PRELIMINARY: The Impact of Climate Risk Disclosure on Housing Search and Buying Dynamics: Evidence from a Nationwide Field Experiment with Redfin

Daryl Fairweather*
Redfin

Matthew E. Kahn
University of Southern California & NBER

Robert D. Metcalfe
University of Southern California & NBER

Sebastian Sandoval-Olascoaga
Massachusetts Institute of Technology

July 31, 2023

Abstract

Climate change presents new risks for every 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. Within this experiment, 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; and (3) the impact of the flood risk information is more pronounced for users conducting searches in high flood risk areas, but does not differ significantly between buyers in Red and Blue Counties. We found that this information resulted in changes to property prices and altered the market's hedonic equilibrium, suggesting that climate adaptation can be forward-thinking and proactive. Overall the experiment affected the purchasing decisions of approximately $135 billion of real estate.

*We would like to thank Chris Costello, Matthew Eby, Cary Frydman, Justin Gallagher, Ed Glaeser, Ed Kearns, John List, John Matsusaka, Jeremy Porter and attendees at NBERSI EEE section for their comments. We also thank Robert Huang for his excellent research assistance.

1 Introduction

The precipitously urgent threat of 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 secondary location is chosen, they can further safeguard themselves by investing capital in defensive measures (Barreca et al., 2016), such as installing air conditioning systems, property stilts, fire-resistant roofs, and sturdy windows.

Adaptations like these are predicated upon individuals' awareness of high-stakes climate risks associated with their properties, 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 may be significantly overvalued, with an aggregate overvaluation estimated at approximately $200 billion (Gourevitch et al., 2023). This exposure to climate change risk is expected to worsen over time as the exposure to climate change risk intensifies (Marcoux and Wagner, 2023).

Furthermore, 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). However, the human cost 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. 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 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, evenly split between treatment and control groups). 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 implemented randomized assignment of complete property-level flood information at the individual customer level. Randomization took place either at the device level or, if the visitor was registered with Redfin and logged in, at the individual level. For each property that a treated customer 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.

In our field experiment, the detailed 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. It has been argued that FSF maps 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 FEMA's flood maps, which primarily serve the requirements of the National Flood Insurance Program, 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. The FSF predictive model has undergone peer review (Armal et al., 2020; First Street Foundation, 2020; Flavelle et al., 2020; Porter et al.,

[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 complained to Redfin about the flood risk information.

2021), and ongoing research efforts aim to validate its model predictions by leveraging recent natural disasters as natural experiments.[3]

Our main hypothesis is that the presence of property-level flood risk information will affect consumer behavior and housing market expectations. We posit that the availability of this 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 the supply side can affect demand. Our emphasis on one's updating beliefs about a place based 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 hypothesis. By testing how information shapes individuals' expectations, we aim to shed light on the role of information in facilitating adaptation to climate change. We believe that this is important, yet many existing 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.[4]

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 comprehensive insights into user behavior without the need of building a search model or

[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. 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.

[4]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 exactly what we do in this paper.

imposing any structure. Redfin employs real estate agents, a 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. 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.

Additionally, we augment our analysis by linking the Redfin data with market data on all U.S. property transactions. This allows us to examine the impact of information disclosure on the hedonic equilibrium of the housing market. By incorporating transaction data, we can assess how the availability of flood risk information influences the overall market dynamics and pricing. 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.

We report three main sets of results. First, we show how the randomized flood risk information changes people's search and 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 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 10% reduction in the flood risk of their searched homes after two months. The mechanism was that consumers learned which properties and locations had high flood risk and created a sense of which properties were to be avoided. Furthermore, the availability of detailed search data allowed us to gain 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 like bike and walk score. This suggests that individuals actively and organically adjusted their search parameters and strategies in response to the flood risk information provided by Redfin.

Notably, our analysis also revealed that treated individuals who were searching for homes in zip codes different from their current residence, and thus potentially had limited local information and knowledge, exhibited a higher sensitivity to the flood risk information. This group showed a more substantial reduction of 23% in the flood risk of their searched homes. Overall, these findings demonstrate that the provision of detailed flood risk information on Redfin influenced users' search behavior, leading to a greater focus on properties with lower flood risk. The analysis of trade-offs and the differential impact on individuals lacking local knowledge provide valuable insights into the behavioral responses to flood risk information.

Our search analysis revealed several interesting secondary findings. By employing machine learning techniques and estimating conditional average treatment effects, we discovered that 62% of all individuals were affected by the flood risk information, meaning they adjusted their searched flood score downward (i.e., searched for homes with lower flood scores). Among individuals who initially searched for homes with high flood risk, the proportion affected by the information increased to 85%. However, it is important to note that we failed to reject several null hypotheses. For instance, we found no difference in the treatment effects for individuals who Redfin identified as more likely to purchase a property. Additionally, individuals across all income levels exhibited similar behaviors in response to the flood risk information. Moreover, there was no difference in treatment effects regardless of the percentage of risky properties browsed by an individual according to FEMA's classification. This suggests that even for properties identified as high-flood risk by FEMA, the federal information fails to reach or to fully inform consumers about properties' actual flood risk; this may be due to a number of reasons, including the data's intelligibility and ease of access.

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, buyers are confronted with tradeoffs and our results suggest that across the political spectrum that a risk adaptation nudge induces, on average, the same behavioral response.

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. Overall, these findings demonstrate that political affiliation, attitudes about climate change, income level, and recent flood events did not significantly impact users' responsiveness to the flood risk information.

Second, our analysis of the impact of flood risk information on physical engagement with homes revealed several interesting findings. While the flood risk information did not significantly change the overall probability of touring a property, placing an offer, or closing a bid (the extensive margin behaviors), 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. Treated individuals also exhibited a lower likelihood of placing offers on waterfront (but not coastal) properties. This aligns with the search behavior findings, indicating that individuals were willing to trade off flood risk for other desirable property attributes. 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, akin to the principles of Charles Tiebout's theory of local public finance. 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.

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. We found that a higher percentage of treated users per property led to a maximum penalty of nearly $7,000 for homes with high flooding risk across the United States (that are not located in the high-risk FEMA zones). 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 best information available on the expectations of climate change impacting high-risk homes.[5]

Notably, these price decreases were observed for properties that were not considered risky by FEMA or not on the waterfront but were identified as risky by FSF. This suggests that the flood risk information provided by FSF, which incorporates future climate change trends and pluvial and fluvial risks, revealed previously unrecognized flood risks that were not captured by FEMA's maps. We found no heterogeneity in terms of the initial property price. This finding indicates that the impact of the flood risk information was consistent across different price ranges. This supports our earlier results, which showed that consumers of all income levels and from different geographic locations were affected by the flood risk 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 reduc-

[5]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".

tion in value due to the newly revealed flood risks provided by FSF's predictive model. The three-month field experiment was very high stakes, 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.

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. While previous studies have used observational data or simulations to analyze climate change adaptation (Massetti and Mendelsohn, 2020),[6] our experiment leverages a unique opportunity to study the causal effects of flood risk information on consumer behavior.

Existing empirical literature has explored how climate risk is capitalized into local home prices, with mixed findings regarding the extent of capitalization.[7] In addition, such studies often assume that market participants are fully aware of the actual risk faced by properties.[8] In contrast, our research challenges this assumption by demonstrating that individuals are averse to high flood risk properties once they are exposed to the new information, leading to our new news hypothesis. The fact that the flood risk information influenced search behavior,

[6]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 inferior FEMA maps that exclude new flood-risk science. We would not find treatment effects in our experiment if previous information sets were complete, available, and accessible, hence our new news interpretation.

[7]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; 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 depends 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).

[8]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 (Kousky and Netusil, 2023). Moreover, any adaptation measures that are taken, such as home elevation, is under-invested because benefits accrue too far into the future (Hovekamp and Wagner, 2023).

bidding behavior, and hedonic equilibrium pricing suggests that the information was not previously known or fully incorporated into market outcomes.

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; Ainsworth et al., 2023; Gao, Song and Timmins, 2023). Our research contributes to the 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 and storms (Balboni, 2019; Hong, Wang and Yang, 2020; Desmet et al., 2021; Fried, 2022; Bilal and Rossi-Hansberg, 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. The results from our natural field experiment suggest that anticipating such risks is important for assessing the general equilibrium welfare effect of increased flooding, consistent with the other work on the climate change adaptation benefits of better weather forecasts (Molina and Rudik, 2022; Downey, Lind and Shrader, 2023; Shrader, Bakkensen and Lemoine, 2023).

First Street Foundation's flood risk scores, readily accessible and comparable on the Redfin app, nudged home buyers to update their beliefs about each property's emerging risks. Such updates to an individual's expectations affect their investment decisions. In this sense, our paper builds on an emerging nudging literature that seeks to improve the 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 for helping 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. The FSF flood risk information in our paper should be thought of as a similar model-based information intervention.[9]

We also build on the literature of housing search. There are not many papers that analyze the search behavior of home buyers because it is usually difficult to observe home buyers' behavior or ascertain the data from search companies. The only paper coming close to the level of data we have is Piazzesi, Schneider and Stroebel (2020).[10] They have data from trulia.com, where they examine 43,000 email alerts from only one metro area in the U.S. (Bay Area) and match their data with a heterogeneous housing search model. However, we have data from the whole of the U.S., we have all of the customers' search, engagement, and offer data (400 million properties searched), we have this data matched to the MLS, and we have randomized information on an important academic and policy-relevant attribute: flood risk. We also then match the experiment to different search populations to test the mechanism of behavior change: "new news" on flood risk.

Our field experiment shows that a new piece of information on climate risk allows investors to update their beliefs and vote with their feet (Banzhaf and Walsh, 2008). Our treatment effect estimates indicate the conditional average response to this "new news." If this information is already known, or if it is ignored, then we should see no treatment effect. Thus, we view our field experiment estimates to be important because they convey how home investors respond to low cost yet salient information about emerging risks.[11] 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.

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.

[9]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.

[10]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).

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

2 The Field Experiment

We present evidence of a nationwide field experiment randomized at the individual (i.e., platform user) level. It is a natural field experiment since users were not aware of the experiment and there was no selection into the experiment (Harrison and List, 2004). 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.[12] 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.

2.1 Background

The non-profit organization First Street Foundation (FSF) created the Flood Factor Score as a tool to predict a property's current and future risk of flooding. 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.[13]

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

[12]The actual start date of the experiment was October 1st, 2020. At that point in time, the macroeconomic environment was between the COVID-19 peaks and a stable economy.

[13]FSF has received funding from donors such as 2040 Foundation, Hightide, and Grantham.

Foundation, 2020).[14]

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.[15]

2.2 The Design of the Field Experiment

In this 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 1 presents the experiment experience using a mobile device for both the control and treatment groups within a property page that has a flood score of 6 (i.e., major flood risk).[16] The control group (Figure 1(a)) did not see the flood risk section while scrolling a property page, whereas the treatment group (Figure 1(b)) had full access to it.[17]

[14] 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 SSP2-45 instead of the extreme scenario of SSP5-85.

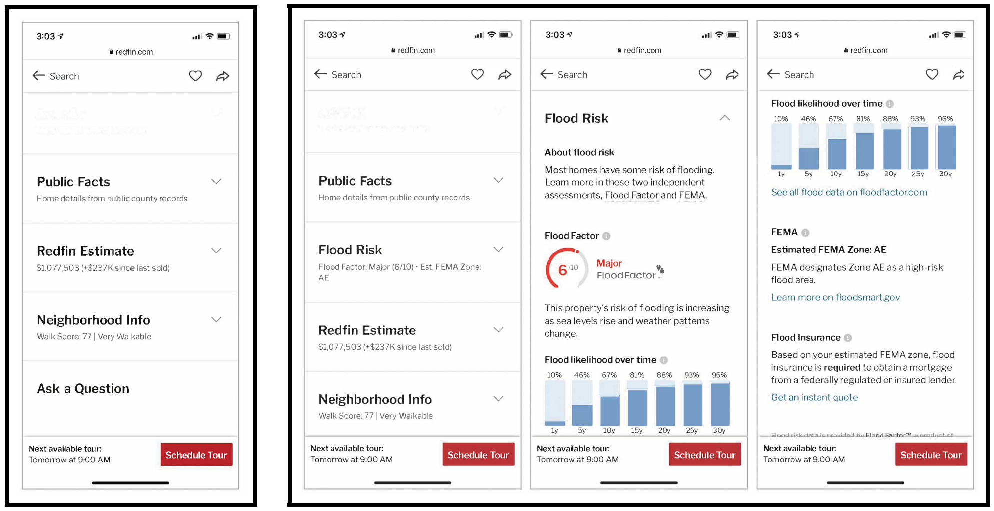
[15] We do not test whether the individuals in our experiment fully update their beliefs or the other mechanisms as to why this information might work in changing behavior.

[16] Figure A2 presents the experiment experience for treated users using a desktop. As another example, Figure A3 shows the visual experience using a mobile device for a property page with a flood score of 4 (i.e., moderate flood risk)

[17] Figure A4 shows the color and labels Redfin used to show a property's flood score within the flood risk section, ranging from a flood score of 1 to 10.

Figure 1: 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 clicked on the flood risk section, they viewed an "about flood risk" paragraph; the colored (i.e., from light green to dark red depending on the risk) Flood Factor Score; the flood likelihood of the property over time (i.e., 1, 5, 10, 15, 20, 25, and 30 years);[18] the home's FEMA official flood risk zone if available, and flood insurance information. We can test whether the FEMA flood risk zones have an impact on treated individuals in the study since some individuals searched for properties within a FEMA flood zone before the experiment began. We find no major differences in treatment effects for those searching in and out of a FEMA flood zone.

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).

[18] 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 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. In our model, 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.[19]

If climate change increases the risk that a given home faces and if this risk is not common knowledge, then the buyer may subsequently regret her investment. If climate increases the risk 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. Below, we sketch out the implications of all three cases.

To simplify the algebra below, we focus on one attribute of housing namely flood safety. 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 F.[20] Consumers only differ by their preference for flood safety (α). It is assumed to be normally distributed with mean $\bar{\alpha}$ and standard deviation σ_α.

We consider the case when the supply of properties is exogenous, and their perceived safety follows the distribution $N(\bar{f}, \sigma_f^2)$. A Consumer's bid depends on the safety of the property, denoted by h. Specifically, $h = \frac{f-\bar{f}}{\sigma_f}$, where f is the perceived level of safety. Due to the transformation, h follows a standard normal distribution. . Consumers do not have full information on $\bar{f}$ and σ_f^2. Their perceived safety of each property depends on the actual

[19] We recognize that different people will have different baseline beliefs about emerging climate risks. Some may embrace the FEMA maps as delineating the risk. 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.

[20] 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.

safety of the property and their belief on climate change ($\bar{f}$ and σ_f^2).

Following the closed form hedonic models presented in Epple (1987) and Giannias (1999), we assume consumers' utility function takes the following form:

$$U(h,x,\alpha) = \epsilon + \gamma_1 h + \gamma_2 \alpha h + \frac{1}{2}\rho h^2 + \omega x h + \theta x \tag{1}$$

and the budget constraint is given by $x + P(h) \leq I$, where $P(h) = \pi_0 + \pi_1 h$ is the equilibrium price function. Then the utility maximization problem can be written as:

$$max_h U(h, I - P(h), \alpha) \tag{2}$$

We substitute $P(h)$ into the utility function and the first order condition is given by:

$$(\gamma_1 + \gamma_2 \alpha + \omega I - \omega \pi_0 - \theta \pi_1) + (\rho - 2\omega \pi_1)h = 0 \tag{3}$$

The demand for safety is $h = \frac{(\gamma_1+\gamma_2\alpha+\omega I-\omega\pi_0-\theta\pi_1)}{(2\omega\pi_1-\rho)}$. Because h is linear in α, which is normally distributed, the aggregate demand for safety is also normally distributed. Its mean is $\frac{(\gamma_1+\gamma_2\bar{\alpha}+\omega I-\omega\pi_0-\theta\pi_1)}{(2\omega\pi_1-\rho)}$ and its variance is $\frac{\gamma_2^2\sigma_\alpha^2}{(2\omega\pi_1-\rho)^2}$.

In equilibrium, aggregate demand will equal aggregate supply. This is equivalent to:

$$\frac{\gamma_1 + \gamma_2 \bar{\alpha} + \omega I - \omega \pi_0 - \theta \pi_1}{2\omega \pi_1 - \rho} = 0 \tag{4}$$

$$\frac{\gamma_2 \sigma_\alpha}{2\omega \pi_1 - \rho} = 1 \tag{5}$$

From the above equations, we know the gradient of the hedonic function $\pi_1 = \frac{1}{2\omega}(\gamma_2\sigma_\alpha + \rho)$ and the intercept $\pi_0 = \frac{1}{\omega}(\gamma_1 + \gamma_2\bar{\alpha} + \omega I - \frac{\theta}{2\omega}(\gamma_2\sigma_\alpha + \rho)$. When we transform the unit to the actual safety level, the hedonic pricing function is given by:

$$P_0(f) = (\pi_0 - \frac{\pi_1 \bar{f}}{\sigma_1}) + \frac{\pi_1}{\sigma_f} f \tag{6}$$

Proposition 1: Due to climate change, the distribution of flood safety shifts such that; $\bar{f}$ decreases to $\bar{f}'$ and σ_f^2 increases to $\sigma_f'^2$. When consumers have full information about this new distribution, properties whose safety has declined will lose value and vice-versa.[21]

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

Consumers reevaluate the safety level of each property based on their new information on climate change. Denote the perceived safety level with and without the new information by h_0 and h_1, respectively. The new hedonic price function will have a smaller gradient (replace σ_f by σ_f' in equation (6)) and a larger intercept (replace $\bar{f}$ by $\bar{f}'$). Denote this new hedonic function by $P_1(f) = \pi_0' + \pi_1' f$. Denote the relative safety level with and without climate change by h_0 and h_1, respectively. Then we calculate the price difference of each property with a given safety level f_0 at the new versus the old equilibrium:

$$P_1(f_0) - P_0(f_0) = \left(\frac{\pi_1 \bar{f}}{\sigma_f} - \frac{\pi_1 \bar{f}'}{\sigma_{f'}}\right) - \left(\frac{\pi_1}{\sigma_f} - \frac{\pi_1}{\sigma_{f'}}\right) f_0 = \frac{f_0 - \bar{f}'}{\sigma_{f'}} - \frac{f_0 - \bar{f}}{\sigma_f} \equiv h_1 - h_0 \tag{7}$$

Consumers reevaluate the safety level of each property based on their new information on climate change. The above equation shows that for properties whose safety level is previously underestimated ($h_0 < h_1$), their prices at the new equilibrium are higher. In contrast, consumers are willing to pay less for properties that are revealed to be riskier due to climate change.

Now suppose only $k\%$ of the population (randomly selected) know that the true distribution of safety is $N(\bar{f}', \sigma_f'^2)$. Consumers' utility depends on the perceived safety level and the price of the property. For those without the new information on climate change, their perceived safety is h_0 despite the actual safety level h_1. These consumers face the following maximization problem, where P_2 denotes the price equilibrium function in this economy without full information:

$$Max_{h_0} U(h_0, I - P_2(h_1), \alpha) \tag{8}$$

while consumers with updated information solve the following problem:

$$Max_{h_1} U(h_1, I - P_2(h_1), \alpha) \tag{9}$$

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 the first case.

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.

Suppose they both bid for a property with safety level f_0, whose relative safety is h0 and h1 respectively before and after climate change. Assume $h_1 > h_0$ (i.e., a safer property under climate change). Their bids can be described as the maximum δ that satisfies the following:

$$U(h, I-\delta, \alpha) \geq U_0 \tag{10}$$

where U_0 is a given utility level. By substitution, the bid function can be written as:

$$\delta \leq \frac{\epsilon + \gamma_1 h + \gamma_2 \alpha h + \frac{1}{2}\rho h^2 + \omega I h + \theta I}{\omega I h + \theta} \tag{11}$$

The bid increase as the perceived safety h increases (given that all the coefficients are assumed to be positive). When $h_1 > h_0$, consumer A would bid higher for the property, given that α is the same for both consumers.[22]

Note that if nobody has updated their information ($k = 0$), the above equation is the same as the baseline case in equation (6). If everyone has updated their information ($k = 1$), this equation is the same as the case when everyone gets the information simultaneously (i.e. substitute the new mean and variance into equation (6)). As k increases, the hedonic price gradient moves gradually from the baseline case to the full information case (see Proposition 1).

[22]The maximization problems in equations (8) and (9) 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 π_1'' and π_0'' are coefficients of $P_2(h)$:

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

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

Since both h_0 and h_1 are linear in α are normally distributed, the aggregate demand is $(1-k)h_0 + kh_1$, which is thus also normal. Its mean is $(1-k)E[h_0] + kE[h_1]$ and its variance is $(1-k)^2 Var(h_0) + k^2 Var(h_1)$, assuming the aggregate demand from the two groups are independent. At equilibrium, aggregate demand should equal aggregate supply of relative safety h_1, which follows a standard normal distribution. Thus, $(1-k)h_0 + kh_1$ should have a mean 0 and a variance 1. We can solve for π_1'' from the following equation and plug it back to solve for π_0'':

$$(1-k)^2 * \frac{\gamma_2\sigma_a}{2\omega\pi_1'' - \rho\frac{\sigma_f'}{\sigma_f}} + k^2 * \frac{\gamma_2\sigma_a}{2\omega\pi_1'' - \rho} = 1 \tag{14}$$

Once we find π_1'' and π_0'', we can transform in the same way as before to obtain the hedonic pricing gradient as a function of the absolute safety level:

$$P(f) = \left(\pi_0'' - \frac{\pi_1''\bar{f}'}{\sigma_f'}\right) + \frac{\pi_1''}{\sigma_1'} f \tag{15}$$

Proposition 3: Consumers with a greater preference for safety have a higher willingness to pay for new information.

For a given consumer, we have shown their demand for safety in both cases when the new information is available. Suppose the utility-maximizing safety level is h_1 and h_0 when this consumer knows or does not know the information respectably. The loss in consumer surplus (in dollar value) can be found by solving for Δx in the following equation:

$$U(h_0, I - P_2(h_0) + \Delta x, \alpha) = U(h_1, I - P_1(h_1) + \Delta x, \alpha) \tag{16}$$

For simplicity, we consider the case that only the mean of the supply of safety decreases, and the standard deviation does not change. By substituting and rearranging, Δx can be shown to be a decreasing function of h_0 and thus an increasing function of α (under the assumption that the coefficients in the utility function are positive, including γ_2).

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.[23]

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

[23] 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 would happen if there are some people who do not believe climate change. In Appendix X, we discuss this case.

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

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.[24] 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).

2.4 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 12$^{\text{th}}$, 2020 and January 3$^{\text{rd}}$, 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) that 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 they have a higher likelihood of actually purchasing a home and we observe their behavior for a longer time frame.[26]

2.4.1 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.

[24] 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).

[25] We had full access to the data from Redfin for one week before the first day of the experiment, starting on October 6$^{\text{th}}$.

[26] Redfin uses registered users to understand the long-term impact of their experiments.

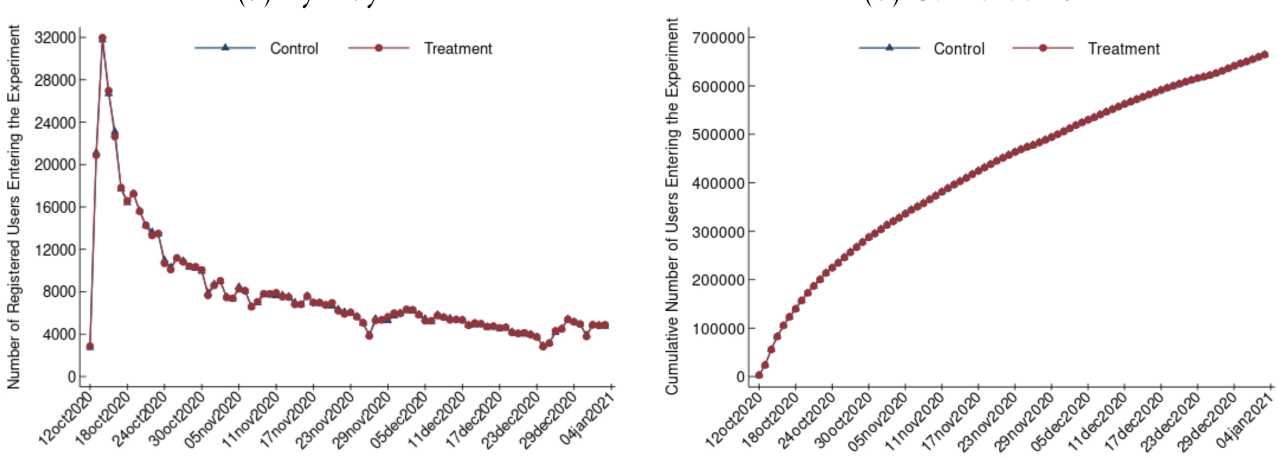
Redfin assigns users to treatment and control cohorts through a hashing algorithm, considering both the unique experiment ID and the unique user ID (i.e., an HTTP cookie). The algorithm begins by first hashing the experiment ID using the SHA-1 algorithm. Following this, the hashed experiment ID is combined 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 while browsing listings. This stage ensures the stickiness of users within each experiment.

Individuals entered the experiment sequentially through time (see Figure 2) 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, every individual had access to the Flood Factor section for each property they viewed. See Figure A5 for the whole 17.5 million Redfin customers entering the experiment.

Figure 2: Number of Registered Users Entering the Experiment

(a) By Day　　　　(b) Cumulative



3 Data and Empirical Strategy

In this section, we describe the data and its sources, the estimation strategy, and then show the randomization balance tests.

3.1 Data

The data sets 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.[27] Every time an individual clicked on a home, the website collected 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 was generated with the following columns: the user's anonymized unique ID and an anonymized login ID;[28] 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 short sale;[29] the year when the property was built; and the walking, transit, and bike scores where the property is located.[30] 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,

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

[28] 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.

[29] 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.

[30] 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.

conducted a tour, etc.). This data also contains the seconds spent per session, the number of sessions, and the number of total and unique listings views, among other variables. In this sense, we have multiple single data points for every property view that a user conducted. 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 data comes from Redfin and covers those regions where the brokerage operates.[31]. 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.

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:

$$y_{it} = \beta_0 + \beta_1 I_{it} + \beta_2 D_i + \beta_3 (I_{it} * D_i) + u_{it} \tag{17}$$

Where, y_{it} is the average outcome of individual, i, during day, t. We will focus on the

[31] 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.

flood risk score of the property as the outcome variable. I_{it} is an indicator that takes 1 if the observation occurs after 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 17 provides an unbiased estimate of the ATE and randomization provides internal validity of the estimate. Standard errors are clustered at the individual level. This estimate will demonstrate the impact of the flood score information across all individuals in the experiment.

Conditional Average Treatment Effect (CATE) across post-treatment time points. We use a similar estimator as in 17 with an interaction term on an observed covariate, $X \in \mathbb{R}$, in the following way:

$$y_{it} = \beta_0 + \beta_1 (I_{it} * X_i) + \beta_2 (D_i * X_i) + \beta_3 (I_{it} * D_i * X_i) + u_{it} \tag{18}$$

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 (17) 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.

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 17, this estimator provides a flexible, dynamic functional form across time, commonly known as a difference-in-differences event-time study:

$$y_{it} = \beta_0 + \sum_{k \neq -1} \beta_k (T_{ik} \cdot D_i) + u_{it} \tag{19}$$

Where, T_{ik}, is an indicator variable for individual, i, in 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 19 is β_k. To provide further evidence that randomization ensured a balance between the treatment and control units, we conduct a joint test of the null hypothesis: $\sum_{t<T_0} \beta_k = 0$. Standard errors are clustered at

the individual level.

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 A3 and A4 provides estimates of regressing outcomes of interest before the experiment began against a treatment dummy variable for registered users. 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 A6 (a) to (f) provide estimates of the event-time study estimator for individuals at any pre-treatment time point to estimate differences in pre-trends. Visually, any pre-treatment confidence interval estimates lie outside the null hypothesis. For every regression, one cannot reject the joint null hypothesis, providing additional evidence that randomization worked and that we have parallel pre-trends. 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 A12 presents the number of registered users within each flood risk category before the experiment began, stratified by treatment assignment for the registered individuals. One cannot reject that both distributions are different (Pearson $\chi^2(5) = 5.1$, p-value = 0.398), suggesting a balance between treatment and control 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.[32] 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.

[32]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.

Given that registered users are more typical of the average individual who is going to buy 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 information had heterogeneous effects (4.4).

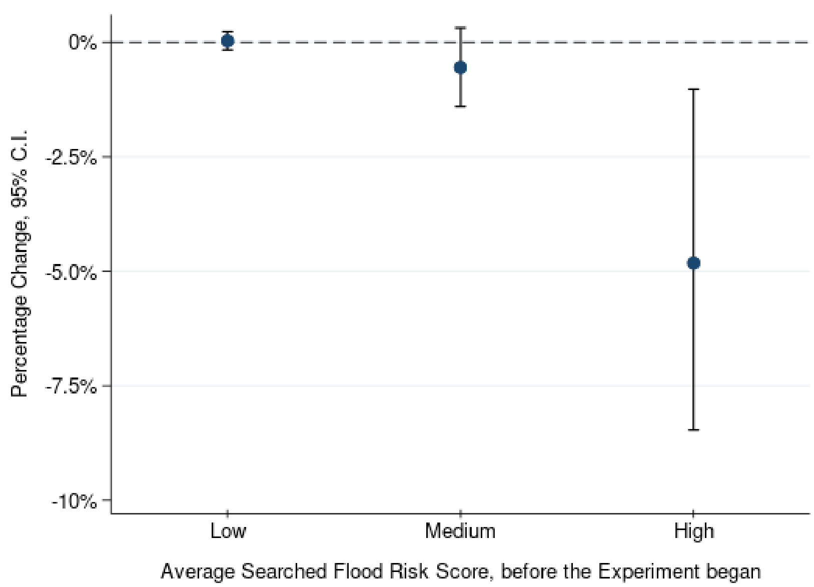
4.1 Home Search Behavior Dynamics

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 (17) for the whole sample, not segmenting by flood risk. Tables A15 (i.e., for all Redfin users) and A17 (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 - 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). On average, the treatment did not change the number of properties a user browsed per day, nor the average number of bathrooms, square feet, or list price of the properties browsed per day. However, users with access to the flood score browsed properties with fewer bedrooms. They also geographically expanded their searches by increasing the number of zip codes searched per day relative to the control.

When stratifying users by their average flood score of all the houses viewed before the experiment began (by estimating the CATE in equation (18)), treated users registered on the platform had a meaningful and significant change in their search behavior with a monotonic decrease in how flood risky the user's searches were before the experiment began. Figure 3 presents estimates of β_3 from equation (18) by baseline average flood score search category. The largest change was among those browsing, on average, high (i.e., severe or extreme) flood risky properties pre-experiment. That is, treated registered users in this category browsed properties with -4.82% lower flood score than their control counterparts (p<0.01). This effect size is large, as it is equivalent to a change in the flood score of 0.5 on a ten point scale. An analogy of this effect size is in terms of the average reduction in long-term flood risk associated with this change in the flood score. The comparable reductions in flood risk over 1, 2, 5, 10, 20 and 30 years are 8.0%, 10.6%, 6.2%, 4.1%, 3.4%, 2.9%, and 2.7%, respectively. However, people looking in relatively small risky areas do not have much range to move out of, so we also report the standard deviation effect size. For our high risk treated group, their standard deviation effect size is X.X. The effect sizes for low and medium risk are 0.03% (s.e. = 0.10) and -0.54% (s.e. = 0.43), respectively.[33]

Figure 3: 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 18. 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.

In Figure 4, we present estimates of β_k from estimator 19 (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

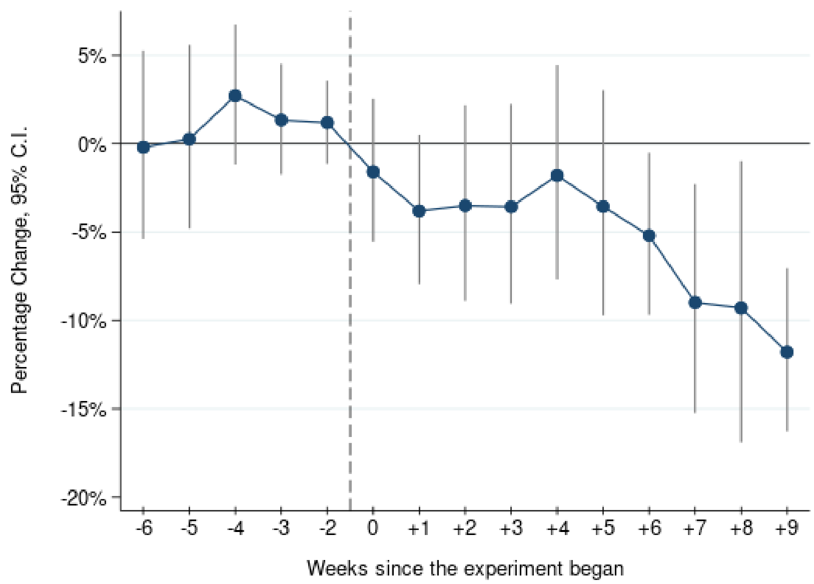
[33]When running the analysis on every user and not just the registered ones, those browsing low, medium, and high risk flood areas pre-experiment browsed properties with 0.00% (s.e. = 0.03), -0.78% (s.e. = 0.17), and -1.73% (s.e. = 0.95) lower flood scores, in that order, relative to their control counterparts.

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.

However, we did not find statistically significant effects in event-time studies involving registered users browsing properties with varying levels of average flood risk prior to the experiment. Specifically, Figures A7 (a) and A7 (b) illustrate the results for users browsing, on average, low and medium risky properties before the experiment began, respectively.

Figure 4: 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 19. 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.

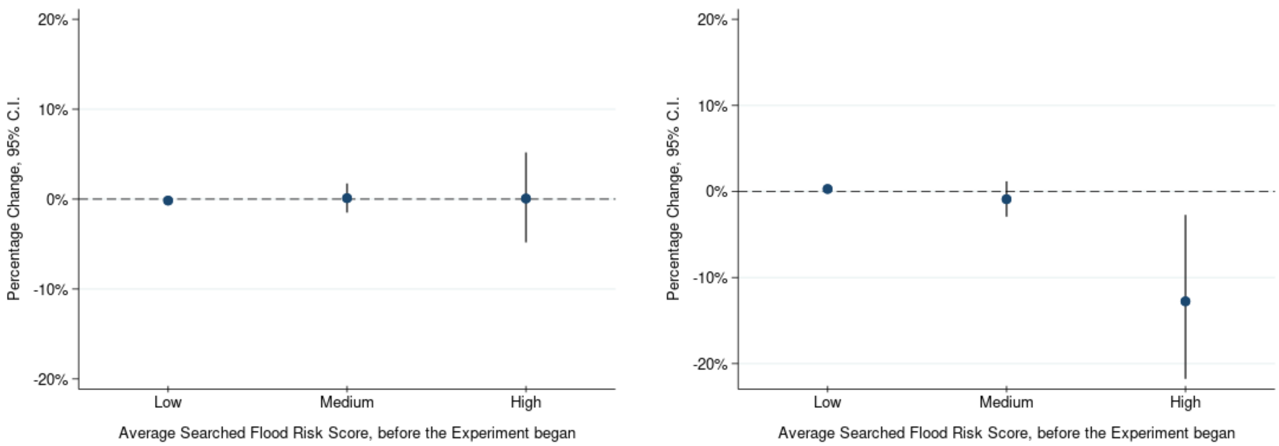
In this sense, we calculated the difference in the mean, standard deviation, and coefficient of variation (CV = (mean/standard deviation)) of the zip code's flood score between an individual's origin and most search destinations at baseline, and we interacted it with the treatment and the average flood score search at baseline to test our previous hypothesis.

We found that for individuals searching, on average, high flood risk homes pre-experiment and that also searched within zip codes with a *higher* flood risk CV than their origin, the average flood risk decreased by 12.77% ($p < 0.01$) after receiving the information (Figure 5 (b)). This reduction could be due to two possible changes: the treated individual searched within zip codes with a lower mean flood risk or within zip codes with a higher standard deviation. It is worth mentioning that interacting the treatment with the difference in the destination's and origin's zip code flood score mean and standard deviation did not have a meaningful or statistically significant effect (Figures A8 and A9, respectively).

Figure 5: 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

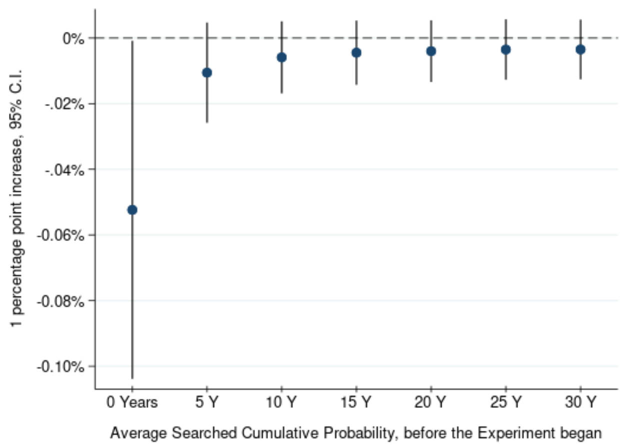
(b) **Higher Coefficient of Variation** Flood Score at Destination Zip Code than Origin



Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. 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.

In addition to displaying flood risk categories to treated users, our study (see Figure 1 for the visual experience of the experiment) provided them with a comprehensive view of the flood risk through a detailed quinquennial cumulative probability of a property flooding. Holding each user's average flood score search category before the experiment constant, we found that a 1 percentage point increase in the treated user's baseline cumulative probability of flooding to the building footprint in 2020 (0 years in Figure 6) decreased the average flood score search by 0.052%. However, we did not observe statistically significant effects for cumulative probabilities in years 5, 10, 15, 20, 25, and 30.

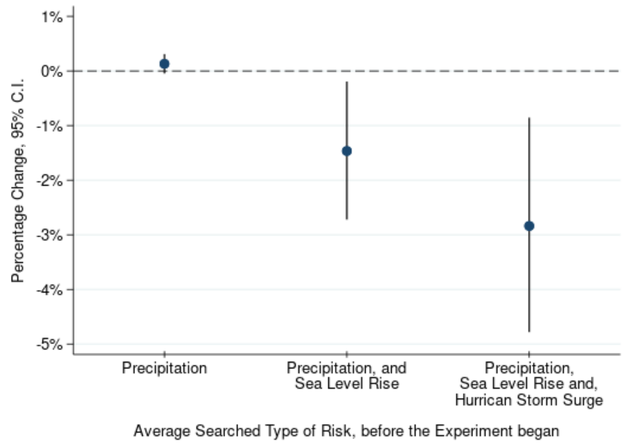
Figure 6: CATE on the Average Flood Score of a Daily Search for Registered Users, by Cumulative Flood Probability at Baseline



Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. 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 7).

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



Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. 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".

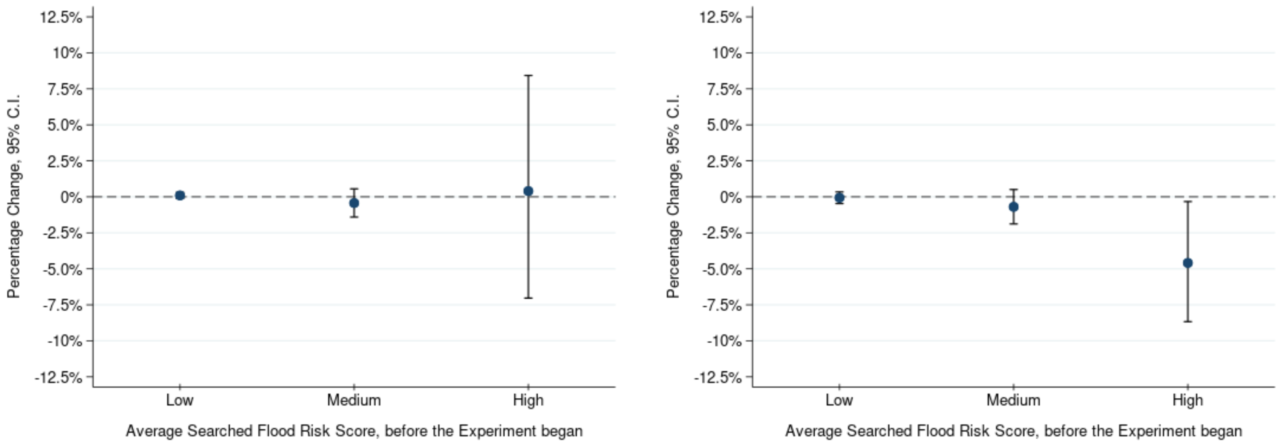
We also analyze the impact of the treatment for different types of people who search for homes that are: (a) either on the waterfront (seas/coastal, rivers, lakes) or not; (b) either in FEMA high risk zones or not; or (c) either on the coast or not; and (d) the various combinations of all these dimensions. We categorize people into various buckets by whether the customer had one of these homes in their search before the experiment took place.

In Figures 8 (a) and (b), we show that the flood risk information had an impact on those customers who had a waterfront property in the search before the experiment started. In Figures 9 (a) and (b), we show that the flood risk information had a similar impact on those customers who had a FEMA high risk property in the search before the experiment started, however, the size of the effect is larger for the without FEMA high property int heir search before the experiment started. In Figure 10 (a) we show that the flood risk information had an impact on those customers who had a waterfront but not coastal property in the search before the experiment started. In Figure 10 (b) we show that the impact of the high flood risk information for those searching for waterfront and coastal properties is more noisy.

Taken together, these results provide us with more evidence for the "new news" hypothesis. The impact of the treatment is coming through for people who are looking at waterfront but not coastal properties, which would not be in NFIP or designated as risky by FEMA.

Figure 8: CATE on the Average Flood Score of a Daily Search for Registered Users

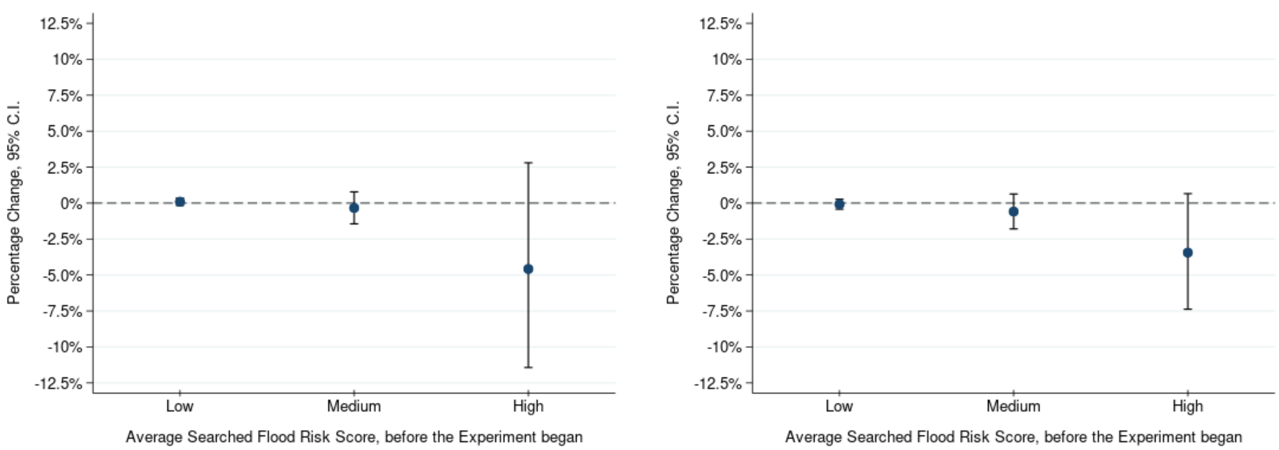
(a) **Without** Waterfront Search at Baseline (b) **With** Waterfront Search at Baseline



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

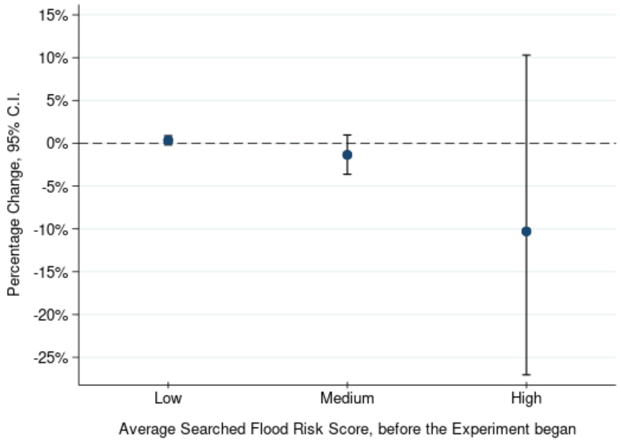
(a) **Without** FEMA Risk Search at Baseline (b) **With** FEMA Risk Search at Baseline



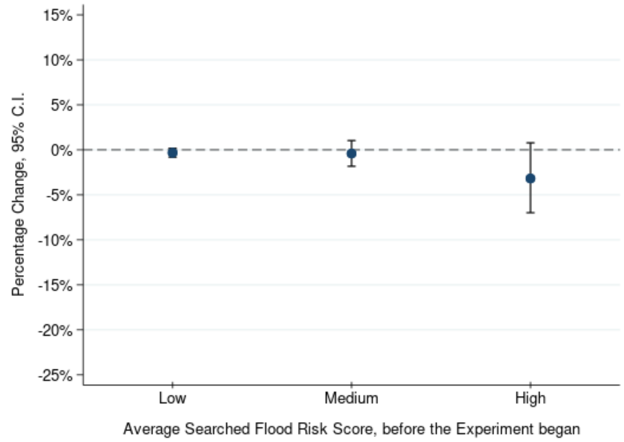
Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who did not browse any property considered risky by 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 10: CATE on the Average Flood Score of a Daily Search for Registered Users

(a) **With** Waterfront and **Without** FEMA Risk Search at Baseline



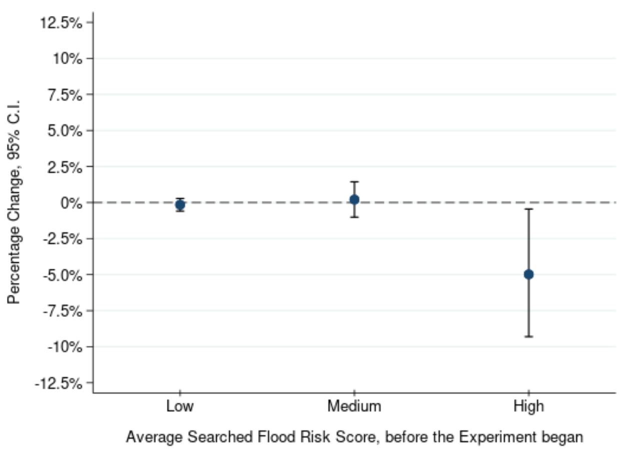
(b) **With** Waterfront and **With** FEMA Risk Search at Baseline



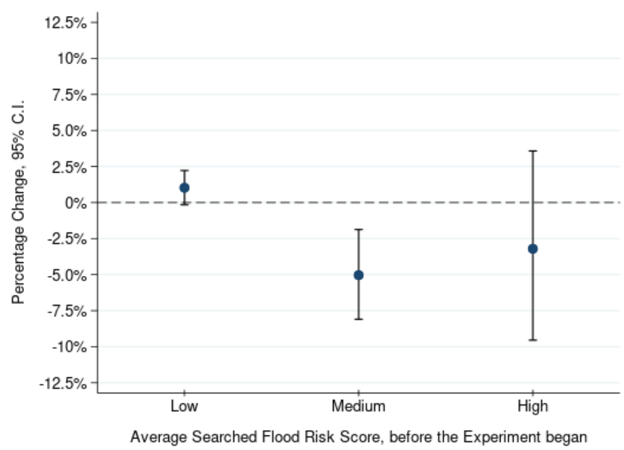
Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who browsed at least one waterfront property before the experiment are classified as "with" waterfront search at baseline. 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

(a) **With** Waterfront and **Without** Coastal Search at Baseline



(b) **With** Waterfront and **With** Coastal Search at Baseline

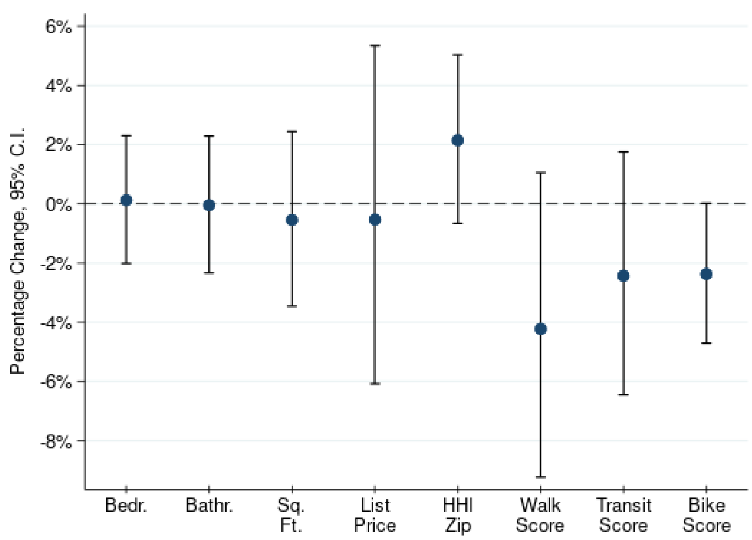


Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who browsed at least one waterfront property before 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 next examine what attributes of the property markets are consumers trading off for reduction in flood score of searches in the main result from Figure 3. In Figure 12 we examine the changes in the values of the property attributes. We do not see people trading off a lower flood score for a change in the number of bedrooms, bathrooms, sq ft, or list price. We see a slight increase in the HHI, meaning that consumers might be more concentrated in their property views within zip codes, although we only have 90% confidence in that result. However, we do find a lower bike score, and similar magnitude decreases in walk and transit score, although the latter two are more noisy. The bike score is calculated by measuring bike infrastructure (lanes, trails, etc.), hills, destinations and road connectivity, and the number of bike commuters. The walk score analyzes hundreds of walking routes to nearby amenities, e.g., grocery stores, schools, parks, restaurants, and retail (points are awarded based on the distance to amenities in each category). The walk score also measures pedestrian friendliness by analyzing population density and road metrics such as block length and intersection density. We suspect that both the walk and bike scores are correlated with: (a) public funds available to improve roads and nearby amenities; and/or (b) how business-friendly an area is to incentivize business creation, both of which are positively demanded but are willing to be trade-off.

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 18. 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.

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 18 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.

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 A18 to A20 show the predicted conditional average treatment effects through causal forests stratified by baseline flood risk categories.

Several results are worth highlighting. Figure A18 shows how the algorithm identified that 80%[34] 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 A19 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 didn't find *negative* statistically significant treatment effects (Figure A20). Nevertheless, we found positive statistically significant effects at the right end of the treatment effects distribution.

[34]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.

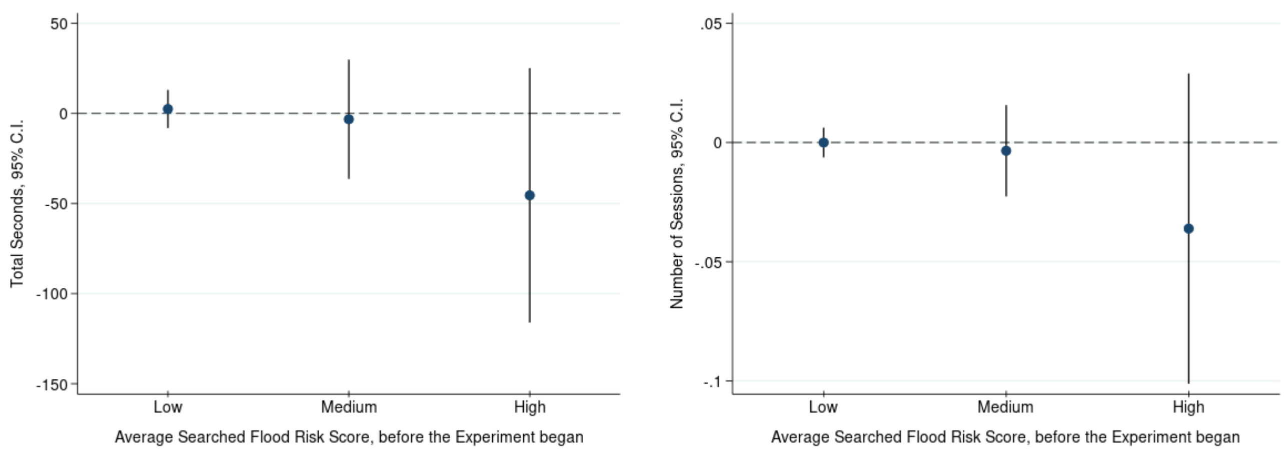
4.2 Engagement

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.

As seen in Figure A13, the treatment did not have a statistically significant impact on the probability of registering on the website. Tables A19 (i.e., for all users) and A20 (i.e., for registered users) shows an average daily increase in the total seconds (3.9) and the number of sessions spent (0.004) in the platform for those registered users in the treatment arm. When stratifying users by their average pre-experiment flood score houses searches, we did not find statistically significant results for the total seconds spent and the number of sessions (Figures 13 (a) and (b)).

Figure 13: CATE on the Time Spent on the Website per Day for Registered Users

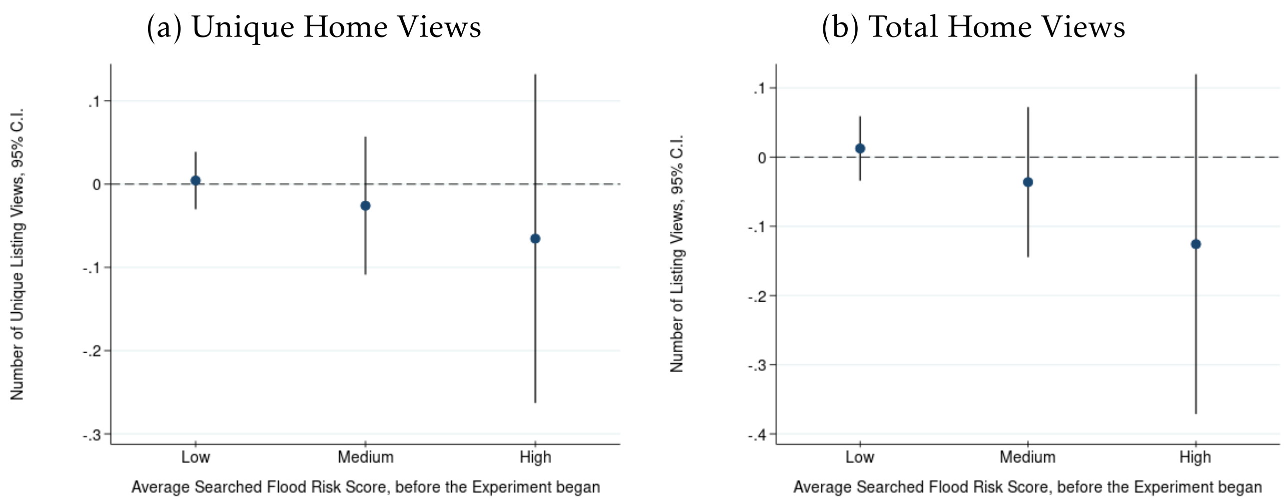
(a) Seconds Spent (b) Number of Sessions



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.

In the same vein, Figures 14 (a) and (b) show no large or statistically significant effects when stratifying by baseline flood scores for the number of unique home views and total home views, respectively.

Figure 14: CATE on the Number of Homes Viewed per Day for Registered Users



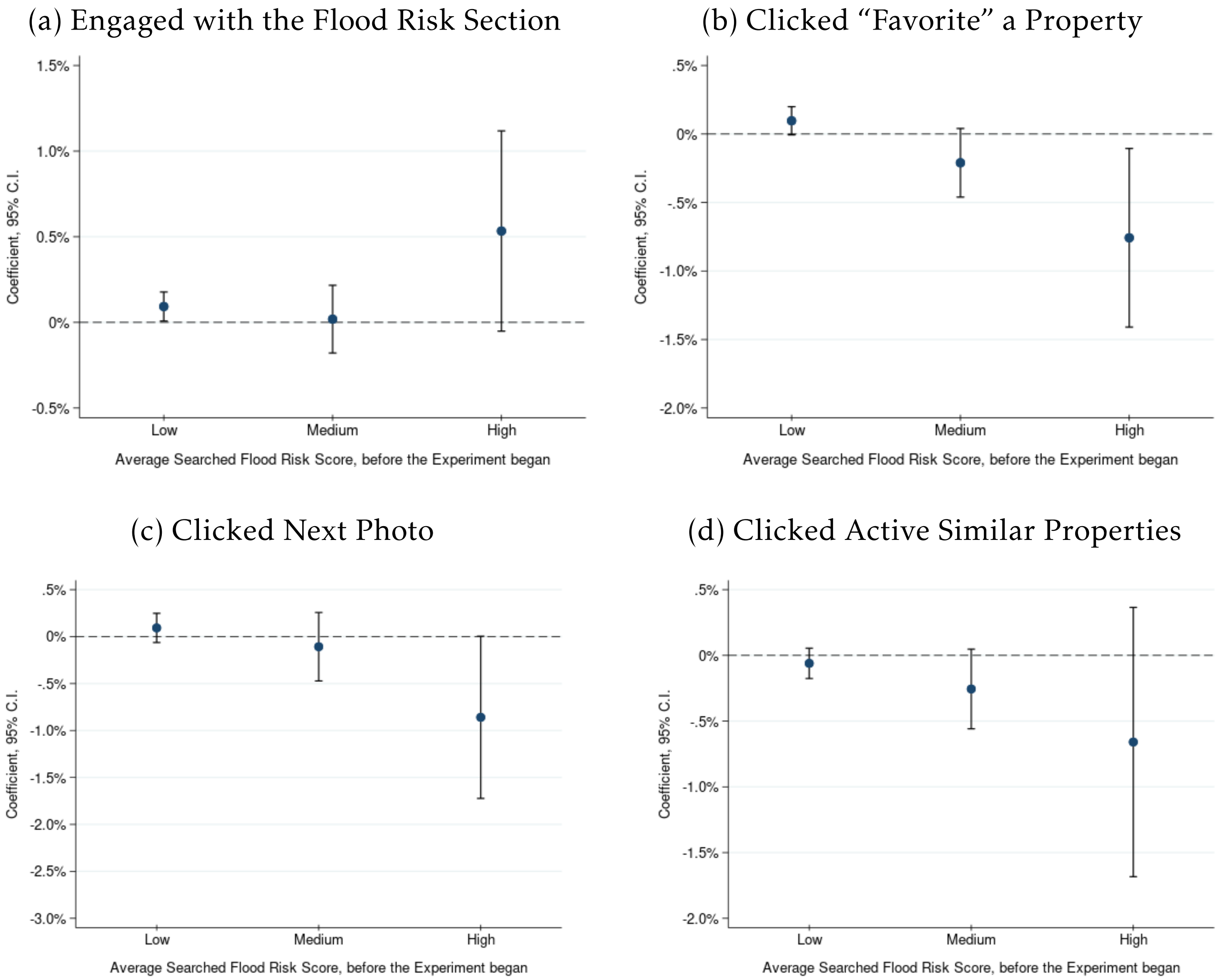
Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

The treatment had an impact on how users engaged with the listings. Figure 15 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[35], (b) "favorite" a 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 15 (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 15 (b)) and clicked fewer times "next photo" (Figure 15 (c)).

Our findings presented above suggest that users previously browsing high risky properties adjust their search behavior once they learn about the flood risk. 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.

[35]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.

Figure 15: CATE on the Percentage of Times 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.

We also examine some of these engagement metrics for different type of properties (based on the user's pre-experiment search history). Figures A15, A16, and A17 in the Appendix show the average treatment effect on the engagement with the flood risk section for users browsing waterfront, FEMA-risky, and coastal properties at baseline. Consistent with the search results, we found that treated users looking at waterfront but not coastal properties are more likely to spend more time searching for the flood risk section.

4.3 Tours, Offers, and Closes

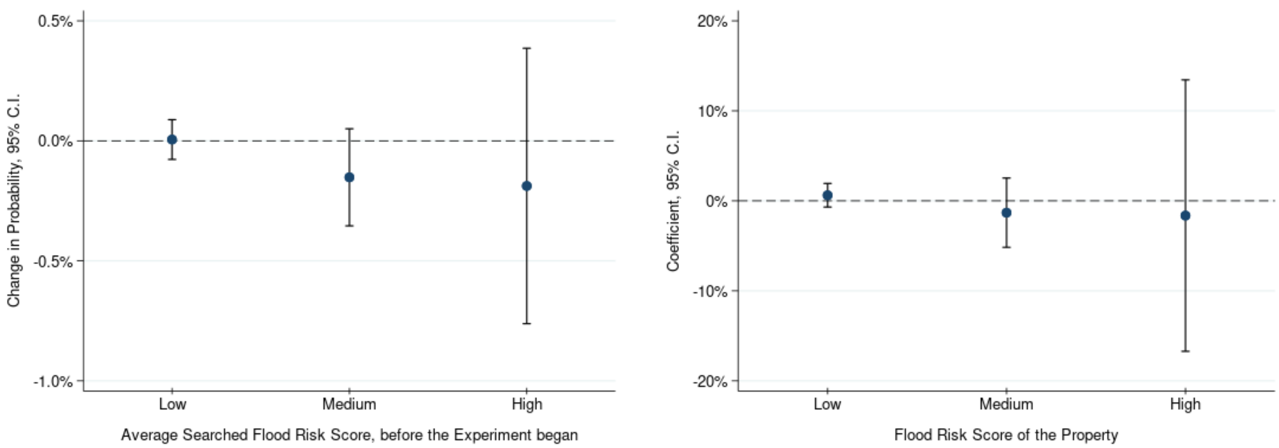
Redfin provides customers with an integrated house purchase process such that home buyers can search for a specific home and then work with a Redfin directed brokerage service.

It gives its users the option to tour properties, place a bid on a particular property, and close a deal. In our experiment, once a treated user views and opens a property, they observe the flood score of that particular unit. For those in the treatment group 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.

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 don't find a statistically significant difference on the probability of booking or canceling a home tour for the treatment 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



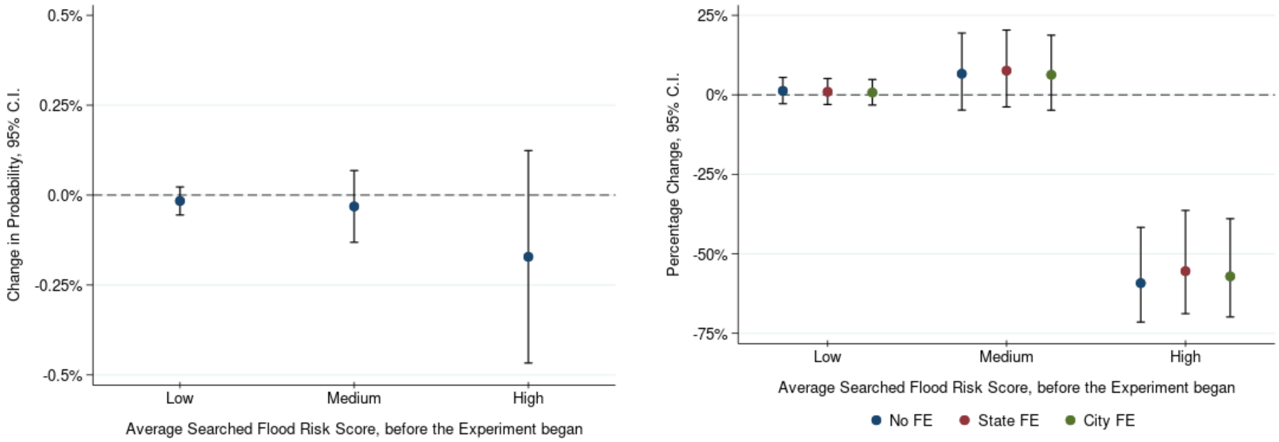
Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents the flood score category of the property.

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) 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.

Figure 17: CATE on Offers

% Change relative to Control

(a) Probability of Placing an Offer (b) Flood Score of the Property

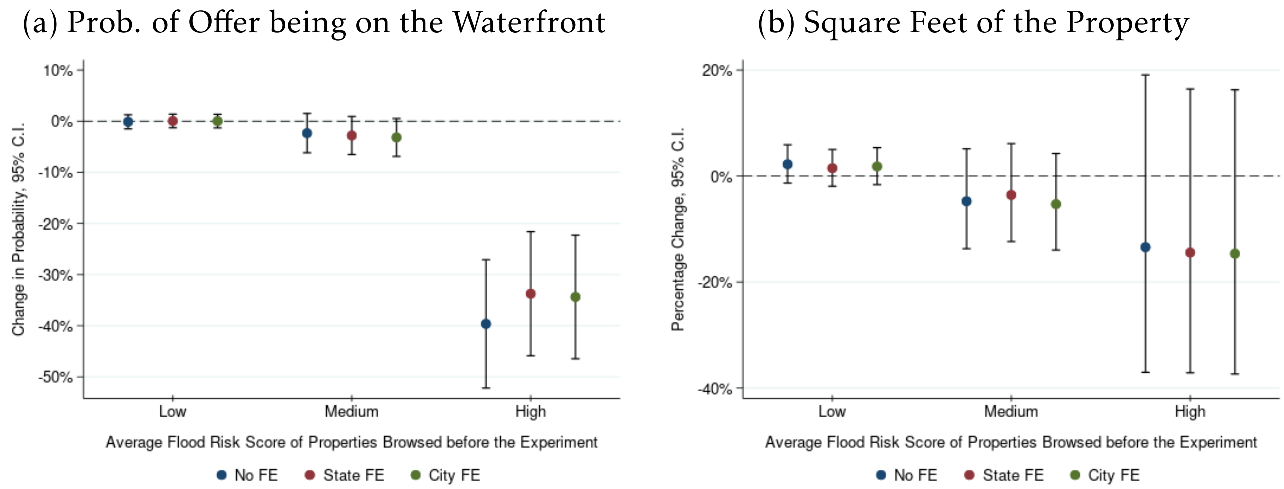


Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. S.E. clustered at the registered user level. FE = Fixed Effects of the location of the Property.

Figure 18 (a) and (b) show how treated groups trade-off characteristics of a property to reduce their flood exposure, as shown in Figure A34 (b). On the one hand, as seen in Figure 18 (a), people browsing riskier properties before the experiment began had a lower probability of placing an offer on waterfront properties. That is, those users with access to flood scores and browsing high risky properties before the experiment began had a -39.6% less probability of placing a bid on a waterfront property. On the other hand, Figure A35 (b) shows that users browsing high risky properties before the experiment began went on to bid properties with -14.6% less square feet (s.e. = 17.08).

Figure 18: CATE on the Characteristics of an Offer

% Change relative to Control

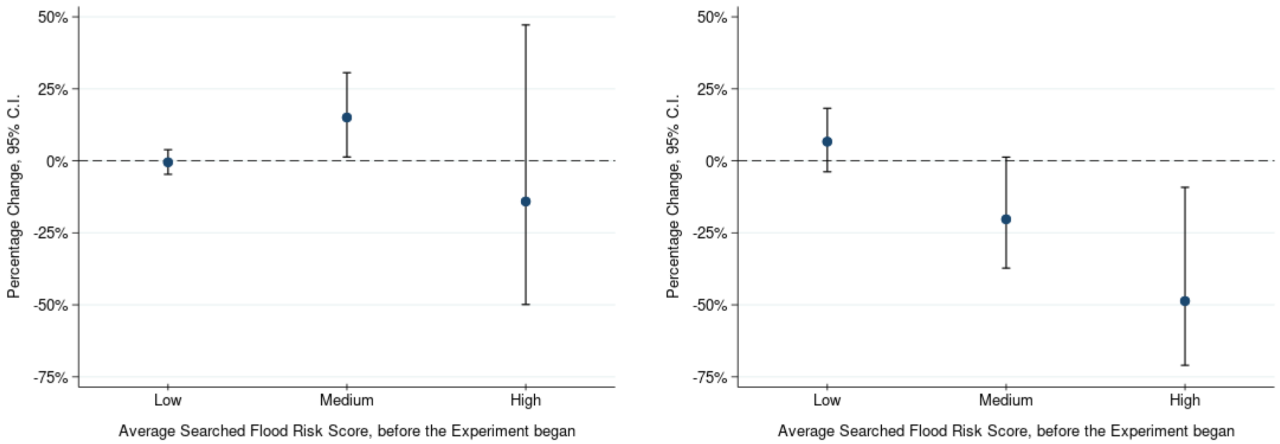


Note: For Figure (b), coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Standard errors clustered at the user level. FE = Fixed Effects of the location of the Property.

We examine how the offers vary by the type of properties that the user searches for. In Figures 19 (a) and (b), we show that the reduction in the flood score of offers is coming from the waterfront properties. FEMA RISK. In Figures 20 (a) and (b), we see small differences between FEMA and non-FEMA high risk, but in Figures 21 (a) and (b), we see that the reductions in flood score are coming from the waterfront properties not on the coast. This again supports our new news hypothesis.

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

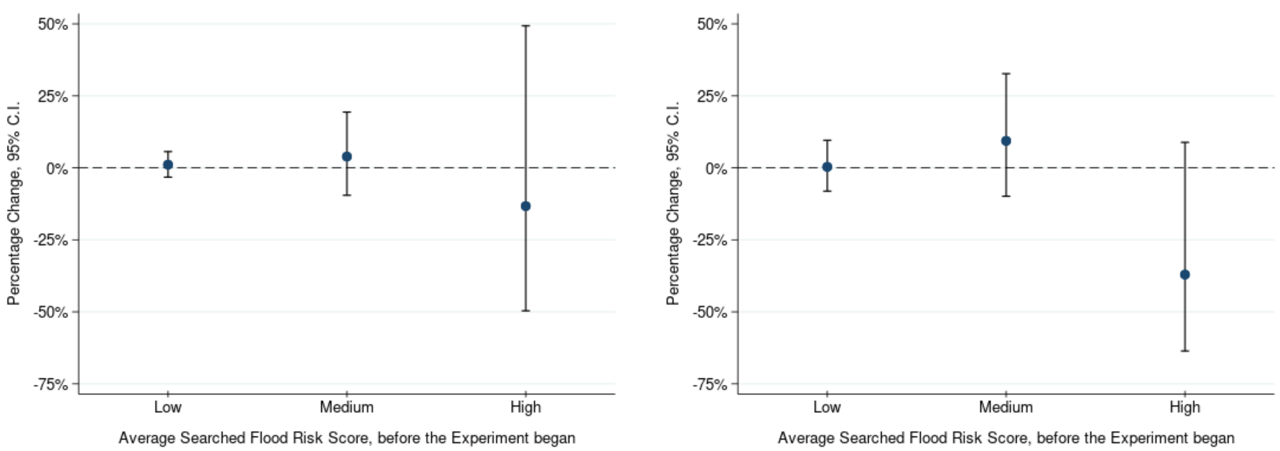
(a) **Without** Waterfront Search at Baseline (b) **With** Waterfront Search at Baseline



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

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

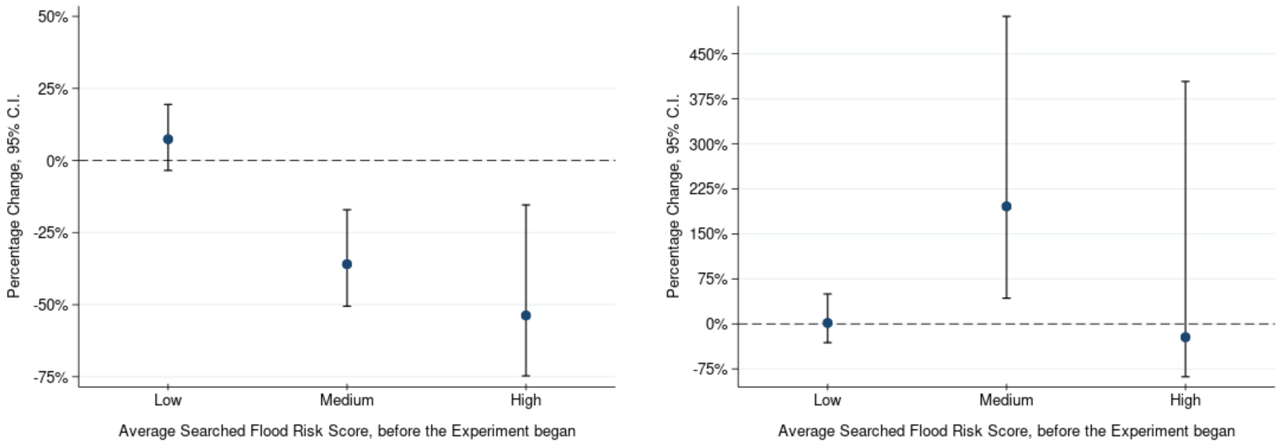


Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who did not browse any property considered risky by 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

(a) **With** Waterfront and **Without** Coastal Search at Baseline

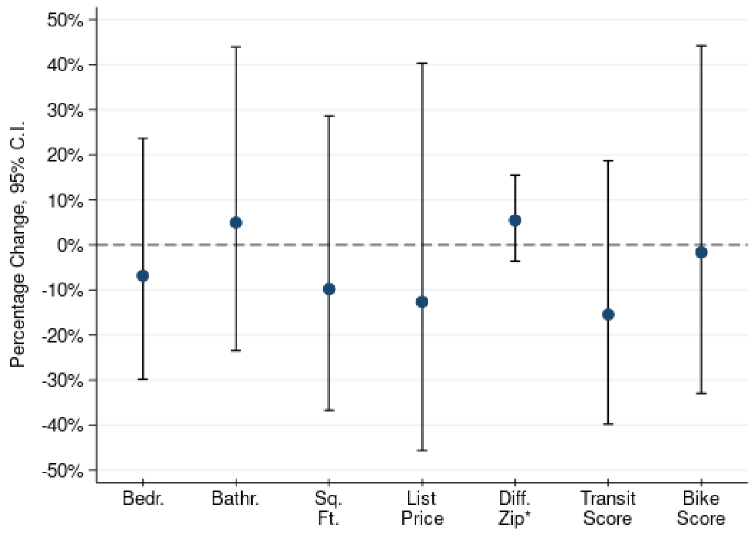
(b) **With** Waterfront and **With** Coastal Search at Baseline



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 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.

For the high flood risk property users, while the flood score of the offered properties decrease, Figure 22 shows that there is nothing driving the trading off of other attributes. The only thing that is not particularly noisy is the different zip code count.

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 18. 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.

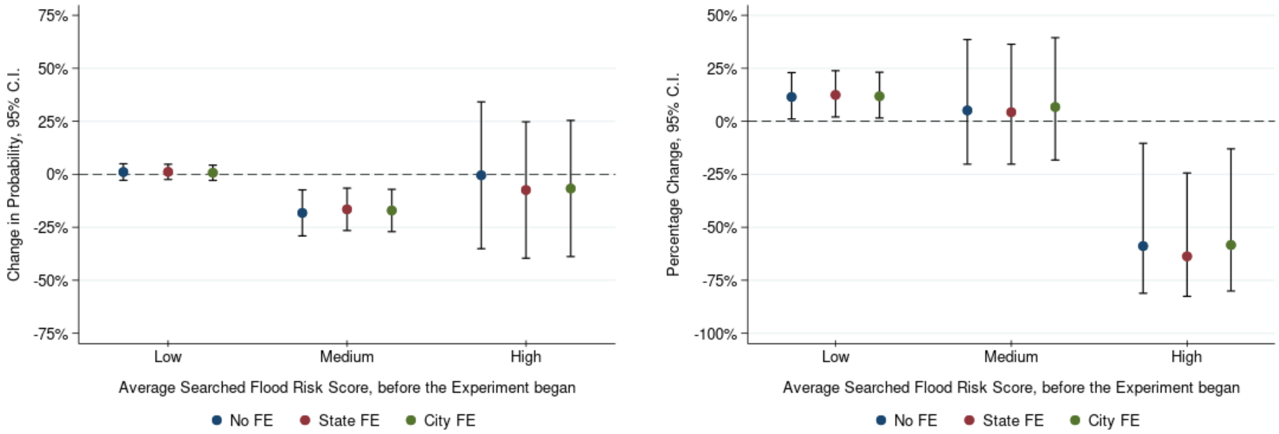
Closing. In the process of selling a home, the "closing" is one of the final steps, as money and legal paperwork are exchanged to finalize the transaction. From basic revealed preference logic, if a home buyer has doubts about following through with a purchase, this is the key time to walk away from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

We now show the probability of an individual closing a house offer and the flood score of a property someone in my experiment closed on, stratified by the baseline average flood score search category and relative to their control counterpart. As seen in Figure 23 (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 23 (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, which suggests that for these Redfin users, they were the marginal winning buyers.

Figure 23: 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



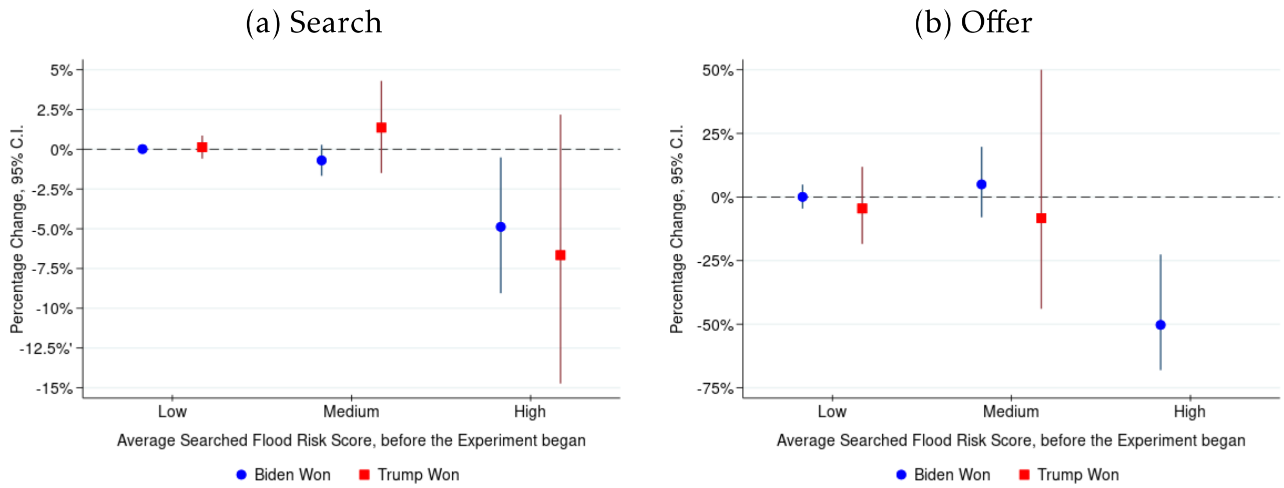
Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before 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 county where the user lives voted for Biden or Trump in the 2020 Presidential election. In Figures 24 (a) and (b), we show the impact of Biden and Trump winning counties for search and offers respectively. For search, we see that both 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 counties respond to the flood score in the same way for both searches and for offers.

Figure 24: Flood Risk by Counties from Where Users Browsed the Most at Baseline, Stratified by Whether Biden or Trump Won in 2020



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. We do not have enough observations to estimate the impact on offers for Trump counties with high flood risk.

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 A29 (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 choose 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. 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%.

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:

$$y_{pt} = \beta_0 + \beta_1 F_p + \beta_2 \text{Frac\_Treat}_p + \beta_3 \left(F_p * \text{Frac\_Treat}_p \right) + \lambda_z + m_t + u_{pt} \tag{20}$$

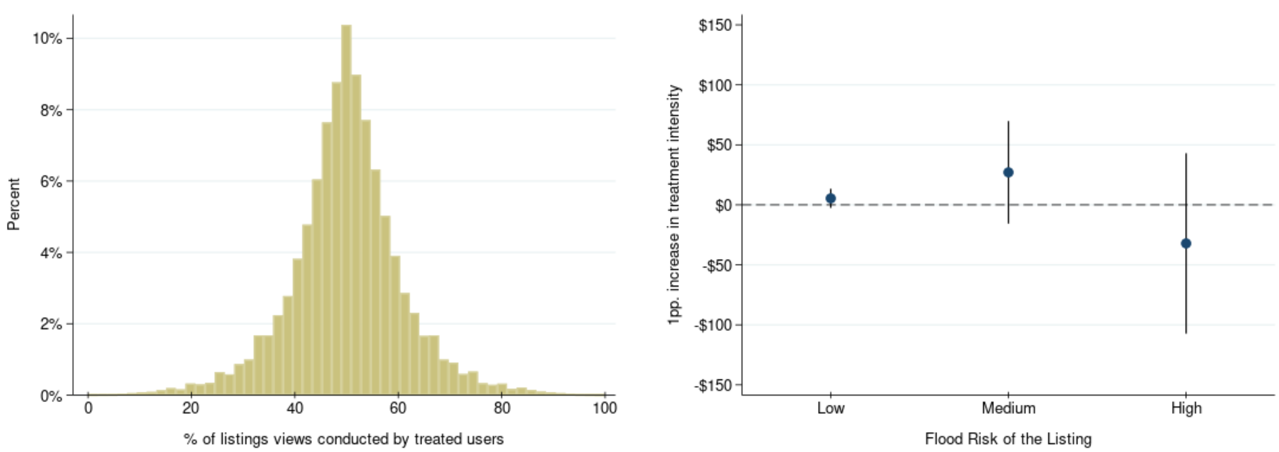
Where, y_{pt}, represents the dollar spread between the sale price and the property listing price, p, sold in the month, t, of the experimental period. F_p shows the property's flood risk category (i.e., low, medium, and high), whereas, Frac_Treat, represents the percentage of people who viewed the property 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 25 (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 25 (b) shows estimates of β_3 from estimator 20. We did not find a statistically significant effect when running estimator 20 on the whole sample of listings sold during the experimental period.

Figure 25: 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.

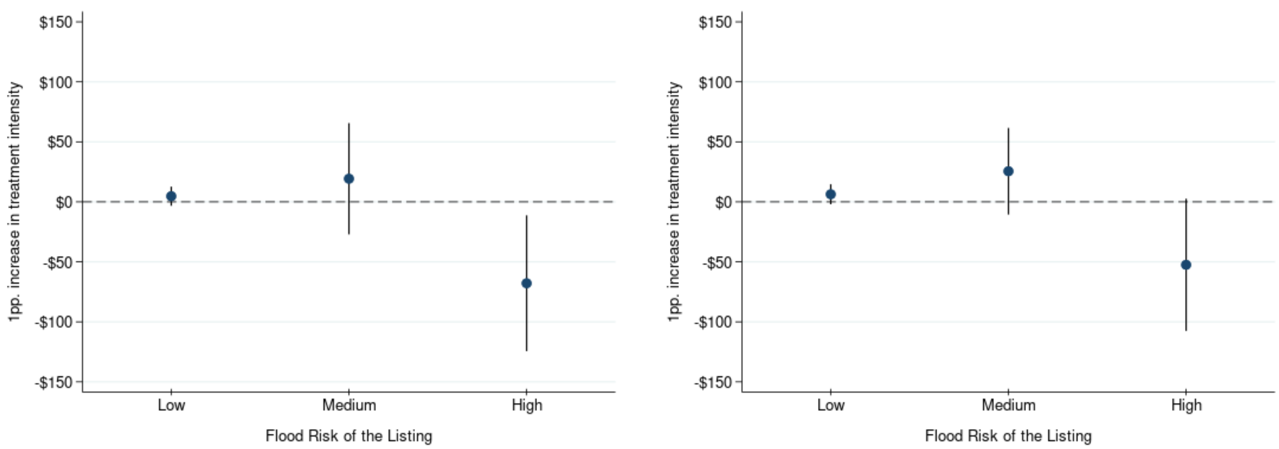
However, when we divide the listings into two groups based on their characteristics —being on the waterfront or being in a FEMA risk zone —we observe that our intensity treatment variable, referred to as Frac_Treat, has an impact on the difference between the sale price and the listing price. Figure 26 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 26 (a)), as well as for properties that are *not* *considered* risky by FEMA (see Figure 26 (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% (everyone having the FSF flood score) in our variable of interest leads to a price penalty of -$6,800 and -$5,300 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).

Figure 26: 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, ($)*



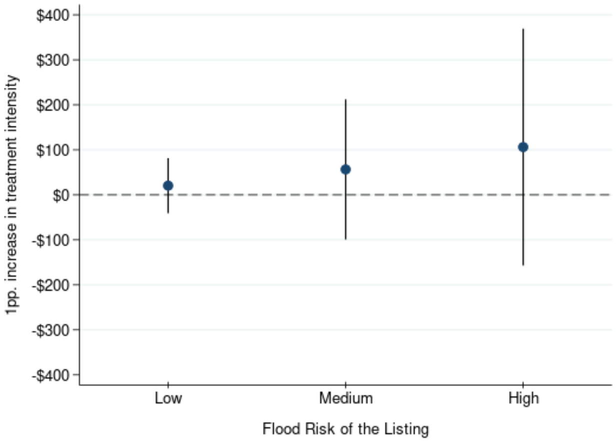
Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. As well, for Figure (b), the x-axis represents the flood score of the property.

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 27), suggesting that flood risk was already priced for those properties.

Figure 27: CATE of an Increase in Exposure Intensity on the *(Sale - Listing Price)*

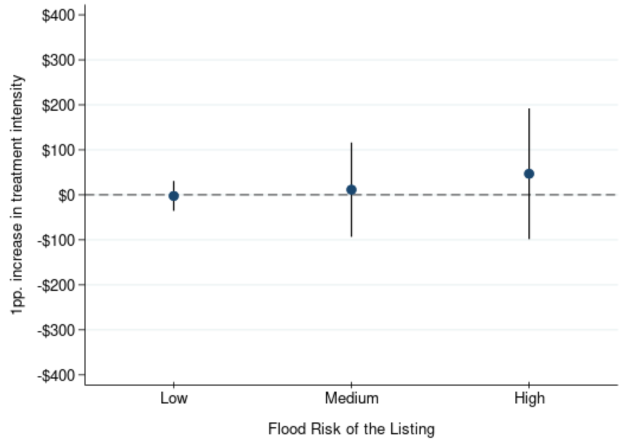
(a) Only Waterfront Listings

1PP Increase in Exposure Intensity, ($)



(b) Only FEMA Risky Listings

1PP Increase in Exposure Intensity, ($)

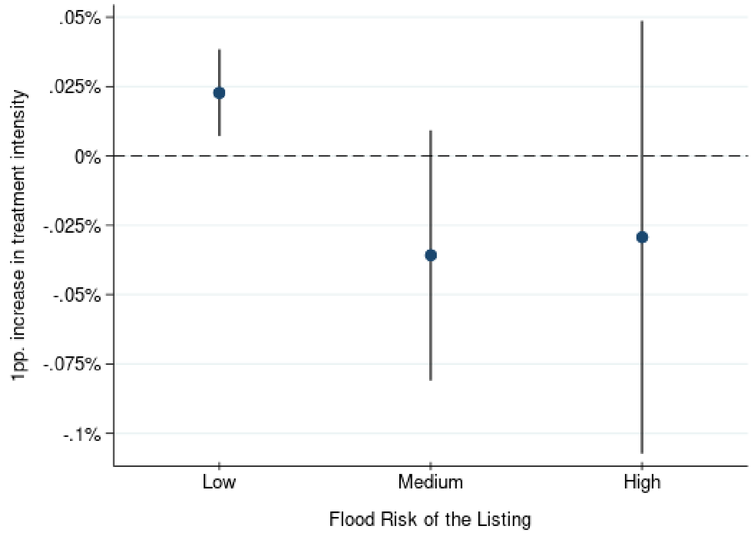


Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents the flood score of the property.

Finally, we have access to information on whether an investor bought a property. 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 28, 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 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 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.

Figure 28: 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.[36] 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

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

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 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.

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 "Peltzman Effects" induced by them (Wang, 2021; Benetton et al., 2022; Bradt and Aldy, 2022; Ostriker and Russo, 2022), 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 affects its impact on decision-making.

Our study has documented that millions of people respond to location specific risk information. This reveals that they trust this information. Going forward, fostering a 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 the risky homes.

Redfin is a for-profit 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 webpage 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, 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, Robert McMillan, Alvin Murphy, and Christopher Timmins. 2016. "A dynamic model of demand for houses and neighborhoods." *Econometrica*, 84(3): 893–942.

Baylis, Patrick, Judson Boomhower, et al. 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, 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.

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*.

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.

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.

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.

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*.

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

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.

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 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.

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.

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.

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

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."

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.

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.

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.

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 Taşpınar. 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.

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."

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 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.

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.

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:

$$Max_{h_1} pU(h_0, I - P_2(h_1), \alpha) + (1-p)pU(h_1, I - P_2(h_1), \alpha) \tag{21}$$

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

$$Max_{h_1} U(h_1, I - P_2(h_1), \alpha) \tag{22}$$

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 $P_2(h)$:

$$h_0 = \frac{(\gamma_1 + \gamma_2\alpha)(p\frac{\sigma_f'}{\sigma_f} + 1 - p) + p(\frac{\rho\sigma_f'}{\sigma_f^2} - \frac{\omega\pi_1''}{\sigma_f})(\bar{f}' - \bar{f}) + \omega(I - \pi_0'')(p\frac{\sigma_f'}{\sigma_f} + 1 - p) - \theta\pi_1''}{2\omega\pi_1''(p\frac{\sigma_f'}{\sigma_f} + 1 - p) - \rho((\frac{\sigma_f'}{\sigma_f})^2 + 1 - p)} \tag{23}$$

$$h_1 = \frac{\gamma_1 + \gamma_2\alpha + \omega I - \omega\pi_0'' - \theta\pi_1''}{2\omega\pi_1'' - \rho} \tag{24}$$

A.2 The treatments

Figure A1: The First Street Foundation flood score matrix calculation

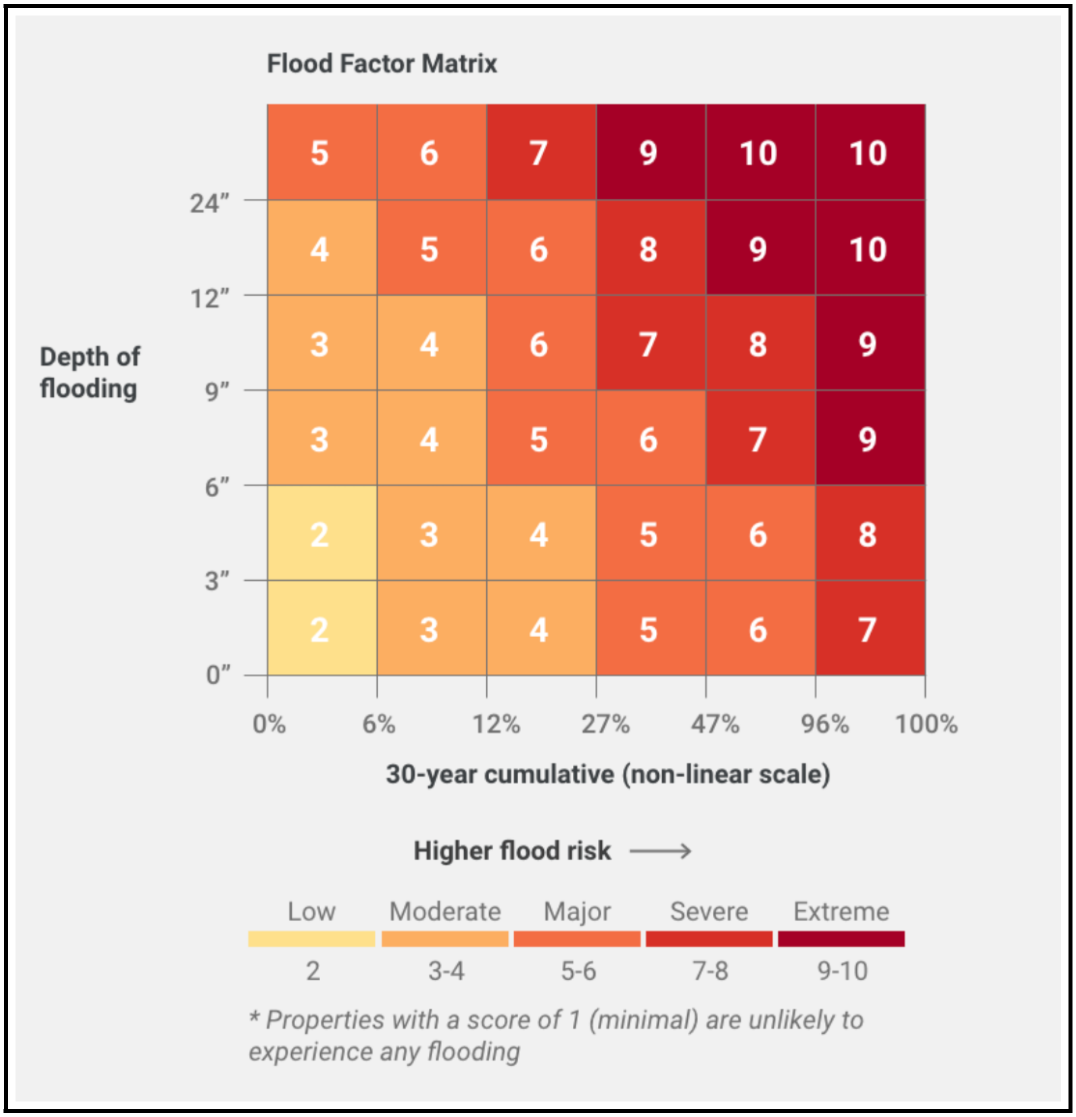


Figure A2: The Visual Experience for the Treatment Group using a Desktop and Browsing a Property with a Flood Score of 4 (i.e., Moderate)

(a) Collapsed *(b) Expanded*

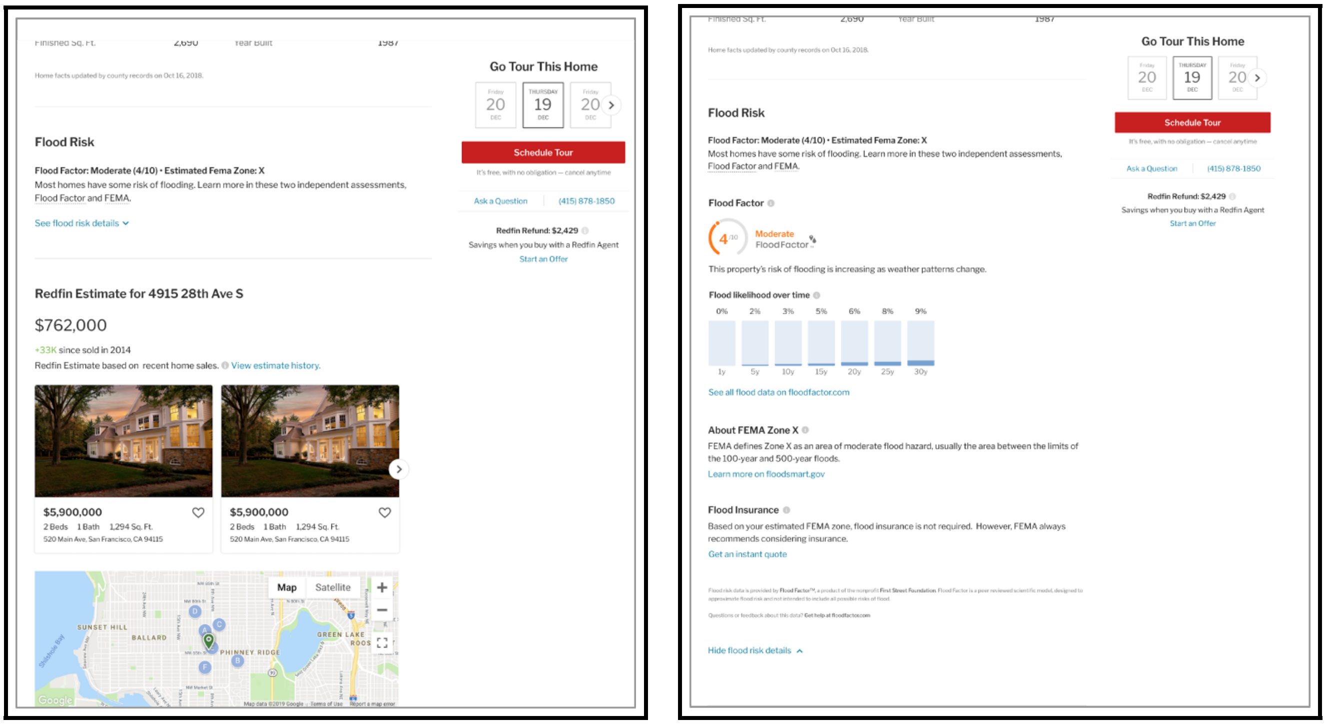


Figure A3: The Visual Experience for a Treated Individual using a Cellphone and Browsing a Property with a Flood Score of 4 (i.e., Moderate)

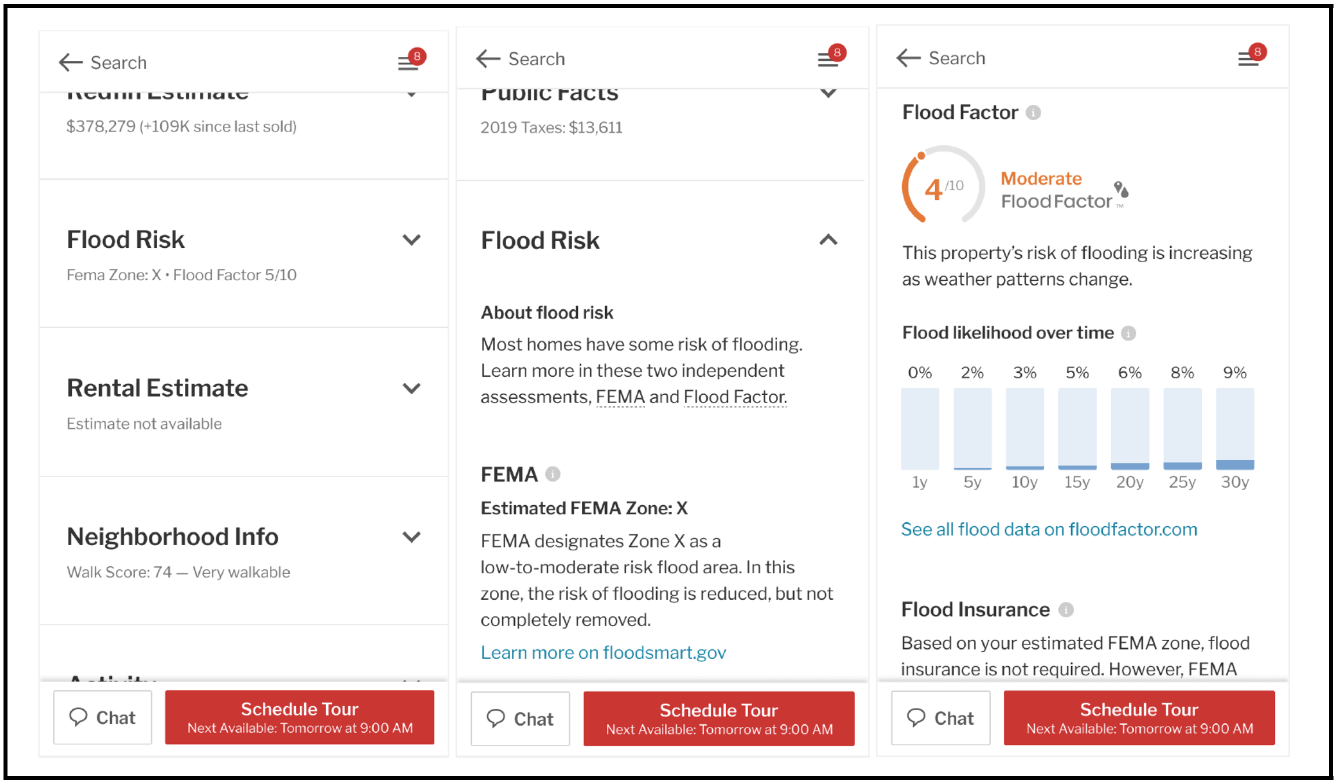
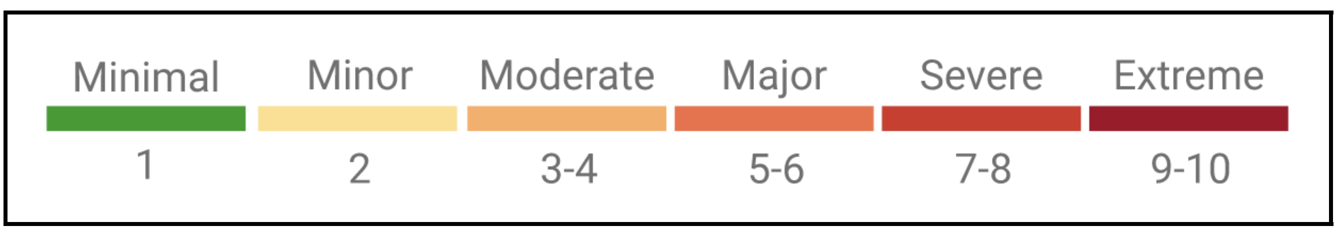


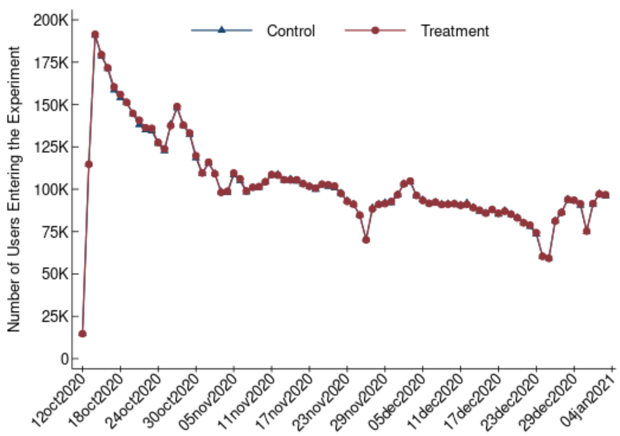
Figure A4: Colors and Labels of Flood Scores Displayed



A.3 Additional figures and tables

Figure A5: Number of Users Entering the Experiment

(a) By Day



(b) Cumulative

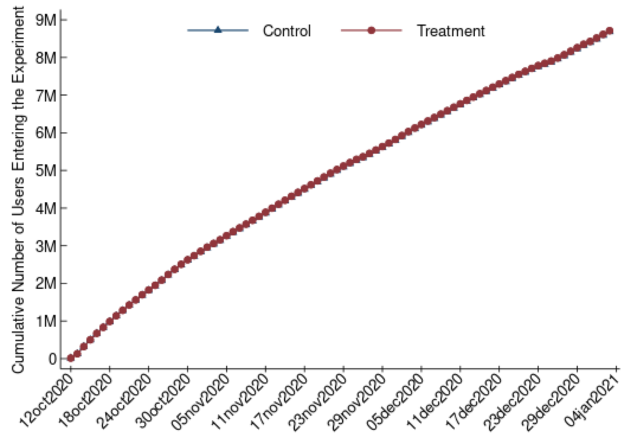


Table A1: Balance Tests

	(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 A2: Balance Tests

	(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 A3: 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 A4: 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 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)

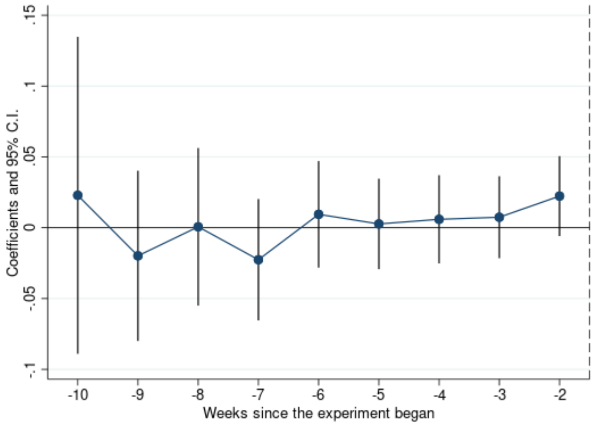
	(1) New Construction	(2) Short Sale	(3) Year Built	(4) Walk Score	(5) Transit Score	(6) Bike Score
Treatment	0.009**	-0.001	0.000	0.034	0.040*	0.018
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Constant	0.030***	0.006***	1977.218***	23.030***	34.823***	40.533***
	(0.000)	(0.000)	(0.458)	(0.490)	(0.414)	(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 $(e^{\beta} - 1)$.

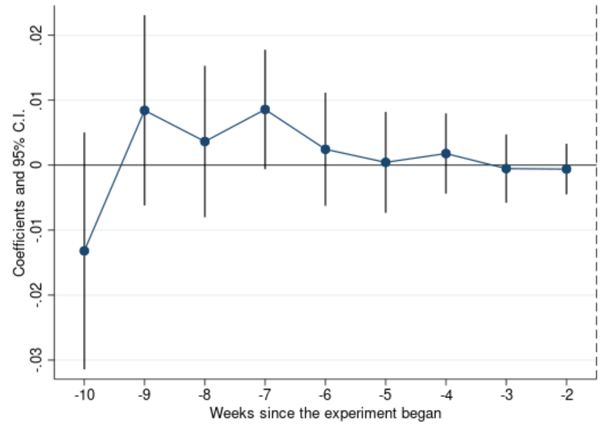
Figure A6: Balance Tests Trajectories

Estimates relative to the week before the experiment began

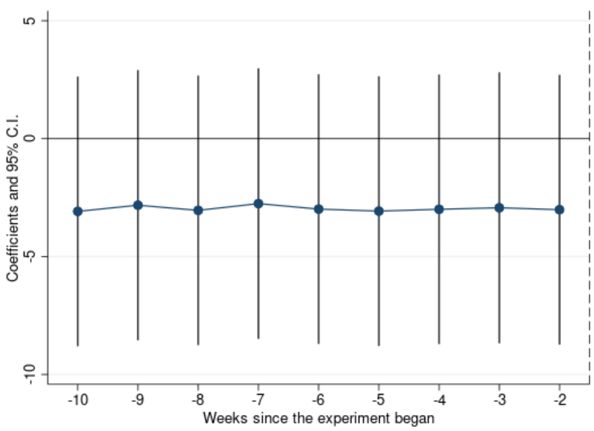
(a) Views



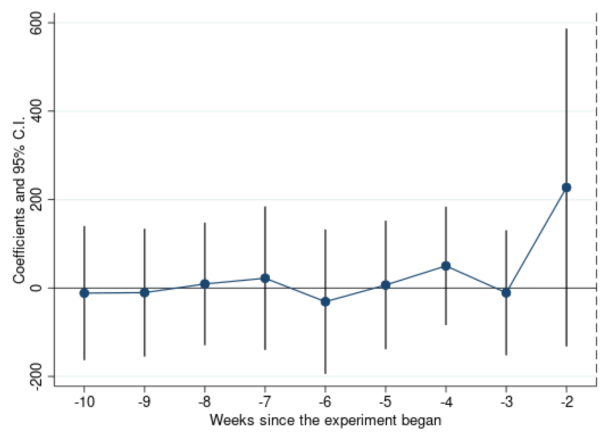
(b) Bedrooms



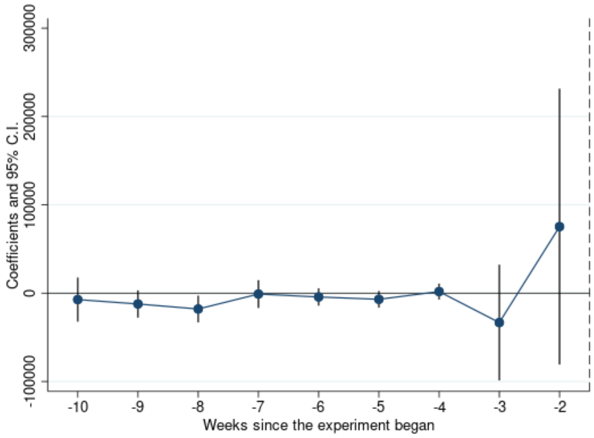
(c) Bathrooms



(d) Sq. Ft.



(e) List Price



(f) Flood Score

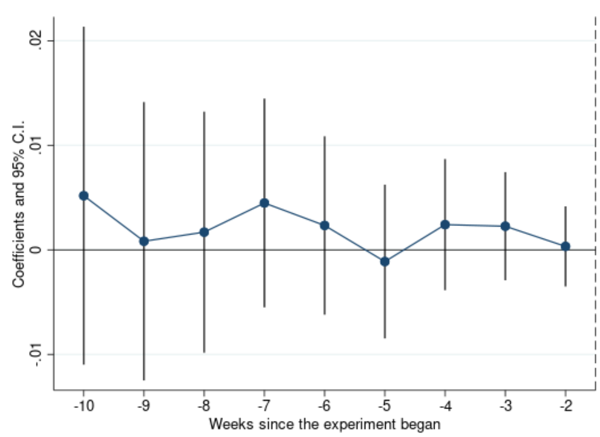


Table A11: Pre-Experiment Distribution of Flood Score for Users by Treatment Status

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 A12: 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 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

Coefficients in terms of Elasticity, % 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 17.

Table A16: ATE on the Characteristics of the Homes Viewed with Pre-Experiment Information

Coefficients in terms of Elasticity, % 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 17.

Table A17: ATE for Registered Users on the Characteristics of the Homes Viewed
Coefficients in terms of Elasticity, % 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 17.

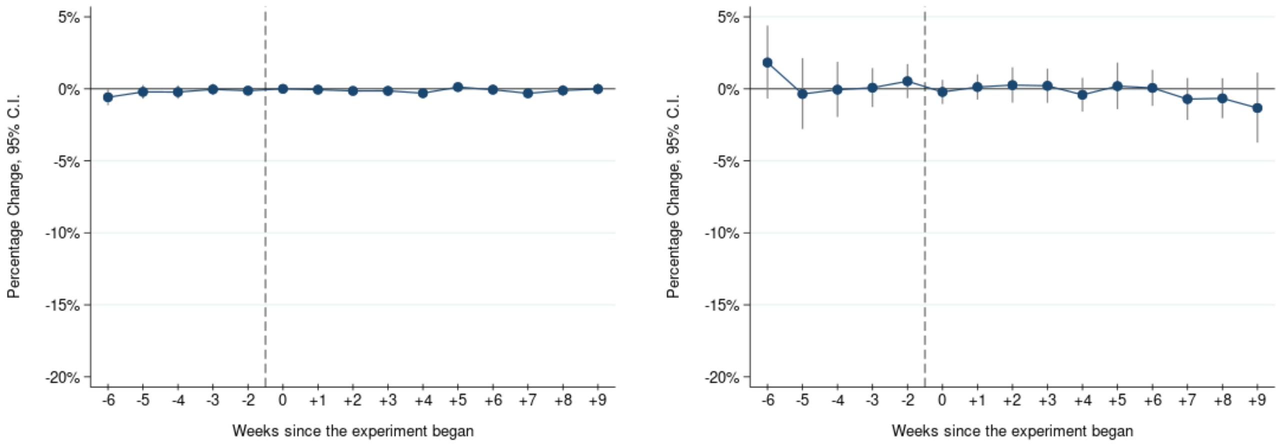
Table A18: ATE for Registered Users on the Characteristics of the Homes Viewed with Pre-Experiment Information
Coefficients in terms of Elasticity, % Change relative to Control

	(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 17.

Figure A7: Event-time Study on the Average Daily Flood Score of Properties Searched for Registered Users

(a) *Low* (b) *Medium*

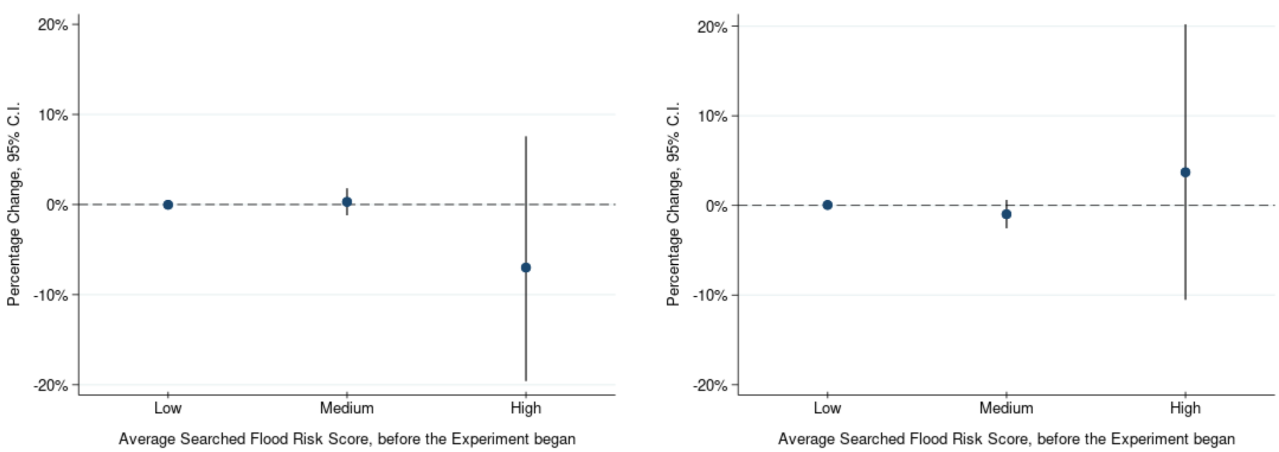


Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 19. Coefficients are relative to the week before a user entered the experiment. Vertical lines crossing the estimates are confidence intervals at the 95% level. The vertical dashed line represents the beginning of the experiment for a user. The x-axis represents each user's baseline average flood score search category before the experiment began.

Figure A8: 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

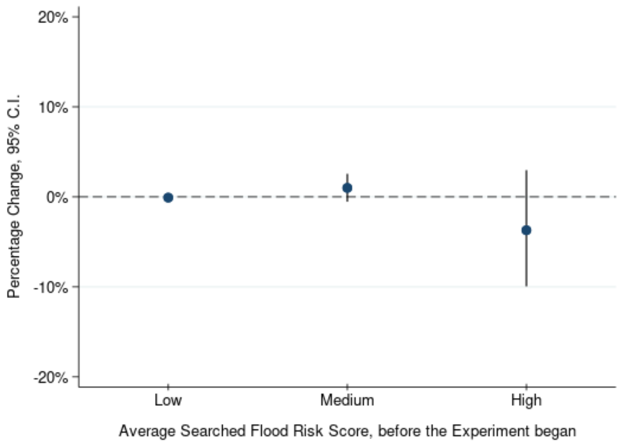
(b) **Higher Mean** Flood Score at Destination Zip Code than Origin



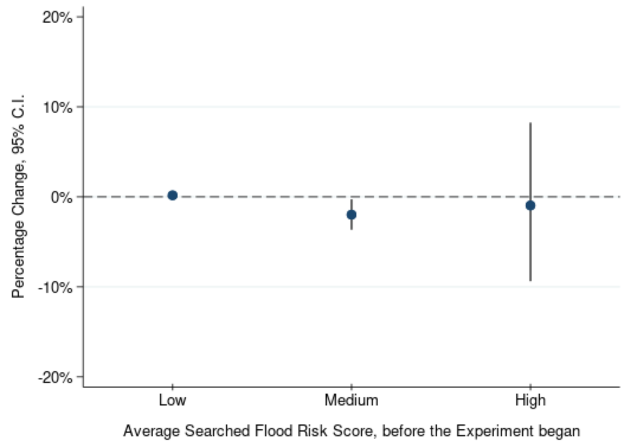
Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

Figure A9: 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



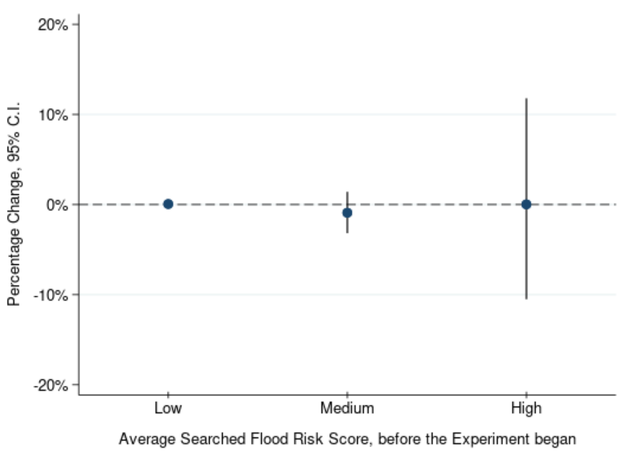
(b) **Higher Standard Deviation** Flood Score at Destination Zip Code than Origin



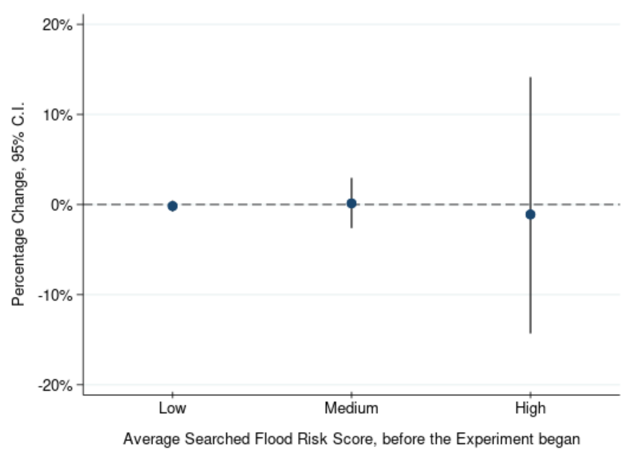
Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

Figure A10: 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



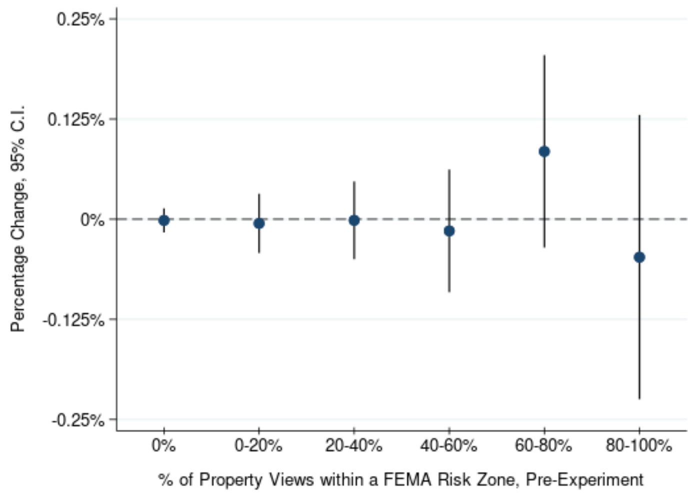
(b) **Top 10** of Redfin's Probability



Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. 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 A11: CATE on the Average Flood Score of a Daily Search for Registered Users, by Percentage of Properties Considered by FEMA to be Risky Searched at Baseline

% Change relative to Control

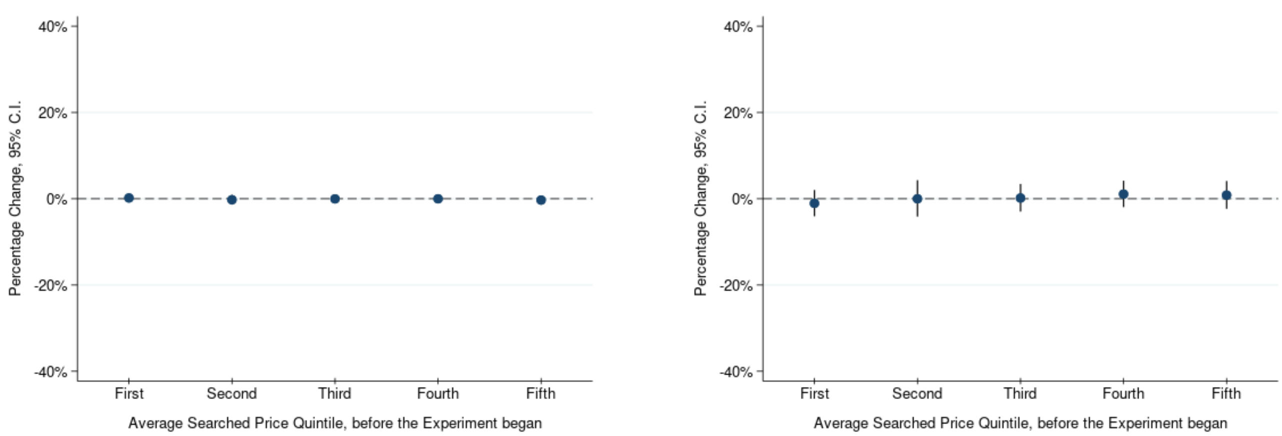


Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

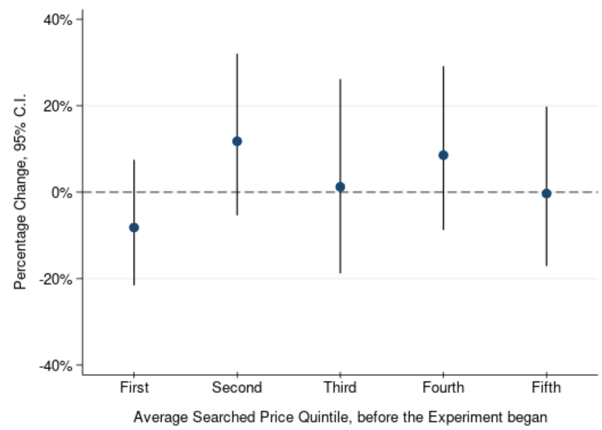
Figure A12: CATE on the Average Flood Score of a Daily Search for Registered Users, by Within-City Average Price Quintile Search at Baseline

Stratified by Average Flood Score Search at Baseline

(a) Low *(b) Medium*



(c) High



Note: Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 19. 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 A13: CATE on the Probability of Platform Registration
% Change relative to Control

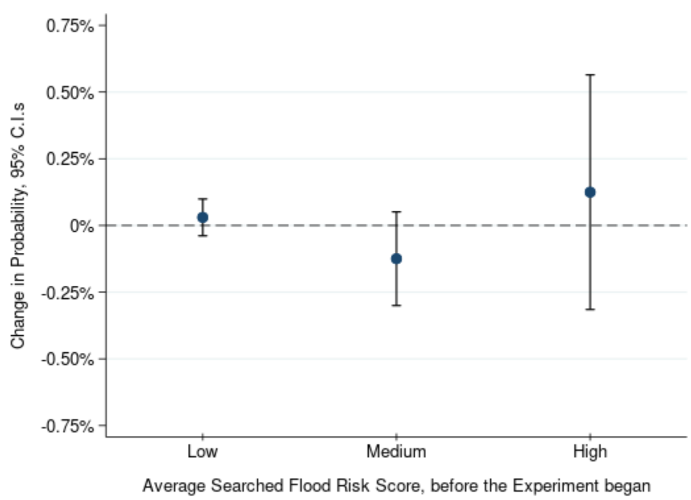


Table A19: Average Treatment Effects on Platform Activity
Coefficients in terms of Elasticity, % Change relative to Control

	(1) Total Seconds	(2) Number Sessions	(3) Unique Home Views	(4) Total Home Views
Experiment began	241.484***	0.137**	0.701***	1.008***
	(59.910)	(0.051)	(0.179)	(0.253)
Treatment	-0.515	-0.001	-0.004	-0.007*
	(0.479)	(0.000)	(0.002)	(0.003)
Diff-in-diffs	2.372**	0.000	0.003	0.005
	(0.849)	(0.001)	(0.003)	(0.005)
Obs.	91,974,850	91,974,850	91,974,850	91,974,850

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 17.

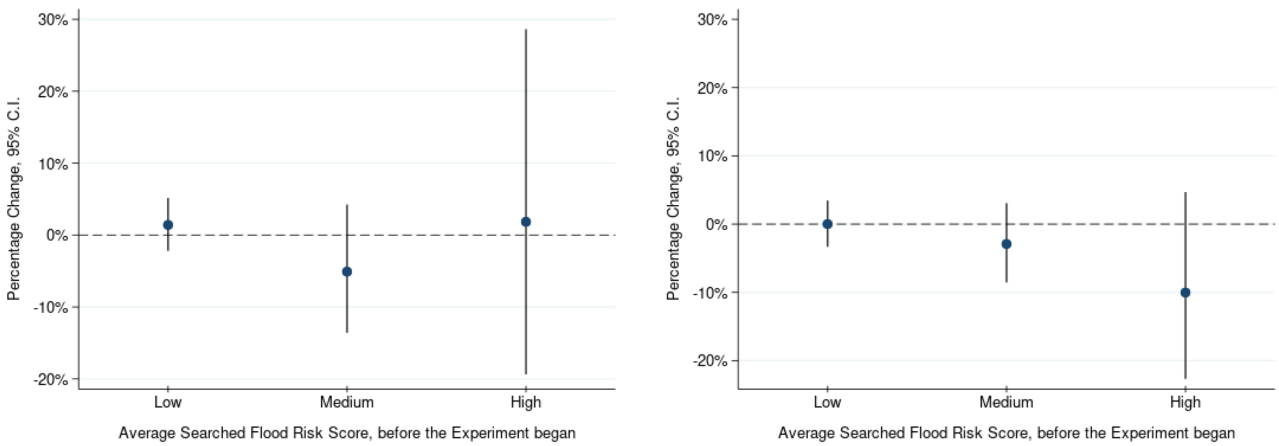
Table A20: ATE for Registered Users on the Activity on the Platform
Coefficients in terms of Elasticity, % Change relative to Control

	(1) Total Seconds	(2) Number Sessions	(3) Unique Home Views	(4) Total Home Views
Experiment began	302.408**	0.207*	0.824**	1.152**
	(99.207)	(0.080)	(0.288)	(0.400)
Treatment	-0.180	-0.002*	-0.002	-0.005
	(1.042)	(0.001)	(0.004)	(0.005)
Diff-in-diffs	3.884**	0.004**	0.005	0.010
	(1.347)	(0.001)	(0.005)	(0.007)
Obs.	27,034,546	27,034,546	27,034,546	27,034,546

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 17.

Figure A14: 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

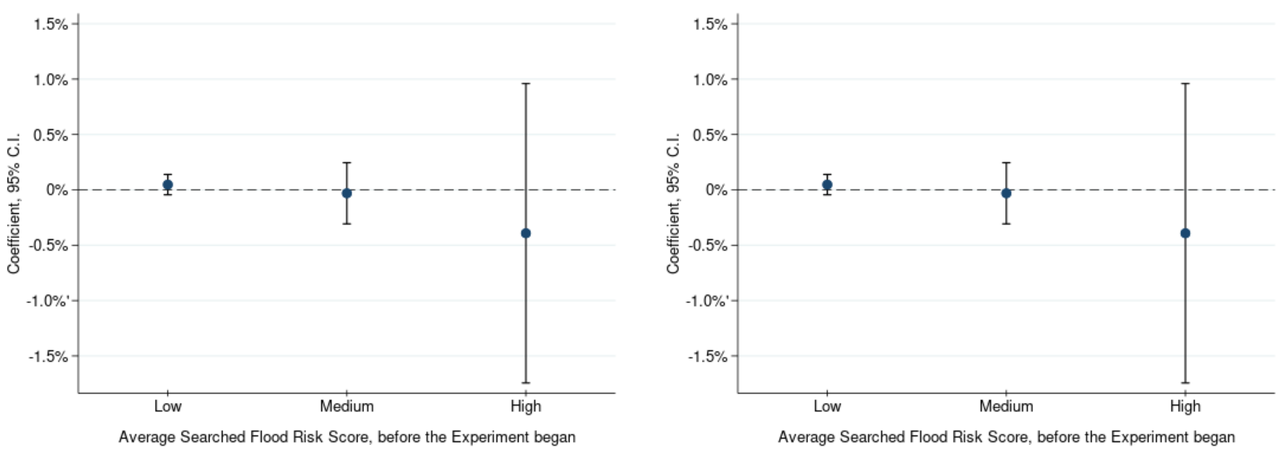
(a) County of Origin (b) County of Destination



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 18. The x-axis represents each user's baseline average flood score search category before the experiment began.

Figure A15: CATE on the Percentage of Times Registered Users Engaged with the Flood Risk Section of a Listing per Day

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

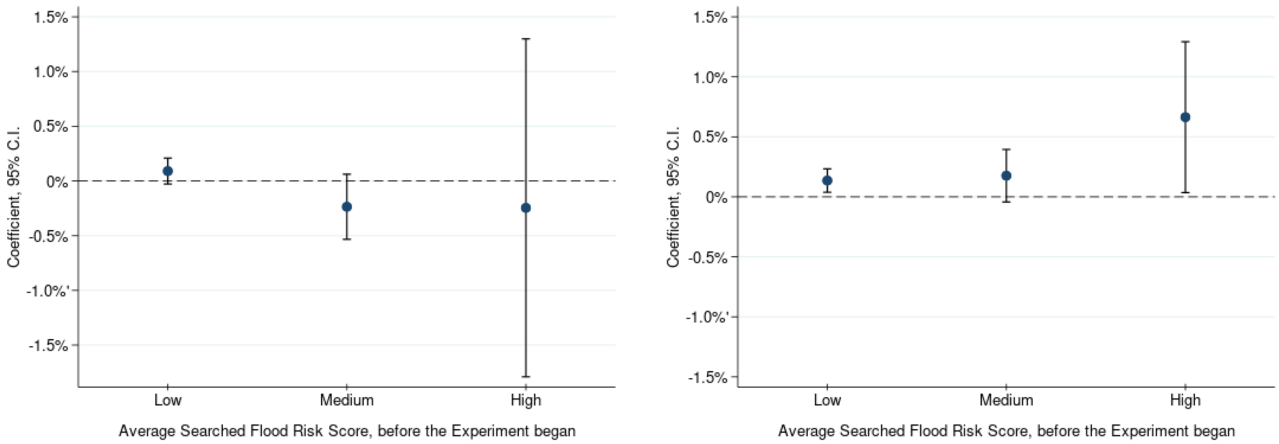


Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who did not browse any waterfront property before 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 A16: CATE on the Percentage of Times Registered Users Engaged with the Flood Risk Section of a Listing per Day

(a) **Without** FEMA Risk Search at Baseline

(b) **With** FEMA Risk Search at Baseline

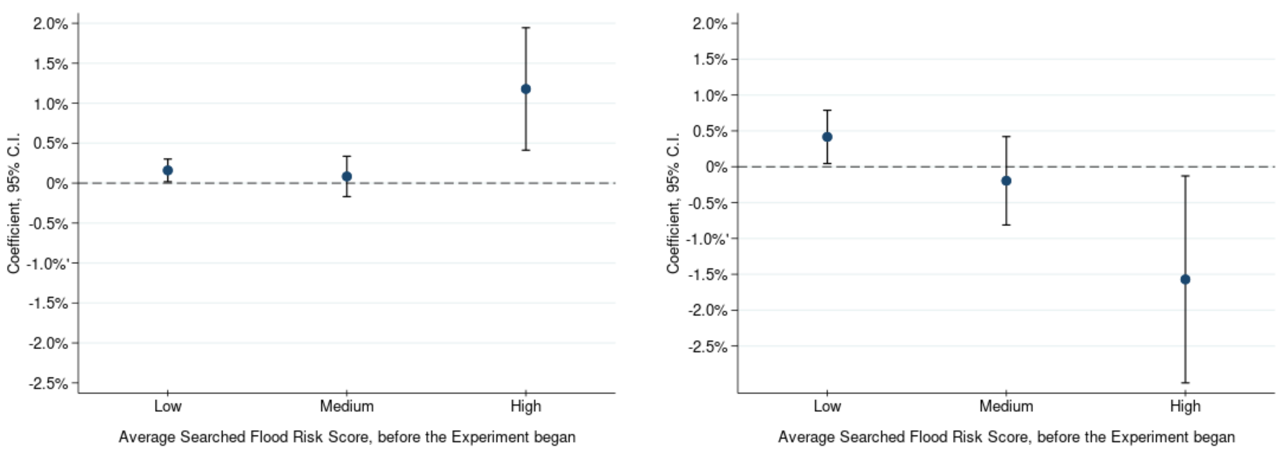


Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began. Users who did not browse any property considered risky by 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 A17: CATE on the Percentage of Times Registered Users Engaged with the Flood Risk Section of a Listing per Day

(a) **With** Waterfront and **Without** Coastal Search at Baseline

(b) **With** Waterfront and **With** Coastal 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 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.

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:

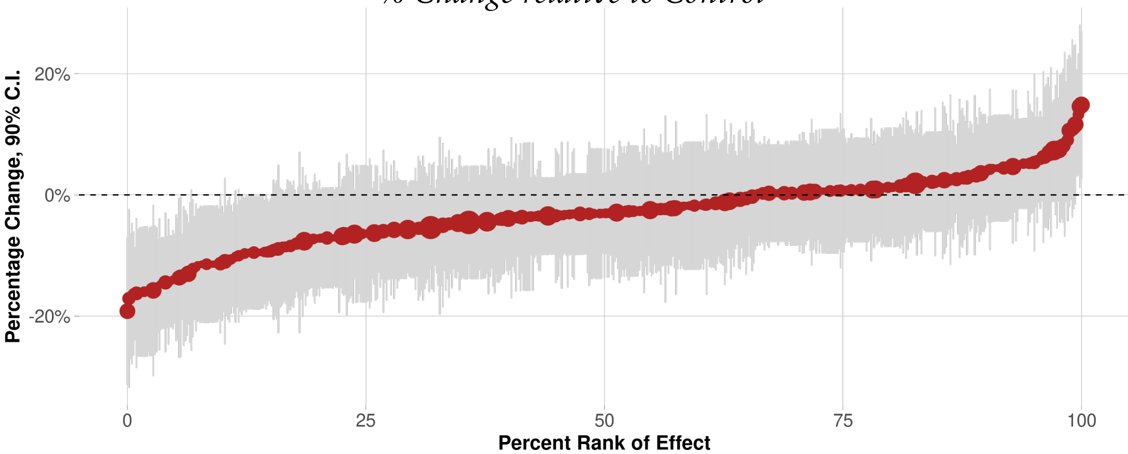
$$\text{CATE} \equiv \tau(X) = \mathbb{E}\left[Y_i^{(1)} - Y_i^{(0)} \mid X_i = x\right] = \mu_1(x) - \mu_0(x) \tag{25}$$

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 18. However, estimator 18 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 A18: Causal Forest—**High** Risk Group

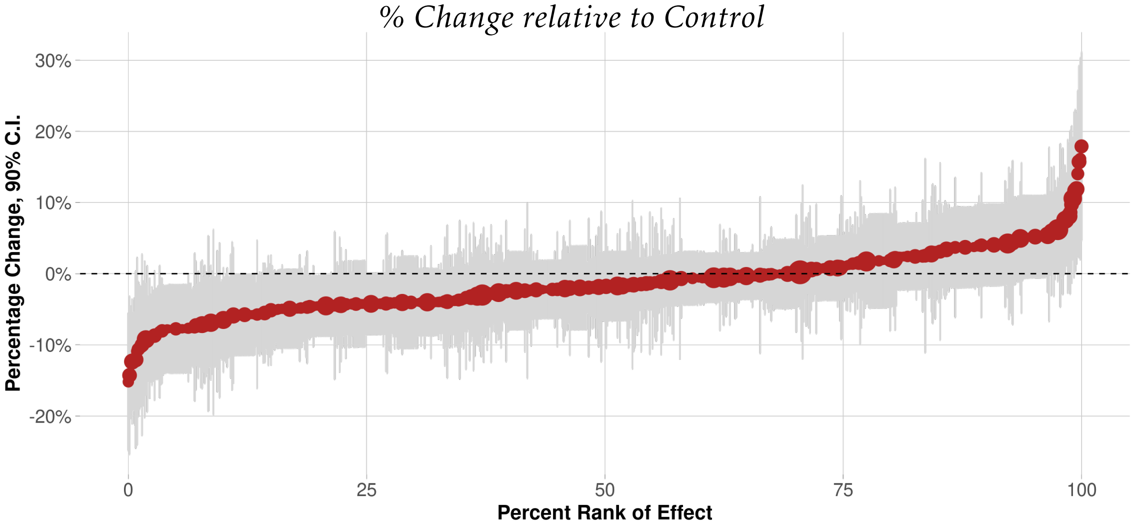
% Change relative to Control



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 A19: Causal Forest—**Medium** Risk Group

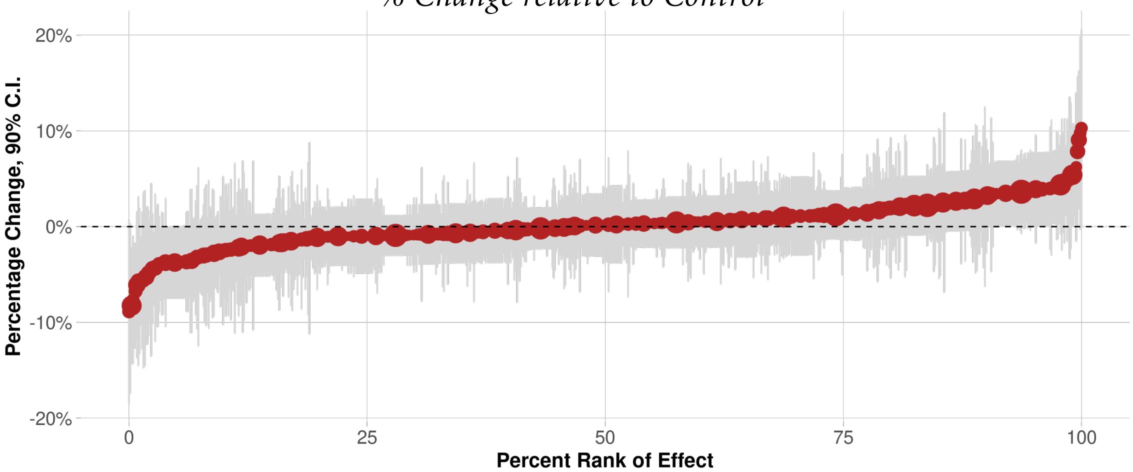
% Change relative to Control



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 A20: 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 A21: Pre-Experiment Distribution of Flood Score for Users by Treatment Status

Number of Users; Column Percentages in Parenthesis

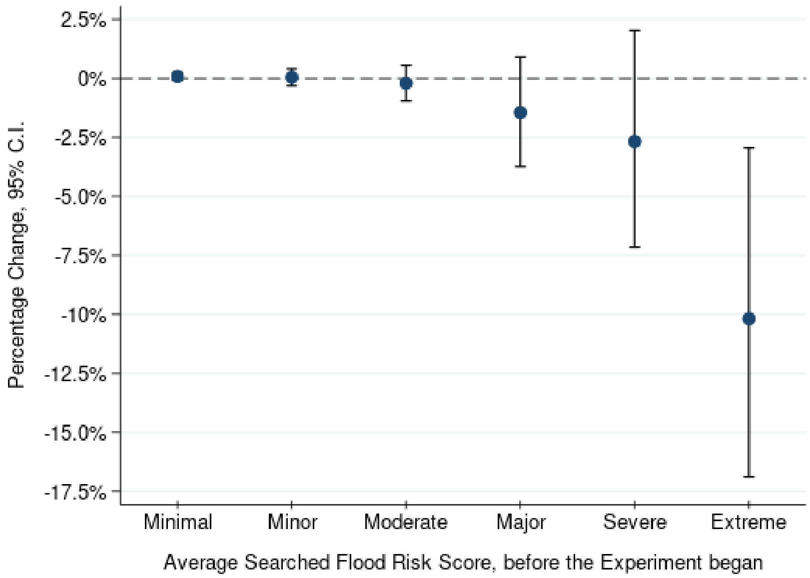
Flood Score Category	Control	Treatment	Total
Minimal	1,962,300	1,963,483	3,925,783
	(68.20)	(68.25)	(68.23)
Minor	419,813	419,611	839,424
	(14.59)	(14.59)	(14.59)
Moderate	323,050	322,315	645,365
	(11.23)	(11.20)	(11.22)
Major	112,001	111,314	223,315
	(3.89)	(3.87)	(3.88)
Severe	29,470	29,681	59,151
	(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 A22: 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 A21: CATE on the Average Flood Score of a Daily Search for Registered Users
% Change relative to Control

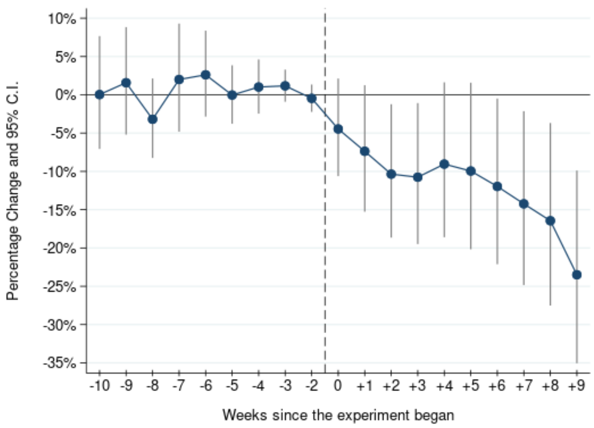


Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

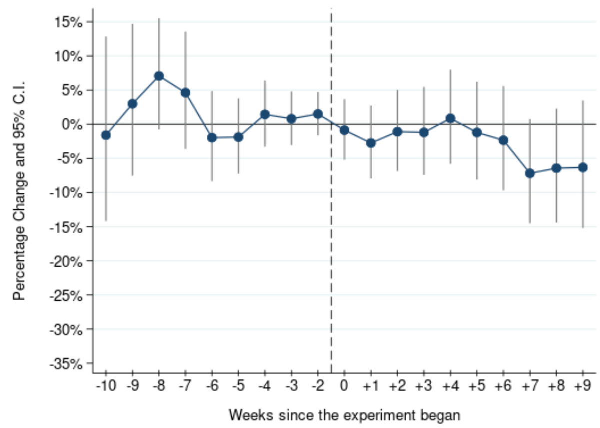
Figure A22: Event-time Study on the Average Daily Flood Score of Properties Searched for Registered Users

% Change relative to Control

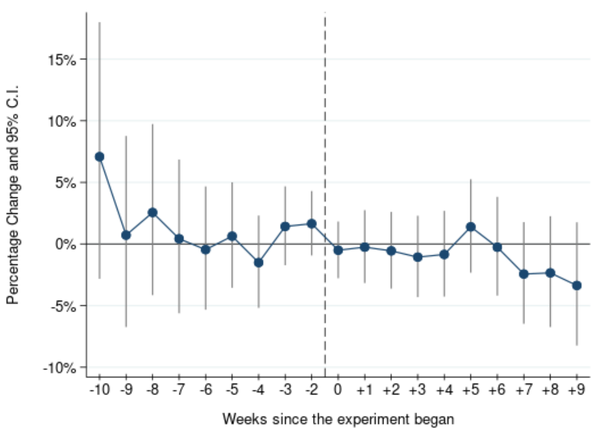
(a) Extreme



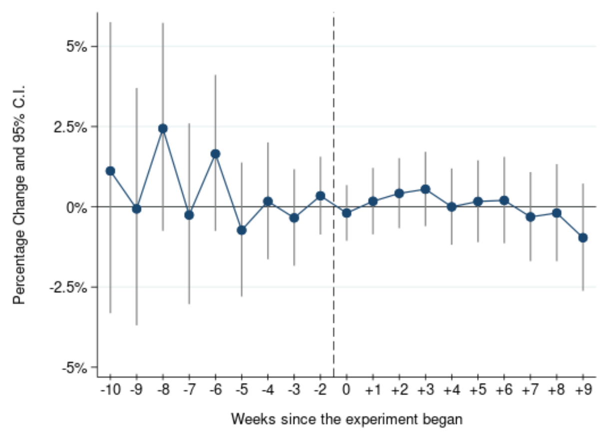
(b) Severe



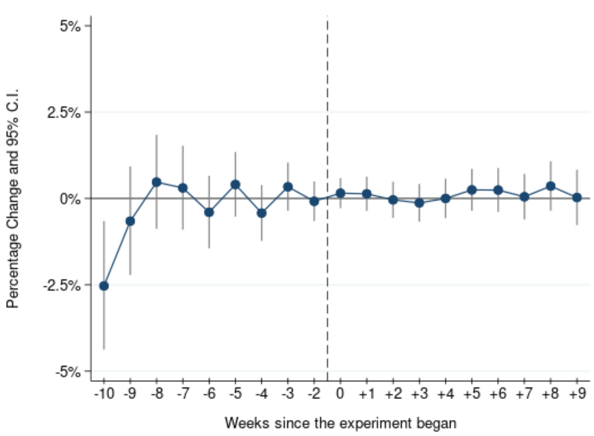
(c) Major



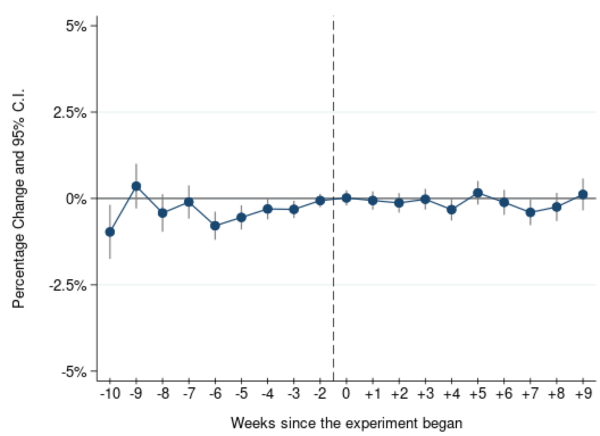
(d) Moderate



(e) Minor



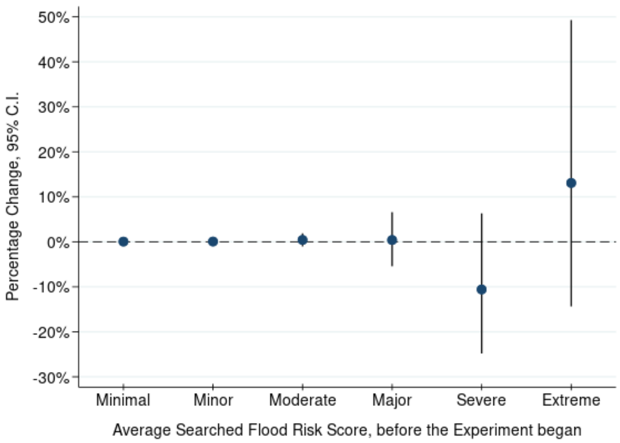
(f) Minimal



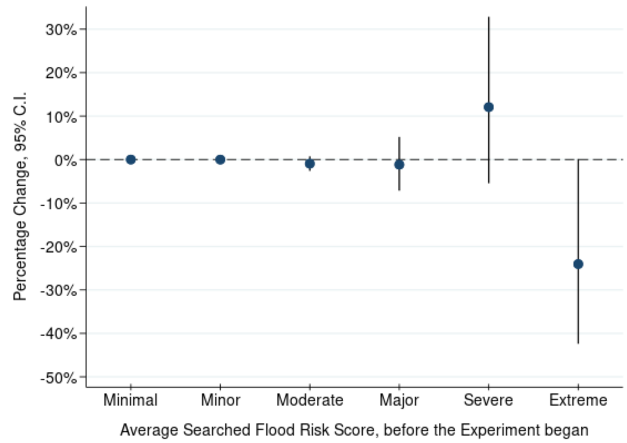
Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 19. Coefficients are relative to the week before a user entered the experiment. Vertical lines crossing the estimates are confidence intervals at the 95% level. The vertical dashed line represents the beginning of the 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



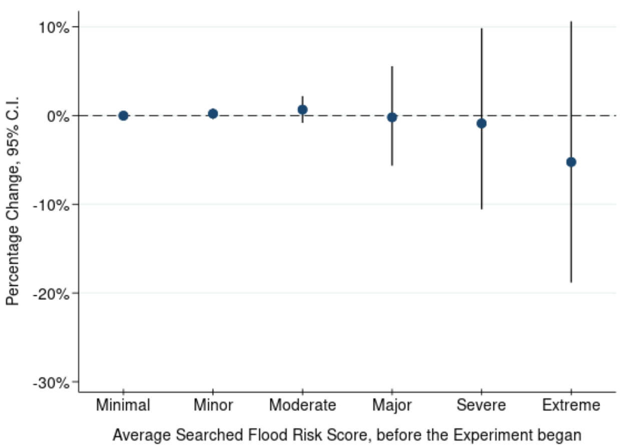
(b) **Higher Mean** Flood Score at Destination Zip Code than Origin



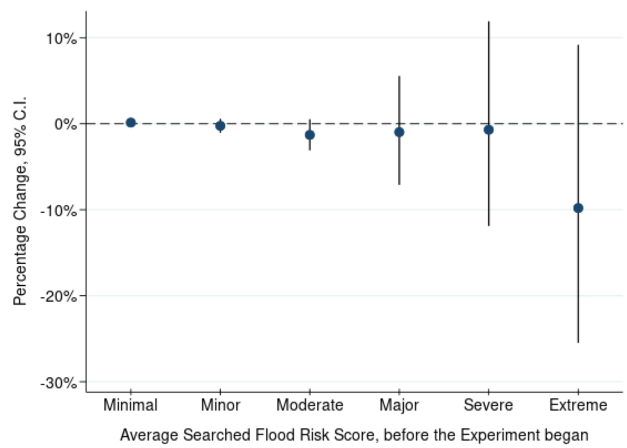
Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before 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



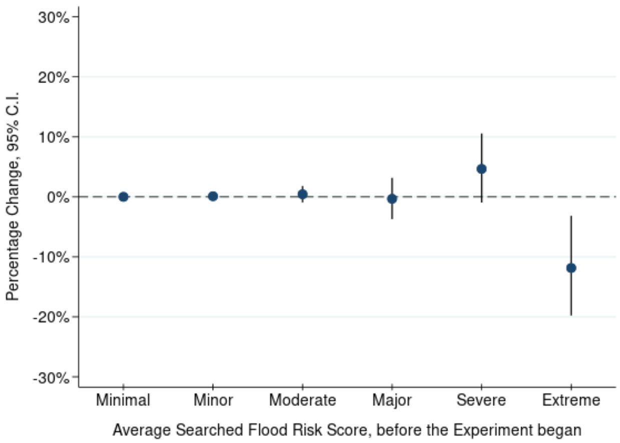
(b) **Higher Standard Deviation** Flood Score at Destination Zip Code than Origin



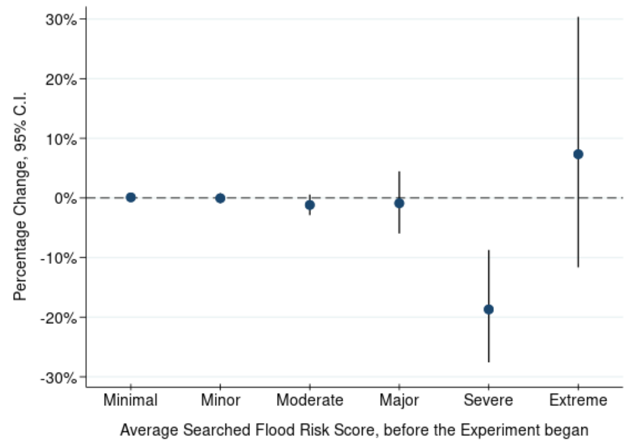
Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before 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



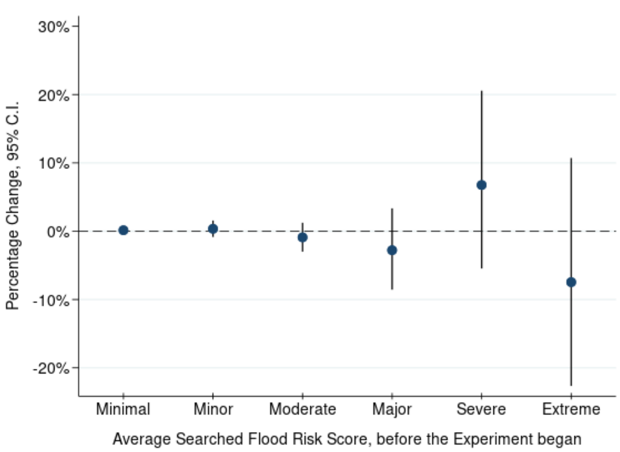
(b) **Higher Coefficient of Variation** Flood Score at Destination Zip Code than Origin



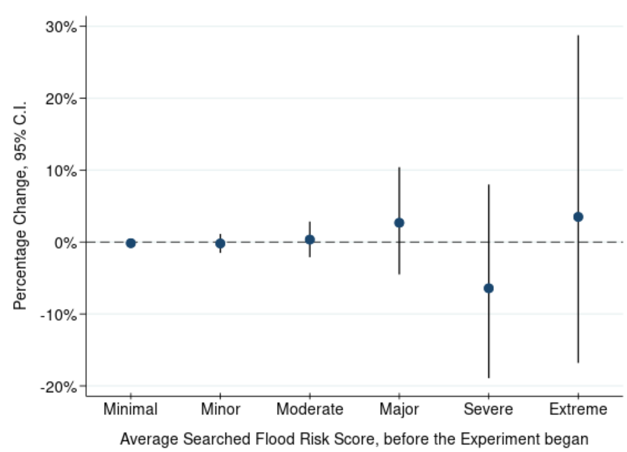
Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's average flood score search category before the experiment 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

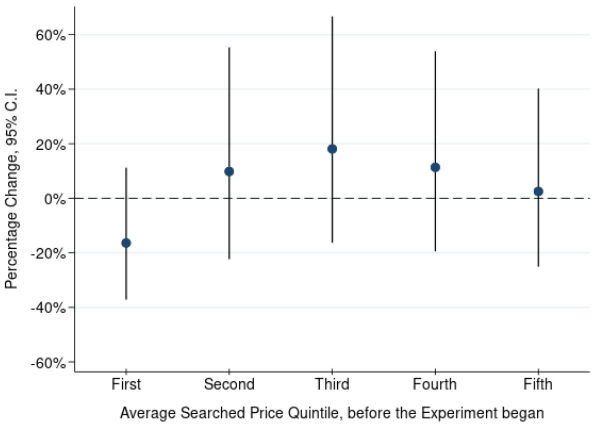


Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

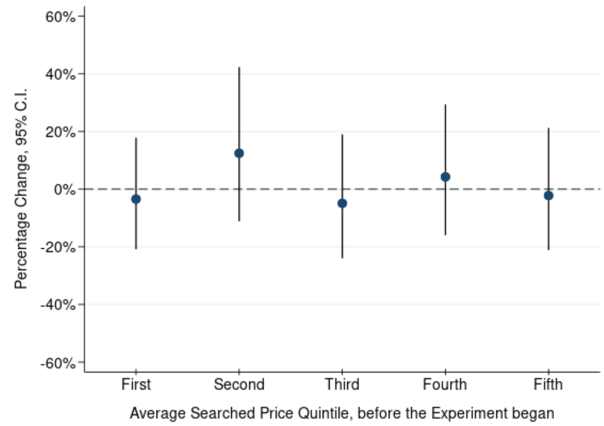
Figure A27: CATE on the Average Flood Score of a Daily Search for Registered Users, by Within-City Average Price Quintile Search at Baseline

Stratified by Average Flood Score Search at Baseline

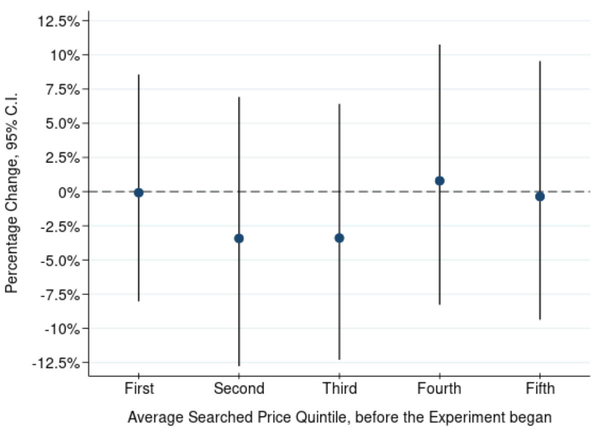
(a) Extreme



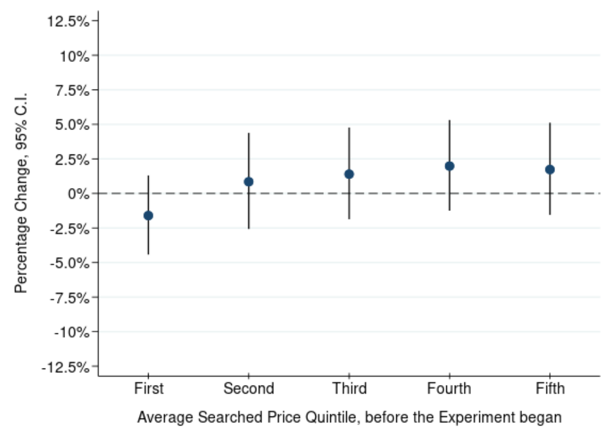
(b) Severe



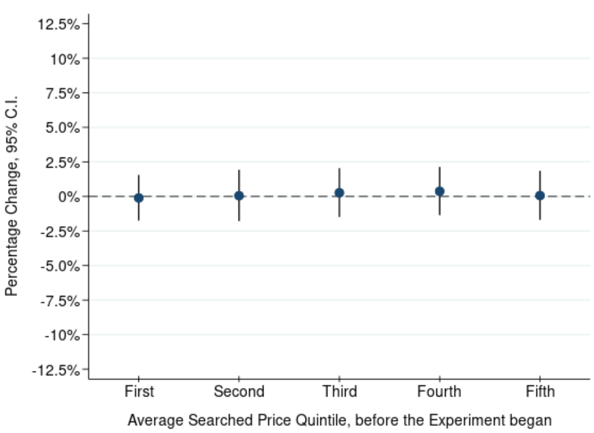
(c) Major



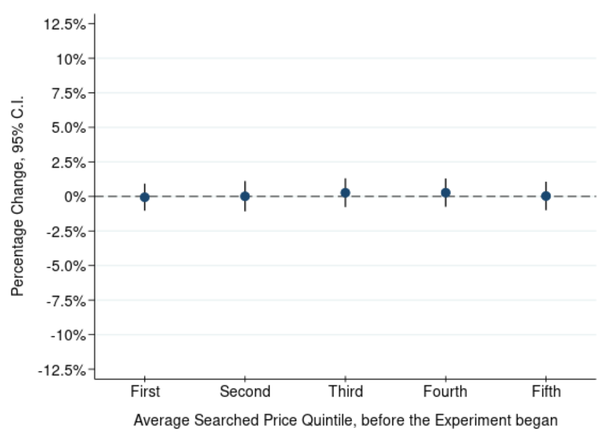
(d) Moderate



(e) Minor



(f) Minimal



Note: Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 19. 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

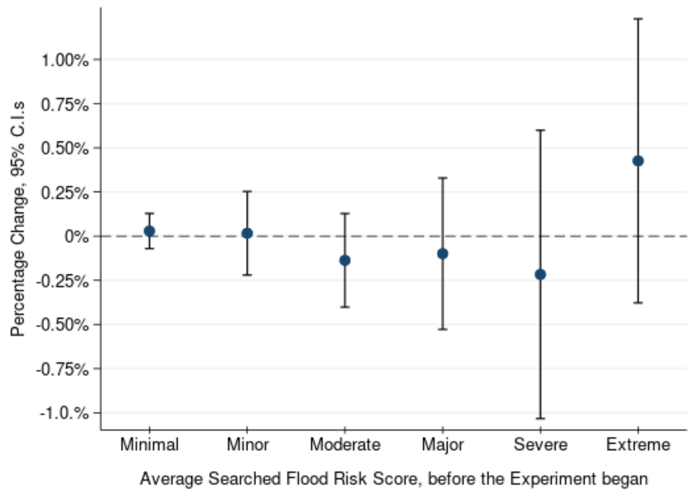
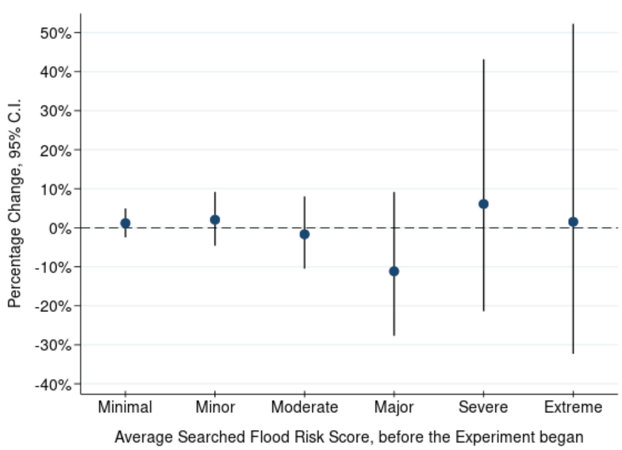
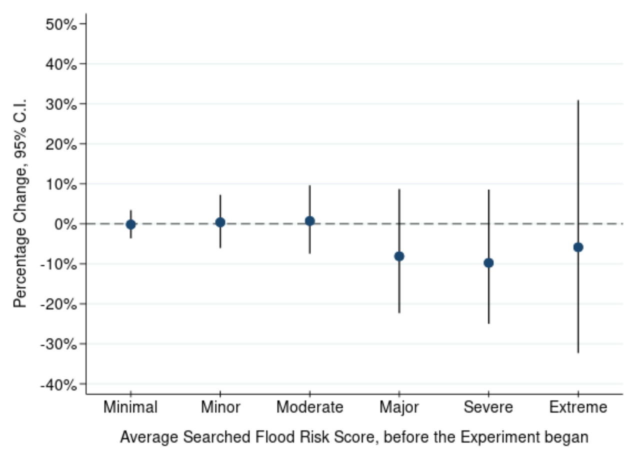


Figure A29: CATE on the Average Flood Score of a Daily Search for Registered Users, by whether the user's county of origin or destination search at baseline experienced a flood shock in the past 7 days

(a) County of Origin

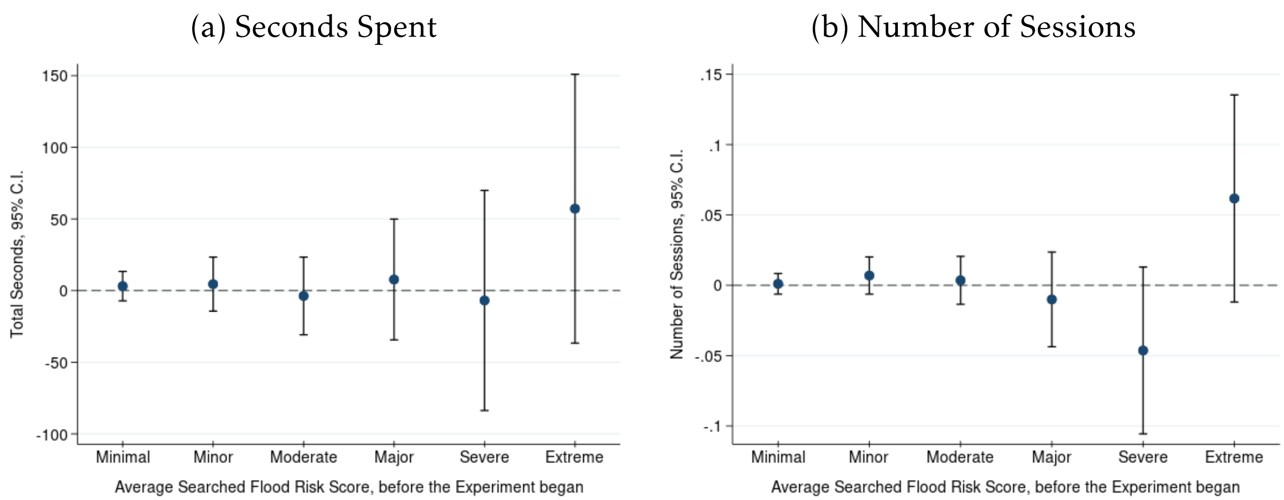


(b) County of Destination



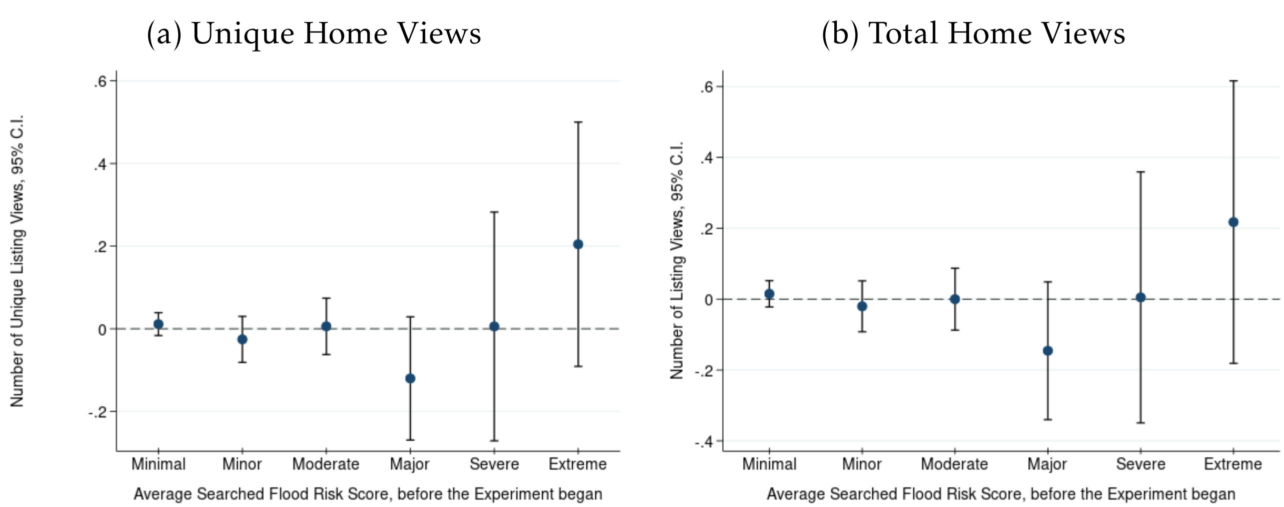
Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. The x-axis represents each user's baseline average flood score search category before the experiment began.

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



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.

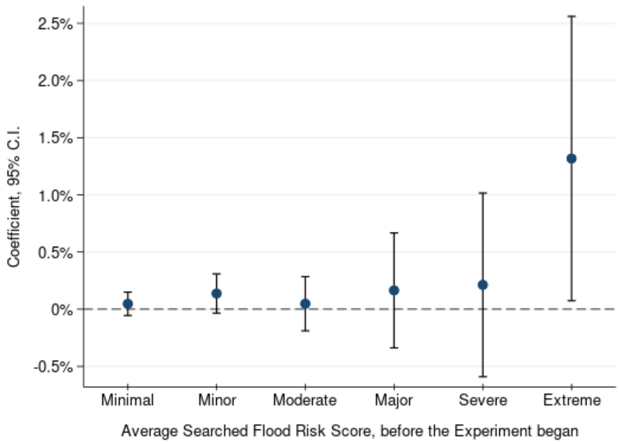
Figure A31: CATE on the Number of Homes Viewed per Day for Registered Users



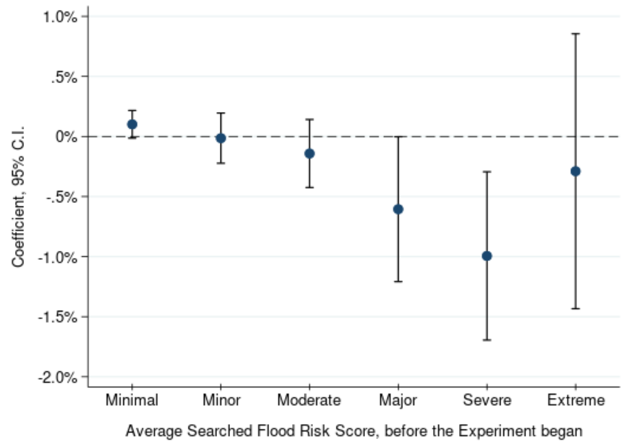
Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

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

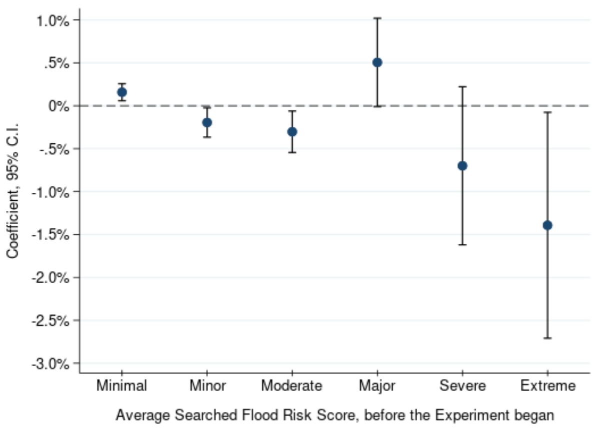
(a) Engaged with Flood Risk Section



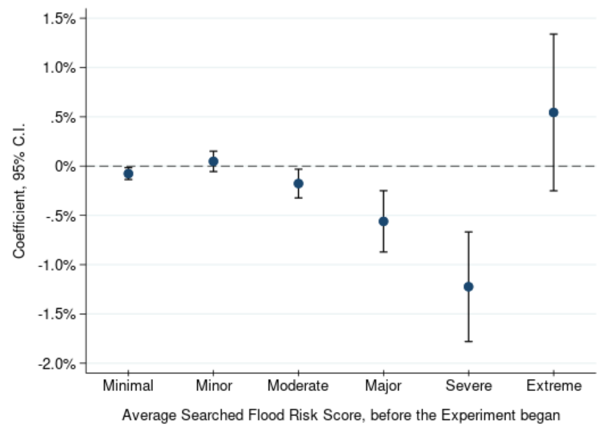
(b) Clicked "Favorite" a Property



(c) Clicked Next Photo



(d) Clicked Active Similar Properties

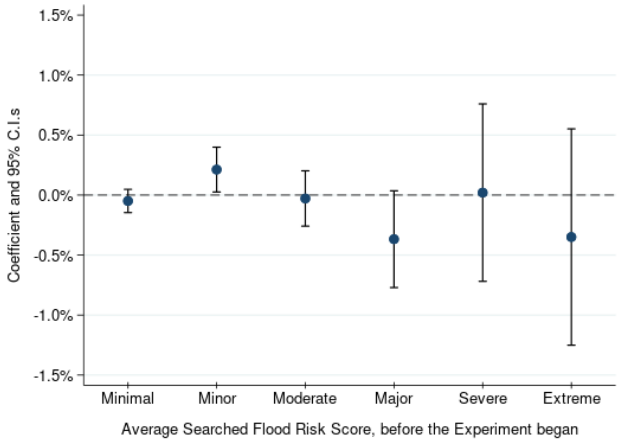


Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before the experiment began.

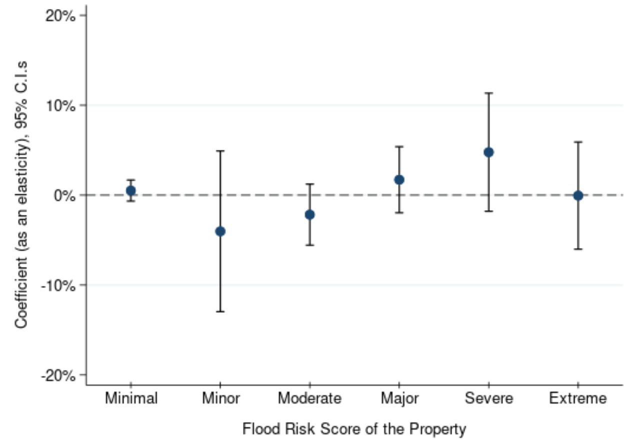
Figure A33: CATE on the Probability of Booking a Tour and Canceling a House Tour

% Change relative to Control for Registered Users

(a) Probability of Booking a Tour



(b) Probability of Cancelling a House Tour

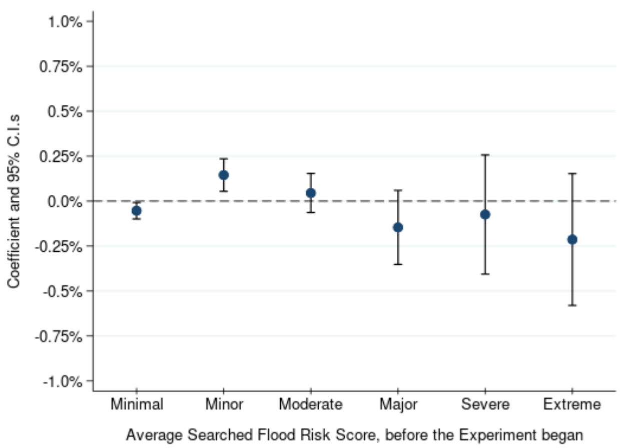


Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents the flood score category of the property.

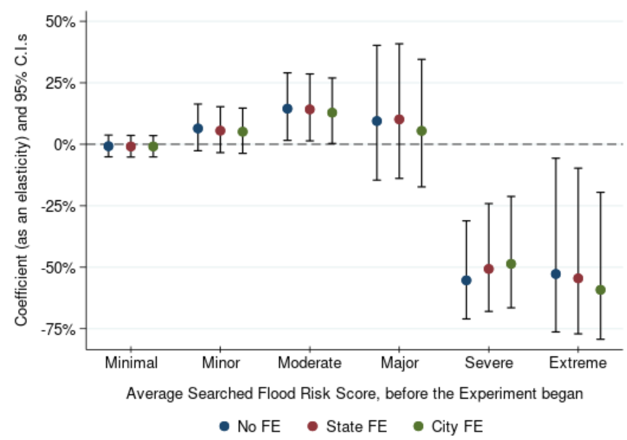
Figure A34: CATE on the Probability of Making an Offer as a Function of the Flood Score

% Change relative to Control

(a) Probability of Placing an Offer



(b) Flood Score of the Property

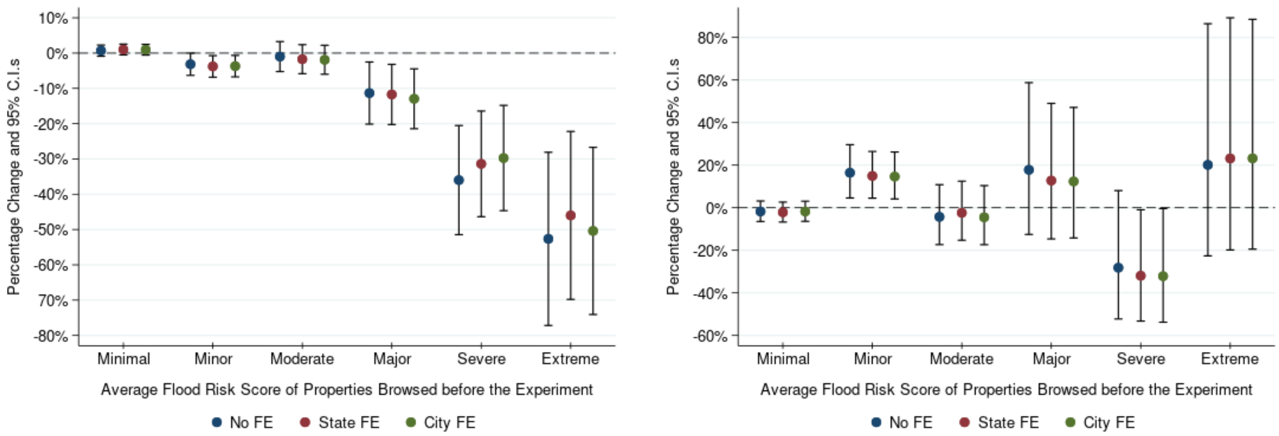


Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search category before 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

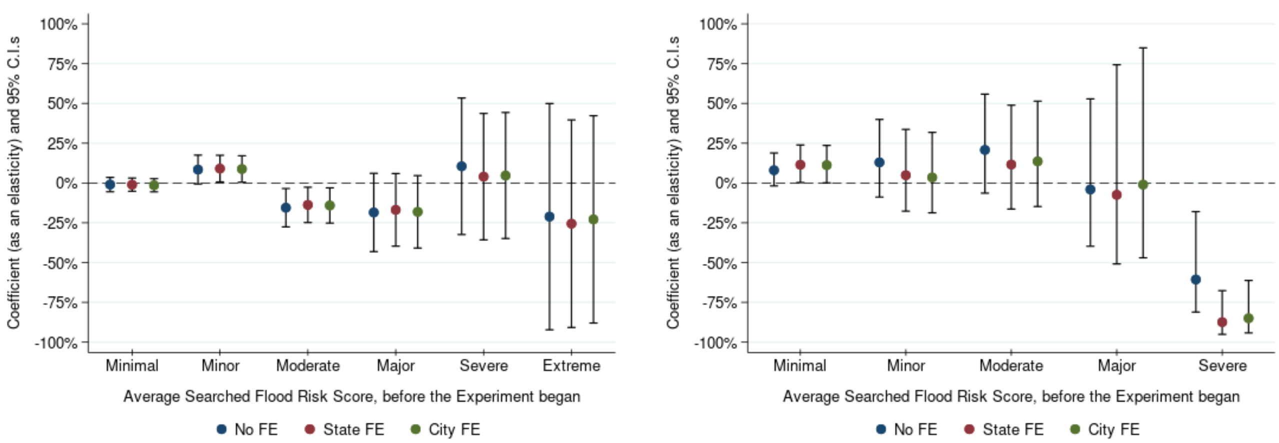


Note: For Figure (b), coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents each user's baseline average flood score search 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

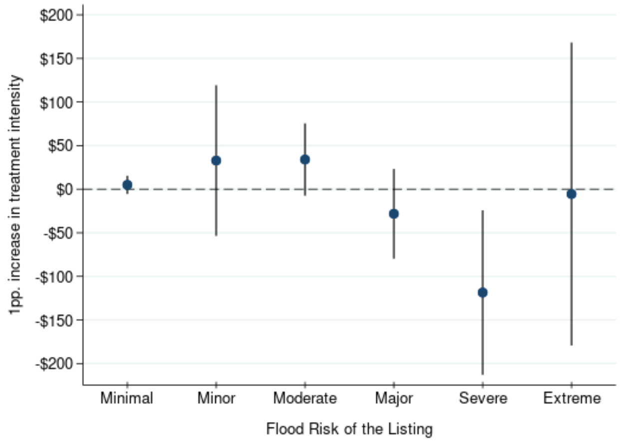
(a) Probability of Closing an Offer (b) Flood Score of the Closed Properties



Note: Coefficients are in the form of $((e^{\beta_3} - 1) \cdot 100)$ from equation 18. 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, ($)

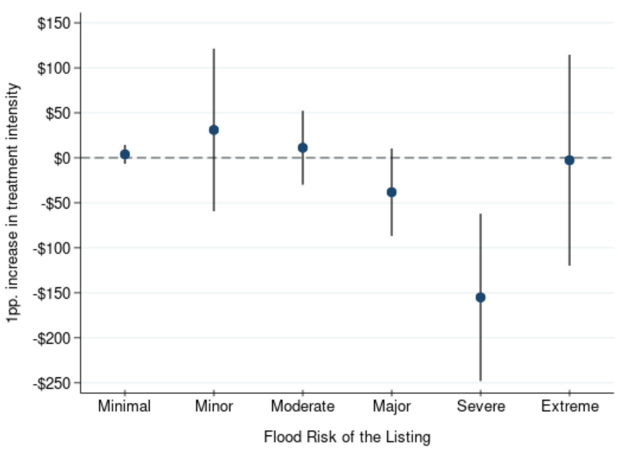


Note: For Figure (b), vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. The x-axis represents the flood score of the property.

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

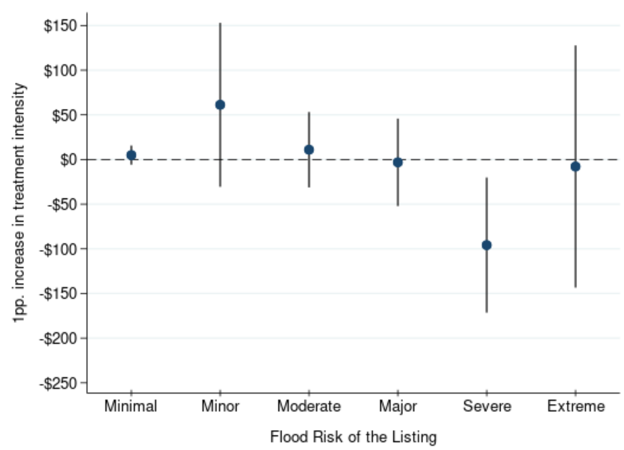
(a) Only Not Waterfront Listings

1PP Increase in Exposure Intensity, ($)



(b) Only Not FEMA Risky Listings

1PP Increase in Exposure Intensity, ($)

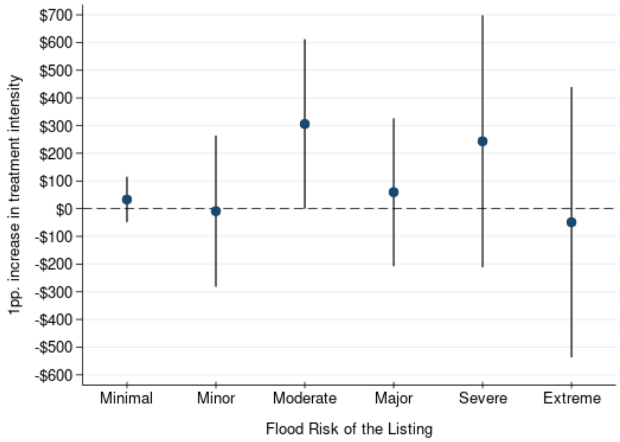


Note: Vertical lines crossing the estimates are confidence intervals, where the cap represents the confidence interval at the 95% level. As well, for Figure (b), the x-axis represents the flood score of the property.

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

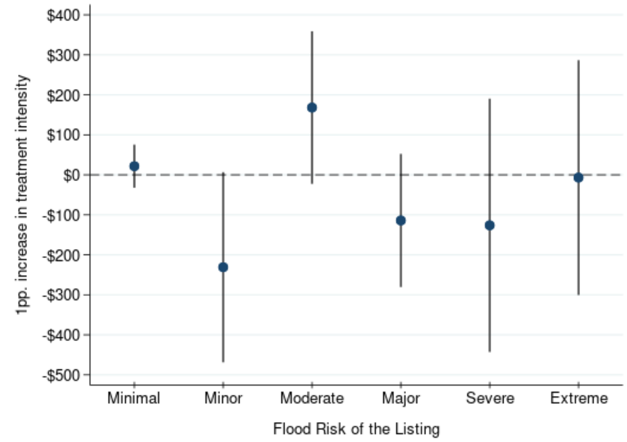
(a) Only Waterfront Listings

1PP Increase in Exposure Intensity, ($)



(b) Only FEMA Risky Listings

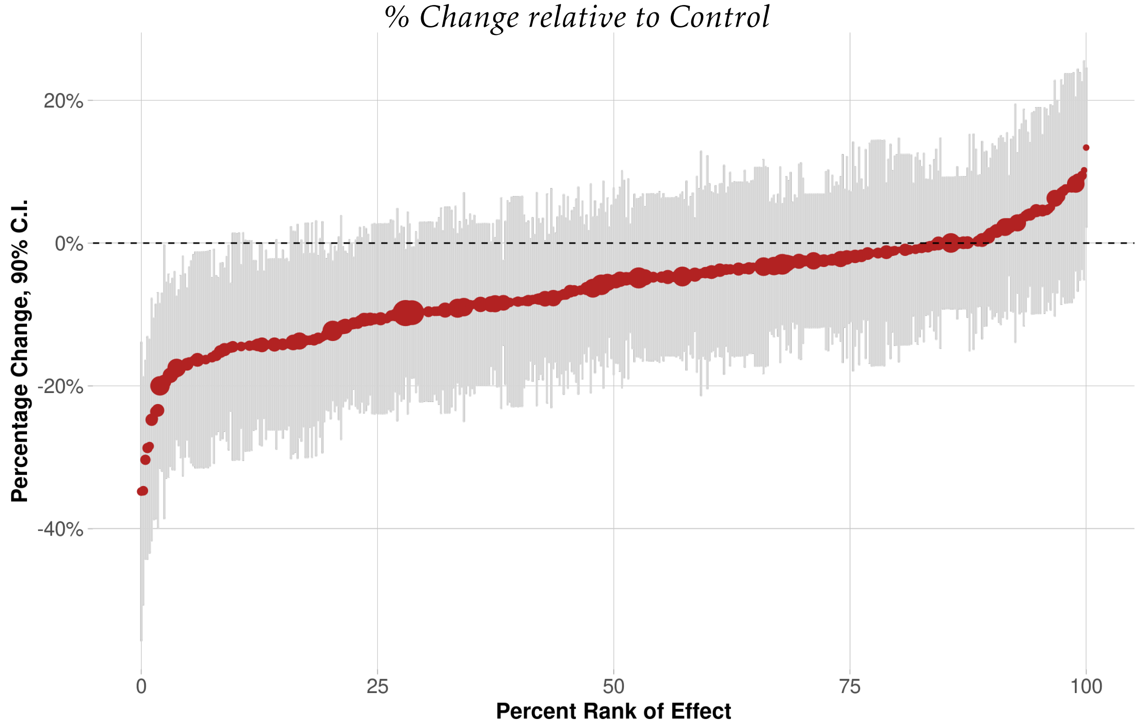
1PP Increase in Exposure Intensity, ($)



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

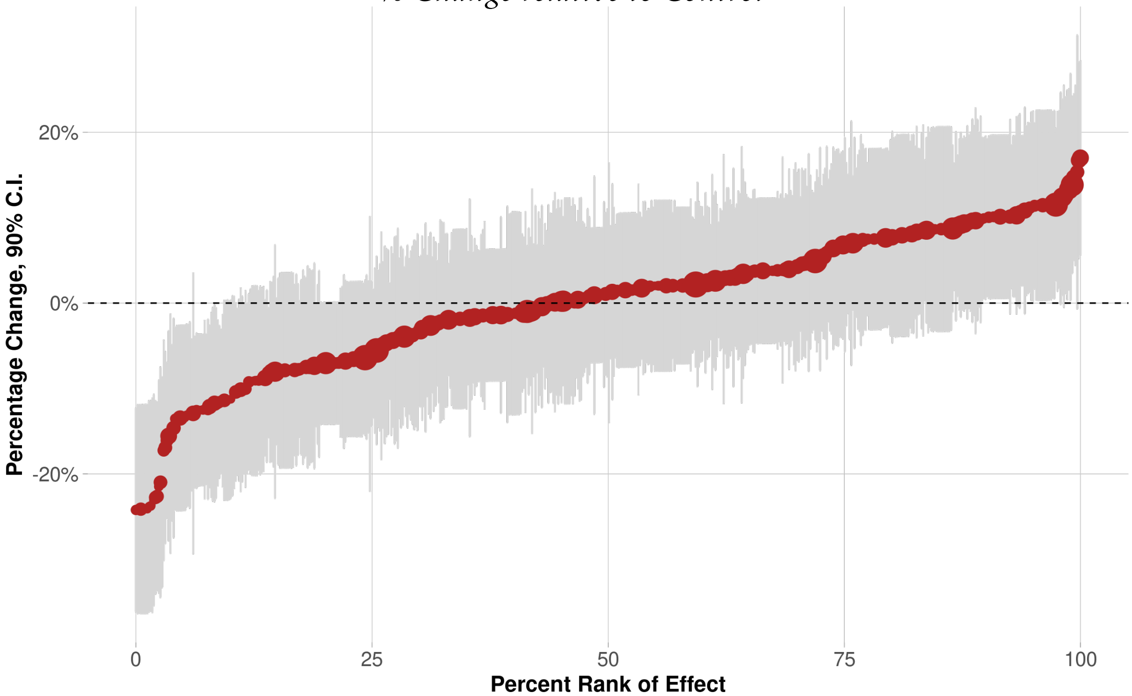
% Change relative to Control



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

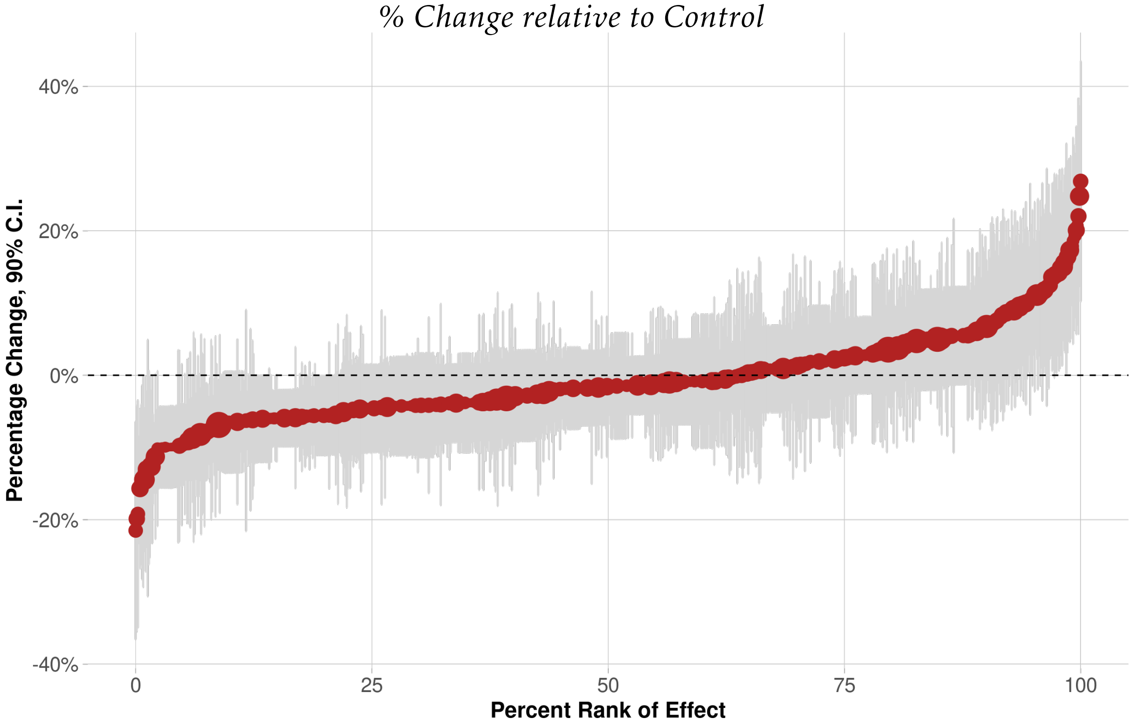
% Change relative to Control



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

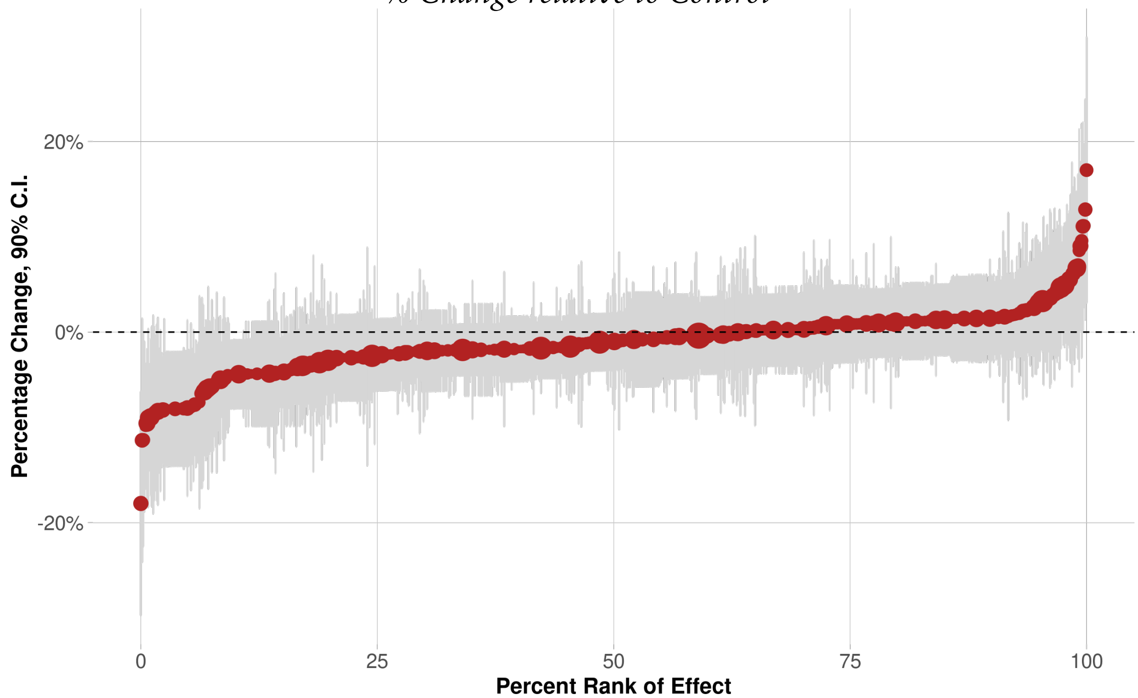
% Change relative to Control



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

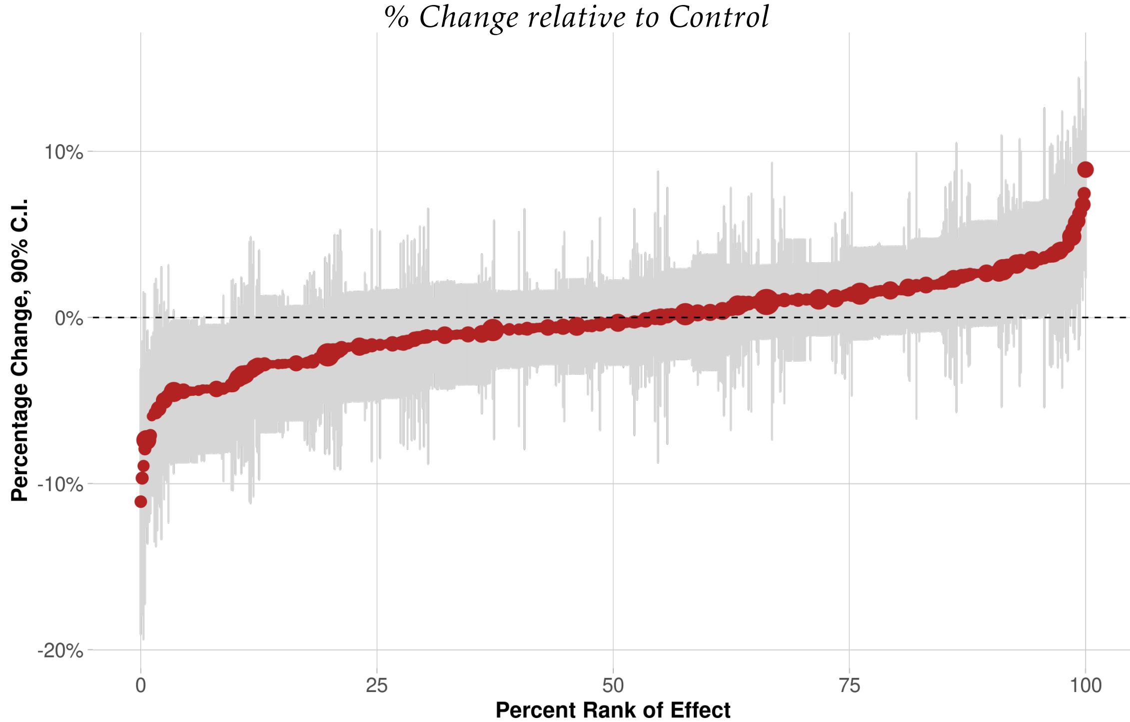
% Change relative to Control



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

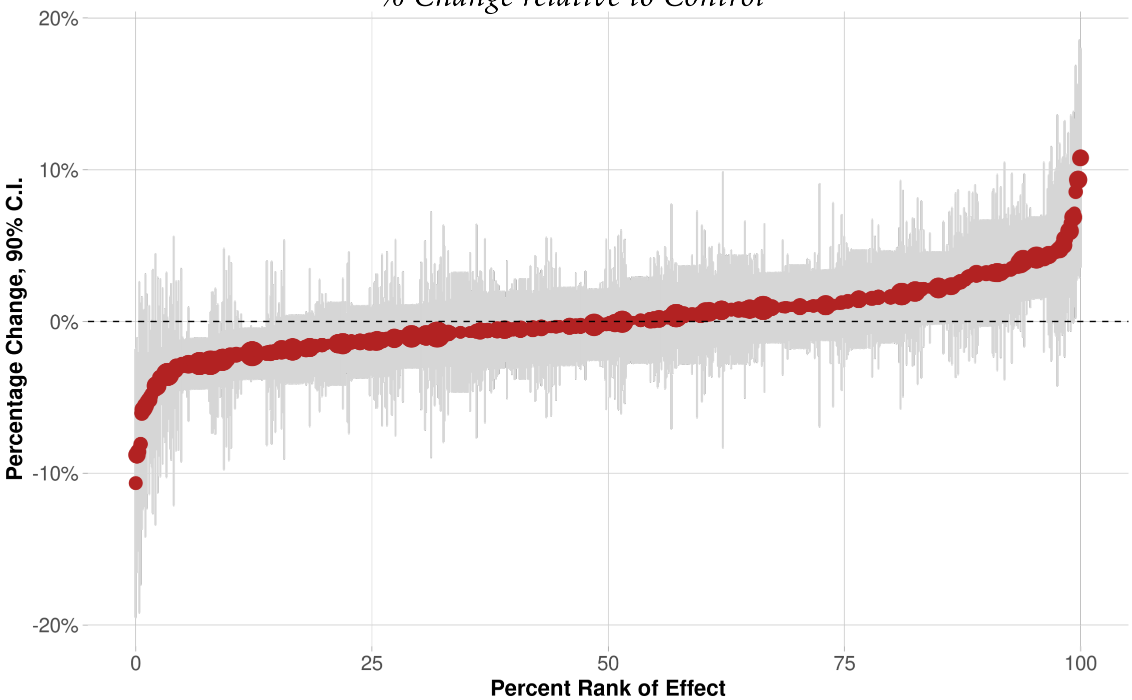
% Change relative to Control



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.