Does Disaster Aid Cause Moral Hazard in the Housing Market? (Preliminary; Please Do Not Circulate)

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Abstract

We examine whether post-disaster aid creates moral hazard in housing markets by reducing private incentives for climate risk mitigation. We exploit a novel identification strategy using counties' social network exposure to disaster aid distributed elsewhere, which plausibly increases local expectations of future aid availability. Our empirical strategy interacts ZIP- or property-level flood risk with county-year variation in social network exposure to disaster aid, controlling for county-year fixed effects. We find that when counties experience high social network exposure to disaster aid, high-flood-risk ZIP codes experience a reduction in flood-proofing permits and flood insurance take-up compared to low-flood-risk ZIP codes within the same county-year. In addition, high-flood-risk properties experience a relative price increase compared to low-risk properties, indicating that anticipated disaster assistance capitalizes into valuations for flood-vulnerable homes. These findings provide novel evidence of moral hazard in disaster policy: the expectation of government assistance diminishes private adaptation incentives while simultaneously inflating property values in climate-vulnerable areas.

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Keywords: moral hazard, disaster aid, housing markets, flood risk, insurance, climate adaptation, social network exposure

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1 Introduction

Climate change is intensifying the frequency and severity of natural disasters, creating mounting pressure on governments to provide post-disaster relief. However, disaster assistance may inadvertently generate moral hazard by reducing households' incentives to invest in risk mitigation measures, potentially undermining long-term adaptation to climate risk. Despite the importance of this issue, such moral hazard effects remain understudied, with one challenge being identifying exogenous variation in disaster aid expectations.

This paper identifies the causal effect of disaster aid expectations by exploiting exogenous variation in exposure to aid through social networks. We address two research questions. First, does the expectation of future disaster assistance reduce private incentives for climate risk mitigation in housing markets, including flood-proofing investments and insurance take-up? Second, is the expectation of disaster aid incorporated in house prices in flood-vulnerable areas?

To measure counties' exposure to disaster aid distributed elsewhere, we leverage the Social Connectedness Index (SCI) developed by Bailey et al. (2018), which quantifies social ties between county pairs based on Facebook friendship patterns. We construct each county's social network exposure to disaster assistance as the weighted average of aid payments received by all other counties, with weights reflecting the strength of social connections as measured by the SCI. We find that when a county experiences greater social network exposure to disaster aid, residents are more likely to search for disaster assistance-related phrases on Google. This result supports our argument that social network exposure to disaster aid can increase awareness of—and thus, expectations about—such assistance.

We examine how three key outcomes respond to social network exposure to disaster aid distributed elsewhere: flood-proofing permits, flood insurance take-up, and residential transaction prices. Our identification strategy exploits within-county-year variation by comparing how high-risk ZIP codes or properties respond relative to lower-risk areas within the same county-year, thereby controlling for confounding factors common to all

locations within a given county and time period. Crucially, for any given level of social network exposure, high-risk ZIPs or properties should experience a larger increase in expected disaster aid, as their elevated flood probability makes future aid receipt more likely. This strategy mitigates concerns that our estimates reflect indirect economic spillovers from disaster-affected to socially connected counties, as such spillovers would be unlikely to disproportionately affect higher-risk ZIP codes and properties within connected counties. We additionally include ZIP code or property fixed effects to account for time-invariant location characteristics. We focus specifically on flood risk because there is rich variation in flood risk within a county. In addition, floods represent one of the most significant and growing disaster threats in the United States due to climate change, with more than 15 million homes—over 10% of the housing stock—currently exposed to flood hazards. Since disaster aid is inherently correlated to disaster occurrence, which may directly affect socially connected areas, we consistently control for each county's social network exposure to disaster damages in connected regions and its interaction with ZIP- or property-level flood risk levels.

We document five main findings. First, when a county experiences greater exposure to disaster aid through social network connections, high-flood-risk ZIP codes reduce flood-proofing permits relative to lower-risk areas within the same county-year. In contrast, social network exposure to disaster damages elsewhere produces the opposite effect, increasing protective investments in high-risk areas. These results suggest that in risky areas, heightened disaster awareness encourages adaptation, while heightened awareness of disaster aid discourages it—consistent with moral hazard. This moral hazard effect is concentrated in lower-income areas, where households are more likely to qualify for disaster grants.

Second, we observe a similar pattern for financial risk mitigation in terms of insurance take-up. When counties experience greater social network exposure to disaster aid, high-risk ZIP codes exhibit relatively larger reductions in flood insurance take-up compared

to lower-risk ZIP codes, consistent with elevated expectations of disaster aid discouraging private risk mitigation. Exposure to disaster damages again generates the opposite response.

Third, we examine effects on residential property values. If expectations of disaster aid increase, this anticipated government support may capitalize into housing prices, particularly for flood-vulnerable properties. Consistent with this prediction, greater exposure to disaster aid raises prices for high-flood-risk properties relative to low-risk properties within the same county-year. Exposure to disaster damages again produces the opposite effect.

Fourth, disaster aid comes in two forms: SBA loans and FEMA IHP grants. Higher-income households are more likely to qualify for the former, while lower-income households are more likely to qualify for the latter. We find that the house price effects of each type of aid are concentrated in ZIP codes where households are more likely to qualify for that specific program.

Fifth, we examine whether ex ante exposure to disaster aid influences subsequent application behavior after disasters. We find that counties with greater prior exposure to disaster aid exhibit a higher share of FEMA claims later identified as involving no damage, particularly in higher-income ZIP codes.

Our findings carry important implications for understanding climate adaptation and the design of disaster policy. From a policy standpoint, our results suggest that as climate change intensifies disaster risk and pressures policymakers to expand relief programs, such expansions could inadvertently discourage the private investments necessary for long-term resilience. These unintended consequences warrant careful consideration in the design of federal disaster programs. More broadly, our findings indicate that disaster relief programs may require mechanisms to preserve or strengthen private incentives for risk mitigation, such as conditioning aid eligibility on ex ante or ex post protective measures and insurance coverage.

1.1 Contribution to the Literature

Our paper contributes to an empirical literature on charity hazard—the hypothesis that expectations of governmental disaster relief reduce private risk mitigation efforts (mostly on insurance takeup), existing studies have produced mixed findings. Some studies find evidence consistent with charity hazard, showing that government aid reduces willingness to pay for flood insurance (Botzen et al., 2009; Botzen and van den Bergh, 2012b,a; Raschky et al., 2013; Davlasheridze and Miao, 2019; Landry et al., 2021). Others find no effect (Seifert et al., 2013; Petrolia et al., 2015) or even a positive relationship between disaster assistance and insurance demand (Browne and Hoyt, 2000; Petrolia et al., 2013). A few studies make theoretical arguments about disaster aids and moral hazards (Baylis and Boomhower, 2019; Kousky et al., 2006; Raschky and Weck-Hannemann, 2007).

Our study advances this literature in several important ways. First, whereas existing studies typically rely on survey-based measures of aid expectations or actual past aid receipt—both of which raise concerns about endogeneity and reverse causality—we exploit a novel source of variation in disaster aid expectations: social network exposure to disaster aid distributed elsewhere. By leveraging the Social Connectedness Index based on Facebook friendship patterns, we construct a plausibly exogenous measure of counties' exposure to information about disaster assistance, allowing us to isolate the causal effect of aid expectations on private behavior. Second, while most prior studies focus on a single outcome such as flood insurance demand or willingness to purchase sandbags, we examine a novel and important set of behavioral margins including physical flood-proofing investments, flood insurance take-up, and residential property values. Third, we distinguish between exposure to disaster aid and exposure to disaster damages, demonstrating that these generate opposite effects—a finding that reconciles some of the conflicting results in the literature by showing that heightened disaster awareness encourages adaptation while heightened awareness of disaster aid discourages it. Fourth, by differentiating between SBA loans and FEMA IHP grants and examining heterogeneous effects across the income

distribution, we provide new evidence on who is most responsive to charity hazard incentives.[1]

Our paper also contributes to the literature on household-level adaptation to climate risk through physical investments in building resilience. A central question in this literature is why households underinvest in cost-effective protective measures despite rising disaster risk (Bubeck et al., 2012; Kousky, 2014). Recent studies have focused primarily on the effects of financing constraints/incentives, behavioral biases, regulation, and information failures on climate adaptation in real estate (Baylis and Boomhower, 2024; Bellon et al., 2025; Baylis et al., 2024; Agarwal et al., 2025; Clara et al., 2023).

We contribute to this literature by providing evidence on a distinct channel: expectations of post-disaster government assistance. Using flood-proofing permits as a measure of physical investment in building resilience, we show that anticipated disaster aid discourages private adaptation in high-risk areas. This finding implies that policies designed to promote household-level climate adaptation must account for how disaster relief programs interact with private mitigation incentives—a consideration largely absent from existing research on the adaptation puzzle.

Our paper also contributes to the literature on demand for natural disaster insurance. Existing work has estimated demand elasticities for flood insurance using quasi-experimental variation in NFIP premiums (Wagner, 2022; Collier et al., 2024; Liao and Mulder, 2021).Sastry et al. (2025) and Cookson et al. (2025) study low coverage in homeowners' insurance more broadly. We contribute to this literature by identifying a novel determinant of insurance demand: expectations of post-disaster government assistance formed through social networks. While prior work has focused on how premium levels, financial constraints, and risk perceptions shape insurance decisions, we show that anticipated disaster aid—transmitted through social connections to aid recipients—reduces flood insurance take-up in high-risk areas. This finding suggests that the well-documented

[1]Our paper also contributes more broadly to the literature on public and private disaster aid (Billings et al., 2022; Collier et al., 2024,?; Cookson et al., 2023; Collier and Ellis, 2024; Collier et al., 2025).

"insurance gap" may partly reflect rational responses to expected government support rather than behavioral frictions or information failures alone.

We also contribute to the literature on climate risk and housing markets. Studies have found that house prices incorporate climate risks (Bernstein et al., 2019; Baldauf et al., 2020; Murfin and Spiegel, 2020; Keys and Mulder, 2020; Giglio et al., 2021; Lopez and Tzur-Ilan, 2023; Ge et al., 2024; An et al., 2024; Van Binsbergen et al., 2025). Our findings highlight that expected disaster aid offset the negative impact of flood risk on house prices. This suggests that disaster aid can potentially distort the pricing of such risks, worsened by climate change, in the housing market.

2 Data and Sample

This section first describes the data sources used in the study and how we construct the sample. We then present summary statistics concerning the primary quantities used in our analysis.

2.1 Disasters and Government Aid

We obtain data on US federal disaster declarations from FEMA. High-level summary data lists each disaster's declaration date, county, and one of 26 disaster types (e.g., flooding, hurricane, fire, etc.). Importantly, it also includes the federal disaster declaration number used in other government reporting, which enables us to link disasters across datasets.

We combine this data with separately reported data on the aid provided to residents and business owners in the aftermath of each disaster. The first program is the housing assistance (HA) program for owners and renters. This program provides free assistance to citizens and permanent residents to cover disaster expenses not covered by existing insurance. Individuals can apply for assistance following a disaster declaration, and are potentially subject to a home inspection to confirm claimed damages are accurate. FEMA

reports both the count of applicants receiving aid, the total dollar amount of aid, and bins of dollar amount of inspected damages (i.e., how many people were inspected for damages of $0, $1-$10k, etc.) The FEMA data only begins reporting the associated payments for disasters starting in November of 2002. The second program is the Small Business Association (SBA) loan program for business owners. This program provides loans, which must be repaid, to homeowners and business owners in the area affected by declared disasters. These loans also must be applied for, and are treated as standard borrowing with credit and income verification. As a result, receiving an SBA disaster loan is more strict than the individual housing assistance. The SBA reports data on loans distributed starting with fiscal year 2000.

While the above assistance data reports the dollar amounts approved for distribution for each disaster, it does not specify the *timing* of the payments distributed to residents. To account for this, we collect annual reports produced by the Department of Homeland Security that trace the money distributed as part of the disaster assistance programs.[2] These summary reports display the realized monthly payments following each disaster. We calculate the percentage of total dollars received each month, and multiply this share to the total aid distributed under each assistance program to get the monthly aid per county. Since the reports start in 2013, the timing for disasters prior to 2013 must be inferred from the available years. We use the median timing for reported disasters to calculate the distributions in this case. The median share distributed by month following each disaster is shown in Figure 1. Over 50% of payments are received within one year from the disaster declaration.

We also acquire data on estimates for the total amount of property damage from the Spatial Hazard Events and Loss Database for the United States (SHELDUS). SHELDUS provides monthly property damage losses from specific event types that took place in a given county. Specifically, we focus on the measure of total property damage in terms of

[2]See `https://www.fema.gov/about/reports-and-data/disaster-relief-fund-monthly-reports`

2014 dollars. This provides us with a measure of disaster impact that is not dependent on residents applying to the federal government for aid.

2.2 Social Connectedness Index

In order to construct a measure of exposure to both disaster losses and government aid, we source measurements from the Social Connectedness Index (SCI), as constructed by Bailey et al. (2018). The SCI provides a quantitative measure for how socially connected areas are with each other based on Facebook friendship connections. The data consists of relative weights that represent how likely it is that a person in the primary area is friends with a person in the other area. We use the SCI based on US counties constructed as of October, 2021, as this matches the most granular disaster data as described in the previous section.

2.3 Construction Permits

We obtain nation-wide data on home building and improvement permits from CoreLogic. This data covers nearly all construction permits requested within over 2,500 counties and cities, including both new builds and existing home improvement projects. The data contains, among other items, the date the permit was requested and completed, the full street address of the work performed, a description of the work performed, and the type of property. We limit the data to only consider work performed on residential properties.

2.4 Housing Transactions

We obtain house characteristics and transactions from ATTOM. These datasets provide substantial coverage of national home sales, with 156 million properties covered and 143 million transactions recorded between 2000 and 2023. The housing characteristics include traditional items, such as property type, number of bedrooms and bathrooms, square

footage, and number of units. The transactions record data items such as the date of the sale, dollar amount paid, and loan-to-value (LTV) ratio if a mortgage was used to purchase the property.

2.5 Flood Risk

We augment both the CoreLogic permit data and ATTOM transaction data with measurements of property flood risk from the First Street Foundation. First Street provides property-level measurements of how exposed that property is to flooding in a middle climate scenario. For our analysis, we focus on the "flood factor" calculated by First Street, which provides a score from 1 (lowest) to 10 (highest) quantifying the risk facing the property. Most properties have a score of 1, indicating minimal exposure. We deem any score higher than 1 as having a "high flood factor". As these three disparate datasets share no central identifiers, we turn instead to matching based on geographic location indexed by latitude and longitude. ATTOM and First Street have these locators in their original data. For CoreLogic, we instead must geocode the street addresses using PlaceKey, a geotagging service which returns latitude and longitude with six decimal digits.[3] For each property in CoreLogic and ATTOM, we then take the flood factor from the closest property in the First Street data. If the closest property is located further than 1 mile away, then the flood factor is set to missing.

2.6 Flood Insurance Policies

Finally, we aggregate administrative data from the National Flood Insurance Program (NFIP). Collected by FEMA, this data reports anonymized individual flood policies starting in 2009. Each policy observation contains the notional amount covered, the premium pay-

[3]Despite returning latitude and longitude with this precision, the geocoding provided by PlaceKey is based on Uber's H3 hexagonal grid system. At it's highest fidelity, these hexagons have a side length of approximately 75 meters. As a result, the geocoding has a true precision of between three and four decimal places.

ment due, the start and end dates of the policy, and the zipcode location of the property covered. We drop policies that do not have any active date associated with their record. However, no individual property identifier or address is provided, so we can only aggregate this data to the zipcode level.

2.7 Census Data

We obtain standard zipcode-level data from the US Census on income, population, and number of housing units. Specifically, we use the median household income, the total population estimate, and the estimated number of housing units (data item H001001), all as of 2010.

2.8 Google Trends Data

Finally, we obtain metropolitan area level data for search trends between 2004 and 2019 from Google Trends. To do this, we query a selection of broad search terms from the Google Trends API, listed in Table A.2. As Google automatically scales individual searches, we always include a reference locality in the query, and then unscale appropriately for each search term. We then aggregate to the fips-year level and then average across all search terms to obtain our measure of "Flood Assistance Searches".

2.9 Sample

First, we construct our measure of exposure to disaster damages and aid. We limit to disaster declarations that concern flood events, specifically "Flood" and "Dam/Levee Break" as reported by FEMA. We aggregate the property damages from SHELDUS and timing-adjusted HA and SBA payments from FEMA into county-year observations, and then take the log of one plus this amount. Then, we merge the relative connection weights from the SCI to each county-year observation, and then take the weighted average of payments

received by connected counties. We set the SCI for self-county connections to zero. Thus, the measure for county c in year y reflects a weighted average of log-transformed payments received by connected counties C, with $c \notin C$, as shown in Equation 1.

$$\text{Payment Exposure}_{c,t} = \sum_{c' \in C} \frac{\text{SCI}_{c,c'} \times \ln\left(1 + \text{Payment}_{c',t}\right)}{\sum_{c' \in C} \text{SCI}_{c,c'}} \tag{1}$$

As the reporting for aid distribution begins in late-2002, and payments are distributed with a lag, the first year with fully realized payments from previous years is 2005. Thus, we limit the range of years to 2005 to 2019, with the latter set to avoid disruptions due to COVID-19. To prevent direct hits from influencing outcomes, we exclude county-years in which there are over $10 million 2014 dollars from our final sample.

For housing permits, we first identify those related to flood-proofing improvement projects by textual inspection of the permit descriptions. We extract whether the description contains a combination of keywords, and classify the permit as climate related if any of those combinations are present. The specific combinations searched for are shown in Table A.1 (with boolean algebra notation when appropriate). We then aggregate the number of permits identified to the zipcode-year level. In order to preserve zeroes, we include zipcode-years where there were permits not identified as climate permits and set those counts to zero. Any zipcode-year combinations with no permits at all remain missing.

For flood policies, we first merge the zipcode level aggregation with census data to obtain the number of housing units as of 2010. We divide the number of policies active in a year by the number of housing units. If this ratio is greater than one, we set it equal to one.

For housing transactions, we first limit to transactions that are at arm's length and not due to foreclosure or default. This ensures that the amounts realized in the sales accurately reflect the market price of the property. Second, we limit to properties that are single-family houses with a non-missing number of bedrooms, bathrooms, and square footage. We drop properties that are coded as single-family houses but have more than

25 bedrooms or bathrooms, or negative square footage, as these are likely data errors. Similarly, we drop sales that transacted for less than $60k dollars or more than $10m dollars.

At times, we do not have access to house-specific measures of flood risk. In these cases, we aggregate the share of houses constructed before a given year in a zipcode that have a high flood factor score. This represents the percentage of houses in an area that are at-risk, and is a proxy for how risky an area is.

2.10 Descriptive Statistics

Table 1 reports the summary statistics for the main variables used in our analysis. The first group shows summary statistics related to the exposure to property damage and federal assistance payments. It shows that, on average, a given county-year is exposed to 3.12 in weighted log-dollars of property damage. Meanwhile, the average county-year is exposed to 0.43 log-dollars of FEMA and SBA payments. The two components of these payments themselves have averages of 0.38 and 0.34. The second group shows climate permit related statistics. The average zipcode-year has 0.07 permits, and in terms of log-permits this is 0.03. This may seem low, but we have defined the qualification for a climate permit very conservatively. The average zipcode-year has 17% of houses classified as having a high flood factor. The third grouping shows summary statistics concerning flood insurance policies. The two statistics show that approximately 164 policies exist per zipcode-year, and that on average, 3% of houses within zipcode-years have a flood policy. Finally, the fourth group shows statistics about housing transactions. The average house has 2.7 bedrooms, 2.4 bathrooms, and sold for an average of 346 thousand dollars. Similar to the 2nd panel, approximately 15% of housing transactions concern a house classified as being high flood risk.

3 Social Network Exposure to Government Aid Increases Awareness of Aid Availability

We begin by demonstrating that exposure to disaster aid via social networks increases awareness of aid programs in socially connected areas. If social networks transmit information about disaster aid, households in counties connected to aid recipients—despite not experiencing a disaster themselves—should exhibit heightened awareness of these programs. To test this hypothesis, we construct a county-year-level measure of assistance-related searches from Google Trends and regress it on our SCI-weighted exposure measures of aid and property damage from the same year.

The results are shown in Table 2. Column (1) includes year and county fixed effects. Column (2) adds social network exposure to property damages as a control, and Column (3) further replaces year fixed effects with state-year fixed effects. Across all specifications, the relationship between social network exposure to disaster aid and Google searches for aid is positive and statistically significant in all three columns. Based on Column (3), a one standard deviation increase in disaster aid exposure is associated with a 30% increase in searches relative to the mean.

This finding establishes that social networks serve as an effective channel for transmitting information about disaster aid availability, providing the foundation for our subsequent analyses of how such exposure shapes household adaptation and insurance decisions.

4 Government Aid and Household Climate-Proofing Projects

To test whether exposure to news about disaster aid receipt affects the likelihood of household climate resilience investments, we estimate Equation 2

$$\begin{aligned}\ln(1+\text{Climate Permits})_{z,c,t} = \alpha_z + \gamma_{c,t} \\ + \beta_1 \times \text{Average 1(High Flood Factor)}_z \times \text{Payment Exposure}_{c,t-1} \\ + \beta_2 \times \text{Average 1(High Flood Factor)}_z \times \text{Damage Exposure}_{c,t-1} \\ + \epsilon_{z,t}\end{aligned} \tag{2}$$

where *z* indexes ZIP code, *c* indexes county, and *t* indexes year. Observations are at the ZIP code-year level. We use disaster aid and property damages from the prior year when constructing the independent variables to allow time for household responses.

The key independent variable is the interaction between social network exposure to disaster aid and *Average 1(High Flood Factor)*, which measures the share of properties classified as high-risk according to First Street Foundation flood factor data. We expect the response to disaster aid expectations to differ by flood risk, as households in high-risk areas face a greater probability of experiencing a disaster and thus stand to benefit more from anticipated government assistance. We control for exposure to property damage to isolate the effect of aid payments themselves, rather than the effect of disaster occurrences. In addition, we control for the standalone terms.

Table 3 presents the results. Column (1) shows the least restrictive specification with only state and year fixed effects. Columns (2) through (4) impose increasingly stringent fixed effects. Our preferred specification with ZIP code and county-by-year fixed effects appears in Column (4). This specification essentially compares ZIP codes within the same county-year that share the same social network exposure to disaster aid but differ in their flood risk profiles. Three results remain robust across all specifications.

First, the positive and statistically significant coefficient on *Average 1(High Flood Factor)* indicates that climate-proofing permits are more prevalent in areas with greater flood risk exposure, as expected.

Second, the interaction between damage exposure and *Average 1(High Flood Factor)* yields a positive and statistically significant coefficient. This suggests that among ZIP codes within the same county-year facing identical disaster damage exposure, those with heightened flood risk respond

more strongly by undertaking additional adaptation projects.

Third and most importantly, the coefficient on the interaction between *Social Exposure to Disaster Aid* and *Average 1(High Flood Factor)* is negative and statistically significant. This indicates that increased expectations of receiving aid reduce mitigation investments in ZIP codes with greater flood risk exposure.

The magnitude is economically meaningful. Using our preferred specification in Column (4), a one standard deviation increase in a county's social exposure to disaster aid is associated with a 2% of (0.009$\times$2) standard deviation decrease in log permit counts for ZIP codes one standard deviation above the mean in flood risk, compared to ZIP codes one standard deviation below the mean. Converting to original units, this corresponds to a 0.00342 decrease in Ln(1 + Permit Count), calculated as 0.009 Ã 2 Ã 0.19. Relative to the mean of 0.03, this effect represents approximately 11.4% of the average permit activity. This result suggests that a higher expectation of disaster aid can reduce private investment in climate adaptation, especially in risky areas.

We further investigate whether this effect varies across ZIP codes with different income levels. Merging ZIP code-level median income data from the American Community Survey, we augment our prior specifications by interacting all variables with an indicator for whether the ZIP code is above the bottom income quartile. The coefficient on the interaction between *Social Exposure to Disaster Aid* and *Average 1(High Flood Factor)* remains negative and statistically significant, with a magnitude approximately twice as large as that in Table 3. This result indicates that disaster aid expectations substantially reduce climate-proofing permits in high-risk, low-income ZIP codes.

The triple interaction with the high-income indicator yields a positive and statistically significant coefficient, with the magnitude substantially offsetting the negative effect. This pattern implies that the moral hazard response to disaster aid is concentrated among low-income areas, with higher-income ZIP codes exhibiting little reduction in climate-proofing investments.

One potential explanation involves financial constraints. As expected government aid increases, the net benefits of private adaptation investments decline. For financially constrained households that effectively face higher discount rates, these investments are more likely to become negative net present value projects. Higher-income households, by contrast, may continue investing in climate-proofing despite reduced expected net benefits, potentially because the investments remain positive

NPV given their lower discount rates.

5 Government Aid and Insurance Take-Up

Beyond physical mitigation through climate-proofing, households can also manage disaster risk through financial instruments, particularly flood insurance. We next examine how insurance take-up responds to disaster aid expectations by repeating the analysis in Table 3, replacing the dependent variable with the number of NFIP flood policies divided by the number of housing units at the ZIP code-year level.

Two notable results emerge, both robust to our most stringent specification with ZIP code and county-by-year fixed effects. First, the interaction between social exposure to disaster damages and the high-risk ZIP code indicator yields a positive and statistically significant coefficient, suggesting that exposure to disaster damage through social networks increases flood insurance take-up in high-risk ZIP codes. This result is consistent with Xu and Box-Couillard (2024).

Second, and more central to our analysis, the interaction between social exposure to disaster aid and the high-risk indicator is negative and statistically significant. This indicates that heightened expectations of disaster aid reduce flood insurance take-up in high-risk areas. In our most stringent specification in Column (3), a one standard deviation increase in a county's social exposure to disaster aid is associated with a decrease of 2.4% of the standard deviation in flood insurance take-up when comparing ZIP codes one standard deviation above versus below the mean in flood risk.

This finding reinforces our earlier results: when households anticipate greater disaster assistance, they reduce private financial protection, particularly in high-risk areas where the expected value of government aid is highest. Together with the climate-proofing results, these patterns suggest that disaster aid expectations crowd out both physical and financial risk mitigation by households most vulnerable to flooding.

6 Effect on House Prices

Do disaster aid expectations capitalize into house prices? We examine this question using property-level transaction data by estimating Equation 3:

$$\begin{aligned}\ln(\text{Price})_{i,c,t} = \alpha_i + \gamma_{c,t} + \beta_1 \times \mathbb{1}(\text{High Flood Factor})_i \times \text{Payment Exposure}_{c,t-1} \\ + \beta_2 \times \mathbb{1}(\text{High Flood Factor})_i \times \text{Damage Exposure}_{c,t-1} + \epsilon_{i,t},\end{aligned} \tag{3}$$

where *i* indexes property, *c* indexes county, and *t* indexes year. The outcome variable is the log transaction price for property *i* in county *c* in year *t*. The key independent variable is the interaction between social network exposure to disaster aid and an indicator for the property having a high flood factor. All specifications include property fixed effects, along with either county-by-year or state-by-year fixed effects.

Table 7 presents the results. Two main findings emerge. First, the interaction between social network exposure to property damages and the property high-risk indicator yields a negative and statistically significant coefficient. This suggests that greater social network exposure to disaster damages leads to relative price declines for high-risk properties, consistent with the housing market updating its risk assessment for flood-prone properties after observing disaster outcomes in socially connected areas.

Second, the interaction between social network exposure to disaster aid and the property high-risk indicator is positive and statistically significant. This indicates that increased awareness or expectation of disaster aid capitalizes into higher prices for flood-prone properties—precisely those most likely to benefit from such assistance.

Using Column (3) to interpret the magnitude, a one standard deviation increase in a county's social exposure to disaster aid is associated with a 3.8 percent of a standard deviation increase in log house prices when comparing properties one standard deviation above versus below the mean in flood risk (2×0.019).

We extend this analysis by interacting the exposure measures with an indicator for whether the ZIP code is above the lowest income quartile. Column (1) of Table 8 presents the results. The coefficient on the interaction between high flood factor and payment exposure remains positive; however, the triple interaction with the high-income indicator is statistically insignificant.

This null result may reflect compositional differences in aid types and the corresponding eligibility. Our payment exposure measure combines FEMA Individual and Households Program (IHP) assistance with SBA disaster loans. Low-income households are more likely to qualify for IHP assistance, while high-income households are more likely to qualify for SBA loans. We therefore investigate whether house prices respond differently to these distinct forms of aid across ZIP codes with varying income levels.

Column (2) presents the results by aid type. The interaction term $\mathbb{1}(\text{High Flood Factor}) \times$ IHP Exposure has a positive and statistically significant coefficient, while its triple interaction with $\mathbb{1}(\text{Above P25 Income})$ has a negative and statistically significant coefficient, with magnitudes that largely offset. This pattern indicates that the capitalization of IHP exposure into high-risk property prices occurs only in low-income neighborhoods, where households are more likely to be eligible for such assistance.

The opposite pattern emerges for SBA disaster loans. The interaction term $\mathbb{1}(\text{High Flood Factor}) \times$ SBA Loan Exposure has a negative but statistically insignificant coefficient, while the triple interaction with $\mathbb{1}(\text{Above P25 Income})$ is positive and statistically significant. This implies that SBA loan exposure capitalizes into high-risk property prices only in higher-income neighborhoods, where households are more likely to qualify for these loans.

Together, these results suggest that disaster aid expectations are capitalized into property values precisely where the relevant form of assistance is most accessible, reinforcing the argument that housing markets incorporate anticipated government transfers into asset prices.

7 Effect on Future Aid Applications

Finally, we examine whether exposure to disaster aid affects households' behavior when applying for assistance following disasters in their own area. Specifically, we test whether social network exposure to aid distributions increases opportunistic applications—cases where FEMA inspectors assess no reimbursable damage. If households become more aware of aid availability through their social networks, they may be more likely to file applications even when they have not sustained qualifying damage.

We regress the share of aid applications resulting in zero inspected damage on our exposure measures from the prior year, with results presented in Table 9. The sample is limited to ZIP code-years in which a flood disaster was declared, as applications are only permitted during these periods. This restriction yields a small sample of approximately 800 ZIP-year observations.

Across all three columns, the coefficient on the interaction between aid exposure and the high-income indicator is positive and statistically significant. This indicates that in higher-income ZIP codes, a greater share of applications result in zero assessed damage following inspection. This finding is consistent with increased opportunistic behavior among households that have become more aware of disaster aid availability through social networks. Higher-income households may be better positioned to navigate the application process, making them more likely to file speculative claims when they anticipate minimal costs from doing so.

8 Conclusion

This paper provides novel evidence that expectations of disaster assistance generate moral hazard in climate risk mitigation. Exploiting variation in social network exposure to disaster aid distributed elsewhere, measured through Facebook-based social connections, we identify the causal effects of aid expectations on flood-proofing investments, insurance take-up, and housing prices. Our identification strategy compares high-risk and low-risk areas within the same county-year, leveraging the fact that high-risk locations should experience larger increases in expected aid given their elevated probability of future disasters.

Our findings consistently demonstrate that greater exposure to disaster aid reduces private adaptation efforts in high-flood-risk areas, while exposure to disaster damages encourages such investments. We further document that disaster aid expectations capitalize into property values, elevating transaction prices for high-risk properties, whereas exposure to disaster damages exerts the opposite effect.

Our results carry important implications for disaster policy design. As climate change increases the frequency and intensity of flooding, policymakers face pressure to expand disaster relief programs. However, our findings suggest that generous and predictable disaster assistance may in-

advertently discourage the private investments needed for long-term climate adaptation. These unintended consequences warrant careful consideration in the design of federal disaster programs.

Several policy responses merit consideration. First, disaster aid programs could be restructured to require or incentivize ex ante or ex post mitigation investments, thereby counteracting moral hazard incentives. Second, policies that encourage flood insurance take-up, such as community-level incentives or informational interventions, could help ensure that households maintain adequate private protection even when disaster aid expectations are elevated.

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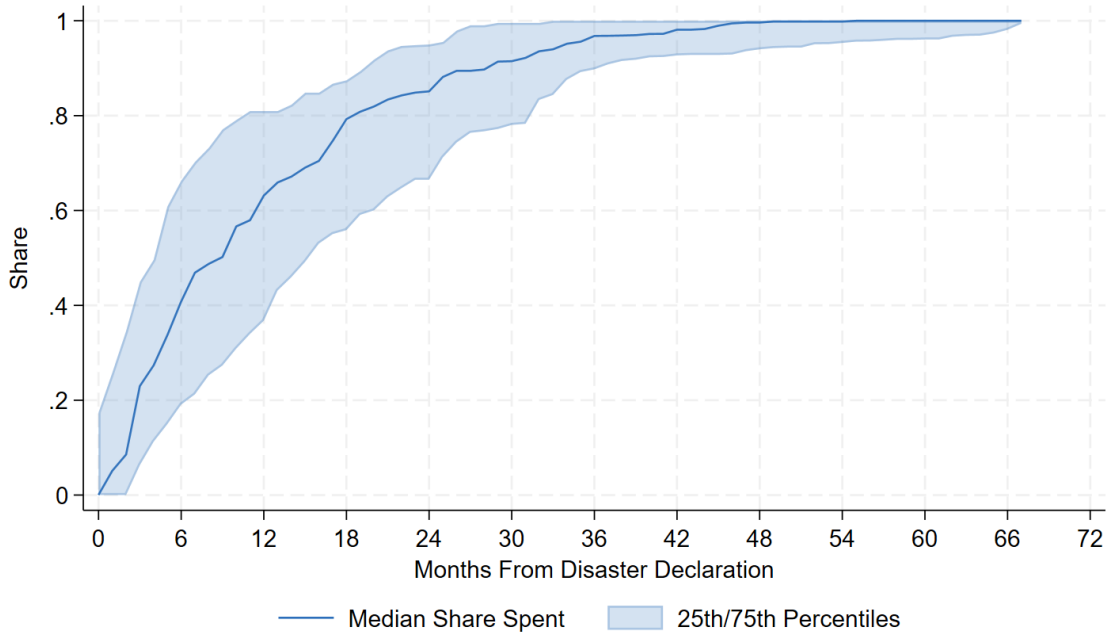
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Figure 1: Median Timing of Aid Distributions



Note: This figure shows the timing of aid distribution sourced from FEMA Disaster Relief Fund (DRF) reports. For each disaster in the report, we sum the realized payments over all months for each disaster, then calculate the share of payments in each month following a disaster that occurs in month zero. We then aggregate across all disasters to calculate the median and 25th/75th percentiles. We truncate the graph at 67 months, as this is when the 75th percentile is equal to one. We exclude disasters related to COVID-19.

Table 1: Summary Statistics

	Mean	SD
Exposure Variables (48,405 County-Years)		
Social Exposure to Property Damage	3.12	2.26
Social Exposure to Disaster Aid	0.43	1.05
Social Exposure to FEMA IHP Disaster Aid	0.38	0.98
Social Exposure to SBA Disaster Aid	0.34	0.83
Climate Permit Variables (273,572 Zipcode-Years)		
Count Climate Permits	0.07	1.14
Ln(1+Count Climate Permits)	0.03	0.19
Average $\mathbb{1}$(High Flood Factor)	0.17	0.20
Flood Policy Variables (293,489 Zipcode-Years)		
Count Flood Policies	163.6	680.6
Flood Policies Per Housing Unit	0.03	0.08
Housing Variables (40,317,954 Transactions)		
Number Bedrooms	2.72	1.48
Number Bathrooms	2.39	1.05
Price (K)	345.7	535.9
Flood Factor	1.74	1.94
$\mathbb{1}$(High Flood Factor)	0.15	0.36

Note: This table shows means and standard deviations for variables used in regression specifications. The first grouping shows variables related to the constructed exposure variables at the county-year level. The second grouping shows climate-proofing construction permit related variables at the zipcode-year level. The third grouping shows NFIP flood policy variables at the zipcode-year level. The fourth grouping shows housing related variables at the transaction level.

Table 2: Disaster Assistance Google Searches

Dependent Variable:	Disaster Assistance Searches$_t$		
	(1)	(2)	(3)
Social Exposure to Disaster Aid$_t$	0.025***	0.024***	0.027***
	(3.41)	(3.57)	(2.71)
Social Exposure to Property Damage$_t$		0.024	0.073
		(0.69)	(0.95)
Year FE	Yes	Yes	No
State-Year FE	No	No	Yes
County FE	Yes	Yes	Yes
N	9,527	9,527	9,447
R^2	0.132	0.132	0.249

Note: This table shows regression specifications relating Google Trend disaster assistance searches to our county-year exposure measures. The dependent variable is a continuous measure of disaster assistance terms. Independent variables are standardized to mean zero and variance one. *t*-statistics, reported in parentheses, are based on standard errors that are clustered at the zipcode level. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Table 3: Household Climate-Proofing Permits

Dependent Variable:	Ln(1+Climate Permits)				
	(1)	(2)	(3)	(4)	(5)
Average $\mathbb{1}$(High Flood Factor)$_{t-1}$	0.006**	0.006**	0.017	0.013	0.020
	(2.06)	(2.07)	(0.81)	(0.59)	(0.88)
Social Exposure to Property Damage$_{t-1}$		0.001	0.002***	0.002	
		(0.83)	(3.44)	(1.56)	
Social Exposure to Disaster Aid$_{t-1}$	-0.002*	-0.003*	-0.004***	0.002	
	(-1.82)	(-1.94)	(-4.78)	(0.70)	
Social Exposure to Disaster Aid$_{t-1}$	-0.003***	-0.003***	-0.003***	-0.004***	-0.003***
$\times$ Average $\mathbb{1}$(High Flood Factor)$_{t-1}$	(-4.34)	(-4.46)	(-3.06)	(-4.76)	(-4.67)
Social Exposure to Property Damage$_{t-1}$		0.003***	0.001	0.002**	0.002**
$\times$ Average $\mathbb{1}$(High Flood Factor)$_{t-1}$		(2.67)	(1.19)	(2.37)	(2.57)
State FE	Yes	Yes	No	No	No
Zipcode FE	No	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	No
State-Year FE	No	No	No	Yes	No
County-Year FE	No	No	No	No	Yes
N	209,504	209,504	209,262	209,247	209,072
R^2	0.043	0.043	0.430	0.446	0.473

Note: This table shows regression specifications relating counts of climate-proofing construction permits at the zipcode-year level to our county-year exposure measures. The dependent variable is the log of the number of climate permits approved in the zipcode-year. All continuous variables are standardized to mean zero and variance one. *t*-statistics, reported in parentheses, are based on standard errors that are clustered at the zipcode level. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Table 4: Household Climate-Proofing Permits with Income Interaction Term

Dependent Variable:	Ln(1+Climate Permits)$_t$		
	(1)	(2)	(3)
Average $\mathbb{1}$(High Flood Factor)$_{t-1}$	0.075	0.085	0.033
	(0.80)	(0.85)	(0.31)
Social Exposure to Property Damage$_{t-1}$	0.001	-0.004	
	(0.35)	(-1.21)	
Social Exposure to Disaster Aid$_{t-1}$	-0.014***	0.005	
	(-3.45)	(0.82)	
Social Exposure to Property Damage$_{t-1}$ × Average $\mathbb{1}$(High Flood Factor)$_{t-1}$	0.007*	0.009**	0.006*
	(1.69)	(2.31)	(1.88)
$\mathbb{1}$(Above P25 Income) × Social Exposure to Disaster Aid$_{t-1}$ × Average $\mathbb{1}$(High Flood Factor)$_{t-1}$	0.017**	0.019**	0.010**
	(2.28)	(2.41)	(2.24)
[1em] Social Exposure to Disaster Aid$_{t-1}$ × Average $\mathbb{1}$(High Flood Factor)$_{t-1}$	-0.020***	-0.023***	-0.016***
	(-2.66)	(-3.20)	(-3.96)
$\mathbb{1}$(Above P25 Income) × Social Exposure to Property Damage$_{t-1}$ × Average $\mathbb{1}$(High Flood Factor)$_{t-1}$	-0.006	-0.006	0.000
	(-1.51)	(-1.30)	(0.00)
$\mathbb{1}$(Above P25 Income) × Social Exposure to Property Damage$_{t-1}$	0.006*	0.010***	0.011***
	(1.88)	(2.81)	(2.84)
$\mathbb{1}$(Above P25 Income) × Social Exposure to Disaster Aid$_{t-1}$	0.007	-0.001	-0.005
	(1.44)	(-0.26)	(-0.92)
$\mathbb{1}$(Above P25 Income) × Average $\mathbb{1}$(High Flood Factor)$_{t-1}$	-0.032	-0.050	0.021
	(-0.30)	(-0.43)	(0.17)
Zipcode FE	Yes	Yes	Yes
Year FE	Yes	No	No
State-Year FE	No	Yes	No
County-Year FE	No	No	Yes
N	239,020	239,018	237,065
R^2	0.435	0.453	0.482

Note: This table shows regression specifications relating counts of climate-proofing construction permits at the zipcode-year level to our county-year exposure measures. The dependent variable is the log of the number of climate permits approved in the zipcode-year. All continuous variables are standardized to mean zero and variance one. *t*-statistics, reported in parentheses, are based on standard errors that are clustered at the zipcode level. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Table 5: Flood Insurance Uptake

Dependent Variable:	Flood Policies Per Unit$_t$		
	(1)	(2)	(3)
Average $\mathbb{1}$(High Flood Factor)$_{t-1}$	-0.026	-0.024	-0.014
	(-0.42)	(-0.39)	(-0.20)
Social Exposure to Property Damage$_{t-1}$	0.003***	0.003***	
	(6.10)	(4.31)	
Social Exposure to Disaster Aid$_{t-1}$	0.014***	0.009***	
	(11.28)	(5.84)	
Social Exposure to Property Damage$_{t-1}$ $\times$ Average $\mathbb{1}$(High Flood Factor)$_{t-1}$	0.010***	0.011***	0.012***
	(9.28)	(10.24)	(7.81)
Social Exposure to Disaster Aid$_{t-1}$ $\times$ Average $\mathbb{1}$(High Flood Factor)$_{t-1}$	-0.007***	-0.009***	-0.012***
	(-4.00)	(-5.24)	(-4.95)
Zipcode FE	Yes	Yes	Yes
Year FE	Yes	No	No
State-Year FE	No	Yes	No
County-Year FE	No	No	Yes
N	275,230	275,230	272,739
R^2	0.965	0.966	0.973

Note: This table shows regression specifications relating the number of flood policies per housing unit to our county-year exposure measures. The dependent variable is the number of NFIP flood policies divided by the number of housing units as of 2010. All continuous variables are standardized to mean zero and variance one. *t*-statistics, reported in parentheses, are based on standard errors that are clustered at the zipcode level. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Table 6: House Price Response

Dependent Variable:	Ln(Price)$_t$			
	(1)	(2)	(3)	(4)
Social Exposure to Property Damage$_{t-1}$				-0.004*
				(-1.69)
Social Exposure to Disaster Aid$_{t-1}$				0.002
				(0.50)
Social Exposure to Property Damage$_{t-1}$ $\times$ $\mathbb{1}$(High Flood Factor)	-0.005**		-0.005**	-0.013***
	(-2.19)		(-2.12)	(-4.28)
Social Exposure to Disaster Aid$_{t-1}$ $\times$ $\mathbb{1}$(High Flood Factor)		0.011***	0.011***	0.019***
		(5.04)	(4.97)	(5.83)
County-Year	Yes	Yes	Yes	No
State-Year	No	No	No	Yes
Property FE	Yes	Yes	Yes	Yes
N	19,354,867	19,354,867	19,354,867	19,385,430
R^2	0.813	0.813	0.813	0.802

Note: This table shows regression specifications relating log house transaction prices to our county-year exposure measures. The dependent variable is the log of the transaction price in USD. All continuous variables are standardized to mean zero and variance one. *t*-statistics, reported in parentheses, are based on standard errors that are clustered at the zipcode-quarter level. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Table 7: House Price Response with Buyer Locations

Dependent Variable:	Ln(Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
Buyer's Property Damage Exposure$_{t-1}$	-0.007		-0.008	-0.008	-0.009	-0.007
	(-0.98)		(-1.10)	(-1.13)	(-1.15)	(-0.67)
Buyer's FEMA/SBA Payment Exposure$_{t-1}$		0.002	0.003	0.005	0.001	-0.006
		(0.29)	(0.44)	(0.49)	(0.18)	(-0.51)
Seller's Property Damage Exposure$_{t-1}$						-0.009
						(-0.89)
Seller's FEMA/SBA Payment Exposure$_{t-1}$						0.083***
						(2.78)
$\mathbb{1}$(High Flood Factor)$\times$Buyer's Property Damage Exposure$_{t-1}$	0.003		0.003	-0.005	0.006	0.002
	(0.53)		(0.45)	(-0.69)	(0.83)	(0.18)
$\mathbb{1}$(High Flood Factor)$\times$Buyer's FEMA/SBA Payment Exposure$_{t-1}$		0.018***	0.018***	0.033***	0.025***	0.040***
		(2.96)	(2.95)	(3.70)	(2.75)	(3.19)
$\mathbb{1}$(High Flood Factor)$\times$Seller's Property Damage Exposure$_{t-1}$					-0.008	-0.014
					(-0.81)	(-1.16)
$\mathbb{1}$(High Flood Factor)$\times$Seller's FEMA/SBA Payment Exposure$_{t-1}$					-0.016	-0.006
					(-1.15)	(-0.34)
County-Year FE	Yes	Yes	Yes	No	Yes	No
State-Year FE	No	No	No	Yes	No	Yes
Property FE	Yes	Yes	Yes	Yes	Yes	Yes
N	788,110	788,110	788,110	789,715	788,110	789,715
R^2	0.844	0.844	0.844	0.821	0.844	0.822

Note:

Table 8: House Price Response with Payment Types and Income Interaction Term

Dependent Variable:	Ln(Price)$_t$	
	(1)	(2)
$\mathbb{1}$(High Flood Factor) $\times$ Social Exposure to Property Damage$_{t-1}$	-0.005	-0.005
	(-1.08)	(-1.04)
$\mathbb{1}$(Above P25 Income) $\times$ Social Exposure to Property Damage$_{t-1}$	0.005	0.005
	(1.46)	(1.47)
$\mathbb{1}$(High Flood Factor) $\times$ Social Exposure to Disaster Aid$_{t-1}$	0.014*	
	(1.88)	
$\mathbb{1}$(Above P25 Income) $\times$ Social Exposure to Disaster Aid$_{t-1}$	-0.018***	
	(-3.10)	
$\mathbb{1}$(High Flood Factor) $\times$ $\mathbb{1}$(Above P25 Income) $\times$ Social Exposure to Property Damage$_{t-1}$	0.000	-0.000
	(0.03)	(-0.02)
$\mathbb{1}$(High Flood Factor) $\times$ $\mathbb{1}$(Above P25 Income) $\times$ Social Exposure to Disaster Aid$_{t-1}$	-0.004	
	(-0.49)	
$\mathbb{1}$(High Flood Factor) $\times$ Social Exposure to FEMA IHP Disaster Aid$_{t-1}$		0.065**
		(2.20)
$\mathbb{1}$(Above P25 Income) $\times$ Social Exposure to FEMA IHP Disaster Aid$_{t-1}$		-0.021
		(-0.89)
$\mathbb{1}$(High Flood Factor) $\times$ Social Exposure to SBA Disaster Aid$_{t-1}$		-0.051
		(-1.56)
$\mathbb{1}$(Above P25 Income) $\times$ Social Exposure to SBA Disaster Aid$_{t-1}$		0.004
		(0.14)
$\mathbb{1}$(High Flood Factor) $\times$ $\mathbb{1}$(Above P25 Income) $\times$ Social Exposure to FEMA IHP Disaster Aid$_{t-1}$		-0.068**
		(-2.20)
$\mathbb{1}$(High Flood Factor) $\times$ $\mathbb{1}$(Above P25 Income) $\times$ Social Exposure to SBA Disaster Aid$_{t-1}$		0.064*
		(1.88)
County-Year-Bedrooms FE	Yes	Yes
Property FE	Yes	Yes
N	19,353,456	19,353,456
R^2	0.813	0.813

Note: This table shows regression specifications relating log house transaction prices to our county-year exposure measures and additional interaction terms. The dependent variable is the log of the transaction price in USD. The first column only includes a triple interaction with the zipcode income indicator. The second column further splits the payment exposure into FEMA payments and SBA loans. All continuous variables are standardized to mean zero and variance one. *t*-statistics, reported in parentheses, are based on standard errors that are clustered at the zipcode-quarter level. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Table 9: Effect of Disaster Aid Exposure on Share of FEMA Inspections with No Damage

Dependent Variable:	No Damage Share$_t$		
	(1)	(2)	(3)
Social Exposure to Property Damage$_{t-1}$			-0.057
			(-0.33)
Social Exposure to Disaster Aid$_{t-1}$			-0.088
			(-0.78)
$\mathbb{1}$(Above P25 Income) $\times$ Social Exposure to Disaster Aid$_{t-1}$	0.184***	0.356***	0.211***
	(3.20)	(3.19)	(2.75)
$\mathbb{1}$(Above P25 Income) $\times$ Social Exposure to Property Damage$_{t-1}$		0.386*	0.259**
		(1.73)	(2.15)
Zipcode FE	Yes	Yes	Yes
County-Year FE	Yes	Yes	No
State-Year FE	No	No	Yes
N	795	795	831
R^2	0.727	0.730	0.648

Note: This table shows regression specifications relating the share of FEMA claims that were inspected and determined to have zero reimbursable damages. All continuous variables are standardized to mean zero and variance one. *t*-statistics, reported in parentheses, are based on standard errors that are clustered at the zipcode level. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Appendix Figures and Tables

Table A.1: Climate-Proofing Permit Combinations

Combinations
"window" & "water"
("flood" | "water") & "proof"
("pump" | "seal") & "basement"
("flood" | "water") & "control"
"floodplain" & "raising"
("barrier" | "drainage") & "flood"
"floodway"
"watershed"

Note: This table shows the combinations of keywords used to identify climate permits in CoreLogic permit data. Each row is a boolean expression indicating the words necessary to label the permit. For example, the first row's criteria is that the description includes both "window" and "water", while the second row's criteria is that the description includes "proof" and either "flood" or "water". If any of the rows evaluates to true, then the permit is flagged as climate-proofing.

Table A.2: Google Trends Assistance Phrases

Search Terms
"Disaster Assistance"
"disasterassistance.gov"
"Fema Assistance"
"Fema Flood Assistance"
"Flood Assistance"

Note: This table shows the search terms used to identify aid related searches from Google Trends data. Each row is the search used to query the Google Trend API, excepting the quotes and with spaces replaced with "+".

Table A.3: Climate Permit Adaptation Per Capita Exposure

Dependent Variable:	Ln(1+Climate Permits)			
	(1)	(2)	(3)	(4)
Average $\mathbb{1}$(High Flood Factor)$_{t-1}$	0.006**	0.018	0.014	0.021
	(2.04)	(0.86)	(0.63)	(0.91)
Social Exposure to Per Capita Property Damage $_{t-1}$	-0.002**	0.002***	0.001	
	(-1.98)	(3.22)	(1.26)	
Social Exposure to Per Capita Disaster Aid$_{t-1}$	-0.004***	-0.005***	0.003	
	(-3.30)	(-6.00)	(1.12)	
Social Exposure to Per Capita Property Damage $_{t-1}$	0.003***	0.001*	0.002***	0.002***
$\times$ Average $\mathbb{1}$(High Flood Factor)$_{t-1}$	(3.02)	(1.83)	(3.36)	(3.85)
Social Exposure to Per Capita Disaster Aid$_{t-1}$	-0.002***	-0.002**	-0.003***	-0.002***
$\times$ Average $\mathbb{1}$(High Flood Factor)$_{t-1}$	(-3.00)	(-2.01)	(-4.12)	(-4.01)
State FE	Yes	No	No	No
Zipcode FE	No	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
State-Year FE	No	No	Yes	No
County-Year FE	No	No	No	Yes
N	209,504	209,262	209,247	209,072
R^2	0.043	0.430	0.446	0.473

Note: This talbe recreates the specifciation for testing climate permits against exposure by using the exposure to per capita payments instead of aggregate payments. Independent variables are standardized to mean zero and variance one. *t*-statistics, reported in parentheses, are based on standard errors that are clustered at the zipcode level. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.