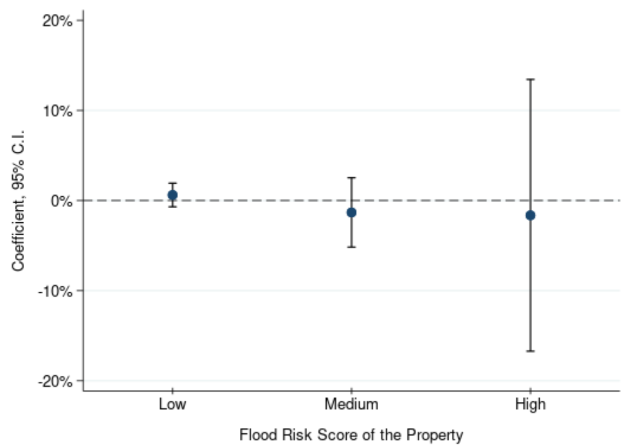
Figure 16: CATE on the Probability of Booking a Tour and Canceling a House Tour

% Change relative to Control for Registered Users

(a) Probability of Booking a Tour



(b) Probability of Cancelling a House Tour



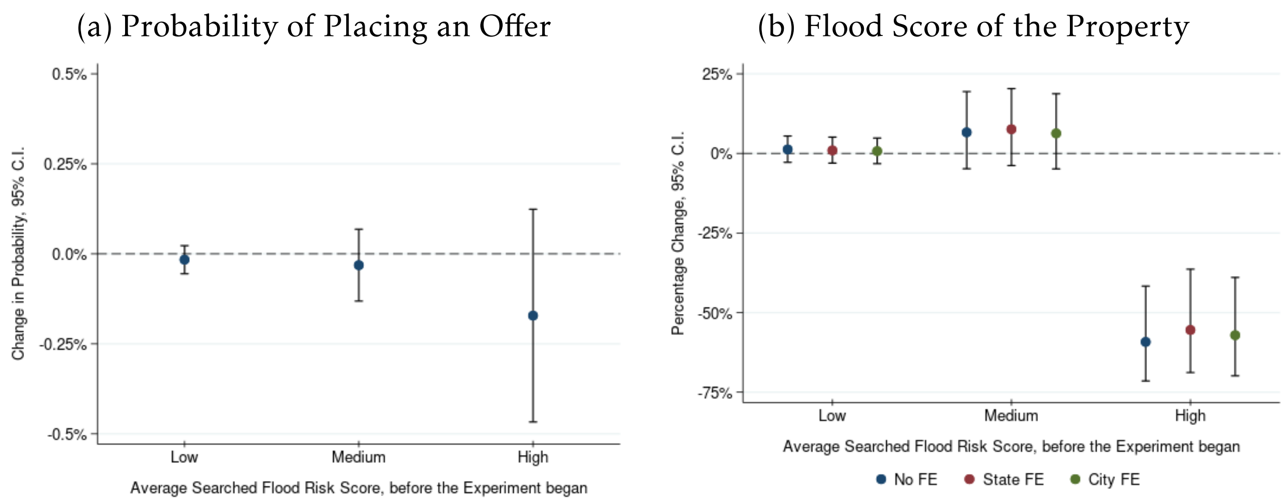
Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents the flood score category of the property.

Offers. Figures 17 (a) and (b) show the probability of an individual placing a house offer and the flood score of a property someone in our experiment bid on, stratified by the baseline average flood score search category and relative to their control counterpart. Figure 17 (a) shows no statistically significant difference in having access to the flood score of properties on the probability of bidding on a property. However, Figure 17 (b) shows that treated users browsing high risky flood properties pre-experiment place bids on properties with -57.1% (s.e. = 19.73) less flood score than their control counterparts. This effect is extremely large. While there are no differences in the likelihood of making an offer from figure 17 (a), we still might have selection of who is making an offer. While we are balanced on pre-experiment baseline risk, there might be a selection of observables. However we show that this result is not a selection effect but a change in where the user makes an offer. We check this by examining the balance of the search prior to the experiment was run for treatment and control users who make an offer (we check for low, medium, and high flood risk). In Appendix Tables A21 to A26, we show that for registered users who eventually placed an offer during the experiment, we cannot statistically reject the null hypothesis across several outcomes, regardless of the baseline flood-risk levels.

Figures 18 (a) and (b) show how treated groups trade off characteristics of a property to reduce their flood exposure. On the one hand, as seen in Figure 18 (a), people who browsed riskier properties before the experiment started had a lower probability of placing an offer on waterfront properties. That is, those users who had access to flood scores and browsing high-risk properties before the experiment started had a -39. 6% lower probability of placing a bid on a waterfront property. On the other hand, Figure 18 (b) shows that users browsing high-risk properties before the experiment began went on to bid properties with -14.6% less square feet (se = 17.08).

Figure 17: CATE on Offers

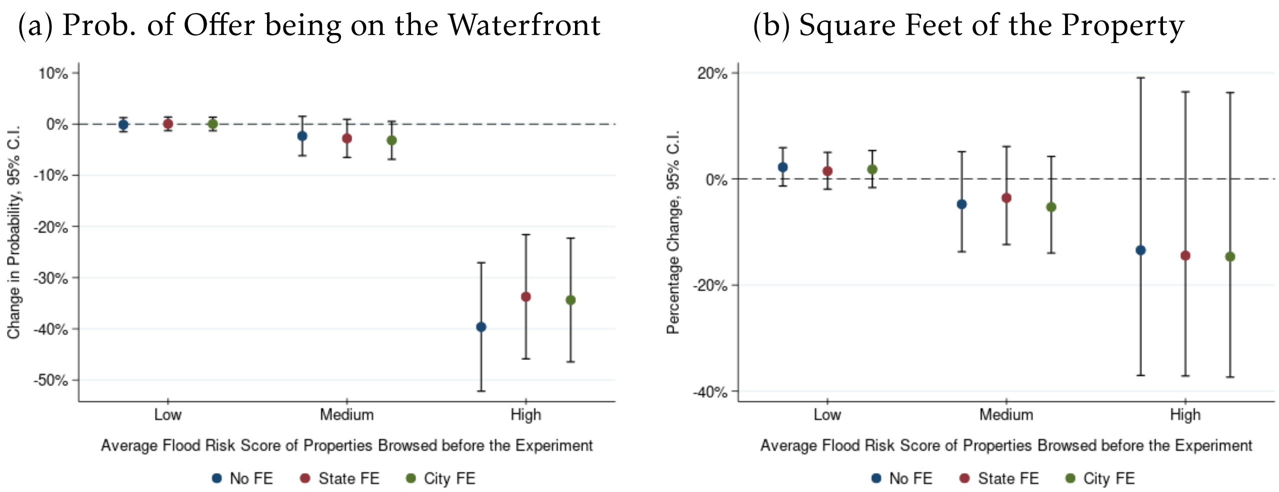
% Change relative to Control



Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7 for figure (b). Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. S.E. clustered at the registered user level. FE = Fixed Effects of the location of the Property.

Figure 18: CATE on the Characteristics of an Offer

% Change relative to Control



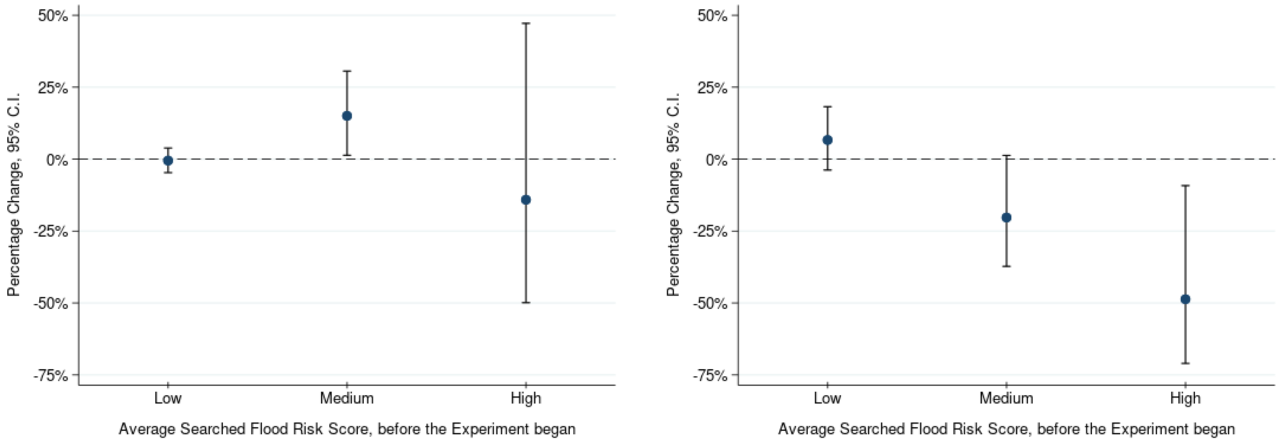
Note: For Figure (b), coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Standard errors clustered at the user level. FE = Fixed Effects of the location of the Property.

Our analysis extends to how property type influences offer behaviors. Figures 19 (a) and (b) indicate that reductions in flood scores for offers predominantly involve waterfront properties. While Figures 20 (a) and (b) reveal minor discrepancies between FEMA high risk and non-FEMA properties, Figure 21 demonstrate that the significant decreases in flood score originate from waterfront properties not situated on the coast, further corroborating the "new news" hypothesis.

Figure 19: CATE on the Flood Score of an Offer for Registered Users

% Change relative to Control

(a) Without Waterfront Search at Baseline (b) With Waterfront Search at Baseline

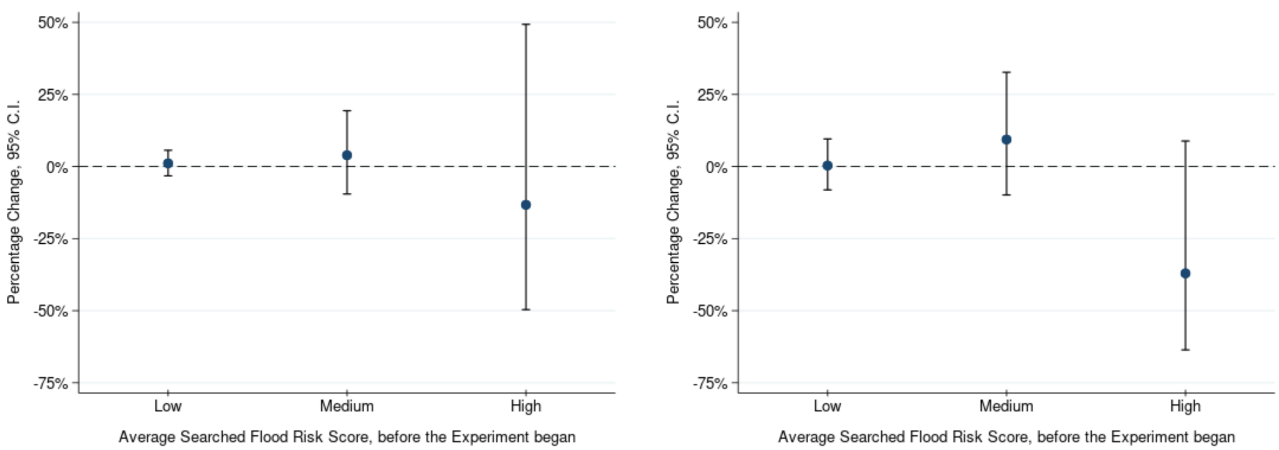


Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who did not browse any waterfront property before the experiment are classified as "without" waterfront search at baseline. On the other hand, users who browsed at least one waterfront property before the experiment are classified as "with" waterfront search at baseline. Estimates are with City Fixed Effects.

Figure 20: CATE on the Flood Score of an Offer for Registered Users

% Change relative to Control

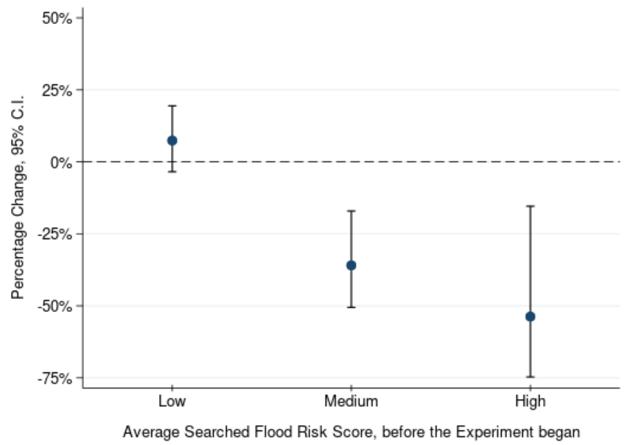
(a) Without FEMA Risk Search at Baseline (b) With FEMA Risk Search at Baseline



Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who did not browse any property considered risky by FEMA before the experiment are classified as "without" FEMA risk search at baseline. On the other hand, users who browsed at least one property considered risky by FEMA before the experiment are classified as "with" FEMA risk search at baseline. Estimates are with City Fixed Effects.

Figure 21: CATE on the Flood Score of an Offer for Registered Users, With Waterfront and Without Coastal Search at Baseline

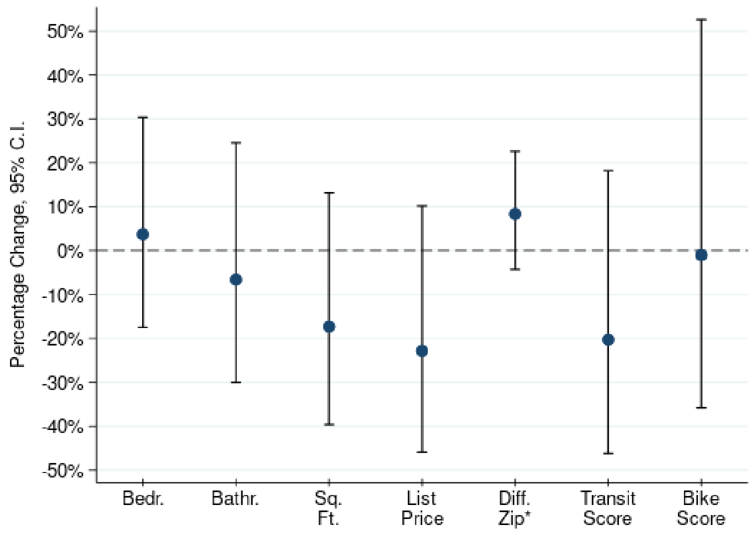
% Change relative to Control



Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who browsed at least one waterfront property before the experiment are classified as "with" waterfront search at baseline. A property is classified as being located on the coast when its geographic coordinates (latitude and longitude) are 200 meters or less from the nearest shoreline. Users who did not browse any coastal property before the experiment are classified as "without" coastal search at baseline. On the other hand, users who browsed at least one coastal property before the experiment are classified as "with" coastal search at baseline.

While we find that treated users searching for high flood risk properties prior to the experiment are significantly less likely to make an offer on a high flood risk home, we are interested to see if there are any trade-offs for the lower flood risk. For the high flood risk property users, while the flood score of the offered properties decreases, Figure 22 shows that there are meaningful changes in the size of the property, the list price, transit score, and submitted an offer for a property in a zip code different from their most frequently browsed one at baseline. However, given the sample size, are estimates are little uncertain.

Figure 22: CATE on the Average Outcomes of the Offers
for Registered Users Browsing High Risk Properties at Baseline
% Change relative to Control

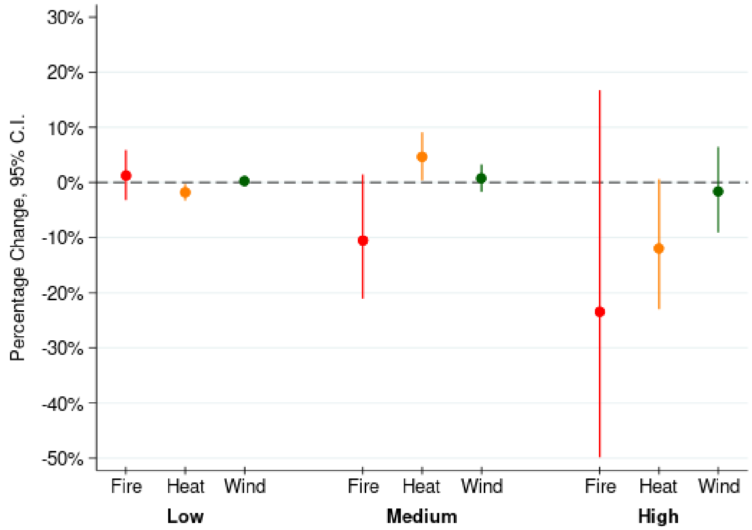


Note: Coefficients are in the form of $((e^{\beta_3}-1)\cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents treatment effects for users browsing high flood risk properties, on average, before the experiment began. *: The outcome variable is a binary indicator that takes a value of one when a user submits an offer for a property in a zip code different from their most frequently browsed one at baseline and zero otherwise. As such, the treatment represents a shift in probability rather than a percentage change, as with the others.

While we demonstrate some convincing evidence that users changed the houses they made offers on with respect to flood risk, we also analyze whether that changes the users' exposure to other climate change risks. Based on the fire, heat, and wind scores from the First Street Foundation, we observed that users relocating from flood risk areas did not show a statistically significant preference for properties with different fire, heat, or wind scores compared to those who had access to flood scores (refer to Figure 23). We find that treated users in the high flood risk group are less likely to make a bid on a home exposed to heat ($p < 0.06$), and that the fire risk was reduced although the estimate is noisy. Altogether, we do not observe that the treatment information made high flood risk users move into properties that are exposed to other climate risks, and it is more likely that they reduced overall climate risk.

Figure 23: CATE on the Average Fire, Heat, and Wind Outcomes of the Offers for Registered Users

% Change relative to Control

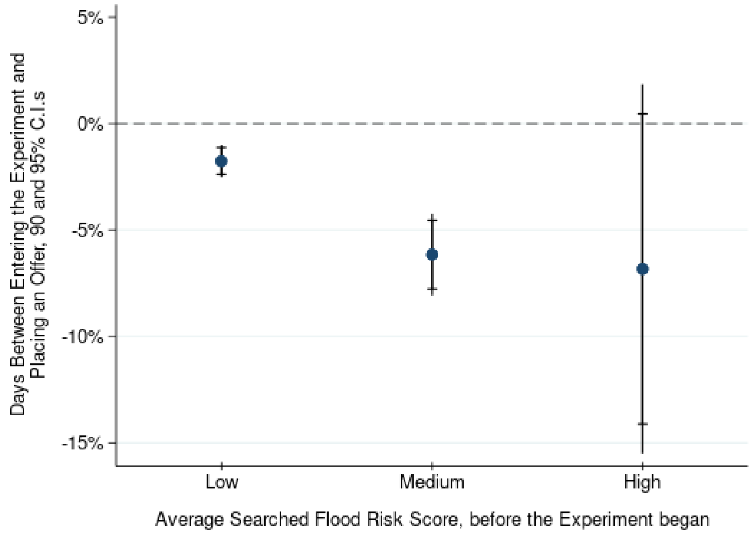


Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents treatment effects for users browsing low, medium, and high flood risk properties, on average, before the experiment began.

We also examine time to make an offer based on experimental group. We observe the time from the start to the experiment to the time of the first offer for all those who are registered and use Redfin for offers. We find that access to a property's flood score reduces the time to make an offer, as Figure 24 demonstrates. Redfin users browsing on average properties of low, medium, and high flood risk before the experiment took -2%, -6%, and -7% fewer days to submit an offer compared to the control group. These results suggest that the information led to increased allocative efficiency in the housing market.

Figure 24: CATE on the Days between Entering the Experiment and Placing an Offer for Registered Users

% Change relative to Control



Note: Coefficients are in the form of incidence rate ratios from equation 7 using a Poisson regression. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 90% and 95% levels, respectively. The x-axis represents treatment effects for users browsing low, medium, and high flood risk properties, on average, before the experiment began.

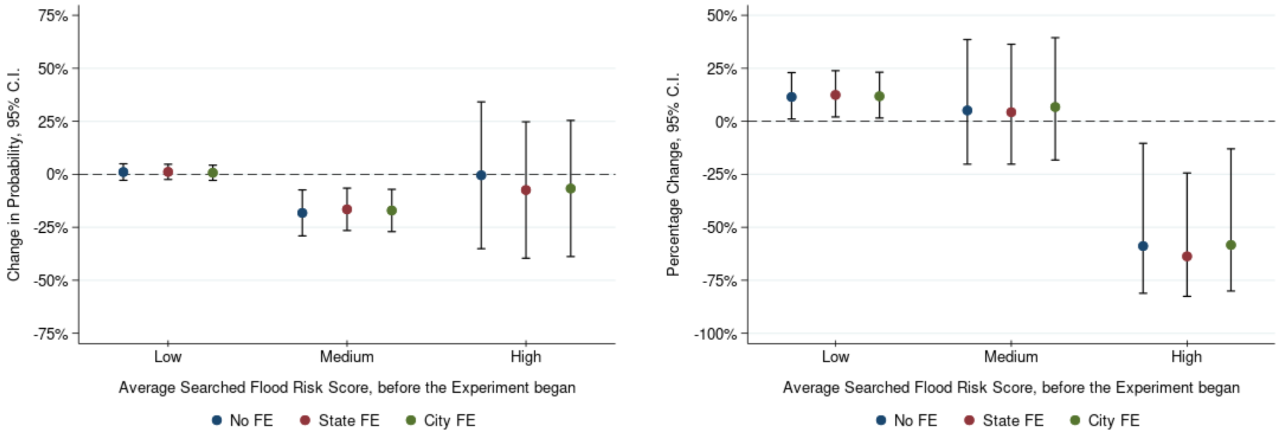
Closing. In the process of selling a home, the "closing" is one of the final steps, as money and legal paperwork are exchanged to finalize the transaction. From basic revealed preference logic, if a home buyer doubts following through with a purchase, this is the key time to walk away from the deal.

We now show the probability of an individual closing a house offer and the flood score of a property on which someone in my experiment closed, stratified by the baseline average flood score search category and relative to their control counterpart. As seen in Figure 25 (a), we found a lower probability (-15%) of closing an offer between treatment and control groups for those browsing medium risky properties pre-experiment. Figure 25 (b) shows the average treatment effects of having access to properties' flood score on the property's closed flood score. On average, registered treated users browsing pre-experiment high flood risk properties closed properties with -58.8% (p < 0.01) less flood risk than their control counterparts. This result is extremely similar to the result on the offers made in Figure 17.

Figure 25: CATE on the Probability of Closing on a Property

% Change relative to Control

(a) Probability of Closing an Offer (b) Flood Score of the Closed Properties



Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. FE = Fixed Effects of the location of the Property.

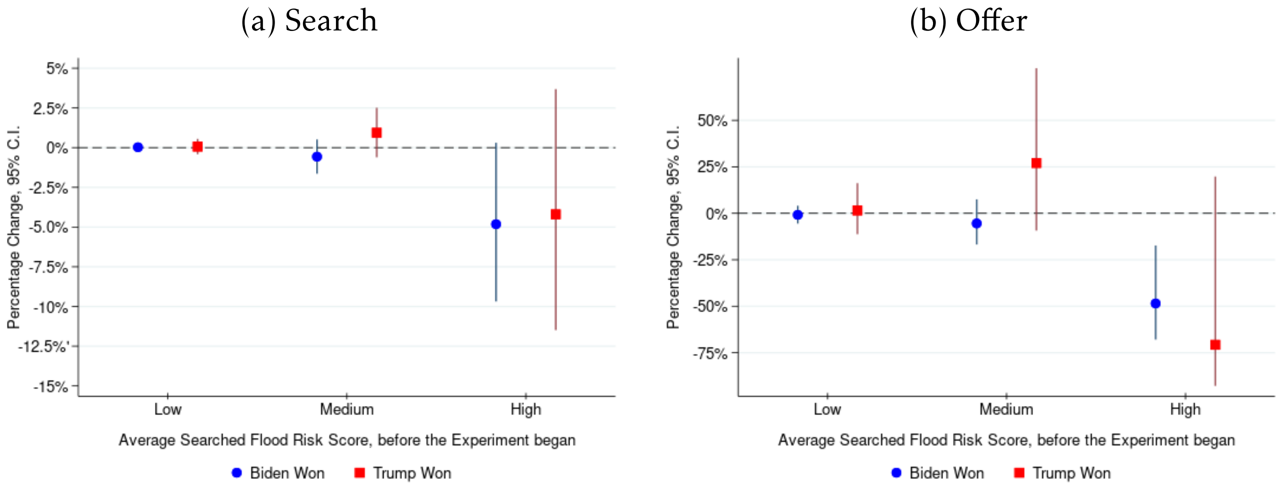
4.4 Does Political Ideology or Recent Flooding Events Influence the Treatment's Effectiveness?

Previous research has noted the political divide concerning interest and climate change concerns (Dunlap and McCright, 2008; Bernstein et al., 2022). Blue state voters and their elected officials routinely express their support for the green economy and subsidies to decarbonize it. Energy conservation nudges focused on peer comparisons tend to be more effective with liberals than conservatives, or areas that are deemed more green (Dunlap and McCright, 2008; Costa and Kahn, 2013; Allcott, 2015).

We test whether political ideology influences the average treatment effect of the flood information. We calculate conditional average treatment effects by whether the zip code where the user lives voted for Biden or Trump in the 2020 Presidential election. In Figures 26 (a) and (b), we show the impact of Biden and Trump winning zip codes for search and offers, respectively. For search, we see that Trump and Biden supporters respond more to high flood risk than medium flood risk ($p < 0.05$). We cannot reject the null that Biden and Trump's counties respond to the flood score in the same way for both searches and offers.

Figure 26: Flood Risk by Counties from Where Users Browsed the Most at Baseline, Stratified by Whether Biden or Trump Won in 2020

% Change relative to Control



Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. We assigned a baseline county to where users browsed the most from at baseline.

Studies have also estimated the impact of flooding events on the real estate market and risk perceptions, finding that home buyers respond to recent major flooding events and adjust their risk perceptions only during a brief period of time (Kousky, 2010; Zhang, 2016; Zhang and Leonard, 2019). We test whether the county from which a user made the most searches and the county a user searched for properties the most at baseline experienced a flooding event in the past seven days to further examine the heterogeneity of our conditional average treatment effects. Figures A17 (a) and (b) show that a flooding event did not have a statistically significant effect on how treated users browsed for properties within counties experiencing a flooding event in the past 7 days.

5 Real Estate Market Price Responses to Property Specific Flood Risk Information

While no home buyer gains utility from owning a home at risk of flood, the population differs with respect to their willingness to pay for such a home. Higher-income people have a higher economic capacity to avoid such risky homes. More risk loving people and those with the ability and economic capacity to upgrade their homes will be more likely to bid for risky homes than risk averse people who do not want to invest the time and effort in upgrading a home (Shogren and Stamland, 2002).

In a setting where buyers and sellers have complete information about climate risks, the climate risks will be capitalized into the sales price of the home. Hedonic real estate regression techniques can be used to recover the marginal value of the home's attributes. Recent papers have followed this strategy to estimate the compensation for flood risk (Ortega and Taṣpınar, 2018; Bernstein, Gustafson and Lewis, 2019). Gao, Song and Timmins (2023) study the responsiveness of regional migration in China to local air pollution. They find that this migration elasticity nearly doubles when the authorities publicize urban air pollution levels. This study's natural experiment demonstrates that people are more responsive and more likely to adapt to a pollution threat when they are informed about it. Our experiment's individual level variation in access to environmental risk information allows us to take the next step here to investigate how different people engage with such information.

Our field experiment's results highlight that home buyers do not have 'complete information about emerging risks. Home buyers are responding to this information in every phase of the search process. In this section, we study how property-specific revelation of flood risk affects the housing hedonic gradient. An ideal field experiment for answering this question would randomize the flood score at the property level (not at the individual searcher level).

For every home sold in the experimental period, there was a random fraction of users who were in the treatment and the control group. This variation is due to random variation of who gets placed into treatment and control with small samples. For example, suppose that 50 Redfin home buyers chosen randomly in the treatment group chose to click on 14 Elm Street, Belmont, MA 02478 when the experiment was going on (the last three months of 2020). Suppose that during that time, 100 Redfin home buyers chosen at random to be in the control group also looked at that home. This means that 50/150 of the Redfin searchers that were randomly selected to be in the experiment knew the home's flood score during the study period–we will call this number the fraction who are treated.[47]

Our dependent variable is the sales price minus the list price. This variable reflects the "new news" associated with the home (Bajari et al., 2012). The First Street Foundation flood score treatment information was an unanticipated event that could not be incorporated into the list price. In our econometric model below, the variable, Frac_Treat represents the ratio of the count of people in the treatment group who visited this property divided by the total count of all Redfin searchers who visited this property. We estimate the following regression:

$$y_{pt} = \beta_0 + \beta_1 F_p + \beta_2 \text{Frac\_Treat}_p + \beta_3 \left(F_p * \text{Frac\_Treat}_p \right) + \lambda_z + m_t + u_{pt} \tag{9}$$

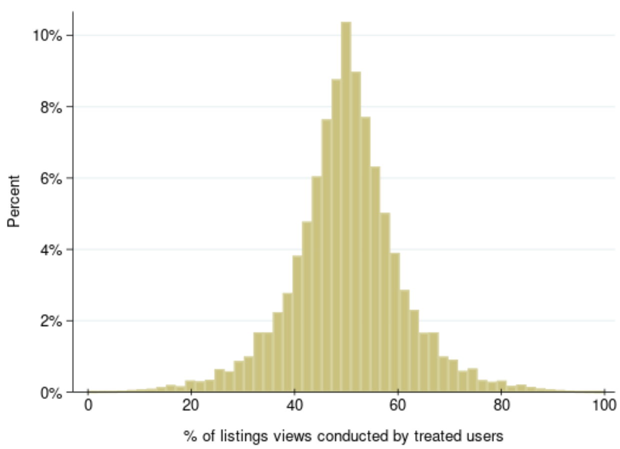
[47] Let's also remember that Redfin allocated around 41% of its total traffic to this experiment. Thus, 59% of its monthly traffic, by definition, didn't know about the flood score. Following the 14 Elm Street example, we can say that 50/336 of Redfin's total searches for this house knew its flood score. If Redfin has a 20 percent market share, then the market wide exposure to treatment for this home equals 50/1680 or about 3%.

where, y_{pt}, represents the dollar spread between the sale price and the property listing price, p, sold in the month, t, of the experimental period. F_p shows the property's flood risk category (i.e., low, medium, and high), whereas, Frac_Treat, represents the percentage of people who viewed the property and were in the treatment group as a fraction of all Redfin viewers. λ_z and m_t represent zip code- and month-fixed effects, respectively. u_{pt} are the residuals. Standard errors are clustered at the zip code level.

Figure 27 (a) shows the distribution of the variable, Frac_Treat, i.e., the percentage of people who viewed the property and were in the treatment group as a fraction of all Redfin viewers, which follows a normal distribution. Figure 27 (b) shows estimates of β_3 from estimator 9. We did not find a statistically significant effect when running estimator 9 on the whole sample of listings sold during the experimental period.

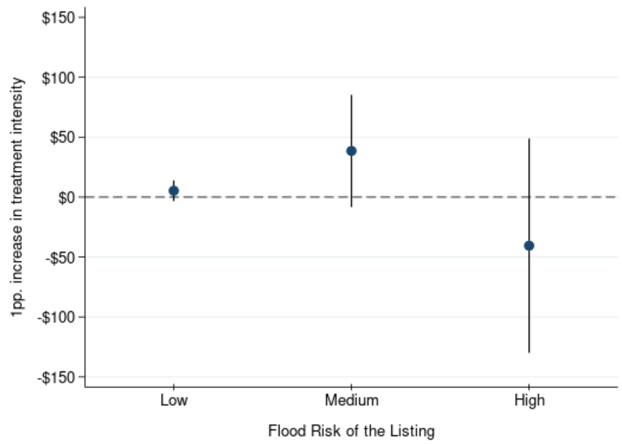
Figure 27: The Association Between Treatment Exposure Intensity and the *(Sale - Listing Price)* Spread

(a) Distribution of Listing Views Conducted by Treated Users per Listing



(b) All Listings

1PP Increase in Exposure Intensity, ($)



Note: For Figure (b), vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents the flood score of the property.

However, when we divide the listings into two groups based on their characteristics —being on the waterfront or being in a FEMA risk zone —we observe that our intensity treatment variable, referred to as Frac_Treat, has an impact on the difference between the sale price and the listing price. Figure 28 illustrates how a 1 percentage point increase in the intensity treatment variable affects the spread between the sale price and the listing price for properties that are *not situated* on the waterfront (see Figure 28 (a)), as well as for properties that are *not considered* risky by FEMA (see Figure 28 (b)), stratified by the listing's flood risk score. For both instances, properties considered *highly* risky by First Street Foundation, incurred a price penalty as the percentage of treated users viewing the listing in Redfin increased.

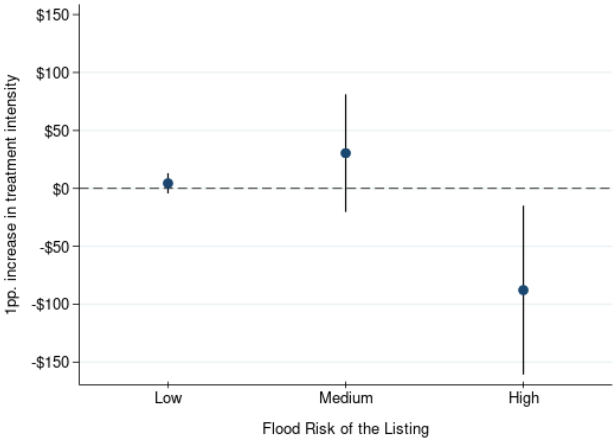
A one percentage point increase in the percentage of views conducted by the treated users led to a negative penalty of -$68 and -$53 for highly risky properties not on the waterfront and not considered risky by FEMA, respectively. In other words, going from 0% (pre-experiment beliefs) to 100% (every user on Redfin having the FSF flood score) in our variable of interest leads to a price penalty of -$6,800 (1.7% of property prices) and -$5,300 (1.3% of property prices) under list price among severely risky properties not on the waterfront and not considered risky by FEMA, in that order. These results suggest that the intervention influenced risk expectations for those properties either not perceived as risky (i.e., not on the waterfront) or not defined as risky by a government institution (i.e., not considered risky by FEMA).

We obtain these hedonic estimates based on a thought experiment where we increase the percentage of people having the flood information from 0% to 100% . However, only roughly 40% of Redfin users were part of the experiment, and Redfin had 20% market share at the time, so zero to one hundred is actually 0% to 8% of the whole market receiving this information. So we have to make some assumptions about moving from the partial to the general equilibrium to value what would happen if all consumers had the information (Banzhaf, 2021). If we assume linearity in the impact of the proportion of people having the information of flood risk and property prices, the overall impact of house prices on high flood risk homes to be around $85,000 (21% of the property prices). Given that FEMA estimates that the average cost for flood damage in the NFIP in the U.S. from 2016 to 2022 was $66,000, these numbers are quite aligned, especially given that the homes for sale on the MLS has a higher value than all homes insured through the NFIP.

Figure 28: CATE of an Increase in Exposure Intensity on the *(Sale - Listing Price)*

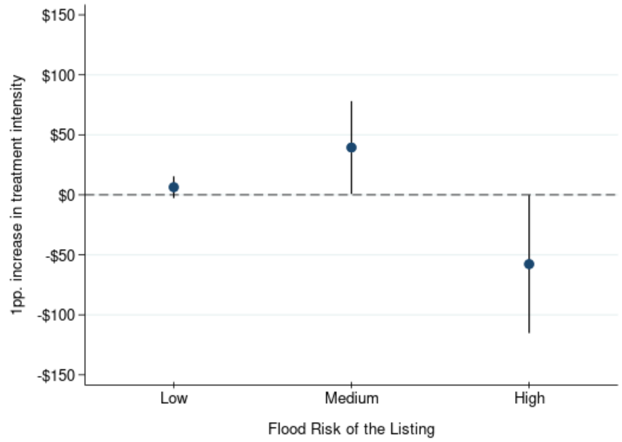
(a) ***Not*** Waterfront Listings

1PP Increase in Exposure Intensity, ($)



(b) ***Not*** FEMA Risky Listings

1PP Increase in Exposure Intensity, ($)



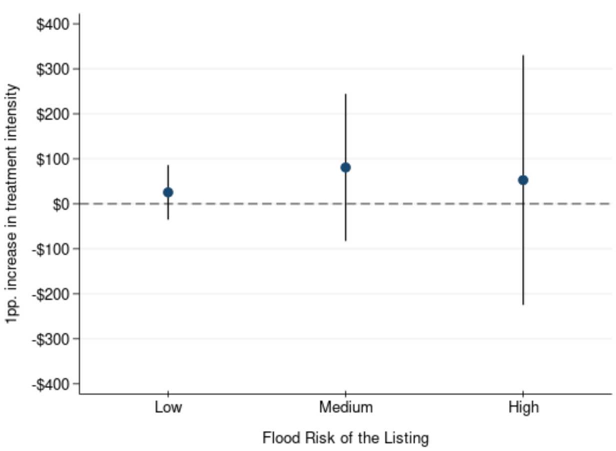
Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. As well, for Figure (b), the x-axis represents the flood score of the property.

However, we did not observe a statistically significant effect of an increase in our treatment intensity variable on the difference between the *sale price* and *listing price* for properties located on the waterfront versus those classified as risky by FEMA (as shown in Figure 29), suggesting that flood risk was already priced for those properties.

Figure 29: CATE of an Increase in Exposure Intensity on the *(Sale - Listing Price)*

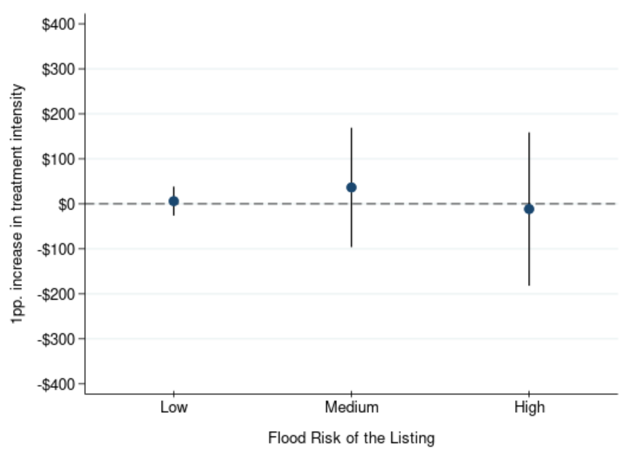
(a) Only Waterfront Listings

1PP Increase in Exposure Intensity, ($)



(b) Only FEMA Risky Listings

1PP Increase in Exposure Intensity, ($)

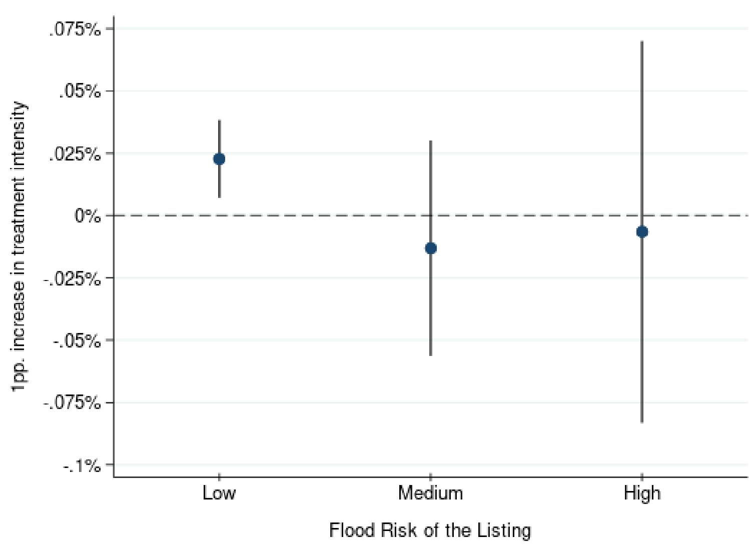


Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents the flood score of the property.

Finally, we have access to information on whether an investor bought a property, the time on the market (for examining some elements of allocative efficiency), and loan value. An investor is defined as any buyer whose name of the buyer of the listing includes at least one of the following keywords: LLC, Inc, Trust, Corp, Homes; or any buyer whose ownership code on a purchasing deed includes at least one of the following keywords: association, corporate trustee, company, joint venture, or corporate trust. In Figure 30, we find that low risk is treated differently by investors than medium and high risk. It seemed that for low flood risk homes, moving from 0 to 100% treated Redfin users led to a 2.5 percentage point increase in the probability of an investor buying the property (over a baseline of 9.76% in the control group). Medium and high risk have a lower likelihood of purchasing a home, although they are more noisy. This result does demonstrate that the flood risk is changing the expected returns of a property, and such returns are more pivotal for investors than regular homeowners. We do not find any impact of the treatment intensity variable on affecting the time on the market (Figure A18), the loan value of the mortgage of the property (Figure A19), and the listing price of not FEMA Risky and not waterfront properties (Figure A20).

Figure 30: CATE of an Increase in Exposure Intensity on the Probability a Listing was Bought by an Investor

% Change relative to Control



Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents the flood score of the property. An investor is defined as any buyer whose name of the buyer of the listing includes at least one of the following keywords: LLC, Inc, Trust, Corp, Homes. We also define an investor as any buyer whose ownership code on a purchasing deed includes at least one of the following keywords: association, corporate trustee, company, joint venture, or corporate trust.

Our interpretation of these results is that the sales price represents the outcome of a type of auction process. For homes located in high flood risk areas for whom this information is made public to a large number of searchers, then these treated individuals are less likely to bid aggressively for the home. The winning bidder for the home will end up paying less for the home. By subtracting the asking price, we standardize the dependent variable.[48] This negative capitalization effect is likely to be even larger in cities experiencing population loss (Glaeser and Gyourko, 2005).

Our findings have implications for hedonic real estate models of amenity and disamenity capitalization. Given that homes are durable goods, dynamic hedonic analysis teaches us that the expected present discounted flow of flood risk is the right "x" variable to include in a hedonic home price regression (Bishop and Murphy, 2011, 2019; Bayer et al., 2016; Severen, Costello and Deschenes, 2018). If home buyers are forward-looking, they will base their bids and purchase price based on the expected future risk stream. This is also consistent with an extrapolative model of home buying (Glaeser and Nathanson, 2017), in that (all else equal) a high flood risk score reduced future demand for the home, and if flood risk scores are spatially correlated, then a zip code that faces overall flood risk could be perceived to be on the decline and this makes the property even less attractive. This discussion highlights the importance of using expectations-based amenity variables when studying real estate price capitalization of climate risks when these place based risks are changing over time.

6 Conclusion

A majority of American adults live in owner-occupied housing. Such housing is often their major asset. Rising global greenhouse gas concentrations pose new place-based risks for such real estate. In the past, trusted information about these place-based risks was difficult to access. As Internet real estate platforms such as Redfin incorporate pinpoint climate risk maps into their platform, this information plays a valuable role in educating home buyers. This information can play a causal role in accelerating the pace of climate change adaptation if home buyers respond to this information by becoming more discerning about how they search and buy.

Thanks to Redfin's integrated real estate platform, we are able to study the entire search process for a randomized treatment group and a control group. A unique feature of this field experiment is our ability to track how the same individuals act when searching on the internet and when they are physically taking actions, such as searching, touring, and closing on homes. We observe a logical consistency in the treatment group's choices at every step in the housing purchase process. At each stage of the housing search process, the flood risk information influenced consumer behavior related to search, bidding, and closing. In the

[48]Given that this is a short run experiment that the seller was unaware was taking place, the asking price is likely independent of the flood score.

market overall, we find real changes in house prices with the flood risk information. All of the evidence from the field experiment in this paper points to the new news hypothesis. People were not previously aware of the risk, but now they are through an understandable piece of information that allows consumers to have the correct flood risk beliefs. This matters for climate change adaptation.

The three-month field experiment was extremely high stakes for the consumers, sellers, and the market overall, in that the experiment affected the sales of 8,150 high flood risk properties (average price = $653,000) totaling $5.3 billion. The information reduced the prices of these high flood risk properties by $57 million. The experiment affected the sales of 186,000 low flood risk properties (average price = $697,000) totaling $129.5 billion. Of this, the information increased prices of these low flood risk properties by around $100 million, suggesting a net benefit welfare effect overall.

Future research could explore demand-side and supply-side factors to gain a deeper understanding of the causal effects of pinpoint climate risk information. Specifically, on the demand side, it would be beneficial to investigate how various individuals update their prior beliefs when presented with climate risk information. For example, do people become scared or more informed about another attribute of the differentiated product (i.e., the home) when they learn it faces higher risk? Given the expense of sea walls, and levees, and given the possibility of moral hazard and "Peltzman Effects" induced by them (Wang, 2021; Benetton et al., 2022; Bradt and Aldy, 2022; Ostriker and Russo, 2022; Hsiao, 2023), it is important to evaluate how to configure demand-side information to accelerate adaptation.

On the supply side, new research could focus on understanding how providers of climate risk information can present it more effectively. For example, what presentation formats most effectively convey risk information to consumers? Additionally, it may be helpful to investigate how the credibility and reliability of the information source affect its impact on decision-making. This understanding might become even more important as the government response to actual flood disasters is very heterogeneous (Eisensee and Strömberg, 2007).

Our study has documented that millions of people respond to location specific risk information (now all large housing search companies provide this flood and climate risk information) . This response reveals that they trust this information. Going forward, fostering competition between spatial risk modeler forecasts and identifying the best models will play an important role in determining the pace of climate risk adaptation. With access to trusted information that becomes common knowledge, real estate developers will be more likely to invest in building in locations and with materials and designs that foster resilience to flooding risk. Insurers will be more likely to engage in risk pricing that provides incentives for greater self-protection investment by those who occupy risky homes.

Redfin is a company whose efforts to educate its customers about climate risks help them to make informed decisions. Redfin chose to incorporate the First Street Foundation risk scores on its platform. Future research could explore how different platforms decide what climate risk information to incorporate into their web page interface. If a platform with a large market share incorporated biased estimates of place based risks, then the scaled dissemination of such information could hinder climate change adaptation.

Throughout this paper, we have assumed that sellers do not strategically respond to the ongoing field experiment. Since Redfin did not receive any complaints from sellers related to the property specific flood information, we do not believe that they were aware that the demand side experiment was unfolding. Going forward, home sellers seeking to sell an objectively climate-risky home (as measured by flood risk, fire risk, and heat risk) will know that potential buyers can go to the FSF webpage and research the home, or this information is just directly on the Redfin platform. Sellers of such risky homes will be likely to have to sell at a discount unless they take proactive and credible steps to upgrade the home's resilience to climate risk. As more sellers seek to offset their homes' climate risk, this will create a new resilience market for goods ranging from better windows to shield the home from PM2.5 from wildfires to anti-flooding strategies (Acemoglu and Linn, 2004). In this sense, the diffusion of emerging risk information accelerates climate change adaptation.

References

Acemoglu, Daron, and Joshua Linn. 2004. "Market size in innovation: theory and evidence from the pharmaceutical industry." *Quarterly Journal of Economics*, 119(3): 1049–1090.

Ainsworth, Robert, Rajeev Dehejia, Cristian Pop-Eleches, and Miguel Urquiola. 2023. "Why do households leave school value added on the table? The roles of information and preferences." *American Economic Review*, 113(4): 1049–1082.

Allcott, Hunt. 2015. "Site selection bias in program evaluation." *The Quarterly Journal of Economics*, 130(3): 1117–1165.

Aragón, Fernando M, Francisco Oteiza, and Juan Pablo Rud. 2021. "Climate change and agriculture: subsistence farmers' response to extreme heat." *American Economic Journal: Economic Policy*, 13(1): 1–35.

Armal, Saman, Jeremy R Porter, Brett Lingle, Ziyan Chu, Michael L Marston, and Oliver EJ Wing. 2020. "Assessing property level economic impacts of climate in the US, new insights and evidence from a comprehensive flood risk assessment tool." *Climate*, 8(10): 116.

Athey, Susan, and Stefan Wager. 2021. "Policy learning with observational data." *Econometrica*, 89(1): 133–161.

Athey, Susan, Julie Tibshirani, and Stefan Wager. 2019. "Generalized random forests."

Atreya, Ajita, and Jeffrey Czajkowski. 2019. "Graduated flood risks and property prices in Galveston County." *Real Estate Economics*, 47(3): 807–844.

Auffhammer, Maximilian. 2018. "Quantifying economic damages from climate change." *Journal of Economic Perspectives*, 32(4): 33–52.

Bajari, Patrick, Jane Cooley Fruehwirth, Christopher Timmins, et al. 2012. "A rational expectations approach to hedonic price regressions with time-varying unobserved product attributes: The price of pollution." *American Economic Review*, 102(5): 1898–1926.

Bakkensen, Laura A, and Lint Barrage. 2022. "Going underwater? Flood risk belief heterogeneity and coastal home price dynamics." *The Review of Financial Studies*, 35(8): 3666–3709.

Balboni, Clare Alexandra. 2019. "In harm's way? infrastructure investments and the persistence of coastal cities." PhD diss. London School of Economics and Political Science.

Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis. 2020. "Does climate change affect real estate prices? Only if you believe in it." *Review of Financial Studies*, 33(3): 1256–1295.

Banzhaf, H Spencer. 2021. "Difference-in-differences hedonics." *Journal of Political Economy*, 129(8): 2385–2414.

Banzhaf, H Spencer, and Randall P Walsh. 2008. "Do people vote with their feet? An empirical test of Tiebout's mechanism." *American Economic Review*, 98(3): 843–863.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro. 2016. "Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century." *Journal of Political Economy*, 124(1): 105–159.

Barwick, Panle Jia, Shanjun Li, Liguo Lin, and Eric Zou. 2019. "From fog to smog: The value of pollution information." National Bureau of Economic Research.

Bates, Paul. 2023. "Fundamental limits to flood inundation modelling." *Nature Water*, 1–2.

Bates, Paul D, Niall Quinn, Christopher Sampson, Andrew Smith, Oliver Wing, Jeison Sosa, James Savage, Gaia Olcese, Jeff Neal, Guy Schumann, et al. 2021. "Combined modeling of US fluvial, pluvial, and coastal flood hazard under current and future climates." *Water Resources Research*, 57(2): e2020WR028673.

Bayer, Patrick, Kyle Mangum, and James W Roberts. 2021. "Speculative fever: Investor contagion in the housing bubble." *American Economic Review*, 111(2): 609–651.

Bayer, Patrick, Robert McMillan, Alvin Murphy, and Christopher Timmins. 2016. "A dynamic model of demand for houses and neighborhoods." *Econometrica*, 84(3): 893–942.

Baylis, Patrick, and Judson Boomhower. 2023. "The economic incidence of wildfire suppression in the United States." *American Economic Journal: Applied Economics*, 15(1): 442–473.

Beltrán, Allan, David Maddison, and Robert JR Elliott. 2018. "Is flood risk capitalised into property values?" *Ecological Economics*, 146: 668–685.

Benetton, Matteo, Simone Emiliozzi, Elisa Guglielminetti, Michele Loberto, and Alessandro Mistretta. 2022. "Do house prices reflect climate change adaptation? Evidence from the city on the water." *Evidence from the City on the Water (November 21, 2022). Bank of Italy Occasional Paper*, , (735).

Bento, Antonio, Noah S Miller, Mehreen Mookerjee, and Edson R Severnini. 2020. "A unifying approach to measuring climate change impacts and adaptation." National Bureau of Economic Research.

Bergman, Peter, Eric W Chan, and Adam Kapor. 2020. "Housing search frictions: Evidence from detailed search data and a field experiment." National Bureau of Economic Research.

Bergman, Peter, Raj Chetty, Stefanie DeLuca, Nathaniel Hendren, Lawrence F Katz, and Christopher Palmer. 2019. "Creating moves to opportunity: Experimental evidence on barriers to neighborhood choice." National Bureau of Economic Research.

Bernstein, Asaf, Matthew T Gustafson, and Ryan Lewis. 2019. "Disaster on the horizon: The price effect of sea level rise." *Journal of Financial Economics*, 134(2): 253–272.

Bernstein, Asaf, Stephen B Billings, Matthew T Gustafson, and Ryan Lewis. 2022. "Partisan residential sorting on climate change risk." *Journal of Financial Economics*, 146(3): 989–1015.

Biardeau, Léopold T, Lucas W Davis, Paul Gertler, and Catherine Wolfram. 2020. "Heat exposure and global air conditioning." *Nature Sustainability*, 3(1): 25–28.

Bilal, Adrien, and Esteban Rossi-Hansberg. 2023. "Anticipating Climate Change Across the United States."

Bin, Okmyung, and Craig E Landry. 2013. "Changes in implicit flood risk premiums: Empirical evidence from the housing market." *Journal of Environmental Economics and Management*, 65(3): 361–376.

Bin, Okmyung, and Jamie Brown Kruse. 2006. "Real estate market response to coastal flood hazards." *Natural Hazards Review*, 7(4): 137–144.

Bin, Okmyung, Thomas W Crawford, Jamie B Kruse, and Craig E Landry. 2008. "Viewscapes and flood hazard: Coastal housing market response to amenities and risk." *Land Economics*, 84(3): 434–448.

Bishop, Kelly C, and Alvin D Murphy. 2011. "Estimating the willingness to pay to avoid violent crime: A dynamic approach." *American Economic Review*, 101(3): 625–29.

Bishop, Kelly C, and Alvin D Murphy. 2019. "Valuing time-varying attributes using the hedonic model: When is a dynamic approach necessary?" *Review of Economics and Statistics*, 101(1): 134–145.

Boomhower, Judson, Meredith Fowlie, and Andrew J Plantinga. 2023. "Wildfire Insurance, Information, and Self-Protection." Vol. 113, 310–315, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Bottan, Nicolas L, and Ricardo Perez-Truglia. 2020. "Betting on the house: Subjective expectations and market choices." National Bureau of Economic Research.

Botzen, WJ Wouter, Howard Kunreuther, and Erwann Michel-Kerjan. 2015. "Divergence between individual perceptions and objective indicators of tail risks: Evidence from floodplain residents in New York City." *Judgment and Decision Making*, 10(4): 365–385.

Botzen, Wouter JW, JCJH Aerts, and Jeroen CJM van den Bergh. 2009. "Dependence of flood risk perceptions on socioeconomic and objective risk factors." *Water Resources Research*, 45(10).

Bradt, Jacob T, and Joseph E Aldy. 2022. "Private Benefits from Public Investment in Climate Adaptation and Resilience."

Bubeck, Philip, Willem Jan Wouter Botzen, and Jeroen CJH Aerts. 2012. "A review of risk perceptions and other factors that influence flood mitigation behavior." *Risk Analysis*, 32(9): 1481–1495.

Burlig, Fiona, Amir Jina, Erin M Kelley, Gregory V Lane, and Harshil Sahai. 2024. "Long-range forecasts as climate adaptation: Experimental evidence from developing-country agriculture." National Bureau of Economic Research.

Burnside, Craig, Martin Eichenbaum, and Sergio Rebelo. 2016. "Understanding booms and busts in housing markets." *Journal of Political Economy*, 124(4): 1088–1147.

Carleton, Tamma, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Robert E Kopp, Kelly E McCusker, Ishan Nath, et al. 2022. "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits." *Quarterly Journal of Economics*.

Castro-Vincenzi, Juanma. 2023. "Climate hazards and resilience in the global car industry." Technical report, Working Paper.

Chetty, Raj, and Nathaniel Hendren. 2018. "The impacts of neighborhoods on intergenerational mobility I: Childhood exposure effects." *The Quarterly Journal of Economics*, 133(3): 1107–1162.

Chetty, Raj, Nathaniel Hendren, and Lawrence F Katz. 2016. "The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment." *American Economic Review*, 106(4): 855–902.

Cole, Shawn, Tomoko Harigaya, and Vaishnavi Surendra. 2023. "Probabilistic Weather Forecasts and Farmer Decision Making in Rural India."

Conell-Price, Lynn, and Philip Mulder. 2024. "Does Good News Wash out the Bad? Belief Updating and Climate Risk Information." *Belief Updating and Climate Risk Information (March 1, 2024). Consumer Financial Protection Bureau Office of Research Working Paper*, , (24-04).

Cooper, CM, S Sharma, RE Nicholas, and K Keller. 2022. "Toward More Actionable Flood-Risk Information." *Earth's Future*, 10(11): e2022EF003093.

Costa, Dora L, and Matthew E Kahn. 2013. "Energy conservation "nudges" and environmentalist ideology: Evidence from a randomized residential electricity field experiment." *Journal of the European Economic Association*, 11(3): 680–702.

Crépon, Bruno, Esther Duflo, Marc Gurgand, Roland Rathelot, and Philippe Zamora. 2013. "Do labor market policies have displacement effects? Evidence from a clustered randomized experiment." *The Quarterly Journal of Economics*, 128(2): 531–580.

Cruz Álvarez, José Luis, and Esteban Rossi-Hansberg. 2021. "The economic geography of global warming." *University of Chicago, Becker Friedman Institute for Economics Working Paper*, , (2021-130).

Daniel, Vanessa E, Raymond JGM Florax, and Piet Rietveld. 2009. "Flooding risk and housing values: An economic assessment of environmental hazard." *Ecological Economics*, 69(2): 355–365.

Davis, Lucas, Paul Gertler, Stephen Jarvis, and Catherine Wolfram. 2021. "Air conditioning and global inequality." *Global Environmental Change*, 69: 102299.

DeFusco, Anthony, Wenjie Ding, Fernando Ferreira, and Joseph Gyourko. 2018. "The role of price spillovers in the American housing boom." *Journal of Urban Economics*, 108: 72–84.

Deschenes, Olivier, Michael Greenstone, and Joseph S Shapiro. 2017. "Defensive investments and the demand for air quality: Evidence from the NOx budget program." *American Economic Review*, 107(10): 2958–2989.

Desmet, Klaus, Robert E Kopp, Scott A Kulp, Dávid Krisztián Nagy, Michael Oppenheimer, Esteban Rossi-Hansberg, and Benjamin H Strauss. 2021. "Evaluating the Economic Cost of Coastal Flooding." *American Economic Journal: Macroeconomics*, 13(2): 444–86.

Dottori, Francesco, Wojciech Szewczyk, Juan-Carlos Ciscar, Fang Zhao, Lorenzo Alfieri, Yukiko Hirabayashi, Alessandra Bianchi, Ignazio Mongelli, Katja Frieler, Richard A Betts, et al. 2018. "Increased human and economic losses from river flooding with anthropogenic warming." *Nature Climate Change*, 8(9): 781–786.

Downey, Mitch, Nelson Lind, and Jeffrey G Shrader. 2023. "Adjusting to rain before it falls." *Management Science*.

Dundas, Steven J, and Roger H von Haefen. 2020. "The effects of weather on recreational fishing demand and adaptation: implications for a changing climate." *Journal of the Association of Environmental and Resource Economists*, 7(2): 209–242.

Dunlap, Riley E, Aaron M McCright, and Jerrod H Yarosh. 2016. "The political divide on climate change: Partisan polarization widens in the US." *Environment: Science and Policy for Sustainable Development*, 58(5): 4–23.

Dunlap, Riley E, and Araon M McCright. 2008. "A widening gap: Republican and Democratic views on climate change." *Environment: Science and Policy for Sustainable Development*, 50(5): 26–35.

Eichholtz, Piet, Eva Steiner, and Erkan Yönder. 2019. "Where, when, and how do sophisticated investors respond to flood risk?" *Available at SSRN 3206257*.

Eisensee, Thomas, and David Strömberg. 2007. "News droughts, news floods, and US disaster relief." *The Quarterly Journal of Economics*, 122(2): 693–728.

Epple, Dennis. 1987. "Hedonic prices and implicit markets: estimating demand and supply functions for differentiated products." *Journal of Political Economy*, 95(1): 59–80.

Favilukis, Jack, and Stijn Van Nieuwerburgh. 2021. "Out-of-town home buyers and city welfare." *Journal of Finance*, 76(5): 2577–2638.

First Street Foundation. 2020. "First street foundation flood model: technical methodology document."

Flavelle, Christopher, Denise Lu, Veronica Penney, Nadja Popovich, and John Schwartz. 2020. "New data reveals hidden flood risk across America." *The New York Times*, 29.

Fried, Stephie. 2022. "Seawalls and stilts: A quantitative macro study of climate adaptation." *Review of Economic Studies*, 89(6): 3303–3344.

Gabrovski, Miroslav, and Victor Ortego-Marti. 2021. "Search and credit frictions in the housing market." *European Economic Review*, 134: 103699.

Gallagher, Justin. 2014. "Learning about an infrequent event: evidence from flood insurance take-up in the United States." *American Economic Journal: Applied Economics*, 206–233.

Gao, Xuwen, Ran Song, and Christopher Timmins. 2023. "Information, migration, and the value of clean air." *Journal of Development Economics*, 103079.

Garbarino, Nicola, and Benjamin Guin. 2021. "High water, no marks? Biased lending after extreme weather." *Journal of Financial Stability*, 54: 100874.

Genesove, David, and Christopher J Mayer. 1997. "Equity and time to sale in the real estate market." *American Economic Review*, 87(3): 255.

Genesove, David, and Lu Han. 2012. "Search and matching in the housing market." *Journal of Urban Economics*, 72(1): 31–45.

Giannias, Dimitrios A. 1999. "Market positioning of differentiated products." *International Journal of the Economics of Business*, 6(1): 29–39.

Gibson, Matthew, and Jamie T Mullins. 2020. "Climate risk and beliefs in new york floodplains." *Journal of the Association of Environmental and Resource Economists*, 7(6): 1069–1111.

Giglio, Stefano, Bryan Kelly, and Johannes Stroebel. 2021. "Climate finance." *Annual Review of Financial Economics*, 13: 15–36.

Giglio, Stefano, Matteo Maggiori, Krishna Rao, Johannes Stroebel, and Andreas Weber. 2021. "Climate change and long-run discount rates: Evidence from real estate." *Review of Financial Studies*, 34(8): 3527–3571.

Glaeser, Edward L, and Charles G Nathanson. 2017. "An extrapolative model of house price dynamics." *Journal of Financial Economics*, 126(1): 147–170.

Glaeser, Edward L, and Joseph Gyourko. 2005. "Urban decline and durable housing." *Journal of Political Economy*, 113(2): 345–375.

Gourevitch, Jesse D, Carolyn Kousky, Yanjun Liao, Christoph Nolte, Adam B Pollack, Jeremy R Porter, and Joakim A Weill. 2023. "Unpriced climate risk and the potential consequences of overvaluation in US housing markets." *Nature Climate Change*, 13(3): 250–257.

Greenstone, Michael. 2017. "The continuing impact of Sherwin Rosen's "Hedonic prices and implicit markets: product differentiation in pure competition"." *Journal of Political Economy*, 125(6): 1891–1902.

Guren, Adam M. 2018. "House price momentum and strategic complementarity." *Journal of Political Economy*, 126(3): 1172–1218.

Hallegatte, Stéphane. 2008. "An adaptive regional input-output model and its application to the assessment of the economic cost of Katrina." *Risk Analysis*, 28(3): 779–799.

Hallstrom, Daniel G, and V Kerry Smith. 2005. "Market responses to hurricanes." *Journal of Environmental Economics and Management*, 50(3): 541–561.

Harrison, David, Greg T. Smersh, and Arthur Schwartz. 2001. "Environmental determinants of housing prices: the impact of flood zone status." *Journal of Real Estate Research*, 21(1-2): 3–20.

Harrison, Glenn W, and John A List. 2004. "Field experiments." *Journal of Economic Literature*, 42(4): 1009–1055.

Head, Allen, Huw Lloyd-Ellis, and Hongfei Sun. 2014. "Search, liquidity, and the dynamics of house prices and construction." *American Economic Review*, 104(4): 1172–1210.

Heutel, Garth, Nolan H Miller, and David Molitor. 2021. "Adaptation and the mortality effects of temperature across US climate regions." *Review of Economics and Statistics*, 103(4): 740–753.

Hinkel, Jochen, Daniel Lincke, Athanasios T Vafeidis, Mahé Perrette, Robert James Nicholls, Richard SJ Tol, Ben Marzeion, Xavier Fettweis, Cezar Ionescu, and Anders Levermann. 2014. "Coastal flood damage and adaptation costs under 21st century sea-level rise." *Proceedings of the National Academy of Sciences*, 111(9): 3292–3297.

Hino, Miyuki, and Marshall Burke. 2021. "The effect of information about climate risk on property values." *Proceedings of the National Academy of Sciences*, 118(17): e2003374118.

Hong, Harrison, Neng Wang, and Jinqiang Yang. 2020. "Mitigating disaster risks in the age of climate change." National Bureau of Economic Research.

Honka, Elisabeth, Ali Hortaçsu, and Matthijs Wildenbeest. 2019. "Empirical search and consideration sets." In *Handbook of the Economics of Marketing*. Vol. 1, 193–257. Elsevier.

Hovekamp, Winston, and Katherine R Wagner. 2023. "Efficient Adaptation to Flood Risk."

Hsiao, Allan. 2023. "Sea level rise and urban adaptation in Jakarta." *Technical Report*.

IPCC. 2021. "Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change."

Ito, Koichiro, and Shuang Zhang. 2020. "Willingness to pay for clean air: Evidence from air purifier markets in China." *Journal of Political Economy*, 128(5): 1627–1672.

Jia, Ruixue, Xiao Ma, and Victoria Wenxin Xie. 2022. "Expecting floods: Firm entry, employment, and aggregate implications." National Bureau of Economic Research.

Kahn, Matthew E. 2020. "The climate change adaptation literature." *Review of Environmental Economics and Policy*.

Kahn, Matthew E, Kamiar Mohaddes, Ryan NC Ng, M Hashem Pesaran, Mehdi Raissi, and Jui-Chung Yang. 2021. "Long-term macroeconomic effects of climate change: A cross-country analysis." *Energy Economics*, 104: 105624.

Keller, Carmen, Michael Siegrist, and Heinz Gutscher. 2006. "The role of the affect and availability heuristics in risk communication." *Risk Analysis*, 26(3): 631–639.

Keys, Benjamin J, and Philip Mulder. 2020. "Neglected no more: Housing markets, mortgage lending, and sea level rise." National Bureau of Economic Research.

Koks, Elco E, Md Bočkarjova, Hans de Moel, and Jeroen CJH Aerts. 2015. "Integrated direct and indirect flood risk modeling: development and sensitivity analysis." *Risk Analysis*, 35(5): 882–900.

Kousky, Carolyn. 2010. "Learning from extreme events: Risk perceptions after the flood." *Land Economics*, 86(3): 395–422.

Kousky, Carolyn, and Noelwah R Netusil. 2023. "Flood insurance literacy and flood risk knowledge: Evidence from Portland, Oregon." *Risk Management and Insurance Review*.

Kousky, Carolyn, Howard Kunreuther, Michael LaCour-Little, and Susan Wachter. 2020. "Flood risk and the US housing market." *Journal of Housing Research*, 29(sup1): S3–S24.

Kuchler, Theresa, Monika Piazzesi, and Johannes Stroebel. 2023. "Housing market expectations." In *Handbook of Economic Expectations*. 163–191. Elsevier.

Kurlat, Pablo, and Johannes Stroebel. 2015. "Testing for information asymmetries in real estate markets." *The Review of Financial Studies*, 28(8): 2429–2461.

Lee, Seunghoon. 2021. "Adapting to natural disasters through better information: Evidence from the home seller disclosure requirement." *MIT Center for Real Estate Research Paper*, , (21/17).

Lemoine, Derek. 2018. "Estimating the consequences of climate change from variation in weather." National Bureau of Economic Research.

List, John A, Azeem M Shaikh, and Atom Vayalinkal. 2023. "Multiple testing with covariate adjustment in experimental economics." *Journal of Applied Econometrics*, 38(6): 920–939.

Manski, Charles F. 2004. "Measuring expectations." *Econometrica*, 72(5): 1329–1376.

Marcoux, Kendra, and Katherine RH Wagner. 2023. "Fifty Years of US Natural Disaster Insurance Policy."

Massetti, Emanuele, and Robert Mendelsohn. 2020. "Measuring climate adaptation: Methods and evidence." *Review of Environmental Economics and Policy*.

McKenzie, Russell, and John Levendis. 2010. "Flood hazards and urban housing markets: The effects of Katrina on New Orleans." *The Journal of Real Estate Finance and Economics*, 40(1): 62–76.

Miller, Stuart, Robert Muir-Wood, and Auguste Boissonnade. 2008. "An exploration of trends in normalized weather-related catastrophe losses." *Climate Extremes and Society*, 12: 225–247.

Molina, Renato, and Ivan Rudik. 2022. "The social value of predicting hurricanes."

Møller, Stig Vinther, Thomas Pedersen, Erik Christian Montes Schütte, and Allan Timmermann. 2023. "Search and predictability of prices in the housing market." *Management Science*.

Mulder, Philip. 2021. "Mismeasuring risk: The welfare effects of flood risk information." Working Paper.

Mulder, Philip, and Carolyn Kousky. 2023. "Risk Rating without Information Provision." Vol. 113, 299–303, American Economic Association.

Muller, Nicholas Z, and Caroline A Hopkins. 2019. "Hurricane katrina floods new jersey: The role of information in the market response to flood risk." National Bureau of Economic Research.

Murfin, Justin, and Matthew Spiegel. 2020. "Is the risk of sea level rise capitalized in residential real estate?" *Review of Financial Studies*, 33(3): 1217–1255.

Myers, Erica, Steven L Puller, and Jeremy West. 2022. "Mandatory energy efficiency disclosure in housing markets." *American Economic Journal: Economic Policy*, 14(4): 453–487.

Ngai, L Rachel, and Kevin D Sheedy. 2020. “The decision to move house and aggregate housing-market dynamics.” *Journal of the European Economic Association*, 18(5): 2487–2531.

Ngai, L Rachel, and Silvana Tenreyro. 2014. “Hot and cold seasons in the housing market.” *American Economic Review*, 104(12): 3991–4026.

NOAA. 2018. “US billion-dollar weather and climate disasters.”

Nordhaus, William D. 1993. “Reflections on the economics of climate change.” *Journal of Economic Perspectives*, 7(4): 11–25.

Ortega, Francesc, and Süleyman Taṣpınar. 2018. “Rising sea levels and sinking property values: Hurricane Sandy and New York’s housing market.” *Journal of Urban Economics*, 106: 81–100.

Ostriker, Abigail, and Anna Russo. 2022. “The Effects of Floodplain Regulation on Housing Markets.”

Ouazad, Amine, and Matthew E Kahn. 2022. “Mortgage finance and climate change: Securitization dynamics in the aftermath of natural disasters.” *Review of Financial Studies*, 35(8): 3617–3665.

Payne, John W, James R Bettman, and Eric J Johnson. 1988. “Adaptive strategy selection in decision making.” *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 14(3): 534.

Piazzesi, Monika, and Martin Schneider. 2009. “Momentum traders in the housing market: Survey evidence and a search model.” *American Economic Review*, 99(2): 406–411.

Piazzesi, Monika, Martin Schneider, and Johannes Stroebel. 2020. “Segmented housing search.” *American Economic Review*, 110(3): 720–759.

Porter, Jeremy R, Evelyn Shu, Michael Amodeo, Ho Hsieh, Ziyan Chu, and Neil Freeman. 2021. “Community Flood Impacts and Infrastructure: Examining National Flood Impacts Using a High Precision Assessment Tool in the United States.” *Water*, 13(21): 3125.

Redfin. 2020. “Redfin Annual Report.”

Romano, Joseph P., and Michael Wolf. 2010. “Balanced control of generalized error rates.” *The Annals of Statistics*, 38(1): 598–633.

Royal, Andrew, and Margaret Walls. 2019. “Flood risk perceptions and insurance choice: Do decisions in the floodplain reflect overoptimism?” *Risk Analysis*, 39(5): 1088–1104.

Seetharam, Ishuwar. 2018. “The indirect effects of hurricanes: Evidence from firm internal networks.” Working Paper.

Severen, Christopher, Christopher Costello, and Olivier Deschenes. 2018. “A Forward-Looking Ricardian Approach: Do land markets capitalize climate change forecasts?” *Journal of Environmental Economics and Management*, 89: 235–254.

Shogren, Jason F, and Tommy Stamland. 2002. "Skill and the Value of Life." *Journal of Political Economy*, 110(5): 1168–1173.

Shrader, Jeffrey. 2023. "Improving climate damage estimates by accounting for adaptation." *Available at SSRN 3212073*.

Shrader, Jeffrey G, Laura Bakkensen, and Derek Lemoine. 2023. "Fatal Errors: The Mortality Value of Accurate Weather Forecasts." National Bureau of Economic Research.

Siegrist, Michael, and Heinz Gutscher. 2006. "Flooding risks: A comparison of lay people's perceptions and expert's assessments in Switzerland." *Risk Analysis*, 26(4): 971–979.

Slovic, Paul. 1987. "Perception of risk." *Science*, 236(4799): 280–285.

Tversky, Amos. 1972. "Elimination by aspects: A theory of choice." *Psychological Review*, 79(4): 281.

Twisk, Jos, Lisa Bosman, Trynke Hoekstra, Judith Rijnhart, Marieke Welten, and Martijn Heymans. 2018. "Different ways to estimate treatment effects in randomised controlled trials." *Contemporary Clinical Trials Communications*, 10: 80–85.

Viviano, Davide, Kasper Wuthrich, and Paul Niehaus. 2021. "(When) should you adjust inferences for multiple hypothesis testing?" UC San Diego.

Wachinger, Gisela, Ortwin Renn, Chloe Begg, and Christian Kuhlicke. 2013. "The risk perception paradox—implications for governance and communication of natural hazards." *Risk Analysis*, 33(6): 1049–1065.

Wagner, Katherine RH. 2022. "Adaptation and adverse selection in markets for natural disaster insurance." *American Economic Journal: Economic Policy*, 14(3): 380–421.

Wang, Haoluan. 2021. "Flood Your Neighbors: Spillover Effects of Levee Building."

Weill, Joakim. 2022. "Perilous flood risk assessments." *Available at SSRN 4143914*.

Wing, Oliver EJ, Paul D Bates, Andrew M Smith, Christopher C Sampson, Kris A Johnson, Joseph Fargione, and Philip Morefield. 2018. "Estimates of present and future flood risk in the conterminous United States." *Environmental Research Letters*, 13(3): 034023.

Wing, Oliver EJ, William Lehman, Paul D Bates, Christopher C Sampson, Niall Quinn, Andrew M Smith, Jeffrey C Neal, Jeremy R Porter, and Carolyn Kousky. 2022. "Inequitable patterns of US flood risk in the Anthropocene." *Nature Climate Change*, 12(2): 156–162.

Wobus, C, P Zheng, J Stein, C Lay, H Mahoney, M Lorie, D Mills, R Spies, B Szafranski, and J Martinich. 2019. "Projecting changes in expected annual damages from riverine flooding in the United States." *Earth's Future*, 7(5): 516–527.

Wu, Lynn, and Erik Brynjolfsson. 2015. "The future of prediction: How Google searches foreshadow housing prices and sales." In *Economic analysis of the digital economy*. 89–118. University of Chicago Press.

Zhang, Lei. 2016. "Flood hazards impact on neighborhood house prices: A spatial quantile regression analysis." *Regional Science and Urban Economics*, 60: 12–19.

Zhang, Lei, and Tammy Leonard. 2019. "Flood hazards impact on neighborhood house prices." *The Journal of Real Estate Finance and Economics*, 58: 656–674.

A Appendix

A.1 Theory extension

We have considered the case when everyone knows the true distribution of property safety, respectively under two states: without and with climate change. Now suppose the true state is that climate change takes place, but only k% of the population (randomly selected) know the true distribution of safety is $N(\bar{f}', \sigma_f'^2$. Consumers' utility depends on their perceived safety level and the price of the property. Their perceived safety hinges upon their belief on climate change. Consider those without the true information. They have a p% probability to believe climate change is not happening and a $(1-p)$% to believe the opposite. They seek to maximize their expected utility. Then these consumers face the following maximization problem, where P_2 denotes the price equilibrium function in this economy without full information:

$$Max_{h_1} pU(h_0, I - P_2(h_1), \alpha) + (1-p)pU(h_1, I - P_2(h_1), \alpha) \tag{10}$$

While consumers with updated information (i.e., know the true distribution, no uncertainty) face the following:

$$Max_{h_1} U(h_1, I - P_2(h_1), \alpha) \tag{11}$$

Note that from the definition of h_1 and h_0, we can rewrite $h_0 = \frac{h_1\sigma_f' + \bar{f}' - \bar{f}}{\sigma_f}$, which would allow us to solve for h1 in the first case.

The maximization problems can be solved by finding the first order conditions. From the first order conditions, the demand for safety for the two groups of consumers can be written as, where n_1'' and n_0'' are coefficients of $P_2(h)$:

$$h_0 = \frac{(\gamma_1 + \gamma_2\alpha)(p\frac{\sigma_f'}{\sigma_f} + 1 - p) + p(\frac{\rho\sigma_f'}{\sigma_f^2} - \frac{\omega\pi_1''}{\sigma_f})(\bar{f}' - \bar{f}) + \omega(I - \pi_0'')(p\frac{\sigma_f'}{\sigma_f} + 1 - p) - \theta\pi_1''}{2\omega\pi_1''(p\frac{\sigma_f'}{\sigma_f} + 1 - p) - \rho((\frac{\sigma_f'}{\sigma_f})^2 + 1 - p)} \tag{12}$$

$$h_1 = \frac{\gamma_1 + \gamma_2\alpha + \omega I - \omega\pi_0'' - \theta\pi_1''}{2\omega\pi_1'' - \rho} \tag{13}$$

A.2 The Treatments

Figure A1: The First Street Foundation flood score matrix calculation

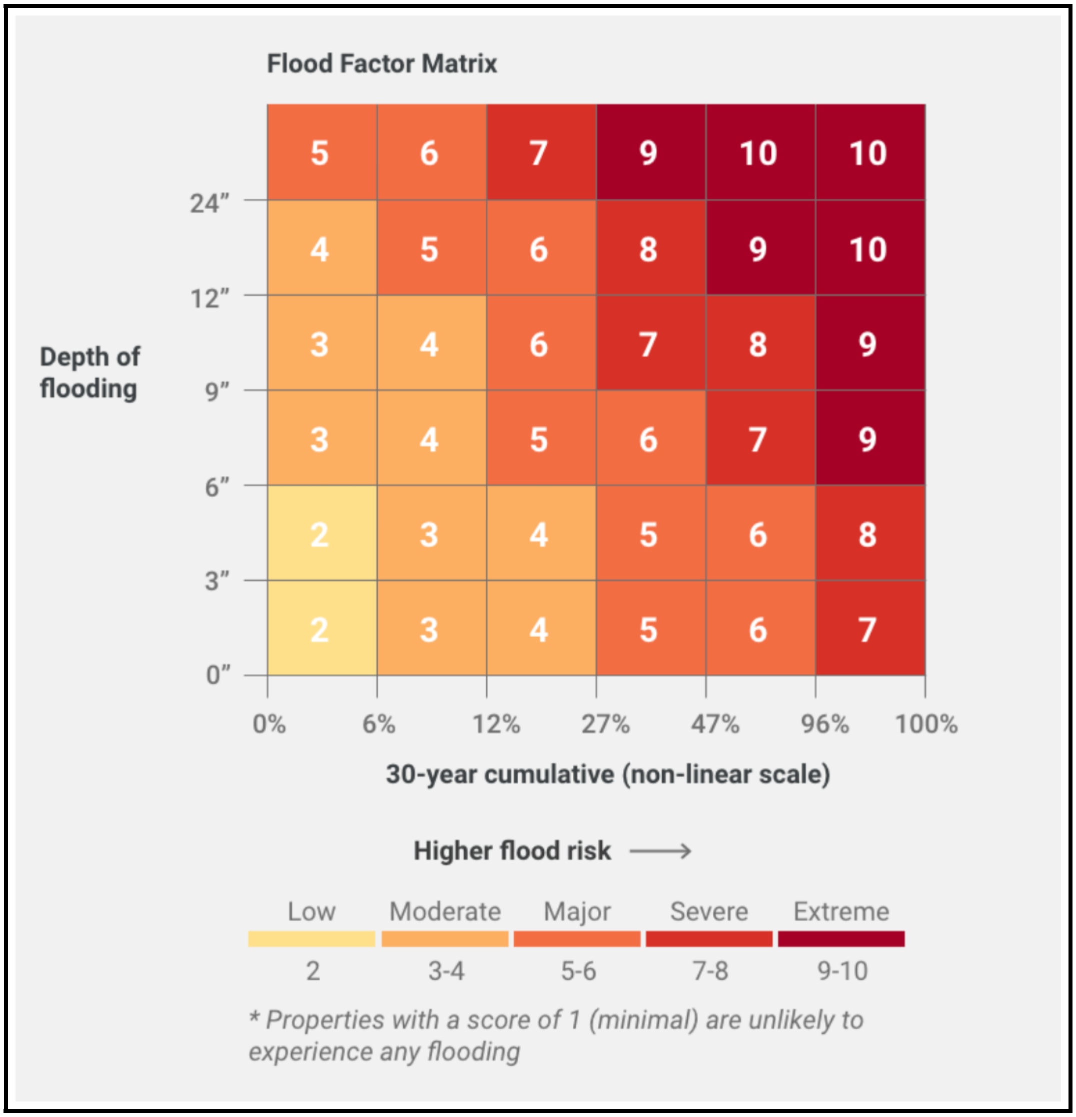
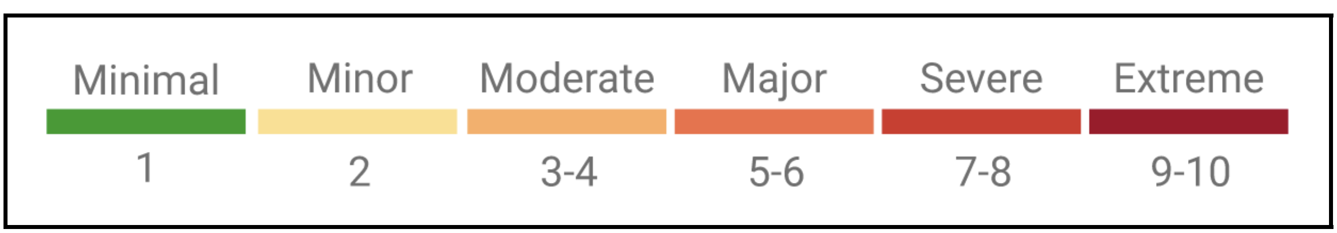


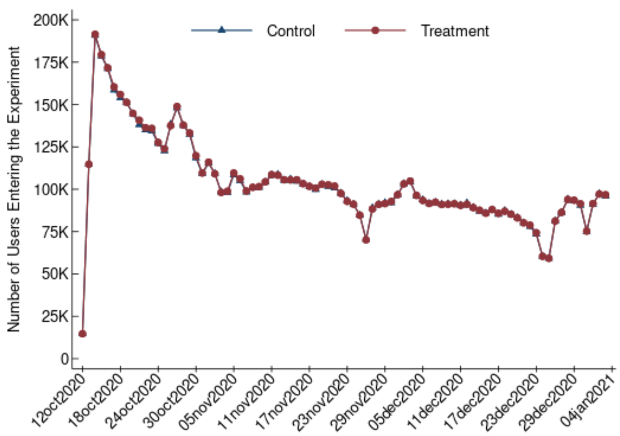
Figure A2: Colors and Labels of Flood Scores Displayed



A.3 Additional figures and tables

Figure A3: Number of Users Entering the Experiment

(a) By Day



(b) Cumulative

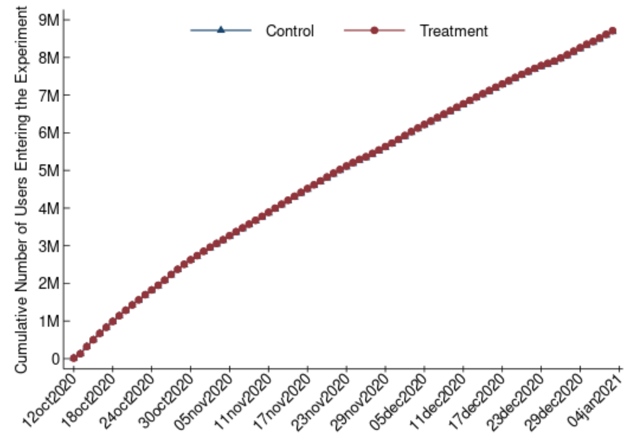


Table A1: Balance Tests for Registered Users

	(1) Views	(2) Bedrooms	(3) Bathrooms	(4) Sq. Ft.	(5) List Price	(6) Flood Score	(7) HHI Zip
Treatment	0.012	-0.004**	-0.040	-20.732	51497.580	0.000	-1.047
	(0.011)	(0.001)	(0.035)	(17.045)	(60686.895)	(0.001)	(5.388)
Constant	4.616***	3.427***	2.717***	2347.868***	798274.542***	1.749***	6974.568***
	(0.343)	(0.006)	(0.071)	(13.855)	(23944.058)	(0.007)	(125.229)
Obs.	3,886,331	3,832,821	3,828,927	3,811,433	3,827,826	3,845,367	3,886,331

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Coefficients are in the form of $(e^{\beta} - 1)$.

Table A2: Balance Tests for Registered Users

	(1) New Construction	(2) Short Sale	(3) Year Built	(4) Walk Score	(5) Transit Score	(6) Bike Score
Treatment	0.000	-0.000	-0.000	0.000	-0.000	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.035***	0.005***	1971.718***	25.411***	32.484***	35.014***
	(0.000)	(0.000)	(0.056)	(0.052)	(0.044)	(0.045)
Obs.	3,756,792	3,756,792	3,687,767	3,479,666	2,197,226	3,609,231

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Except for columns (1) and (2), coefficients are in the form of $(e^{\beta} - 1)$.

Table A3: Balance Tests for All Users

	(1) Views	(2) Bedrooms	(3) Bathrooms	(4) Sq. Ft.	(5) List Price	(6) Flood Score	(7) HHI Zip
Treatment	-0.000	0.000	0.000	0.000	-0.000	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.179***	2.286***	1.357***	2024.415***	485799.127***	0.369***	7085.469***
	(0.001)	(0.001)	(0.000)	(0.711)	(333.888)	(0.000)	(2.706)
Obs.	20,263,675	19,553,720	19,749,101	19,702,920	19,276,527	20,007,907	20,263,675

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Coefficients are in the form of $(e^{\beta} - 1)$.

Table A4: Balance Tests for All Users

	(1) New Construction	(2) Short Sale	(3) Year Built	(4) Walk Score	(5) Transit Score	(6) Bike Score
Treatment	0.000	0.000	0.000	-0.003**	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.037***	0.007***	1972.515***	24.693***	32.771***	34.417***
	(0.000)	(0.000)	(0.021)	(0.019)	(0.016)	(0.016)
Obs.	20,263,675	20,263,675	19,710,317	18,362,013	10,963,216	19,221,707

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Except for columns (1) and (2), coefficients are in the form of $(e^{\beta} - 1)$.

Table A5: Balance Tests for Registered Users (Low Flood Score)

	(1) Views	(2) Bedrooms	(3) Bathrooms	(4) Sq. Ft.	(5) List Price	(6) Flood Score	(7) HHI Zip
Treatment	0.001	-0.001	-0.002	-0.003	-0.007*	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.688***	2.306***	1.368***	2043.907***	509464.695***	0.243***	5967.618***
	(0.065)	(0.003)	(0.002)	(2.925)	(2336.592)	(0.000)	(112.946)
Obs.	3,201,727	3,150,989	3,164,474	3,154,546	3,157,116	3,192,673	3,201,727

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Coefficients are in the form of $(e^{\beta} - 1)$.

Table A6: Balance Tests for Registered Users (Low Flood Score)

	(1) New Construction	(2) Short Sale	(3) Year Built	(4) Walk Score	(5) Transit Score	(6) Bike Score
Treatment	0.000	-0.000	-0.000	-0.001	-0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.036***	0.005***	1971.660***	25.146***	32.104***	34.440***
	(0.000)	(0.000)	(0.203)	(0.113)	(0.253)	(0.070)
Obs.	3,201,727	3,201,727	3,156,132	2,984,810	1,897,289	3,093,164

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Except for columns (1) and (2), coefficients are in the form of $(e^{\beta} - 1)$.

Table A7: Balance Tests for Registered Users (Medium Flood Score)

	(1) Views	(2) Bedrooms	(3) Bathrooms	(4) Sq. Ft.	(5) List Price	(6) Flood Score	(7) HHI Zip
Treatment	-0.002	-0.002	-0.004	-0.005	-0.011	0.003	0.004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.479***	2.061***	1.255***	1871.379***	490104.659***	1.693***	6393.800***
	(0.049)	(0.004)	(0.002)	(5.119)	(2866.718)	(0.007)	(102.238)
Obs.	496,765	484,654	487,313	484,647	489,071	495,171	496,765

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Coefficients are in the form of $(e^{\beta} - 1)$.

Table A8: Balance Tests for Registered Users (Medium Flood Score)

	(1) New Construction	(2) Short Sale	(3) Year Built	(4) Walk Score	(5) Transit Score	(6) Bike Score
Treatment	-0.001	-0.000	-0.000	0.006	0.001	0.004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.034***	0.006***	1971.419***	27.544***	34.902***	38.944***
	(0.000)	(0.000)	(0.171)	(0.184)	(0.220)	(0.138)
Obs.	496,765	496,765	485,020	454,676	282,374	473,876

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Except for columns (1) and (2), coefficients are in the form of $(e^{\beta} - 1)$.

Table A9: Balance Tests for Registered Users (High Flood Score)

	(1) Views	(2) Bedrooms	(3) Bathrooms	(4) Sq. Ft.	(5) List Price	(6) Flood Score	(7) HHI Zip
Treatment	-0.014	0.011	0.014	0.018	0.006	-0.005	-0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.346***	1.750***	1.251***	1744.026***	501075.050***	6.417***	7333.455***
	(0.040)	(0.015)	(0.012)	(21.034)	(12133.754)	(0.031)	(103.815)
Obs.	34,191	33,072	33,295	33,127	33,716	33,992	34,191

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Coefficients are in the form of $(e^{\beta} - 1)$.

Table A10: Balance Tests for Registered Users (High Flood Score)

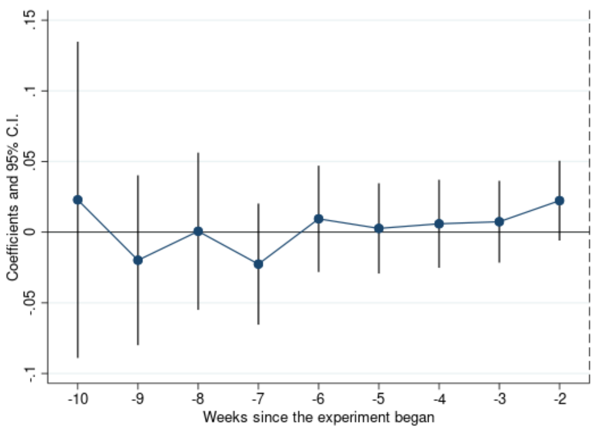
	(1) New Construction	(2) Short Sale	(3) Year Built	(4) Walk Score	(5) Transit Score	(6) Bike Score
Treatment	0.009**	-0.001	0.000	0.034	0.040*	0.018
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Constant	0.030***	0.006***	1977.218***	23.030***	34.823***	40.533***
	(0.000)	(0.000)	(0.458)	(0.490)	(0.414)	(0.377)
Obs.	34,191	34,191	33,193	30,790	13,613	32,271

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Except for columns (1) and (2), coefficients are in the form of $(e^{\beta} - 1)$.

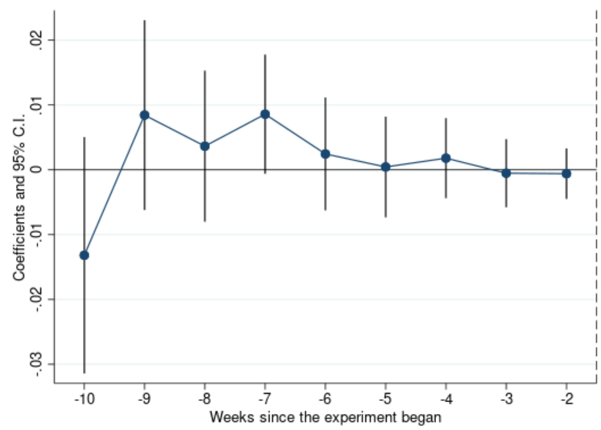
Figure A4: Balance Tests Trajectories

Estimates relative to the week before the experiment began

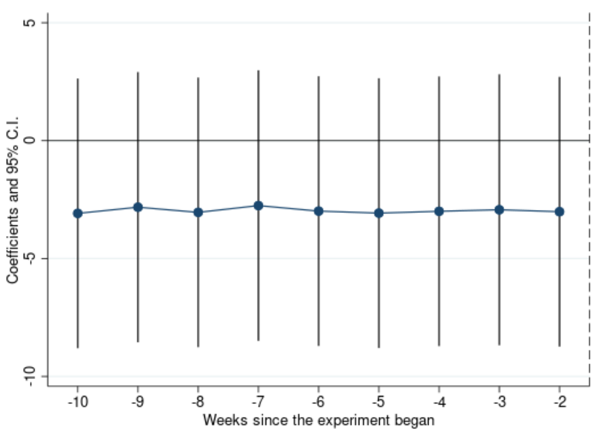
(a) Views



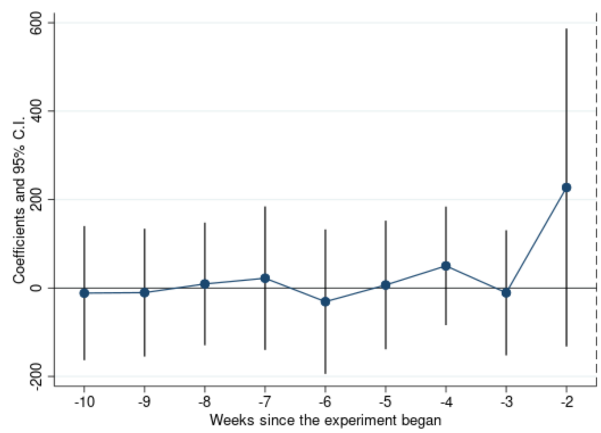
(b) Bedrooms



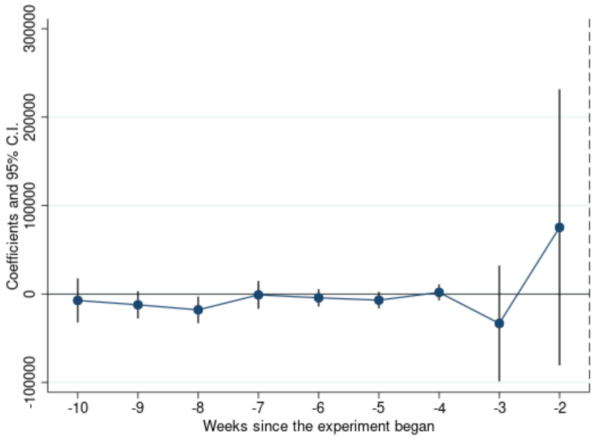
(c) Bathrooms



(d) Sq. Ft.



(e) List Price



(f) Flood Score

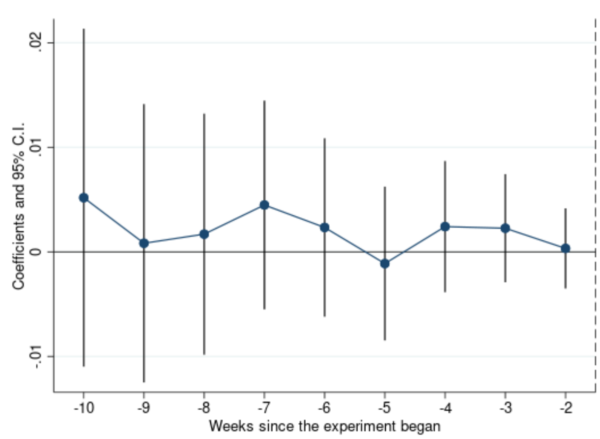


Table A11: Pre-Experiment Distribution of Flood Score for Registered Users by Treatment Status

Number of Registered Users; Column Percentages in Parenthesis

Flood Score Category	Control	Treatment	Total
Low	369,997	369,779	739,776
	(83.41)	(83.46)	(82.82)
Medium	66,976	66,566	133,542
	(15.10)	(15.02)	(15.10)
High	6,592	6,707	13,299
	(1.49)	(1.51)	(1.50)
Total	443,565	443,052	886,617
	(100.00)	(100.00)	(100.00)

Table A12: Pre-Experiment Distribution of Flood Score for Users by Treatment Status

Number of Users; Column Percentages in Parenthesis

Flood Score Category	Control	Treatment	Total
Low	2,382,113	2,383,094	4,765,207
	(82.79)	(82.84)	(82.82)
Medium	435,051	433,629	868,680
	(15.12)	(15.07)	(15.10)
High	60,086	60,037	120,123
	(2.07)	(2.08)	(2.08)
Total	2,877,250	2,876,760	5,754,010
	(100.00)	(100.00)	(100.00)

Table A13: Registered vs. Non-Registered Users During the Pre-Experiment Phase

	(1) Views	(2) Bedrooms	(3) Bathrooms	(4) Sq. Ft.	(5) List Price	(6) Flood Score	(7) HHI Zip
Registered	0.313***	-0.009***	-0.003***	-0.007***	0.063***	0.031***	-0.194***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.023***	2.292***	1.356***	2025.810***	475826.054***	0.359***	7508.680***
	(0.000)	(0.000)	(0.000)	(0.547)	(249.535)	(0.000)	(2.022)
Obs.	19,091,234	18,401,110	18,592,661	18,551,868	18,117,389	18,848,928	19,091,234

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Coefficients are in the form of $(e^{\beta} - 1)$.

Table A14: Registered vs. Non-Registered Users During the Pre-Experiment Phase

	(1) New Construction	(2) Short Sale	(3) Year Built	(4) Walk Score	(5) Transit Score	(6) Bike Score
Registered	-0.002***	-0.003***	-0.001***	0.042***	-0.011***	0.027***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.037***	0.008***	1972.762***	24.336***	32.853***	34.106***
	(0.000)	(0.000)	(0.016)	(0.014)	(0.013)	(0.013)
Obs.	19,091,234	19,091,234	18,558,011	17,264,853	10,223,715	18,090,938

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Except for columns (1) and (2), coefficients are in the form of $(e^{\beta} - 1)$.

Table A15: ATE on the Characteristics of the Homes Viewed

% Change relative to Control

	(1) Views	(2) Bedrooms	(3) Bathrooms	(4) Sq. Ft.	(5) List Price	(6) Flood Score	(7) HHI Zip
Experiment began	21.896***	0.091***	0.100***	-0.346***	-2.783***	1.082***	-7.009***
	(0.056)	(0.022)	(0.026)	(0.034)	(0.065)	(0.035)	(0.039)
Treatment	-0.026	0.061	0.020	0.030	0.031	-0.065	0.043
	(0.075)	(0.033)	(0.039)	(0.051)	(0.100)	(0.050)	(0.054)
Diff-in-diffs	-0.010	-0.044	-0.004	-0.016	-0.027	-0.015	-0.060
	(0.079)	(0.032)	(0.037)	(0.048)	(0.092)	(0.049)	(0.055)
Obs.	82,829,780	79,522,502	80,268,396	80,114,762	78,399,668	81,365,064	82,829,780

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Note: Coefficients are in the form of $((e^{\beta}-1)\cdot 100)$ from equation 6.

Table A16: ATE for Registered Users on the Characteristics of the Homes Viewed

% Change relative to Control

	(1) Views	(2) Bedrooms	(3) Bathrooms	(4) Sq. Ft.	(5) List Price	(6) Flood Score	(7) HHI Zip
Experiment began	20.278***	0.336***	0.288***	-0.311***	-2.917***	0.837***	-7.926***
	(0.155)	(0.058)	(0.069)	(0.090)	(0.175)	(0.087)	(0.109)
Treatment	0.023	-0.118	-0.230*	-0.295*	-0.731**	-0.068	0.029
	(0.209)	(0.087)	(0.103)	(0.135)	(0.268)	(0.128)	(0.153)
Diff-in-diffs	-0.021	0.096	0.091	0.116	0.193	-0.078	-0.183
	(0.219)	(0.082)	(0.097)	(0.126)	(0.246)	(0.123)	(0.154)
Obs.	15,074,700	14,779,817	14,837,436	14,771,224	14,834,564	14,889,899	15,074,700

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Note: Coefficients are in the form of $((e^{\beta}-1)\cdot 100)$ from equation 6.

Table A17: ATE on the Characteristics of the Homes Viewed with Pre-Experiment Information

% Change relative to Control

	(1) Views	(2) Bedrooms	(3) Bathrooms	(4) Sq. Ft.	(5) List Price	(6) Flood Score	(7) HHI Zip
Experiment began	28.066***	0.210***	0.463***	-0.136***	0.704***	1.586***	-12.333***
	(0.065)	(0.025)	(0.029)	(0.038)	(0.072)	(0.038)	(0.045)
Treatment	-0.032	0.062	0.020	0.032	0.031	-0.065	0.040
	(0.076)	(0.033)	(0.039)	(0.051)	(0.100)	(0.050)	(0.055)
Diff-in-diffs	0.070	-0.048	-0.008	-0.036	0.019	-0.023	-0.059
	(0.091)	(0.035)	(0.041)	(0.053)	(0.102)	(0.053)	(0.063)
Obs.	60,606,062	59,045,933	59,514,136	59,398,412	58,427,212	60,459,949	60,606,062

Note: *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Standard Errors Clustered at the User Level. Note: Coefficients are in the form of $((e^{\beta}-1)\cdot 100)$ from equation 6.

Table A18: ATE for Registered Users on the Characteristics of the Homes Viewed with Pre-Experiment Information

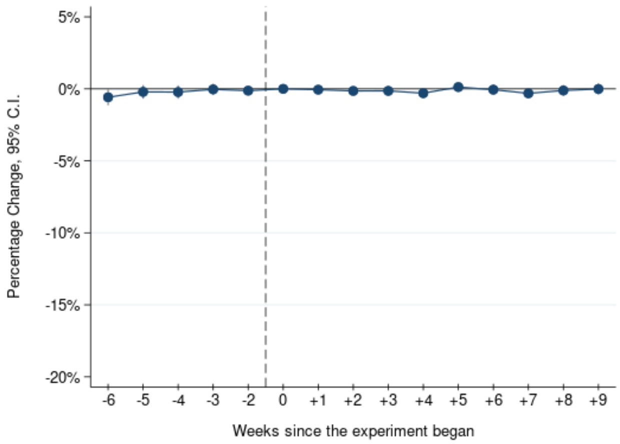
% Change relative to Control

	(1) Views	(2) Bedrooms	(3) Bathrooms	(4) Sq. Ft.	(5) List Price	(6) Flood Score	(7) HHI Zip
Experiment began	19.570***	0.498***	0.485***	0.065	-1.488***	0.868***	-9.129***
	(0.160)	(0.060)	(0.070)	(0.092)	(0.179)	(0.089)	(0.113)
Treatment	0.032	-0.109	-0.226*	-0.279*	-0.701**	-0.068	0.018
	(0.210)	(0.087)	(0.103)	(0.135)	(0.269)	(0.128)	(0.153)
Diff-in-diffs	-0.059	0.083	0.097	0.137	0.289	-0.055	-0.098
	(0.227)	(0.084)	(0.099)	(0.129)	(0.252)	(0.126)	(0.159)
Obs.	13,746,356	13,538,474	13,588,603	13,544,431	13,584,855	13,704,992	13,746,356

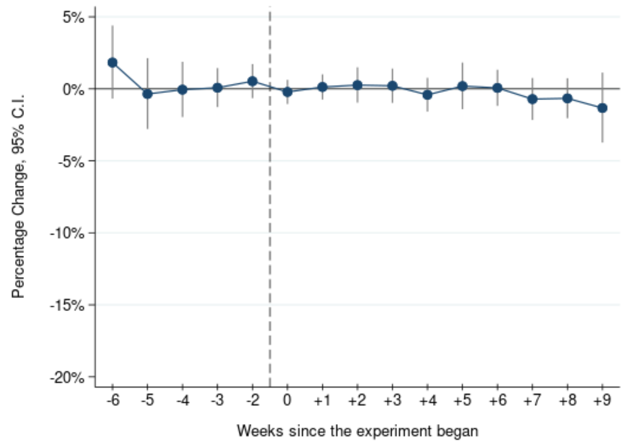
Note: *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Standard Errors Clustered at the User Level. Note: Coefficients are in the form of $((e^{\beta}-1)\cdot 100)$ from equation 6.

Figure A5: Event-time Study on the Average Daily Flood Score of Properties Searched for Registered Users

(a) *Low*



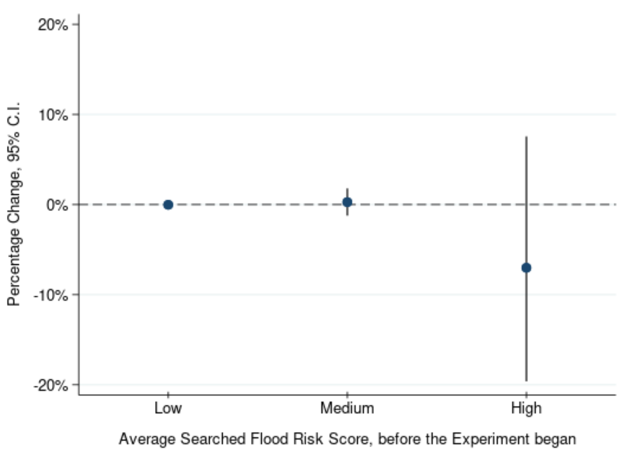
(b) *Medium*



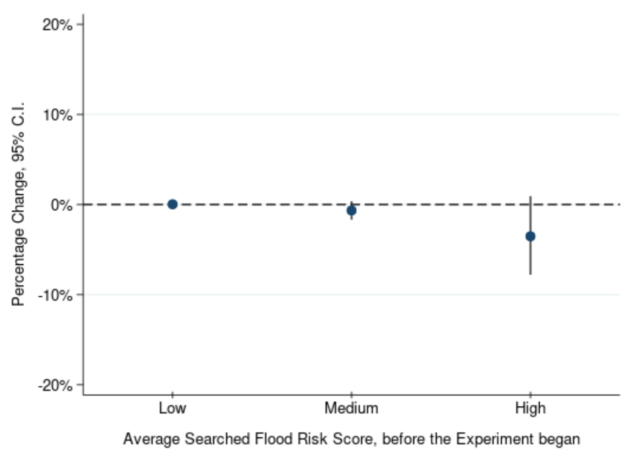
Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 8. Coefficients are relative to the week before a user entered the experiment. Vertical lines crossing the estimates are confidence intervals at the 95% level. The vertical dashed line represents the beginning of the experiment for a user. The x-axis represents each user's baseline average flood score search category before the experiment began.

Figure A6: CATE on the Average Flood Score of a Daily Search for Registered Users, by Characteristics of Most Searched Destination and Origin Zip Code at Baseline

(a) **Lower Mean** Flood Score at Destination Zip Code than Origin



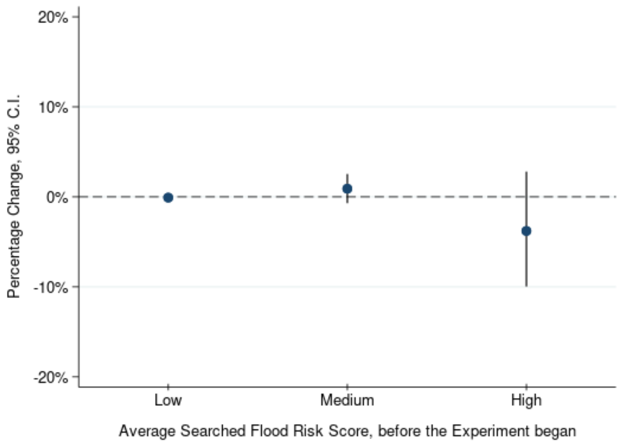
(b) **Higher Mean** Flood Score at Destination Zip Code than Origin



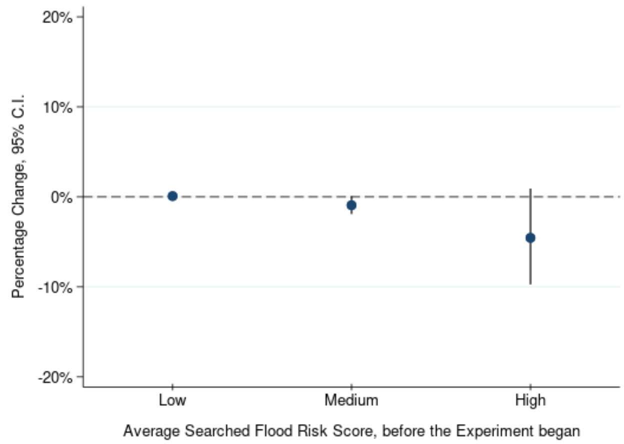
Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

Figure A7: CATE on the Average Flood Score of a Daily Search for Registered Users, by Flood Characteristics of the Most Searched Destination and Origin Zip Code at Baseline

(a) **Lower Standard Deviation** Flood Score at Destination Zip Code than Origin



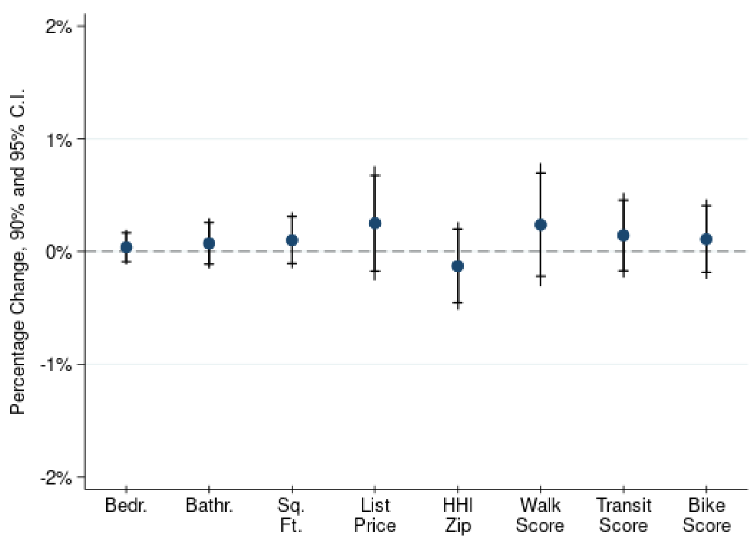
(b) **Higher Standard Deviation** Flood Score at Destination Zip Code than Origin



Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

Figure A8: CATE on the Average Outcomes of a Daily Search for Registered Users Browsing Low Risk Properties at Baseline

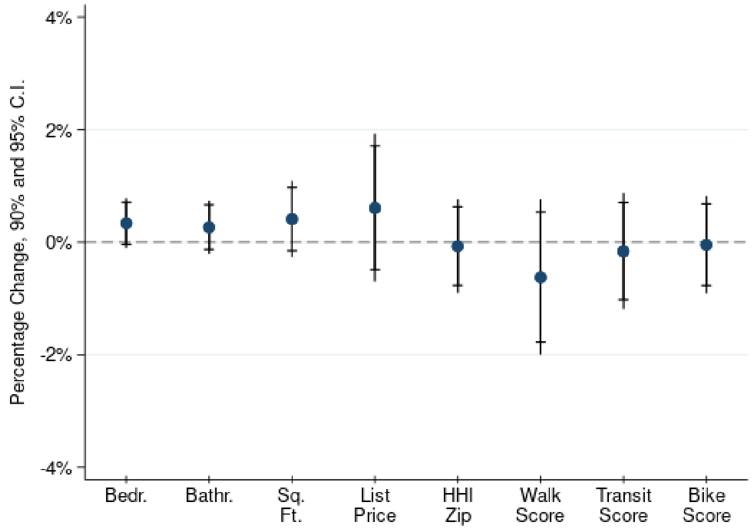
% Change relative to Control



Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 90% and 95% levels. The x-axis represents treatment effects for users browsing low flood risk properties, on average, before the experiment began.

Figure A9: CATE on the Average Outcomes of a Daily Search for Registered Users Browsing Medium Risk Properties at Baseline

% Change relative to Control



Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 90% and 95% levels. The x-axis represents treatment effects for users browsing medium flood risk properties, on average, before the experiment began.

Figure A11: CATE on the Probability of Platform Registration

% Change relative to Control

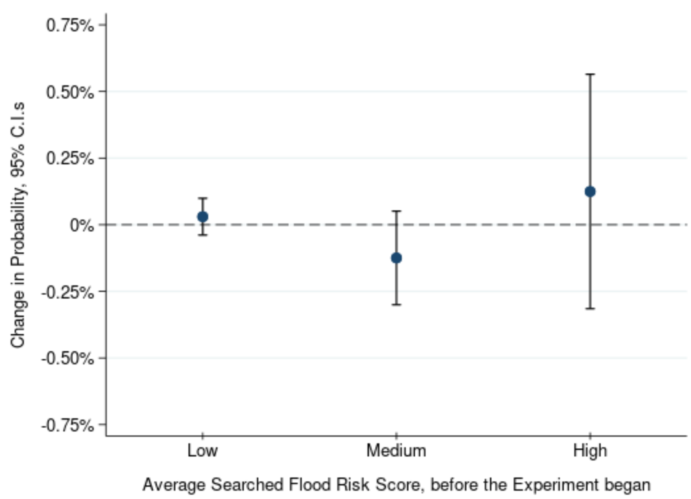


Table A19: Average Treatment Effects on Platform Activity

Coefficients in terms of Elasticity, % Change relative to Control

	(1) Total Seconds	(2) Number Sessions	(3) Unique Home Views	(4) Total Home Views
Treatment	-0.432	-0.000	-0.001	-0.002
	(1.335)	(0.001)	(0.002)	(0.002)
Experiment began	294.450***	0.156***	0.296***	0.328***
	(18.732)	(0.011)	(0.019)	(0.023)
Diff-in-diffs	3.827**	0.000	0.003	0.004
	(1.338)	(0.001)	(0.002)	(0.002)
Obs.	67,880,318	67,880,318	67,880,318	67,880,318

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Estimates from columns 2, 3, and 4 were calculated using a Poisson regression.

Table A20: ATE for Registered Users on the Activity on the Platform

Coefficients in terms of Elasticity, % Change relative to Control

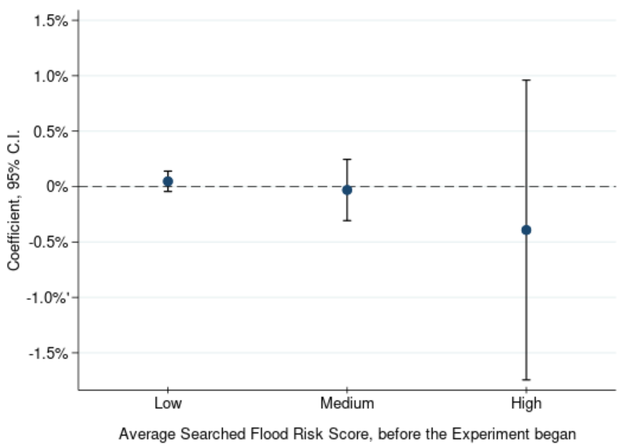
	(1) Total Seconds	(2) Number Sessions	(3) Unique Home Views	(4) Total Home Views
Treatment	0.123	-0.001	-0.000	-0.001
	(4.048)	(0.001)	(0.004)	(0.004)
Experiment began	290.309***	0.123***	0.210***	0.242***
	(30.415)	(0.013)	(0.030)	(0.036)
Diff-in-diffs	4.067	0.002	0.000	0.001
	(4.288)	(0.001)	(0.004)	(0.004)
Obs.	23,909,318	23,909,318	23,909,318	23,909,318

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level. Estimates from columns 2, 3, and 4 were calculated using a Poisson regression.

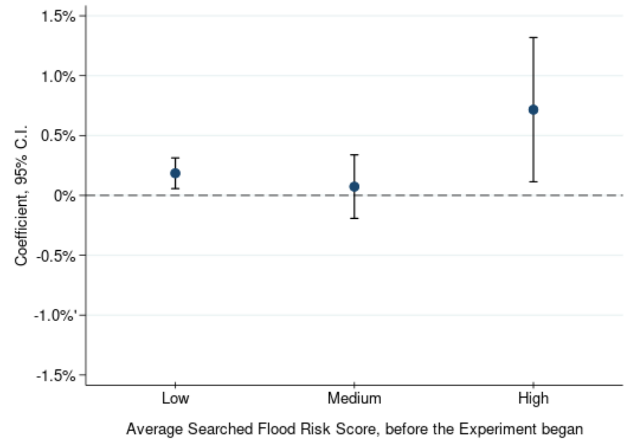
Figure A12: CATE on the Percentage of Times Registered Users Engaged with the Flood Risk Section of a Listing per Day

% Times User Engaged with Feature for Listings Viewed per Day

(a) Without Waterfront Search at Baseline



(b) With Waterfront Search at Baseline

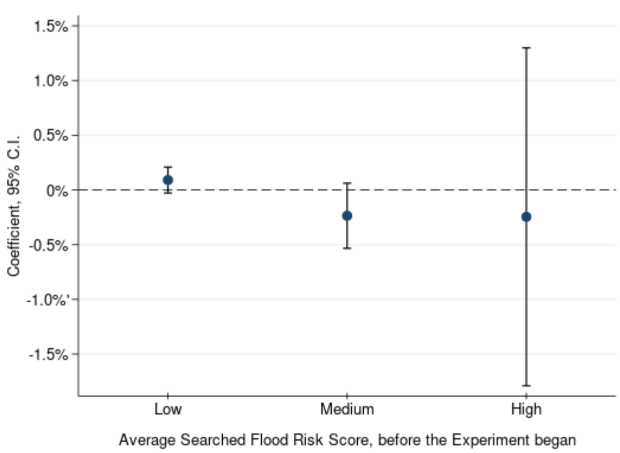


Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who did not browse any waterfront property before the experiment are classified as "without" waterfront search at baseline. On the other hand, users who browsed at least one waterfront property before the experiment are classified as "with" waterfront search at baseline.

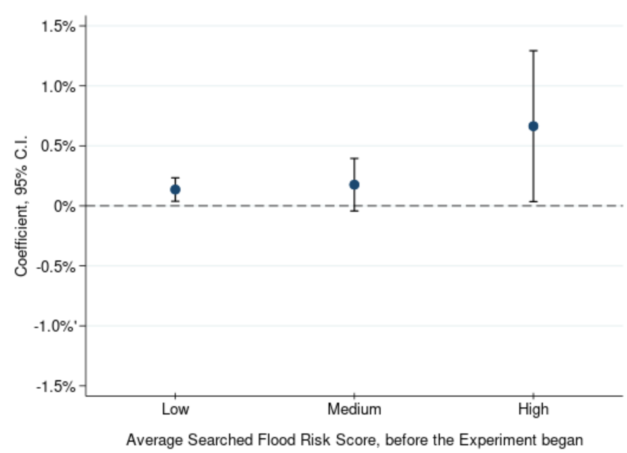
Figure A13: CATE on the Percentage of Times Registered Users Engaged with the Flood Risk Section of a Listing per Day

% Times User Engaged with Feature for Listings Viewed per Day

(a) Without FEMA Risk Search at Baseline



(b) With FEMA Risk Search at Baseline



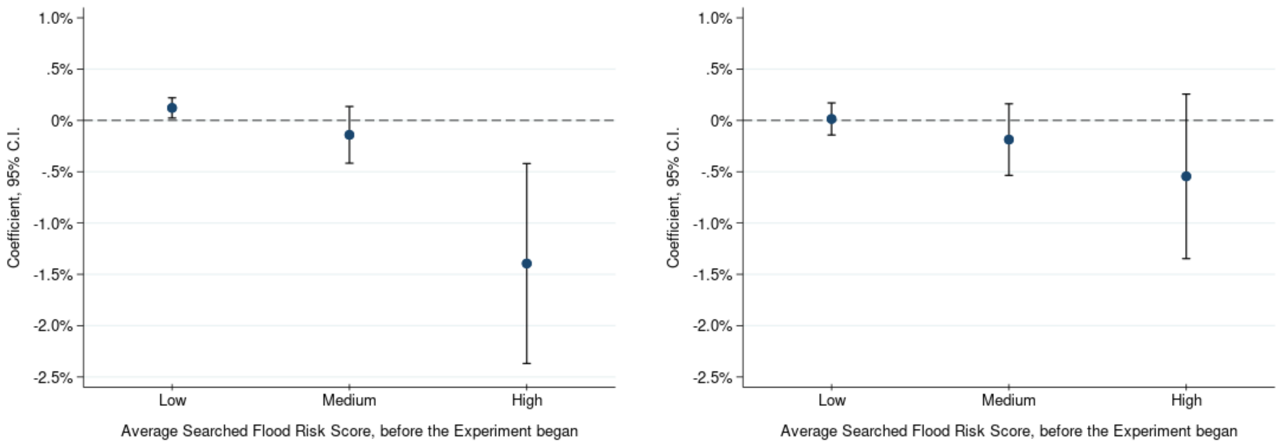
Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who did not browse any property considered risky by FEMA before the experiment are classified as "without" FEMA risk search at baseline. On the other hand, users who browsed at least one property considered risky by FEMA before the experiment are classified as "with" FEMA risk search at baseline.

Figure A14: CATE on the Percentage of Times Registered Users Clicked "Favorite" a Property per Day

% Times User Engaged with Feature for Listings Viewed per Day

(a) Without Waterfront Search at Baseline

(b) With Waterfront Search at Baseline



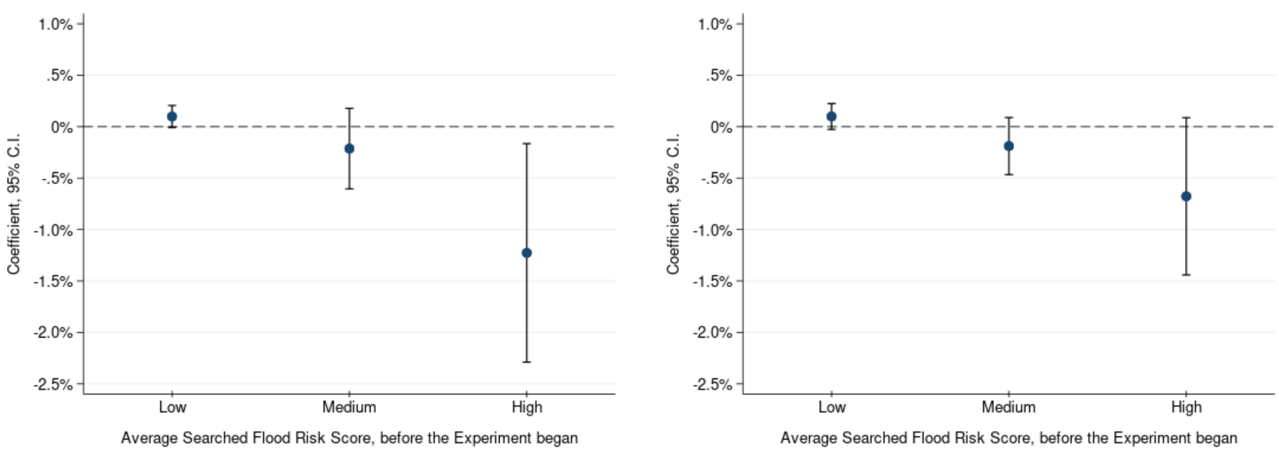
Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who did not browse any waterfront property before the experiment are classified as "without" waterfront search at baseline. On the other hand, users who browsed at least one waterfront property before the experiment are classified as "with" waterfront search at baseline.

Figure A15: CATE on the Percentage of Times Registered Users Clicked "Favorite" a Property per Day

% Times User Engaged with Feature for Listings Viewed per Day

(a) Without FEMA Risk Search at Baseline

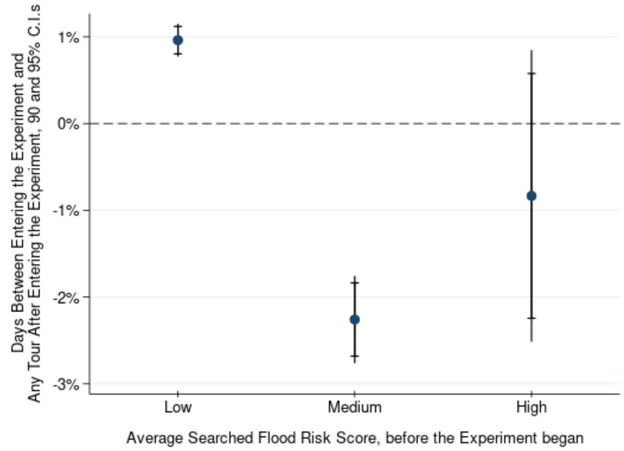
(b) With FEMA Risk Search at Baseline



Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who did not browse any property considered risky by FEMA before the experiment are classified as "without" FEMA risk search at baseline. On the other hand, users who browsed at least one property considered risky by FEMA before the experiment are classified as "with" FEMA risk search at baseline.

Figure A16: CATE on the Days between Entering the Experiment and Going on a House Tour for Registered Users

% Change relative to Control



Note: Coefficients are in the form of incidence rate ratios from equation 7 using a Poisson regression. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 90% and 95% levels, respectively. The x-axis represents treatment effects for users browsing low, medium, and high flood risk properties, on average, before the experiment began.

Table A21: Balance Tests for Registered Users That Eventually Placed an Offer (Low Flood Score)

	(1) Views	(2) Bedrooms	(3) Bathrooms	(4) Sq. Ft.	(5) List Price	(6) Flood Score	(7) HHI Zip
Treatment	0.054	-0.007	-0.003	-0.009	0.012	0.012	-0.026
	(0.032)	(0.011)	(0.012)	(0.016)	(0.027)	(0.009)	(0.020)
Constant	1.331***	1.205***	0.861***	7.616***	13.130***	0.225***	8.531***
	(0.020)	(0.007)	(0.008)	(0.011)	(0.019)	(0.006)	(0.014)
Obs.	21,983	21,823	21,866	21,807	21,881	21,975	21,983

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level.

Table A22: Balance Tests for Registered Users That Eventually Placed an Offer (Low Flood Score)

	(1) New Construction	(2) Short Sale	(3) Year Built	(4) Walk Score	(5) Transit Score	(6) Bike Score
Treatment	-0.002	-0.003	0.000	0.016	0.013	0.038
	(0.003)	(0.002)	(0.001)	(0.034)	(0.025)	(0.022)
Constant	0.037***	0.008***	7.588***	3.345***	3.480***	3.628***
	(0.002)	(0.002)	(0.000)	(0.023)	(0.015)	(0.015)
Obs.	21,983	21,983	21,830	21,162	14,858	21,558

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level.

Table A23: Balance Tests for Registered Users That Eventually Placed an Offer (Medium Flood Score)

	(1) Views	(2) Bedrooms	(3) Bathrooms	(4) Sq. Ft.	(5) List Price	(6) Flood Score	(7) HHI Zip
Treatment	-0.079	-0.053	-0.036	-0.064	0.012	-0.050	-0.001
	(0.071)	(0.028)	(0.031)	(0.039)	(0.069)	(0.032)	(0.046)
Constant	1.259***	1.159***	0.828***	7.547***	13.055***	1.036***	8.633***
	(0.050)	(0.020)	(0.025)	(0.030)	(0.048)	(0.023)	(0.030)
Obs.	3,108	3,074	3,079	3,073	3,090	3,104	3,108

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level.

Table A24: Balance Tests for Registered Users That Eventually Placed an Offer (Medium Flood Score)

	(1) New Construction	(2) Short Sale	(3) Year Built	(4) Walk Score	(5) Transit Score	(6) Bike Score
Treatment	-0.004	0.003	0.002	0.015	0.027	0.007
	(0.006)	(0.002)	(0.001)	(0.089)	(0.061)	(0.049)
Constant	0.032***	0.003***	7.586***	3.449***	3.554***	3.783***
	(0.005)	(0.001)	(0.001)	(0.068)	(0.044)	(0.036)
Obs.	3,108	3,108	3,064	2,964	2,051	3,044

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level.

Table A25: Balance Tests for Registered Users That Eventually Placed an Offer (High Flood Score)

	(1) Views	(2) Bedrooms	(3) Bathrooms	(4) Sq. Ft.	(5) List Price	(6) Flood Score	(7) HHI Zip
Treatment	-0.036	-0.072	0.039	0.084	-0.179	-0.010	0.016
	(0.234)	(0.182)	(0.133)	(0.193)	(0.360)	(0.047)	(0.203)
Constant	0.999***	0.965***	0.782***	7.379***	13.337***	1.997***	8.799***
	(0.160)	(0.079)	(0.068)	(0.092)	(0.179)	(0.038)	(0.134)
Obs.	214	211	212	212	214	214	214

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level.

Table A26: Balance Tests for Registered Users That Eventually Placed an Offer (High Flood Score)

	(1) New Construction	(2) Short Sale	(3) Year Built	(4) Walk Score	(5) Transit Score	(6) Bike Score
Treatment	0.016	0.002	0.003	-0.186	-0.004	0.060
	(0.024)	(.)	(0.003)	(0.284)	(0.101)	(0.154)
Constant	0.021	0.000	7.589***	3.483***	3.652***	3.716***
	(0.020)	(.)	(0.002)	(0.177)	(0.041)	(0.126)
Obs.	214	214	212	199	92	211

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard Errors Clustered at the User Level.

Table A27: Romano-Wolf Corrected P-Values for Search Main Results

Figure #	Risk Score at Baseline	Clustered SE P-Value	Romano-Wolf P-Value
4	Low	0.56	0.82
	Medium	0.33	0.43
	High	0.02	0.01
9(a)	Low	0.30	0.37
	Medium	0.47	0.69
	High	0.90	0.95
9(b)	Low	0.90	0.95
	Medium	0.43	0.61
	High	0.02	0.01
10(a)	Low	0.37	0.50
	Medium	0.78	0.95
	High	0.25	0.25
10(b)	Low	0.77	0.95
	Medium	0.34	0.46
	High	0.07	0.01
11	Low	0.59	0.84
	Medium	0.71	0.93
	High	0.02	0.01

Note: Standard Errors Clustered at the User Level for both p-values. 1,000 resamples for the Romano-Wolf p-value.

Table A28: Romano-Wolf Corrected P-Values for Offer Main Results

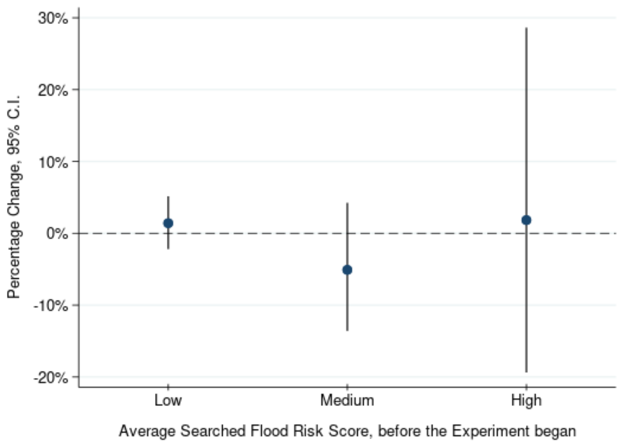
Figure #	Risk Score at Baseline	Robust SE P-Value	Romano-Wolf P-Value
17(b)	Low	0.68	0.99
	Medium	0.39	0.97
	High	0.00	0.07
19(a)	Low	0.79	0.99
	Medium	0.14	0.75
	High	0.76	0.99
19(b)	Low	0.14	0.75
	Medium	0.30	0.93
	High	0.05	0.48
20(a)	Low	0.58	0.99
	Medium	0.63	0.99
	High	0.77	0.99
20(b)	Low	0.93	0.99
	Medium	0.45	0.98
	High	0.11	0.70
21	Low	0.12	0.70
	Medium	0.03	0.36
	High	0.05	0.47

Note: Robust Standard Errors at the User Level for both p-values. 3,000 resamples for the Romano-Wolf p-value.

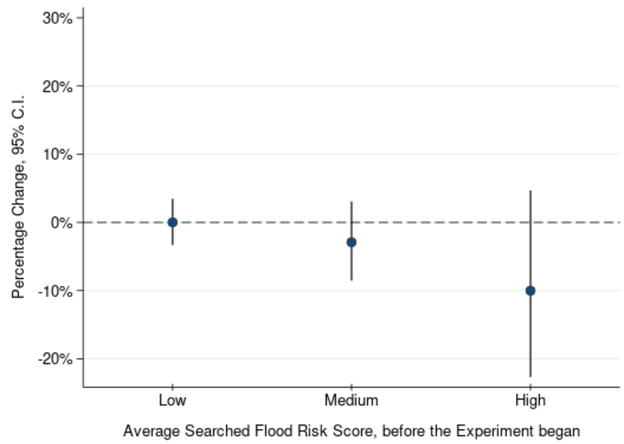
Figure A17: CATE on the Average Flood Score of a Daily Search for Registered Users, by whether the user's county of origin or destination search at baseline experienced a flood shock in the past 7 days

% Change relative to Control

(a) County of Origin



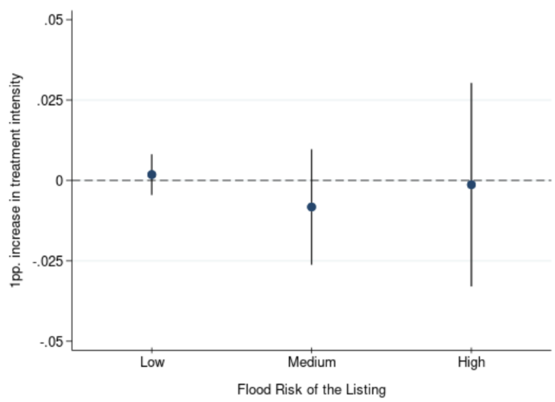
(b) County of Destination



Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. Coefficients are in the form of $((e^{\beta_3}-1)\cdot 100)$ from equation 7. The x-axis represents each user's baseline average flood score search category before the experiment began.

Figure A18: The Association Between Treatment Exposure Intensity and the Time on the Market for All Listings

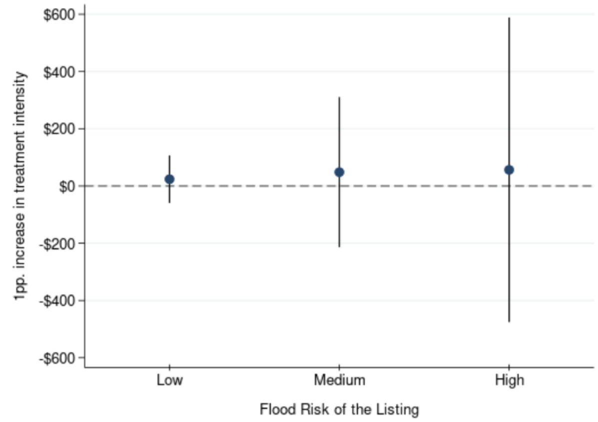
1PP Increase in Exposure Intensity, ($)



Note: For Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents the flood score of the property.

Figure A19: The Association Between Treatment Exposure Intensity and Loan Value for All Listings

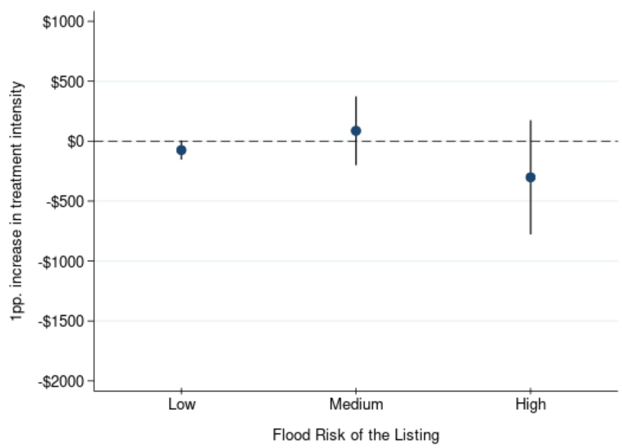
1PP Increase in Exposure Intensity, ($)



Note: For Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents the flood score of the property. Only listings that were bought with a loan.

Figure A20: The Association Between Treatment Exposure Intensity and Listing Price for Not Waterfront and Not FEMA Risky Listings

1PP Increase in Exposure Intensity, ($)



Note: For Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents the flood score of the property.

A.4 Nonparametric Heterogeneous Treatment Effects

We seek to identify the conditional average treatment effect on the treated (CATE), which seeks to identify differences in treatment effects within the population and how big these differences are with an estimand defined as:

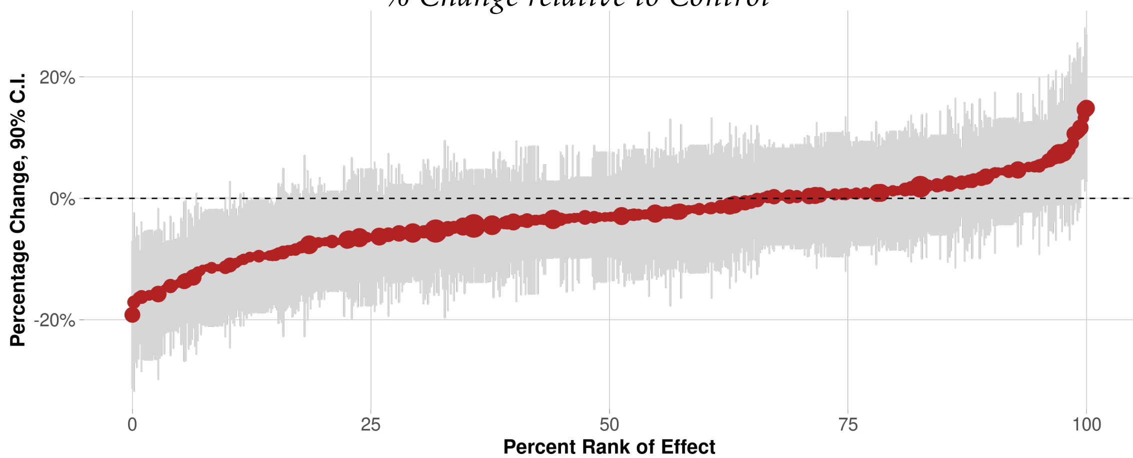
$$\text{CATE} \equiv \tau(X) = \mathbb{E}\left[Y_i^{(1)} - Y_i^{(0)} \mid X_i = x\right] = \mu_1(x) - \mu_0(x) \tag{14}$$

Where $Y_i^{(1)}$ and $Y_i^{(0)}$ are the potential outcomes of outcome, Y, with observed covariates, $X \in \mathbb{R}$, for individual, i. The goal is to identify the CATE or $\tau(X)$ which is the difference in potential outcomes that equates to the difference in the conditional expectation of x: $\mu_1(x)-\mu_0(x)$. Given that our treatment was randomized, we could estimate $\tau(x)$ via estimator 7. However, estimator 7 relies on the linearity assumption of the effect that covariates, X_i, have on the treatment. If these effects were non-linear, our calculated estimates would be biased or wouldn't cover the entire distribution of heterogeneous treatment effects. We rely on causal forests, a Generalized Random Forest algorithm, to relax this assumption and not provide a parametric form (Athey, Tibshirani and Wager, 2019; Athey and Wager, 2021). Causal forests are built to identify how treatment effects vary across users by maximizing the difference in the relationship between our target variable (i.e., our outcome variable) and a specific feature (i.e., our treatment indicator) within other features (i.e., our baseline covariates). This method employs a splitting criterion optimized for detecting splits that reveal treatment effect heterogeneity. The objective is to identify leaf nodes where the treatment effect is constant but distinct from other leaves.

In our analyses, we utilize baseline variables as covariates, X. We use the most searched city, the device most used by the user to browse the web (i.e., mobile or desktop), the number of weeks since the user entered the experiment, and the baseline average flood of all the houses viewed by user, i. We randomly split our data into training (70%) and testing (30%) samples. We used the training sample to fit a causal forest with 50,000 trees grown in the forest and four grown trees on each subsample. After training the causal forest, we predicted conditional treatment effects on the testing sample and a 90% confidence interval around each one. On each graph presented below, we show the percent rank of the conditional average treatment effects with a 90% confidence interval, where a bigger coefficient size tells us that more observations lie within the branch of the calculated conditional average treatment effect.

Figure A21: Causal Forest—**High** Risk Group

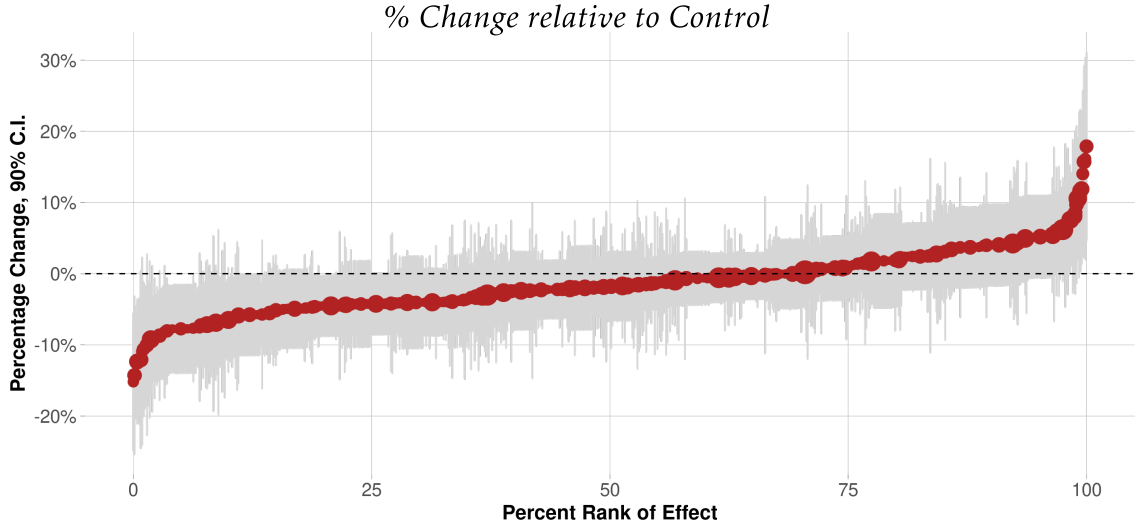
% Change relative to Control



Note: The causal forest was trained on 70% of the extreme risk universe, and the plotted effects are calculated on 30% of the rest. We use 50,000 trees to grow the forest. We use baseline variables to fit the model. A bigger size of the circle effects tells us that more observations lie within the branch of the calculated conditional average treatment effect.

Figure A22: Causal Forest—**Medium** Risk Group

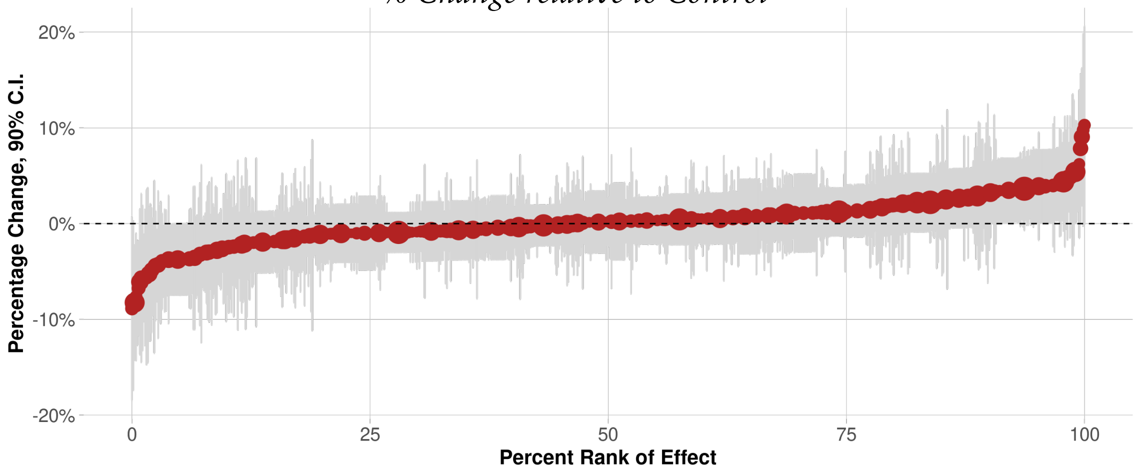
% Change relative to Control



Note: The causal forest was trained on 70% of the severe risk universe, and the plotted effects are calculated on 30% of the rest. We use 50,000 trees to grow the forest. We use baseline variables to fit the model. A bigger size of the circle effects tells us that more observations lie within the branch of the calculated conditional average treatment effect.

Figure A23: Causal Forest—**Low** Risk Group

% Change relative to Control



Note: The causal forest was trained on 70% of the major risk universe, and the plotted effects are calculated on 30% of the rest. We use 50,000 trees to grow the forest. We use baseline variables to fit the model. A bigger size of the circle effects tells us that more observations lie within the branch of the calculated conditional average treatment effect.

A.5 Six Categories

Table A29: Pre-Experiment Distribution of Flood Score for Users by Treatment Status

Number of Users; Column Percentages in Parenthesis

Flood Score Category	**Control**	**Treatment**	**Total**
Minimal	1,962,300	1,963,483	3,925,783
	(68.20)	(68.25)	(68.23)
Minor	419,813	419,611	839,424
	(14.59)	(14.59)	(14.59)
Moderate	323,050	322,315	645,365
	(11.23)	(11.20)	(11.22)
Major	112,001	111,314	223,315
	(3.89)	(3.87)	(3.88)
Severe	29,470	29,681	59,151
	(1.02)	(1.03)	(1.03)
Extreme	30,616	30,356	60,972
	(1.05)	(1.05)	(1.05)
Total	2,877,250	2,876,760	5,754,010
	(100.00)	(100.00)	(100.00)

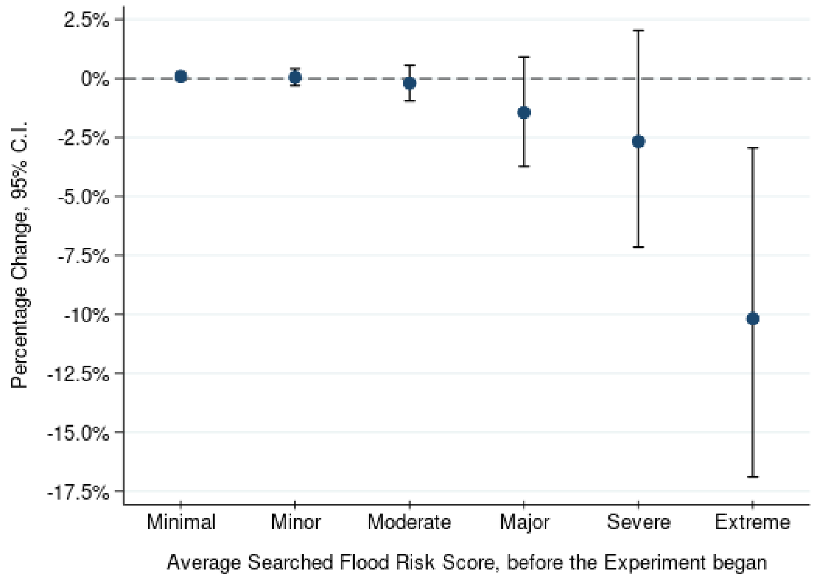
Table A30: Pre-Experiment Distribution of Flood Score for Registered Users by Treatment Status

Number of Registered Users; Column Percentages in Parenthesis

Flood Score Category	**Control**	**Treatment**	**Total**
Minimal	275,765	275,476	551,241
	(62.17)	(62.18)	(62.17)
Minor	94,232	94,303	188,535
	(21.24)	(21.28)	(21.26)
Moderate	53,124	52,913	106,037
	(11.98)	(11.94)	(11.96)
Major	13,852	13,653	27,505
	(3.12)	(3.08)	(3.10)
Severe	3,799	3,825	7,624
	(0.86)	(0.86)	(0.86)
Extreme	2,793	2,882	5,675
	(0.63)	(0.65)	(0.64)
Total	443,565	443,052	886,617
	(100.00)	(100.00)	(100.00)

Figure A24: CATE on the Average Flood Score of a Daily Search for Registered Users

% Change relative to Control

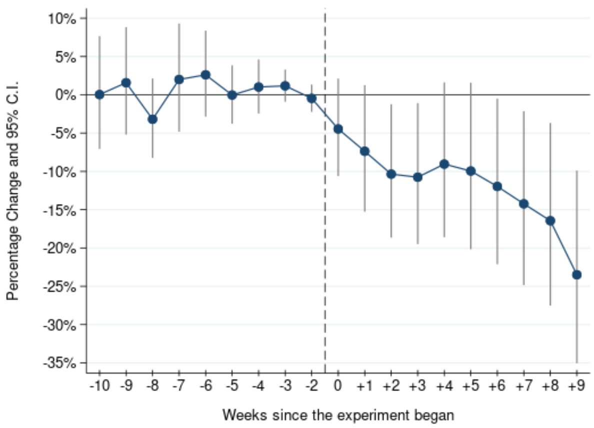


Note: Coefficients are in the form of $((e^{\beta_3}-1)\cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

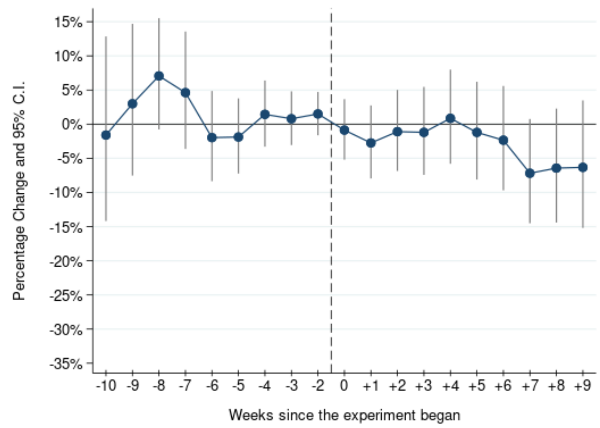
Figure A22: Event-time Study on the Average Daily Flood Score of Properties Searched for Registered Users

% Change relative to Control

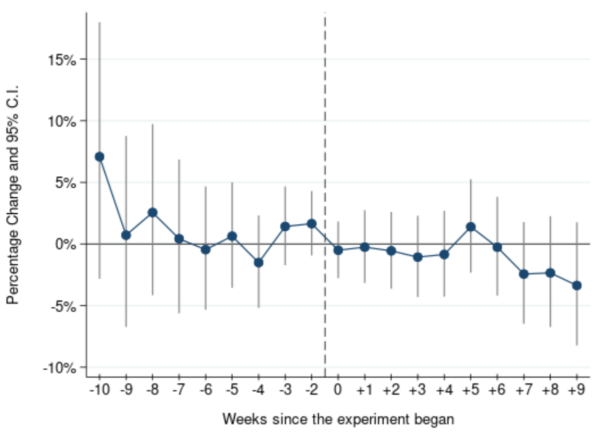
(a) Extreme



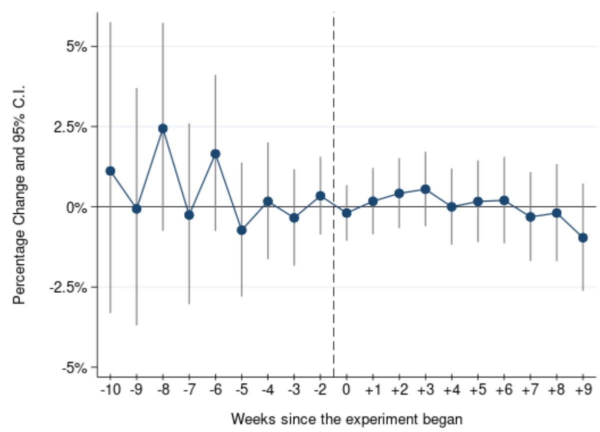
(b) Severe



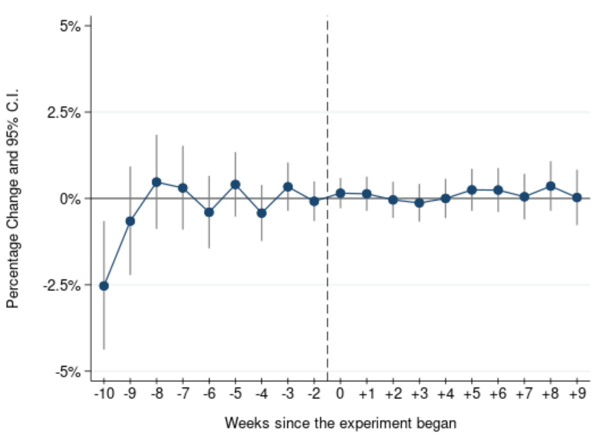
(c) Major



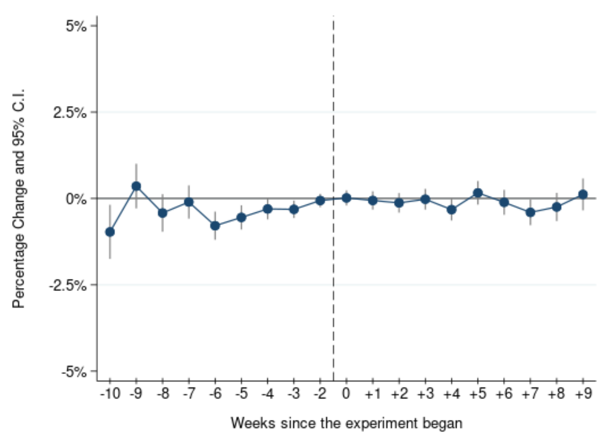
(d) Moderate



(e) Minor



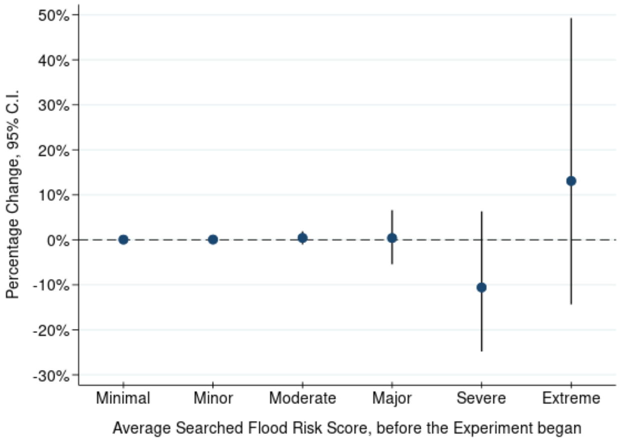
(f) Minimal



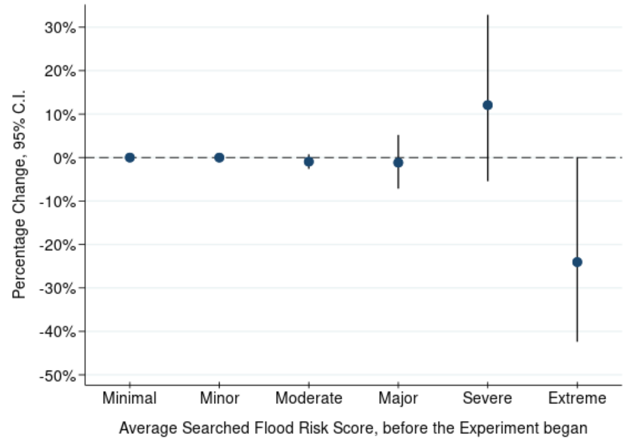
Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 8. Coefficients are relative to the week before a user entered the experiment. Vertical lines crossing the estimates are confidence intervals at the 95% level. The vertical dashed line represents the beginning of the experiment for a user. The x-axis represents each user's baseline average flood score search category before the experiment began.

Figure A23: CATE on the Average Flood Score of a Daily Search for Registered Users, by Characteristics of Most Searched Destination and Origin Zip Code at Baseline

(a) **Lower Mean** Flood Score at Destination Zip Code than Origin



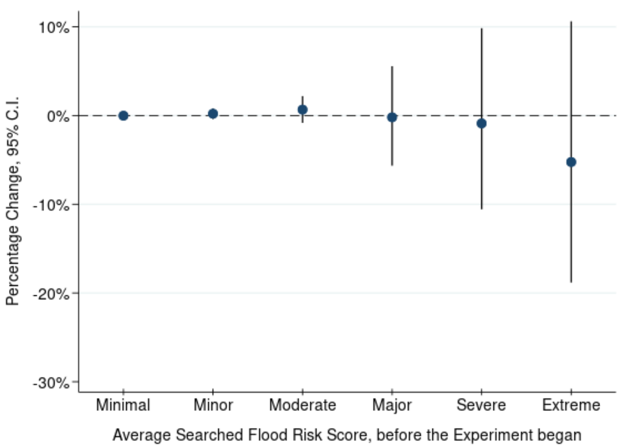
(b) **Higher Mean** Flood Score at Destination Zip Code than Origin



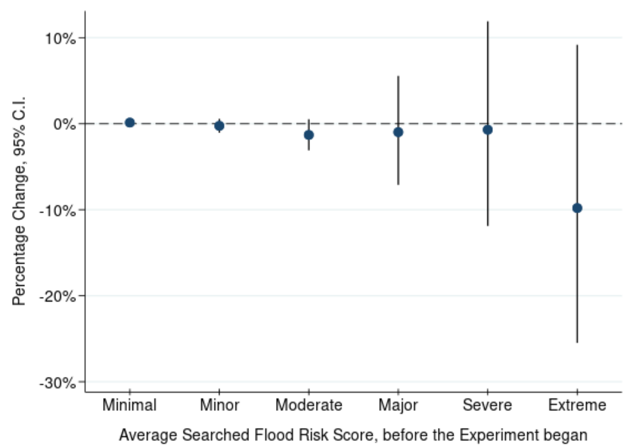
Note: Coefficients are in the form of $((e^{\beta_3}-1)\cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

Figure A24: CATE on the Average Flood Score of a Daily Search for Registered Users, by Flood Characteristics of the Most Searched Destination and Origin Zip Code at Baseline

(a) **Lower Standard Deviation** Flood Score at Destination Zip Code than Origin



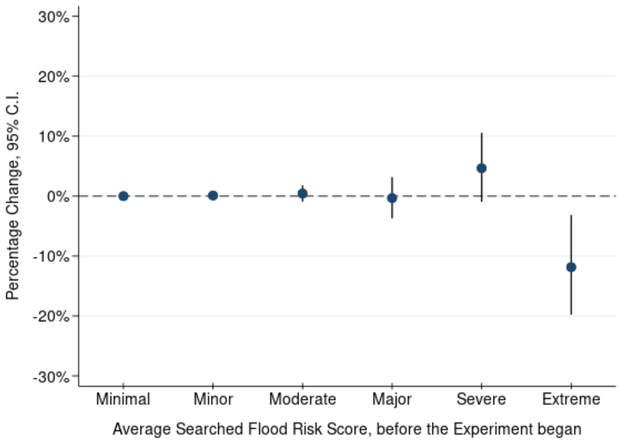
(b) **Higher Standard Deviation** Flood Score at Destination Zip Code than Origin



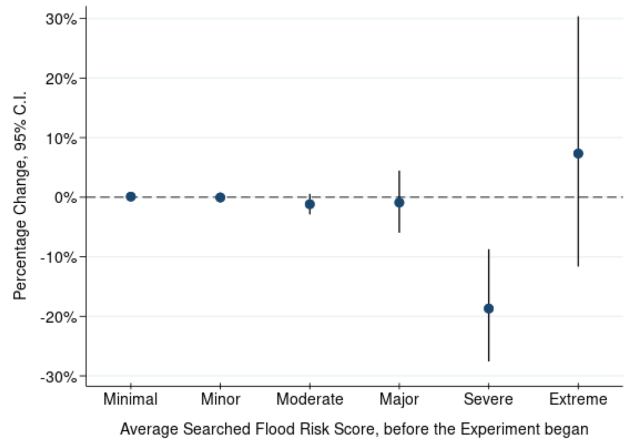
Note: Coefficients are in the form of $((e^{\beta_3}-1)\cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

Figure A25: CATE on the Average Flood Score of a Daily Search for Registered Users, by Characteristics of Most Searched Destination and Origin Zip Code at Baseline

(a) **Lower Coefficient of Variation** Flood Score at Destination Zip Code than Origin



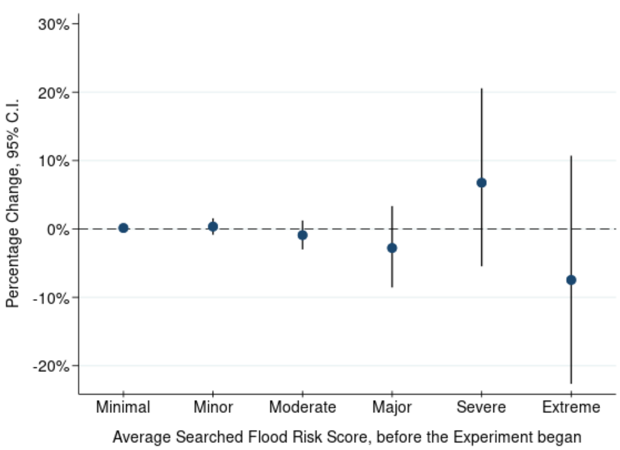
(b) **Higher Coefficient of Variation** Flood Score at Destination Zip Code than Origin



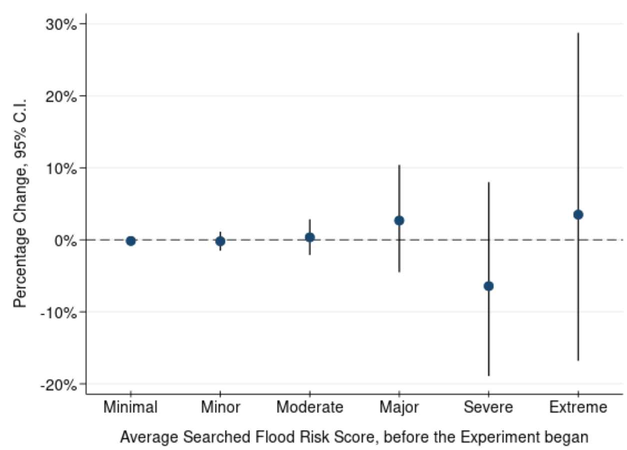
Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's average flood score search category before the experiment began.

Figure A26: CATE on the Average Flood Score of a Daily Search for Registered Users, by Redfin's Probability of Registered User Buying a House at Baseline

(a) **Bottom 90** of Redfin's Probability



(b) **Top 10** of Redfin's Probability

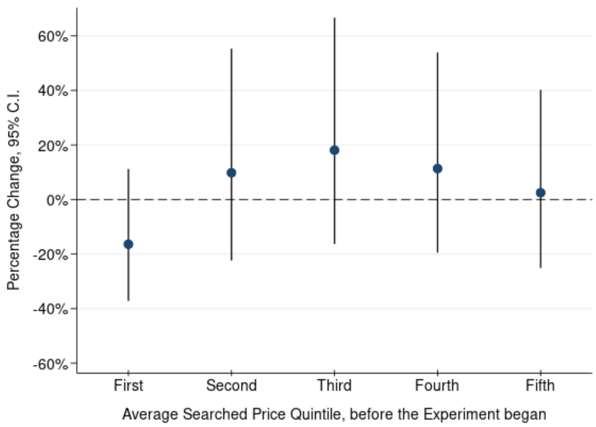


Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

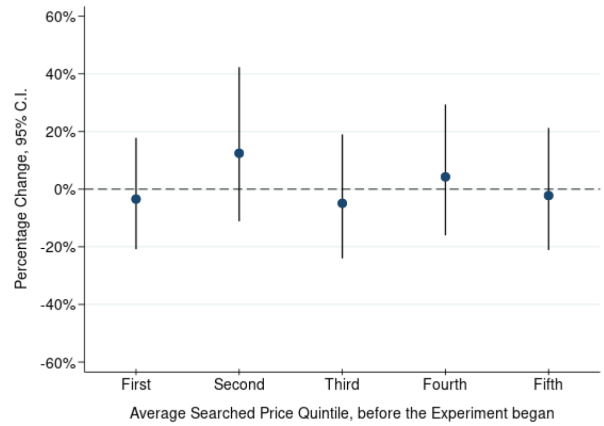
Figure A27: CATE on the Average Flood Score of a Daily Search for Registered Users, by Within-City Average Price Quintile Search at Baseline

Stratified by Average Flood Score Search at Baseline

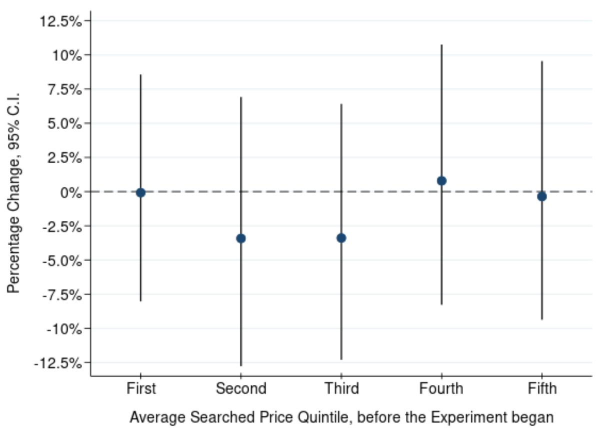
(a) Extreme



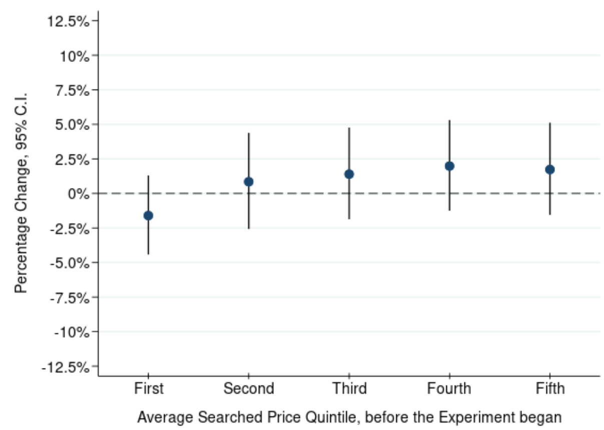
(b) Severe



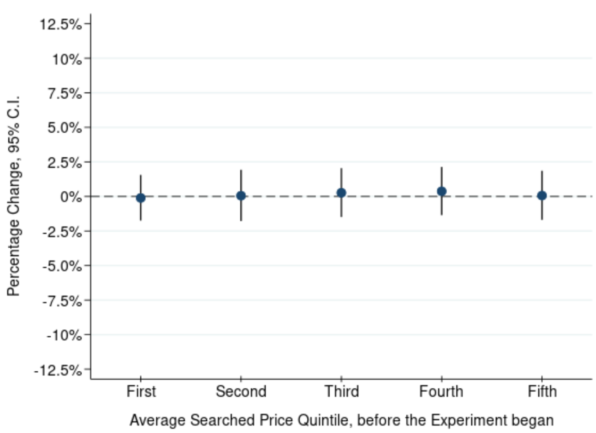
(c) Major



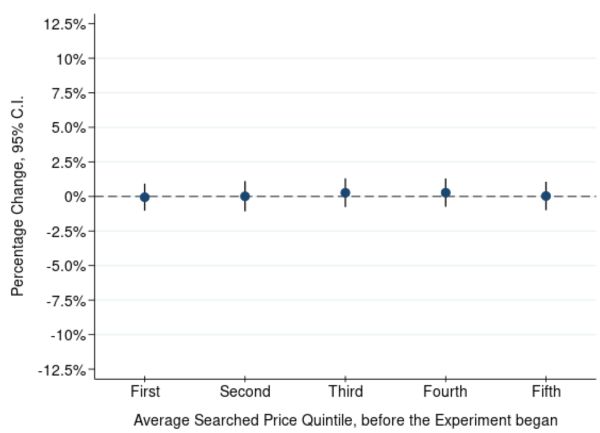
(d) Moderate



(e) Minor



(f) Minimal



Note: Note: Coefficients are in the form of $((e^{\beta_3}-1)\cdot 100)$ from equation 8. Vertical lines crossing the estimates are confidence intervals at the 95% level. The x-axis represents the baseline average listing price quintile within a city search category of each user pre-experiment.

Figure A28: CATE on the Probability of Platform Registration

% Change relative to Control

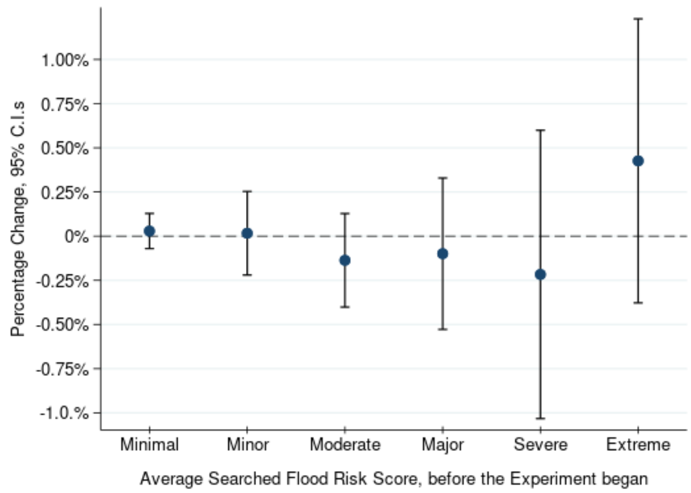
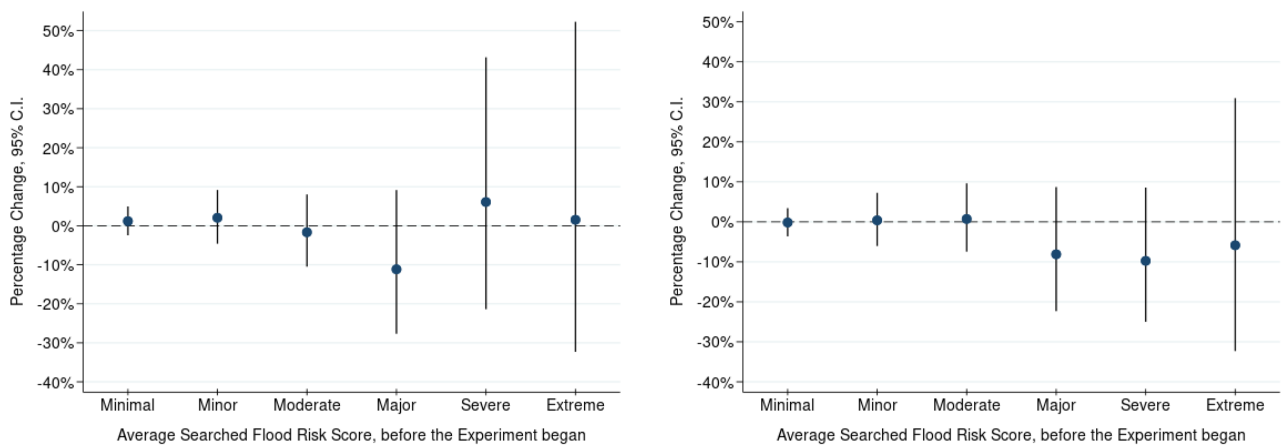


Figure A29: CATE on the Average Flood Score of a Daily Search for Registered Users, by whether the user's county of origin or destination search at baseline experienced a flood shock in the past 7 days

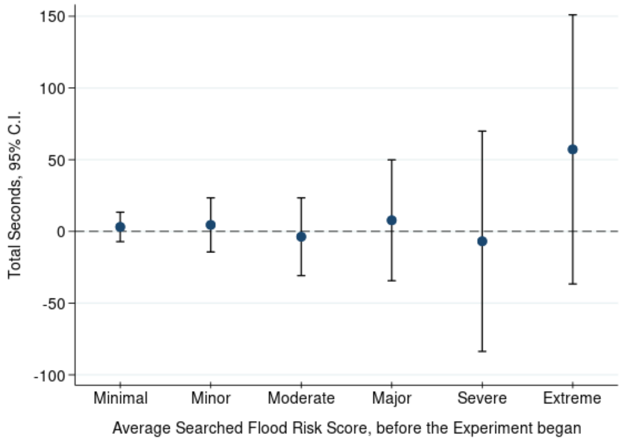
(a) County of Origin | (b) County of Destination



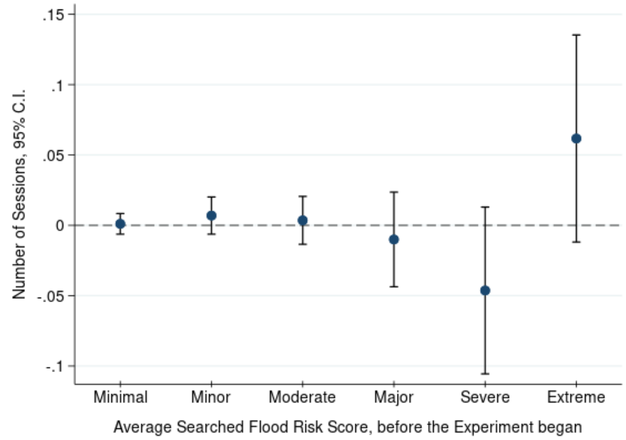
Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. The x-axis represents each user's baseline average flood score search category before the experiment began.

Figure A30: CATE on the Number of Homes Viewed per Day for Registered Users

(a) Seconds Spent



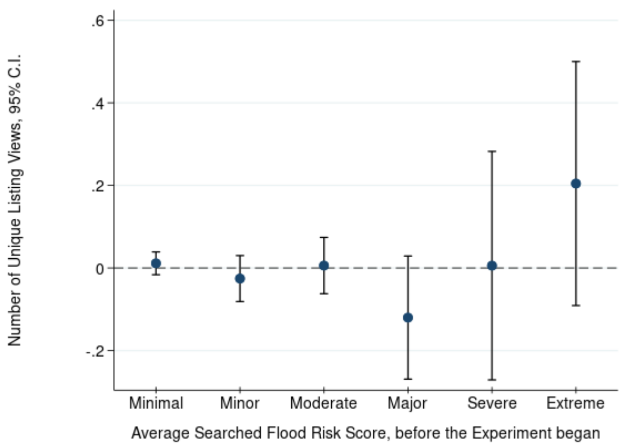
(b) Number of Sessions



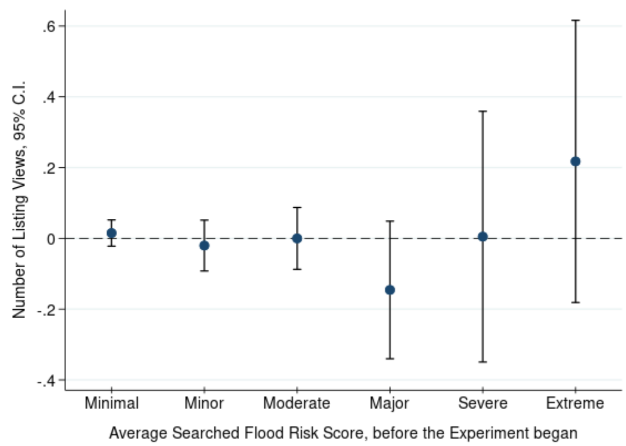
Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

Figure A31: CATE on the Number of Homes Viewed per Day for Registered Users

(a) Unique Home Views

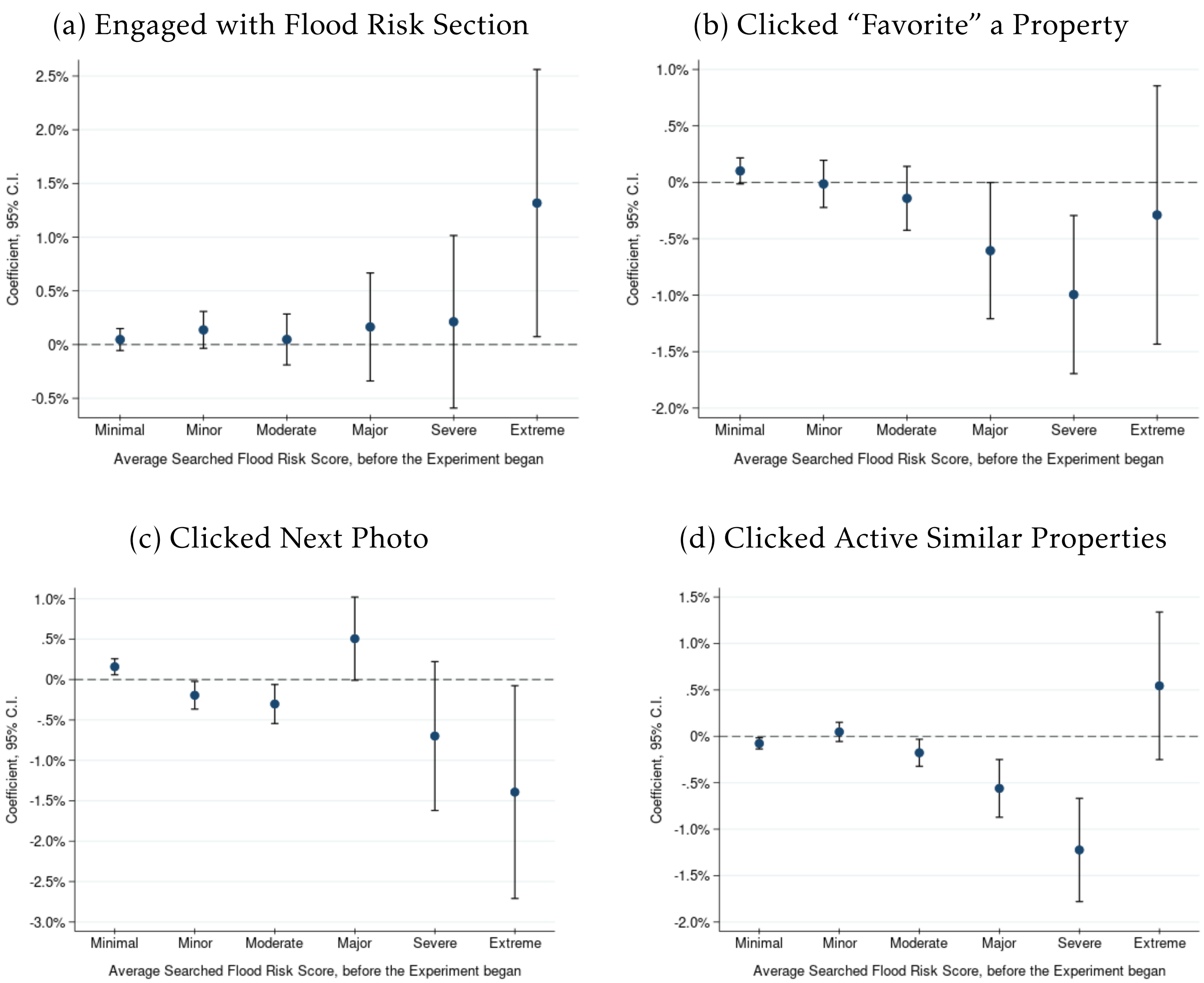


(b) Total Home Views



Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

Figure A32: CATE on the Percentage of Times for Registered Users Engaged with a Specific Property's Features per Day



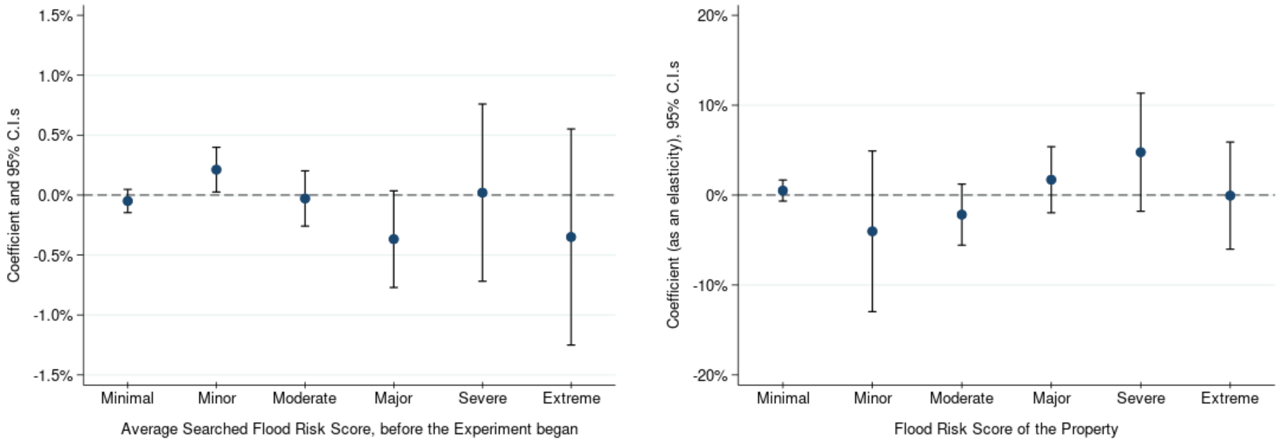
Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

Figure A33: CATE on the Probability of Booking a Tour and Canceling a House Tour

% Change relative to Control for Registered Users

(a) Probability of Booking a Tour

(b) Probability of Cancelling a House Tour



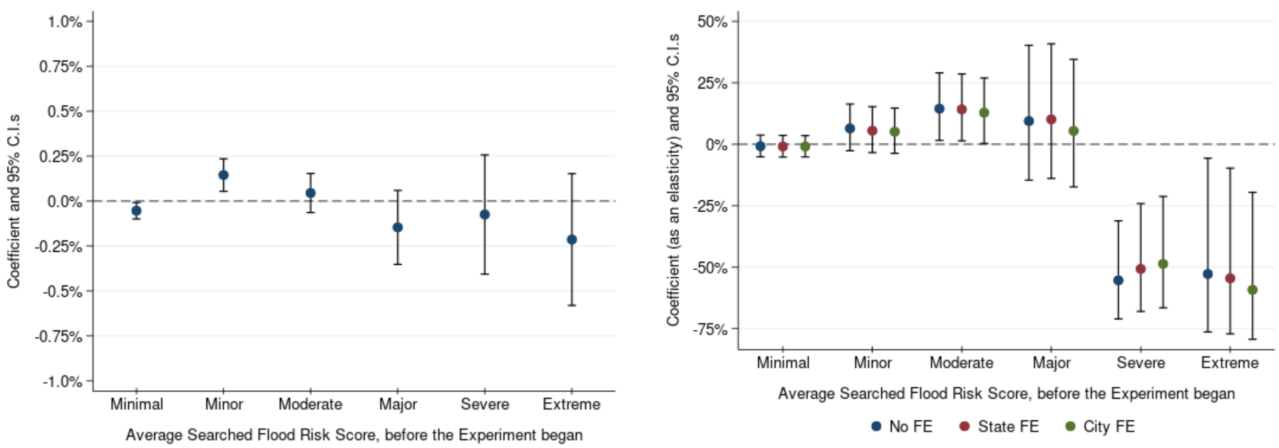
Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents the flood score category of the property.

Figure A34: CATE on the Probability of Making an Offer as a Function of the Flood Score

% Change relative to Control

(a) Probability of Placing an Offer

(b) Flood Score of the Property

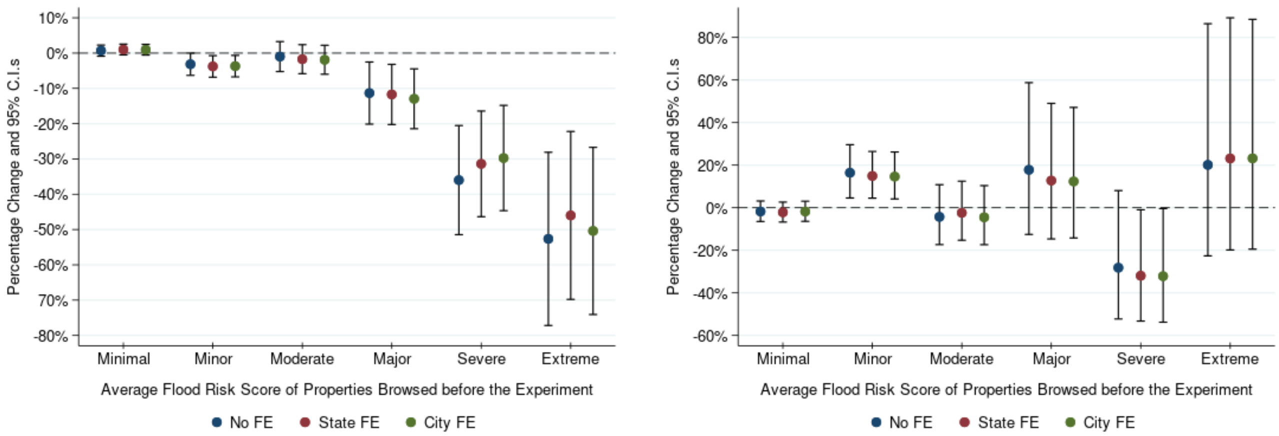


Note: Coefficients are in the form of $((e^{\beta_3}-1)\cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. S.E. clustered at the registered user level. FE = Fixed Effects of the location of the Property.

Figure A35: CATE on the Characteristics of an Offer

% Change relative to Control

(a) Prob. of Offer being on the Waterfront (b) Square Feet of the Property

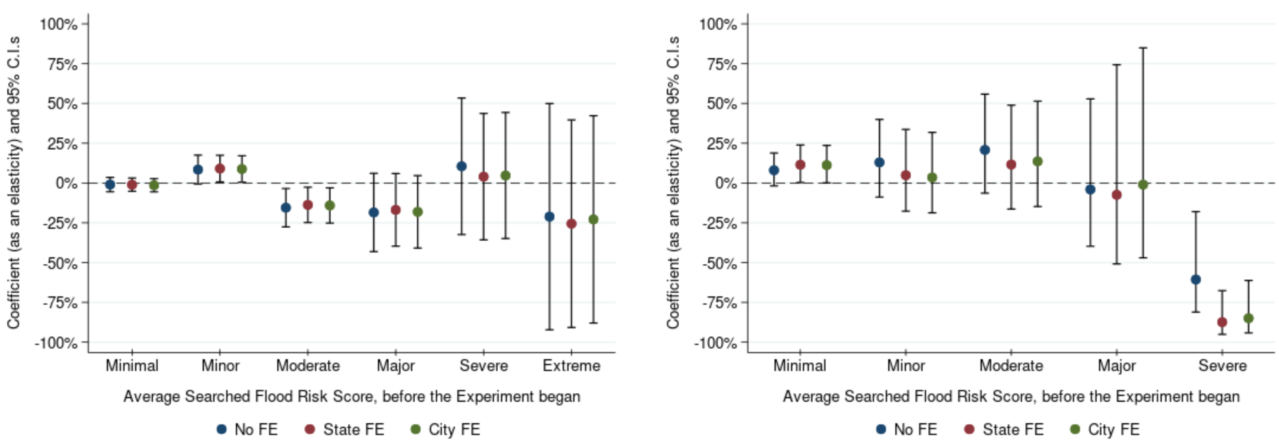


Note: For Figure (b), coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Standard errors clustered at the user level. FE = Fixed Effects of the location of the Property.

Figure A36: CATE on the Probability of Closing on a Property

% Change relative to Control

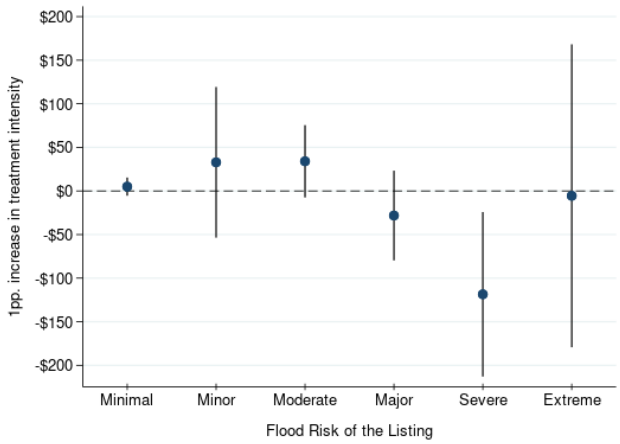
(a) Probability of Closing an Offer (b) Flood Score of the Closed Properties



Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 7. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. FE = Fixed Effects of the location of the Property.

Figure A37: The Association Between Treatment Exposure Intensity and the *(Sale - Listing Price)* Spread for All Listings

1PP Increase in Exposure Intensity, ($)

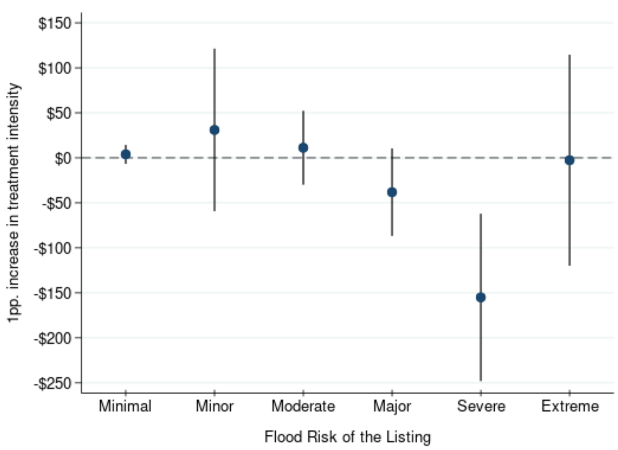


Note: For Figure (b), vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents the flood score of the property.

Figure A38: CATE of an Increase in Exposure Intensity on the *(Sale - Listing Price)*

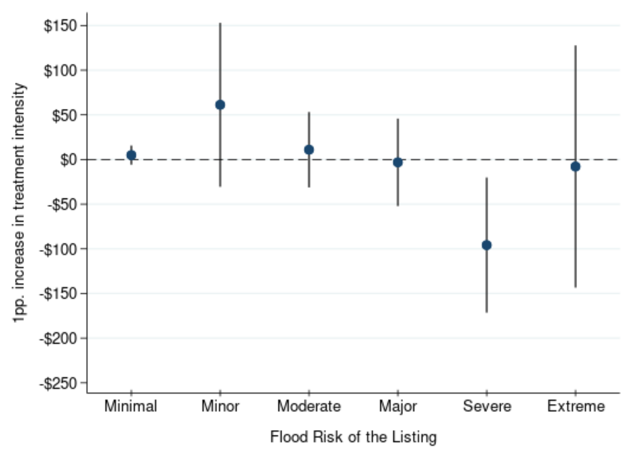
(a) Only Not Waterfront Listings

1PP Increase in Exposure Intensity, ($)



(b) Only Not FEMA Risky Listings

1PP Increase in Exposure Intensity, ($)

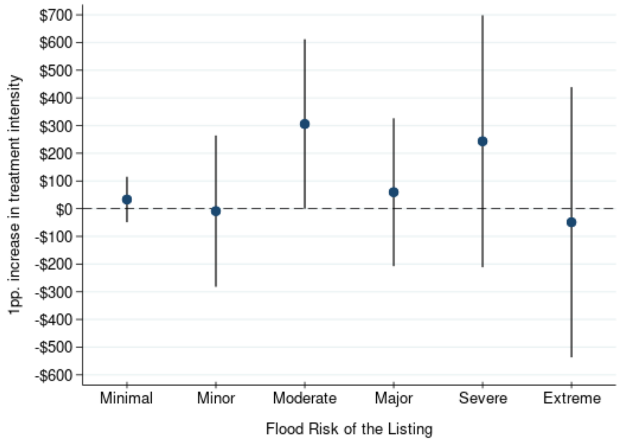


Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. As well, for Figure (b), the x-axis represents the flood score of the property.

Figure A39: CATE of an Increase in Exposure Intensity on the *(Sale - Listing Price)*

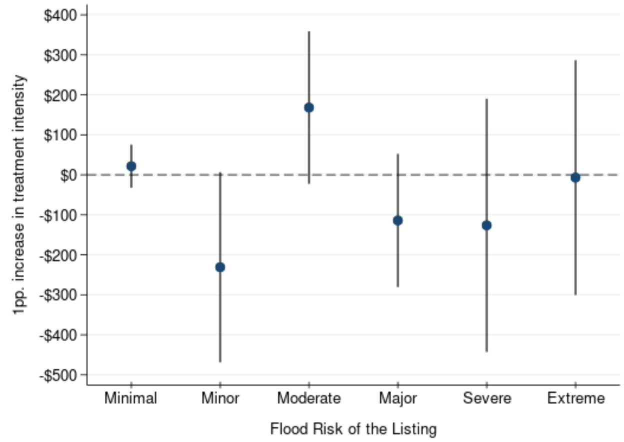
(a) Only Waterfront Listings

1PP Increase in Exposure Intensity, ($)



(b) Only FEMA Risky Listings

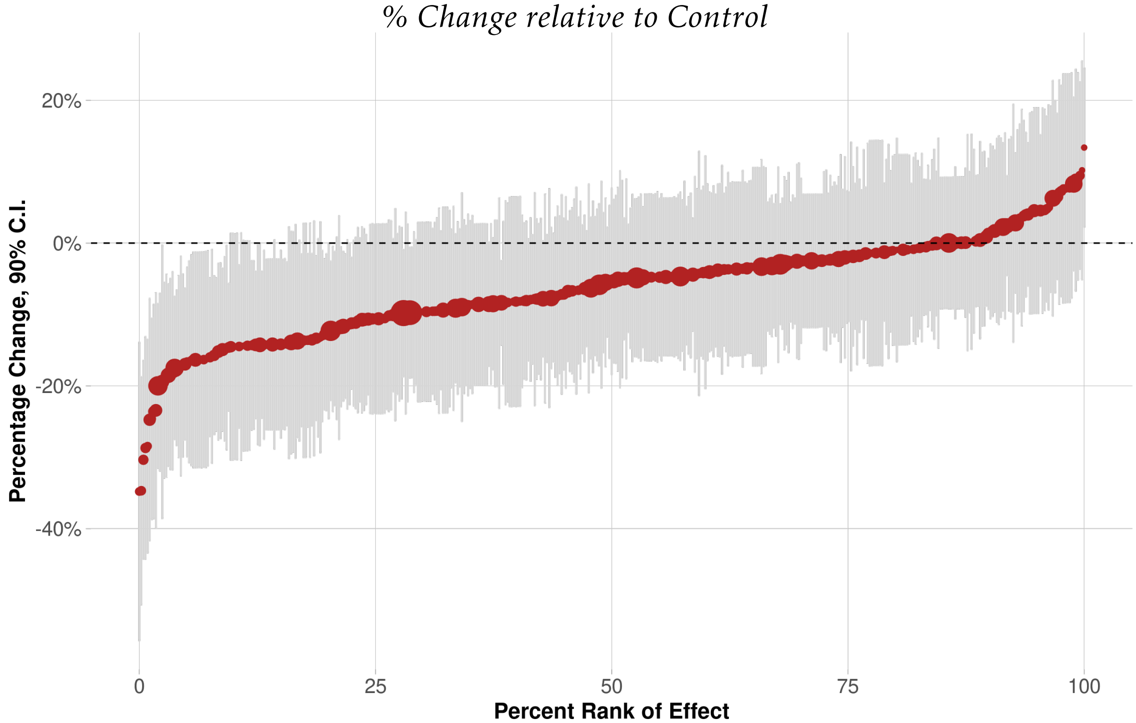
1PP Increase in Exposure Intensity, ($)



Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents the flood score of the property.

Figure A40: Causal Forest—**Extreme** Risk Group

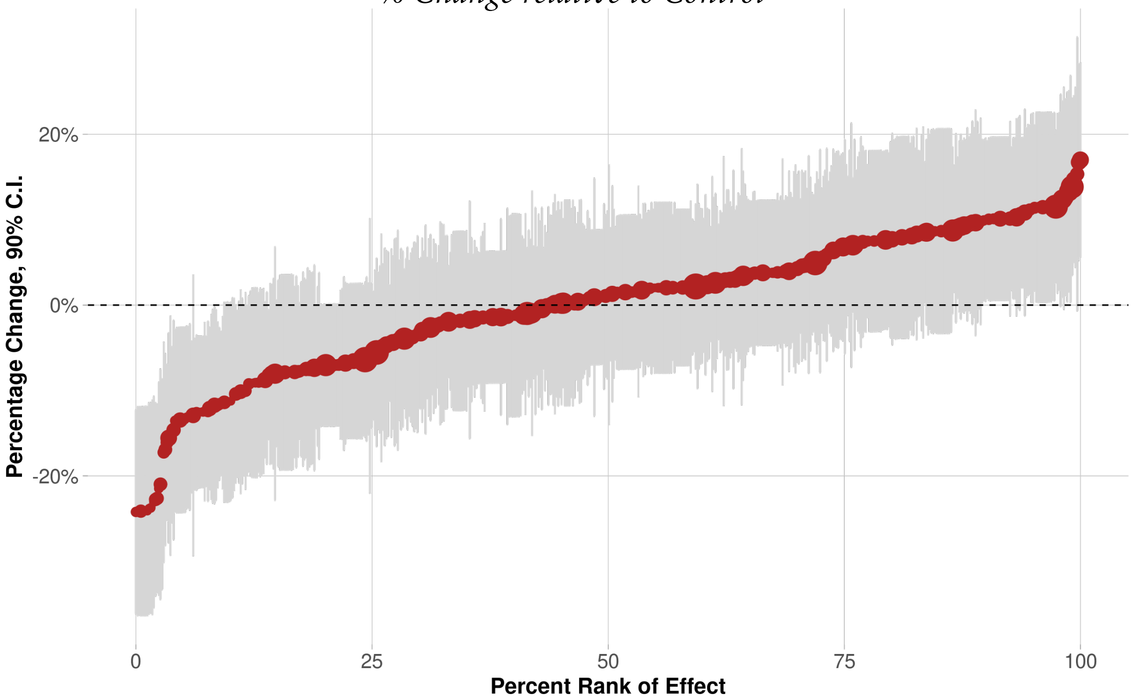
% Change relative to Control



Note: The causal forest was trained on 70% of the extreme risk universe, and the plotted effects are calculated on 30% of the rest. We use 50,000 trees to grow the forest. We use baseline variables to fit the model. A bigger size of the circle effects tells us that more observations lie within the branch of the calculated conditional average treatment effect.

Figure A41: Causal Forest—**Severe** Risk Group

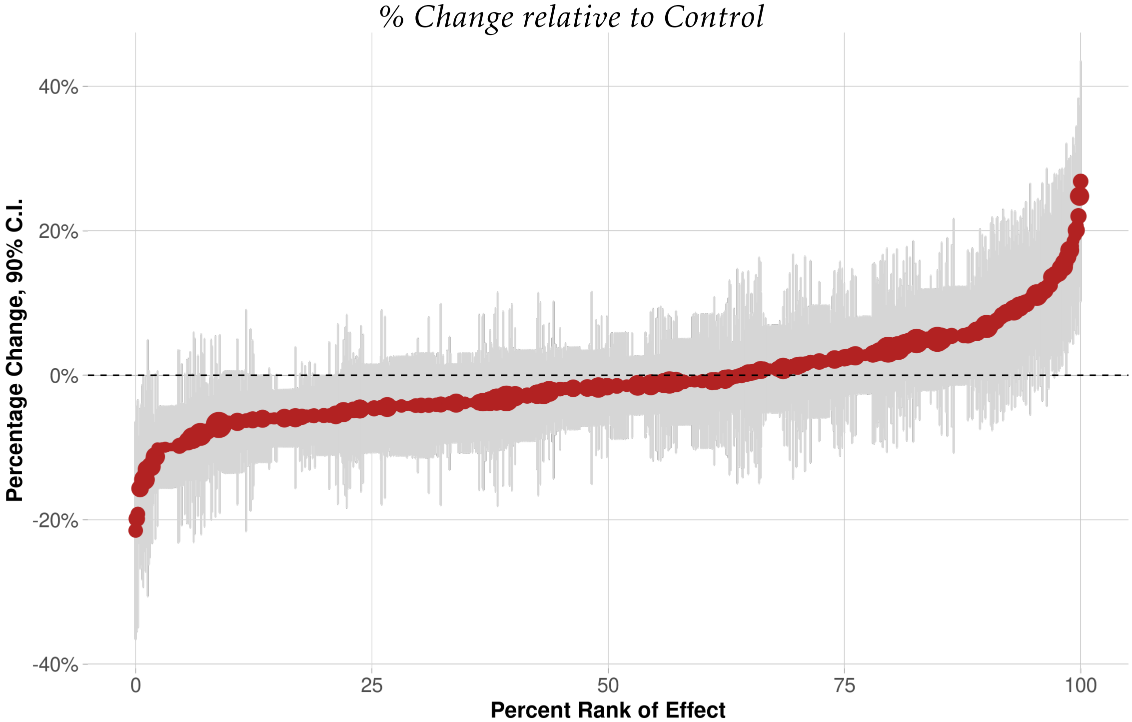
% Change relative to Control



Note: The causal forest was trained on 70% of the severe risk universe, and the plotted effects are calculated on 30% of the rest. We use 50,000 trees to grow the forest. We use baseline variables to fit the model. A bigger size of the circle effects tells us that more observations lie within the branch of the calculated conditional average treatment effect.

Figure A42: Causal Forest—**Major** Risk Group

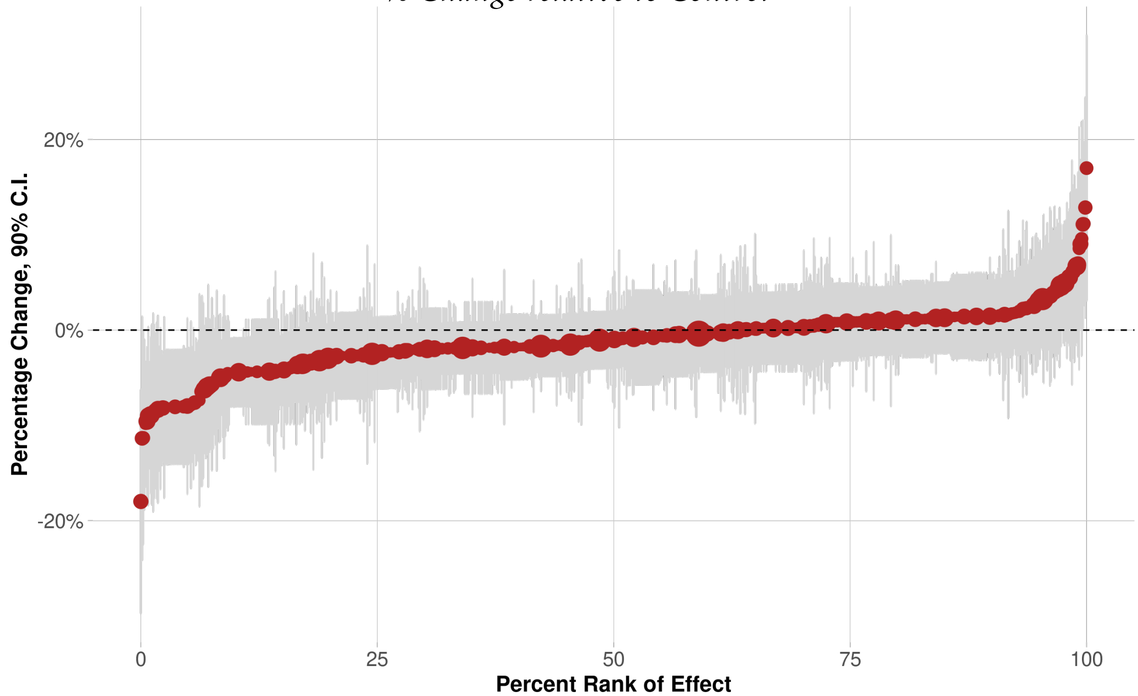
% Change relative to Control



Note: The causal forest was trained on 70% of the major risk universe, and the plotted effects are calculated on 30% of the rest. We use 50,000 trees to grow the forest. We use baseline variables to fit the model. A bigger size of the circle effects tells us that more observations lie within the branch of the calculated conditional average treatment effect.

Figure A43: Causal Forest—**Moderate** Risk Group

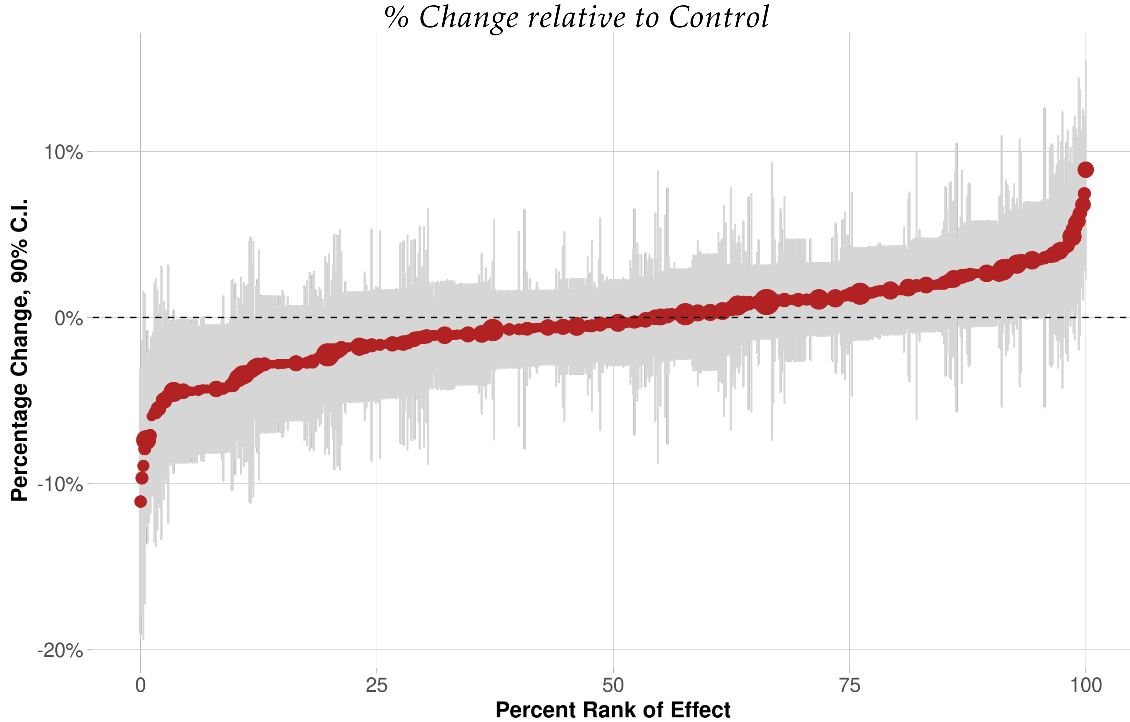
% Change relative to Control



Note: For computational reasons, we used 20% of the moderate risk universe. From that sample, the causal forest was trained on 70% of it, and the plotted effects are calculated on the 30% rest. We use 50,000 trees to grow the forest. We use baseline variables to fit the model. A bigger size of the circle effects tells us that more observations lie within the branch of the calculated conditional average treatment effect.

Figure A44: Causal Forest—**Minor** Risk Group

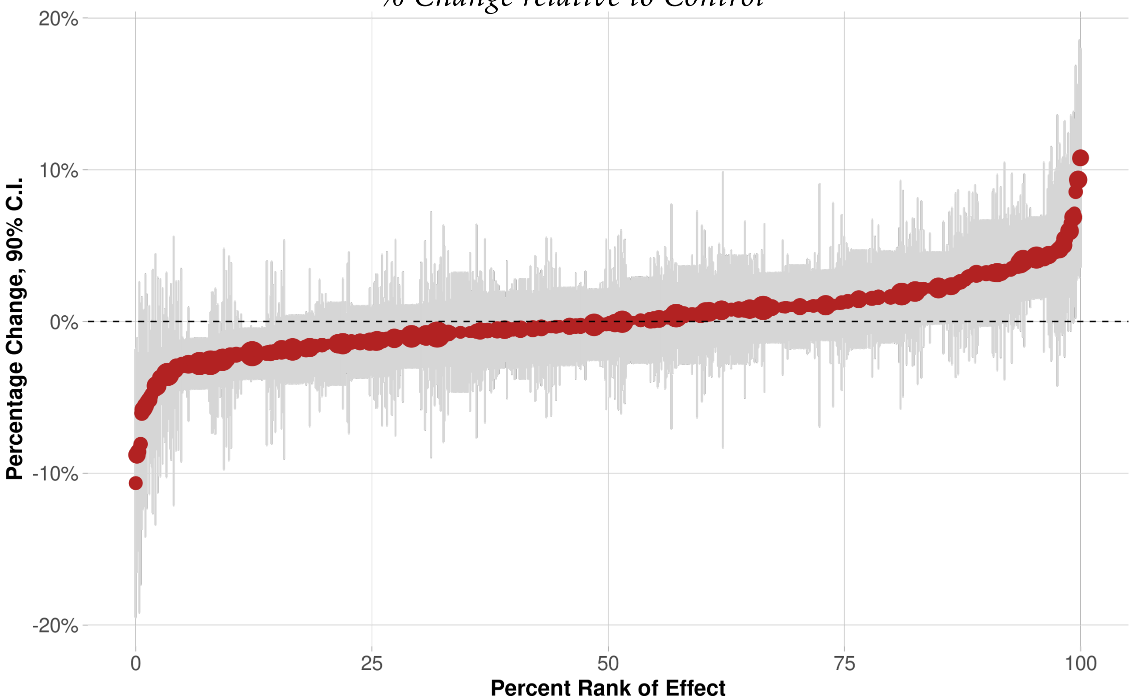
% Change relative to Control



Note: For computational reasons, we used 10% of the minor risk universe. From that sample, the causal forest was trained on 70% of it, and the plotted effects are calculated on the 30% rest. We use 50,000 trees to grow the forest. We use baseline variables to fit the model. A bigger size of the circle effects tells us that more observations lie within the branch of the calculated conditional average treatment effect.

Figure A45: Causal Forest—**Minimal** Risk Group

% Change relative to Control



Note: For computational reasons, we used 5% of the minimal risk universe. From that sample, the causal forest was trained on 70% of it, and the plotted effects are calculated on the 30% rest. We use 50,000 trees to grow the forest. We use baseline variables to fit the model. A bigger size of the circle effects tells us that more observations lie within the branch of the calculated conditional average treatment effect.