Evaluating the Effectiveness of Flood Mitigation Policies in the U.S.

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ABSTRACT

We employ a two-stage random utility model (RUM) to estimate people' marginal willingness to pay (WTP) for enhancing community-level floodplain management activities reflected in the National flood insurance program (NFIP)'s Community Rating System (CRS) program. CRS is a voluntary program, which provides the participating communities with discounts on flood insurance premium in exchange for strengthened flood protection activities. Results show that people with different demographics react differently to flood risk and generally value flood protection activities. We find that among the CRS program activities, people place the highest value on activities concerning repetitive flood loss reduction, with the second highest being public information disclosure about flood risk. In addition, results suggest that people significantly value structural mitigation projects such as flood- and debris- control dams. Importantly, our results suggest that water body as an amenity measure is perceived positively in people's location choices, nonetheless flood risk information disclosure diminishes the amenity value.

Keywords: Flood Insurance; Community Rating System; Tiebout Sorting; Locational Equilibrium

JEL Codes: Q51, Q54 and Q58

1. Introduction

According to the U.S. Geological Survey, floods were the number one natural catastrophe in the United States during the 20th century (Perry, 2000). In recent years, not only has the magnitude of losses risen dramatically, but also has the frequency of flood incidents increased over time (HVRI, 2012). The number of catastrophic flood incidents in 2010 increased by approximately six times relative to the year 1960. Sea level rise under changes in climate is likely to exacerbate the impacts of floods and storm-related hazards on coastal communities (IPCC, 2012; Emanuel, 2013).

Despite the dramatic increase in number of flood events, a growing consensus in the scientific community holds that the impacts of physical events are greatly intensified by population growth and subsequent economic development (Pielke et al. 2008; Mileti, 1999). Often times risk exposure is unintentionally intensified because of public investment in protective structures, continuous rebuilding of disaster stricken areas and generosity of disaster assistance programs. For example, construction of dams, sea walls and levees can induce private development and alter risk perception if individuals and firms feel overly secured in areas protected by these structures (Kousky, at. al. 2006; Kousky and Olmstead 2010; Sadowski and Sutter, 2005; Mileti, 1999) These protection policies seem to also indirectly affect individuals' adaptive behavior via their direct effects on other adaptation policies. A good example of such a chain policy affect is a newly constructed and FEMA accredited levee system in New Orleans, which made into news headlines as "clearing way for lower flood insurance rates for many" (Schleifstein, 2014). The levee system not only entices further development because of the security it provides but also makes protected areas desirable to live because of low insurance costs, holding other costs (e.g. cost of living, housing prices) constant.

Another source of perverse incentives concerning individuals' private adaptive behavior is continuous and generous public assistance in response to major disasters. Limited financial liabilities for disaster loss often lead to more risk exposure and gives rise to a moral or charity hazard issue, which rises when individuals are less likely to take necessary precautions given more public assistance and subsidized programs (Lewis and Nickerson 1989; Kunreuther 2001; Raschky and Weck-Hannemann 2007). Nonetheless, flood impacts can be substantially mitigated through effective land-use planning and development regulation as well as increasing public awareness of flood hazards locally (Brody et al., 2011; Mileti, 1999; Davlasheridze et al., 2012). The latter is important because risk awareness and experience potentially motivate private adaptive behavior including a relocation and migration decision.

In this paper we employ a residential sorting model to examine residential location choices under changes in flood risk and flood mitigation policies implemented locally as reflected in the Community rating System (CRS) program. The CRS Program is a voluntary program and was initiated by the National Flood Insurance Program as part of the National Flood Insurance Reform Act (NFIR) enforced in 1994. The basic premise of the CRS program is to recognize communities for their flood control programs as well as further incentivize them to implement stringent regulatory policies in exchange for discounts on flood insurance premiums (FEMA 2013). The broad variety of activities from the CRS program allows us to examine individuals' location decisions in response to series of flood control activities including information disclosure concerning flood hazards as well as flood warning and safety programs. Employing heterogeneous willingness-to-pay (WTP) measures we also estimate the values individuals place on improved flood protection activities.

Our results show that retirees are more sensitive to flood risk compared to younger population. College graduates are found to be less averse to flood risk relative to people without college degree, perhaps this population potentially has more job opportunities thus are more mobile. Another reason might be that people with higher educational attainment are potentially wealthier and may have their own resources to self-insure and are willing and able to pay for improved local public services that mitigate flood impacts. Hispanics are less sensitive to flood risk relative to other races. Results indicate that people are generally willing to pay a significant amount to strengthen the community-level floodplain management activities. Among the CRS programs, individuals value flood damage reduction related to existing buildings and structures at the highest level, with the second highest being public information disclosure concerning natural hazards. In addition, our results show that people are more likely to locate in the areas with a large number of flood- and debris- control dams, which provide empirical support for a notion of a "levee effect" and a "false sense of security". Perception of high flood risk seems to be partially blunted by the perception of protectiveness of these structures. We find that size of water bodies (e.g. lakes, rivers, ponds, ocean, etc.) as an amenity measure are perceived positively in people's location choices but the magnitude of positive effect diminishes after information concerning flood risk is disclosed.

The present paper contributes to two different strands of literature. First, the present paper contributes to the sorting literature built on the idea by Tiebout (1956) that individuals "vote with feet" by moving away from a less desirable location (Klaiber & Phaneuf, 2010; Bayer et al., 2009; Fan et al., 2012). Flood hazard risk differs across locations, hazard mitigation and adaptation policies also vary across local jurisdictions. Subsequently, individuals' decisions on where to live to some extent are influenced by those public services that concern disaster mitigation. However, there is no previous study, to our knowledge, that applies the structural sorting model to examine the effectiveness of NFIP's CRS program by capturing migration costs and preference heterogeneity.

Second, we contribute to literature examining persistent disaster impacts (Hornbeck, 2012; Smith et al., 2006) and migration decision in response to natural disaster (Boustan, Kahn, & Rhode, 2012; Cameron, Saif, & Duquette, 2012; Joarder and Miller, 2013). While existing studies provide support for heterogeneous responses to disaster impacts, they do not explicitly account for other public adaptation strategies that might potentially affect relocation decision. We compliment these studies by explicitly accounting for hazard risk and local mitigation and adaptation policies in individuals' location decisions. By considering individual's preference heterogeneity, we also estimate marginal WTP for improved floodplain management activities reflected in the CRS program. Separating amenity value from flood risk is another important contribution of the paper to existing valuation literature (Hallstrom and Smith, 2005; Bin and Polasky 2004; Bin, Kruse, and Landry, 2008; Carbone et al., 2005).

2. Econometric Model

We closely follow the model structure by Bayer et al. (2009) and assume households i sort themselves into MSA j, where they maximize utility given budget constraint and other's location choices. We derive the indirect utility function that allows for changes in budget constraint and costs of public goods and services across location j. The household i's indirect utility function of choosing MSA j is shown in equation (1):

(1) $U_{ij} = V(X_j, \rho_j, HH_i^q, M_{ij}, I_{ij}, \xi_j) + \eta_{ij}$

where X_j represents MSA-specific attributes including measures of flood risk and NFIP's CRS credit scores by series of activities associated with each location. ρ_j represents housing price index for MSA *j* obtained from an auxiliary hedonic housing regression. HH_i^q contains individual *i*'s demographics including age, race, birth region, and educational attainment, indexed by *q*. M_{ij} is an individual and location specific measure of migration costs. I_{ij} is the predicted household income for household *i* possibly living in MSA *j*. Error terms capturing unobservable attributes of location *j* are represented by ξ_j while an idiosyncratic term is given by η_{ij}.

Following the logic of the random utility model, household *i* chooses location *j* as opposed to other location *k* if the utility in the chosen location is equal or greater than utility in any other locations:

(2) $U_{ij} > U_{ik} \; \forall k \neq j$

In order to recover the heterogeneous parameters associated with the flood related variables that are of our interest, we break our estimation process into two stages, which is closely related to the estimation strategies discussed by Berry et al. (2004) and Bayer et al. (2009). In the first stage, we recover preference heterogeneity through interaction terms of individuals' demographics and location-specific flood related variables, along with mean indirect utility through MSA fixed effects. Derived from utility maximization by choosing optimal levels of numeraire consumption and housing services and substituting those into a logged version of equation (1), the structural form of indirect utility is written as the following (Fan, Klaiber, and Fisher-vanden, 2012):

(3) $ln U_{ij} = \beta_I \, ln \hat{I}_{ij} + \sum_{q=1}^{Q} \beta_{qx} (HH_i^q \times X_j) + \beta_m M_{ij} + \hat{\Theta}_j + \eta_{ij}$

The main difference between equation (1) and the empirical specification in (3) is an inclusion of MSA fixed-effects $\hat{\Theta}_j$ in the latter equation, which will be estimated through the coefficients of MSA-specific constants. The inclusion of a complete set of *j-1* location specific fixed effects was shown by Berry (1994) to result in perfect prediction of observed shares in a multinomial logit model.

In equation (3), $\hat{I}_{ij}$ is estimated from an auxiliary income regression, from which we could obtain the estimated household income for the same household had they chosen to locate in a different location. Details of the income regression are shown in the fourth section. To obtain the discrete choice model in stage one, the idiosyncratic term in equation (3) is specified as a type I extreme value and multinomial logit model is used for estimation. The closed form expression for the probability of household *i* choosing location *j* is shown in equation (4) based on the specification by McFadden (1974):

$$(4)\quad P_{ij} = Prob(U_{ij} > U_{ik}\ \forall k \neq j) = \frac{e^{V_{ij}}}{\sum_k e^{V_{ik}}}$$

The first-stage discrete choice model is estimated via maximum log likelihood:

$$(5)\quad ll = \sum_i \sum_j Y_{ij}\, ln\, P_{ij}$$

where Y_{ij} represents the dummy variable that indicates whether household *i* chooses location *j*, and P_{ij} is probability of shown in equation (3).

In the 2nd stage of the estimation, we decompose the estimated coefficients of MSA-specific constants obtained from the 1st stage into MSA-specific attributes including housing price index associated with each location $\hat{\rho}_j$. Similar to the predicted household income discussed below equation (3), the housing price index is estimated from a hedonic housing price regression, with more details to be discussed in section 4. Given the concern that housing prices are likely to be endogenous, we move the housing price index to the left hand side of the equation and add this variable to the mean indirect utility and form dependent variables. In order to control for location-specific unobservables we estimate the 2nd stage model using region fixed effects denoted as r_k in equation (6).

(6) $\hat{\Theta}_j + \hat{\beta}_\rho \ln \hat{\rho}_j = \beta_0 + \beta_x \ln X_j + r_k + \xi_j$.

where we estimate $\hat{\beta}_h$ following the specification derived by Fan et al., (2012) using $\hat{\beta}_h = \beta_I(\hat{\rho}_j H_i / \hat{I}_{ij})$. β_I is the coefficient of predicted income $\hat{I}_{ij}$ obtained from the 1st stage of the estimation, and we assume the number of property consumed by household *i* is 1.

Policy variables (i.e. CRS credit points by activities) are likely to be correlated with omitted variables such as economic activities and community demographics associated with MSAs, we use instrumental variable (IV) for these endogenous variables. IVs such as cumulative number of fatalities before the year 1990 and cumulative spending on housing and community development are obtained from the U.S. Census of Government. The detailed information of IVs will be discussed in section 4.

3. Data

The primary dataset used for the empirical analysis is obtained from Integrated Public Use Microdata Sample (IPUMS), which draws a 5% microdata sample from the 2000 US Population Census. This datasets contains detailed housing information such as housing prices and housing attributes, along with household-specific characteristics. Location-specific variables including wage rates by sector, natural amenities, and entertainment opportunities at the metropolitan statistical area (MSA) level are acquired from multiple sources. Dataset for extreme precipitation (i.e. annual number of days with daily maximum precipitation over 1 inch) is derived from the National Climate Data Center (NCDC). Floodplains and National Flood Insurance program's (NFIP) community rating system (CRS) related variables are obtained from the U.S. Federal Emergency Management Agency (FEMA). The number of flood control dams is obtained from the US Army Corps of Engineers. In this section, we describe our choice set first followed by detailed information of household- and location-specific characteristics in our sample. We then describe the matching process of generating CRS variables at the MSA level.

3.1. **Choice Set and Regions by Flood Risk**

We define the choice set as 281 metropolitan statistical areas (MSAs) across the US (Figure 1). The lowest geographic unit in the IPUMS dataset is the Public Use Microdata Area

(PUMA), which is defined as the geographic area with at least 100,000 people. To map PUMA locations to the choice set of MSAs used in this paper, we overlay MSAs with PUMAs and identify the overlapped geographical area for each MSA.

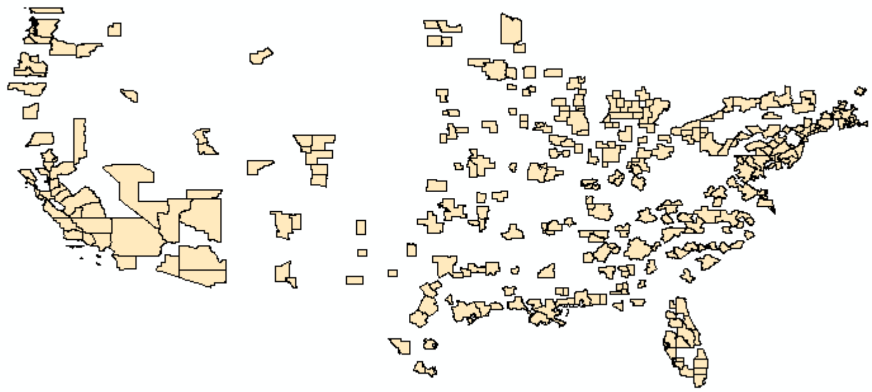

Figure 1: 281 MSAs Identified by IPUMS Data

We further classify each individual's birth state as belonging to a specific region, which is defined based on flood and hurricane hazard ranks (Figure 2). Flood risk map are obtained from Pipeline and Hazardous Materials Safety Administration (PHMSA)[2], and the original map was derived from a study conducted by FEMA. We define five regions based on flood and hurricane hazards rank: 1) Gulf and North-East coastal high risk states that fall into the category of hurricane rank 85-100; 2) west coastal high risk state that falls into the category of flood rank 85-100. This region include only the state of California; 3) inland high risk states that falls into the category of flood rank 85-100; 4) inland moderate risk states that fall into the category of flood risk 70-84; 5) inland low risk states that fall into the category of flood risk 0-69. The map that shows the flood rank is displayed in Appendix A.

[2] https://www.npms.phmsa.dot.gov/data/data_natdis.htm

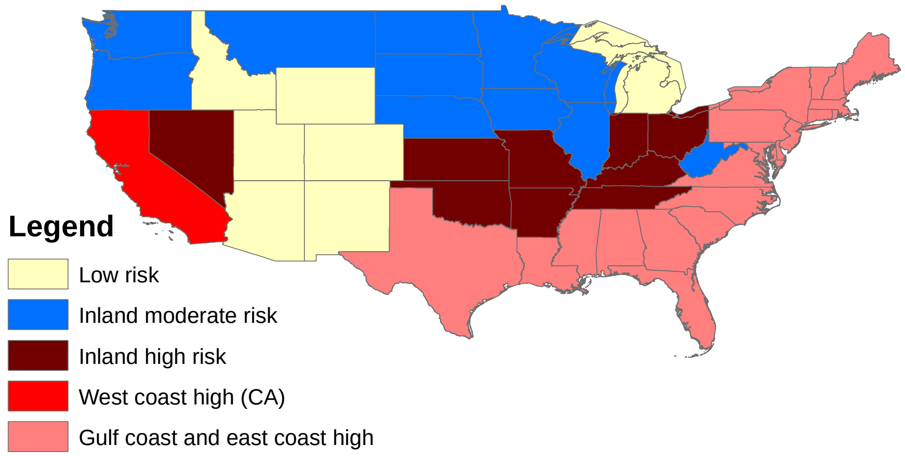

Figure 2. Regions by Flood Risk

3.2 IPUMS Demographics

Based on the IPUMS dataset we identify 1.8 million households located across the 281 Metropolitan Statistical Areas (MSAs) in the US in the year 2000 (immigrants, residents in Alaska and Hawaii, households with zero income, and home renters are excluded). Assuming the head of household is the decision maker, we focus on his/her demographic factors. Demographic characteristics of the household decision maker are summarized in Table 1.

To capture preference heterogeneity among different population segments, we include households with different income sources including wages, earnings from people's own businesses, and retirement benefits. One reason of including retirees is that we believe this population segment is likely to respond to (dis)amenity including flood risk and relevant public policies differently compared to the working-age population. While retirees may place a higher value on amenities in general and are more likely to be sensitive to flood risk, job opportunities are likely to influence the location decisions for working-age individuals more than amenities.

The geographic variables in the IPUMS dataset provide information on individual's birth state, which are used to generate interaction terms of individual's characteristic—birth region categorized by flood and hurricane risk, with MSA-specific attribute—flood risk measure at the MSA level. These interaction terms can reveal individual's perception of flood risk based on one's previous experience and knowledge about adverse impacts from flooding. In addition, our econometric model includes a migration dummy variable that indicates whether MSA *j* is out of one's birth region, where regions are four economic macro-regions defined by the U.S. The economic region rather than flood risk regions here is used to reveal one's psychological cost of moving far away from family roots—macroeconomic region that an individual was born.

3.3 MSA-Specific Attributes

MSA-specific attributes are obtained from a variety of sources. Wage rates by sector including construction, production, and service are obtained from the U.S. Bureau of Labor Statistics (BLS). Service wage is calculated as a weighted average of business wage, health wage, sales wage, and transportation wage. Total number of establishments of businesses in arts, entertainment and recreation is obtained from the U.S. Census. This variable is divided by land area to serve as an index that indicates the abundance of cultural establishments. The area of the water body of all kinds including ocean, lakes, rivers, ponds, etc. at the MSA level is also obtained from the U.S. Census and is considered as a natural amenity measure. Summary statistics are in shown in Table 1.

3.4 Floodplains Data

Floodplains at the MSA level are derived from total Special Flood Hazard Area (SFHA) maps and are measured in square miles. SFHA are defined as areas that will be inundated by the 100-year flood event. The areas were calculated by overlaying National Flood Hazard Layer (NFHL)[3] with the MSA map for every individual state. NFHL were obtained from FEMA CD-ROMs through FOIA. These areas include totals of high risk (labeled as Zone A, Zone AO, Zone AH, Zones A1-A30, Zone AE, Zone A99, Zone AR, Zone AR/AE, Zone AR/AO, Zone AR/A1-A30, Zone AR/A) and the high risk coastal areas (Zone V, Zone VE, and Zones V1-V30)[4]. In our model SFHA approximates potential flood risk as identified and mapped in each MSA.

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[3] National Flood Hazard Layer (NFHL) dataset is a compilation of effective Digital Flood Insurance Rate Map (DFIRM) databases. Currently, not all areas of a State or Territory have effective DFIRM data.

[4] Definitions of FEMA floodzone designations can be found: https://msc.fema.gov/webapp/wcs/stores/servlet/info?storeId=10001&catalogId=10001&langId=-1&content=floodZones&title=FEMA%2520Flood%2520Zone%2520Designations

3.5. Flood Mitigation and Adaptation Data

Adaptation variables in our sample are defined at the county level[5]. To identify counties within MSA's boundary we overlay MSA map with county map using ArcGIS. Majority of MSAs in our sample perfectly enclose one or more counties within their geographic boundaries. Where appropriate, to derive MSA level estimates we aggregate county level data by simply adding up observations across MSA-inclusive counties (e.g. number of dams). In cases where simple summation deemed inappropriate for particular variables (e.g. CRS credit points), we calculate weighted average of all counties within a MSA boundary, and weights are defined by corresponding county's population share out of the MSA population.

Number of flood control dams is county level observation based on the National Inventory of Dams in the United States obtained from the US Army Corps of Engineers (USACE, 2013). USACE maintains the inventory of both private and public dams identified by purpose types (e.g. irrigation, flood control, water supply and more), height, condition and various other physical characteristics. Given the nature of our study, we only consider total number of flood and debris control dams as a proxy for structural measures aiming to mitigate flood hazard and related debris risk.

The major policy variable of interest in our analysis is the Community Rating System's credit points by category. The variable proxies flood mitigation and adaptation programs implemented at the local level. The Community Rating System (CRS) is a program developed as part of the National Flood Insurance Reform Act (NFIR) enforced in 1994. It is a voluntary, incentive-based initiative that provides discounts on insurance premiums for participating communities that adopt more restrictive regulatory and protective measures than those mandated under the National Flood Insurance Program. The program serves 3 primary goals: (1) reduce damages to insurable property, (2) strengthen the insurance aspect of NFIP and (3) encourage comprehensive approach to floodplain management. In order to be recognized in the insurance rating system, participating communities should undertake specified creditable activities categorized in 4 broader series referred to as series 300 (public information), series 400

5 In the disaster literature adaptation and mitigation are used interchangeably and both are viewed in terms of coping and risk management strategies related to weather extremes such as floods, storms, droughts and other natural hazards (Burton, 1997; see also FEMA definition http://www.fema.gov/what-mitigation#1).

(mapping and regulation), series 500 (flood damage reduction) and series 600 activities (flood preparedness).

The activities defined under the series of 300 and 400 concern primarily new developments and substantially improved existing property. These series activities focus on flood disclosure, mapping, floodplain management regulation and outreach programs. The 500 series activities complement series 300-400 activities and deal with existing buildings. The 500 series activities also entail measures such as relocation, acquisition, retrofitting, general flood protection measures and drainage system maintenance. Last, the 600 series activities include warning systems, emergency response and evacuation plans for the entire community as well as safety measures for dams and levees and other flood protection structures. The safety activities entail not only the maintenance of these structural projects but also the emergency action plans in cases these structures fail to provide protection (FEMA, 2013).

Total points earned for various flood mitigation activities undertaken subsequently define classes for communities. Class 1 is granted for the most significant flood protection improvement and provides a 45% discount in insurance premium, whereas Class 10 refers to the basic NFIP regulations and thus entails no additional improvement beyond minimum requirements and correspondingly grants no discounts (Appendix E). Communities are required to recertify or re-verify that they continue to perform activities that have been credited by the CRS. If a community is not properly or fully implementing credited activities, its credit points, and possibly its CRS classification, will be revised. As such, CRS program provides fully informed and quantifiable tool for adaptation/mitigation activities that are implemented by local authorities to attenuate flood related losses and hazard (Brody et al., 2011).

We consider total credit points earned by communities for the year 2000 as well as credit points earned for 4 individual series activities (300-series, 400-series, 500-series and 600-series). In cases where MSA area enclosed more than one county, we calculated a weighted average of participating counties' CRS credit points. Weights were defined as a share of CRS participating county's population to the total of MSA inclusive counties' populations that were part of CRS program in 2000. Where no county within MSA was reported in the CRS program, we proxied MSA credit points by a city level credit points. In cases where neither a city nor a county within a MSA boundary were in the CRS program, the credits points naturally were considered as zero.

Including zero values for non-participating communities, we essentially assume that those communities do not have mitigation measures beyond what are mandated by the NFIP. We believe that communities that make significant contributions in mitigating flood risk should be willing to join the CRS program to have their mitigation efforts recognized and rewarded through premium discounts. Higher credit points (either total points or points by activities) imply more mitigation activities implemented at the local level. Subsequently, we expect individuals to highly value the increased provision of flood hazard mitigation programs while choosing locations.

4. Results

In this section, we focus on the empirical results of the two-stage sorting model. The estimation results from the auxiliary regressions are presented in the appendix.

4.1 First-stage Sorting Results

Table 2 presents the parameter estimates from the first stage of the sorting model shown in equations (3) (4) and (5). We find significant evidence of heterogeneity in perception of flood risk and preferences for local flood control activities. The marginal utility of income is found to be 1.00. This coefficient is used to calculate the coefficient of housing price index, which was discussed below equation (6). Focusing on flood risk, we find that individuals over 65 years of age are more averse to flood risk than younger people. College graduates are less sensitive to flood risk compared with individuals without college degrees. One explanation might be that more educated hence more skilled workers are more mobile and thus less vulnerable to flood risk. Additionally, college graduates are likely to earn higher wages and have ability to adapt to flood risk with their own resources (e.g. building more resilient homes, etc.).

People with difference races tend to respond to flood risk differently. Hispanics seem to be less sensitive to flood risk relative to other races. This is consistent with the previous findings by Smith et al. (2006) that Hispanic households are likely to move into the damaged areas due to lower housing prices. These findings provide important insights into assessing different adaptation strategies based on risk attitudes and migration behaviors over different demographics.

A series of interaction terms with individuals' birth regions are used to examine whether individual's previous experience and knowledge about adverse impacts of flood hazards would affect individual's location decisions facing flood risk. We find that people born in inland high risk areas are more responsive to flood risk compared to other populations, with the second responsive group being those born in coastal high risk areas. Results suggest that people who are more familiar with the adverse impacts of flood and hurricane hazards tend to be more averse to flood risk in their location decision decisions.

Table 2 presents results for five different model specifications which examine people's responses to CRS programs in their location choices. Each model focuses on a different series of CRS activities. In particular, column (1) shows results from the model in which CRS total credit points are interacted with household demographics. Columns (2) though (5) show individuals' reactions to CRS series 300, CRS series 400, CRS series 500, and CRS series 600, respectively. Results from the five model specifications consistently show that retirees positively value CRS activities and are likely to locate in the places where more public efforts are devoted to flood mitigation. The CRS program-recognized flood management activities are found to positively affect college graduates' location choices. The results also suggest that retirees and college graduates place the highest value on CRS series 600 activities, which credits mitigation programs concerning flood preparedness activities, such as flood warning program, levee and flood control dam structures.

A primary motivation for the use of a structural sorting model is the ability to control for migration costs. Our results reveal that there is a significant utility cost associated with leaving one's birth region. In addition to these estimates, the 1st stage sorting model also recovers estimates of the mean indirect utility associated with each MSA in our sample, which serve as the dependent variable together with housing price index in our second stage of estimation shown in equation (6).

4.2. Second-stage Sorting Results

In the second stage of the sorting model, the mean indirect utility for each MSA is added to an additional term capturing the housing price index for each MSA to form the dependent variable (see equation (6)). CRS variables are likely to be endogenous and may be correlated with omitted variables such as economic activities and other local policies at the MSA level, we use IV regression for these endogenous variables. IV candidates are tested based on two qualifications: 1) IV is correlated with the endogenous variable; 2) IV is exogenous and is not correlated with the error term. A test by Cragg and Donald (1993) is used to test for "weak instrument". The cumulative number of fatalities resulted from flood related incidents from 1970 till 1990 is served as IV for the CRS variable in each model variant except CRS credit points for CRS series 600 (activities for flood preparedness such as flood warming, levee safety, and dam safety programs). For CRS series 600, the cumulative spending on housing & community development projects (construction and operation of housing and redevelopment projects) from 1970 till 1990 is used as IV.

The first set of results presents naïve OLS results while the second set of results in Table 3 shows results from IV regression that includes region dummies. These region fixed effects capture potential regional unobservables. We find that using IV for the endogeneous variable significantly increases the magnitude of these CRS variables compared to OLS results, which suggests OLS regression underestimates the values of flood management activities.

Results from column (1) to (5) present results corresponding to 5 models as shown in Table 2. From column (1), we find the consistent result that the mean effect of high risk flood zone is not significant with a negative sign. One reason may be that the heterogeneity terms in the 1st stage soak up some of the effects. In column (1), results suggest that CRS total credit that recognizes all types of public flood mitigation activities in our model positively affects household location choice. Comparing results across models, we find that the mean effect is of the CRS series 500 activities is the largest, followed by CRS series 300.

Additionally we find that the area of water bodies as an amenity measure is positively significant. However, the negative and significant coefficient associated with the interaction term between the water body and the series 300 points suggest that the value conditional on flood risk disclosure decreases. The result implies that individuals significantly value amenities in their location choices but the value declines as people are informed of the potential flood risk. Our model also controls for climate variables such as extreme precipitation. We find that heavy rainfall negatively affect people's location choices.

In addition to the main results regarding flood related variables, we also find that wage rates by sector are used to measure the impact of job opportunities. Service wage rate is positively significant, and indicate that job opportunity tends to be a significant driver in people's location decisions for working-age population.

5. Marginal Willingness-to-Pay (WTP) Measures

Based on IV regression results, we report MWTP for improving CRS series activities and flood control structures in Table 4. These estimates combine the estimated coefficients from both the 1st and 2nd stage of estimation. As such, we report the mean WTP for all households in our sample, as well as heterogeneous WTP that vary across household demographics and birth region.

The 1st column of Table 4 reports WTP measures using the mean demographic characteristics of our data sample. Overall, these results suggest that households are willing to pay a significant amount to improve community flood mitigation activities. In particular, the implied MWTP for additional credit point in CRS series 300 is \$230, \$170 for additional credit point of CRS series 400, \$348 for a marginal increase in credit points of CRS series 500, and \$66 for an additional point in CRS total credit. WTP for increasing additional credit point of CRS series 600 is not reported due to the insignificance of the mean effect of CRS series 600 in the 2nd stage. It is of no surprise that individuals attach highest value on the series CRS 500 activities. These activities address repetitive flood losses and entail relocation, retrofitting and acquisition of existing structures and building from floodplains, as well as various storm water drainage management activities. Calculating credit point for different creditable activities is a complicated process, which considers community adjustments in terms of changes in population growth, size of protection relative to total risk exposure and many more. We consider a simplest example here to understand the meaning of a marginal increase in credit point. According to CRS coordinator's manual, if the community preserves 200 acres as an open space in the 1000 acre SFHA, it will receive 20% of the maximum of 900 attainable points in the open space preservation activities, which is a maximum of 180 credit points. This implies that additional one credit point is equivalent to 1.11 acres of open space preservation in the 1000 acre SFHA.

We also find that different segments of population with different demographics are willing to pay a different amount. College graduates and higher-income groups are generally willing to pay relatively higher amount than other groups of people, which is not surprising given that more educated people and wealthier communities tend to demand higher levels of improved public services.

6. Discussion and Policy Implications

The aim of this section is to highlight important findings from our analysis in the context of the existing literature as well as flood-control and mitigation policies.

Our study reveals that responses to flood risk are heterogeneous and they depend on population demographics. We find Hispanics are more likely to locate in MSAs where flood risk is relatively high, relative to other race. This is consistent with previous findings regarding households' adjustments in response to hurricane Andrew in Dade County by Smith et al. (2006), even though we examine individuals' adjustment in relation to a general risk perception (e.g. proxied by high flood risk areas) rather than hurricane events. In addition, consistent with the latter study our results also indicate that wealthier people are less sensitive to flood risk because they have their own resources to self-insure and are more willing to pay for improved local public services. Boustan, Kahn, and Rhode (2012) studying individuals' behavior in response to flood risk during 1920-1930 and 1935-1940, although ignoring racial differences, also find that the general population and particularly young men in the United States tend to live in flooded areas but are likely to avoid areas hit by a tornado.

Relative insensitivity of individuals to flood risk can be explained by individuals' preferences for communities with flood control dams. Flood- and debris-control dams are found to positively affect people's location choices, but the mean effect of flood risk is found to be insignificant. Muted effects of flood risk on people's location choices that we find from our results may be explained by "moral hazards" when people are over optimistic about public assistance. Perception of high risk can be partially blunted by the perception of protectiveness of these structures. Increased sense of security provided by these structures, which has been proved by a levee failure during the Hurricane Katrina in New Orleans to be misleading, seems to drive these responses. Our finding about people's positive valuation of structural measures provides empirical support of Kousky, Luttmer and Zechauser (2006) theoretical model, in which authors explain that private development can be induced in response to public protection.

Our results also suggest that the amenity, captured by the area of water body in a sample MSA, is a significant factor in individuals' location choice. We additionally interact the amenity measure in the model with the CRS series 300 activities to essentially capture its value conditional on awareness of flood risk. A limitation from previous studies is a lack of separating flood risk from amenity value (Hallstrom and Smith, 2005). Interaction term allows us to examine the two effects in conjunction and our results show that amenity is perceived positively, but the value of amenity decreases if the information on flood hazard risk is disclosed. Kousky & Kunreuther (2013) also show that areas with high amenity values attract high-income households nevertheless they are aware of flood risk and are able to afford necessary flood insurance.

Major finding of our study is the importance of local adaptation recognized by the NFIP's CRS program. While responses to CRS programs are heterogeneous across racial groups, we found that more educated individuals and senior citizens valued CRS program highly and in particular value series 500 (flood damage reduction concerning existing structures) and 300 (public information) at the higher level. In the second stage, when we decomposed mean indirect utility, in all model specifications (both for total credit points and points for an individual activity) was found to be a significant determinant of individuals' location decisions. Our findings are consistent with several previous studies that examined major determinants of communities' participations in the CRS program (Landry and Li, 2011; Brody et al. 2007, 2009c; Posey, 2009). In addition, we find that education is an important factor determining a communities' participation in the program. Our findings of high value that retirees place on contradicts results of Landry and Li (2011) in which the authors show that a higher percentage of retirees in the community lowers the likelihood of communities participation in the program among 100 North Carolina counties. The possible explanation for the reverse sign is the influx of senior migrants to North Carolina and the possibility of being uninformed about flood hazard and thus subsequent benefits associated with local flood mitigation policies. Another reason may relate to retiree's income and purchasing power. In our sample, we particularly exclude retirees who do not receive income and only include those over 65 years old with income earned from wages, people's own business, and retirement income. Significant response of retirees to public information disclosures further supports the latter argument.

There has been a shift in the recent climate policy agenda towards sustainable disaster mitigation direction with particular emphasis on local level adaptation efforts and their linkage to external risk mitigation options (IPCC, 2012). Local public adaptation is an important aspect in the national level adaptation policies and especially when the adaptation to extreme events is concerned, because these events are primarily localized (Horwich, 2000). Evidence suggest that flood impacts are exacerbated if policies related to land-use and development regulation are poorly enforced and administered by local authorities (Brody et al, 2009). Many occasions show that adaptation to extreme events also depends on the political will of the local public sector and in particular uninterested government can pose a significant impediment for many mitigation policies (Kousky, 2010).

The CRS program, because it entails incentives in terms of discounts in flood insurance premiums, establishes the link between the public adaptation (local governments commit and implement flood mitigation activities to earn credit points) and ex-ante private adaptation (e.g. individuals living in CRS communities purchase flood insurance and enjoy benefits from reduced flood insurance premiums). Full benefits associated with the program naturally cannot be measured in dollar terms. The most straightforward benefits being in the CRS program is reduction in the insurance premium as well as benefits associated with enhanced public safety, reduction in property damage and avoidance of economic and human losses (Davlasheridze et al., 2012; Brody et al., 2011). Our research further shows that individuals highly value the benefits they expect from flood protection programs implemented locally and in particular those related to public information disclosure and flood warning, levee and dam safety systems.

Despite significant benefits of being in the CRS program, participation rate in the program remains low across the country. As of 2011 there were 1164 communities in the CRS program at different jurisdiction levels (municipality, city, borough and county) receiving premium discounts, of which 237 are counties (9.5 % of all NFIP participating counties). While participation in the CRS program is free, lack of participation could be explained by the flood control costs. The present studies provides important incentive for many counties currently not in the CRS program to join the program, as flood control activities seem to be a positive factor in people's location choices.

7. Conclusion

We employ a residential sorting model to examine individuals' location decision in response to flood risk and public adaptation policies concerning flood hazard. In particular, we focus on NFIP CRS program represented by series 300, 400, 500 and 600 activities. Overall, results reveal that individuals highly value improved flood mitigation and adaptation programs in their location decisions, including both structural (dams) and non-structural (e.g. hazard information disclosure, flood warning and dam and levee safety) programs. Nonetheless individuals' demographic heterogeneity matters both in terms of perception of risk as well as valuation of flood protection against this risk. We find that among the CRS program activities, people place the highest value on CRS series 500 activities concerning reducing flood impacts on existing structures and buildings (e.g. relocation, retrofitting), with the second highest being public information disclosure about flood risk (series 300). Importantly, our results suggest that water body as an amenity is perceived positively in people's location choice, nonetheless flood risk information disclosure diminishes the amenity value.

While high risk floodplains provide a good proxy for flood hazard locally, coastal communities also face other risks from extreme events and in particular the risk of inundation because of the sea level rise under changes in climate. Future direction of the present study involves conducting welfare analysis based on changes in consumer surplus (CS) under multiple scenarios of future climate (e.g. changes in frequency of heavy rainfall, sea level rise, and flood risk) and policy scenarios (e.g. changes in flood mitigation policies). We will also extend current study by updating feedback from the sorting process and addressing endogeneity of housing prices and household income due to re-sorting behaviors under changes in flood risk and flood control policies.

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Table 1: Variable Description and Summary Statistics

Variable	Description	Mean	Std. Dev.	Min	Max
MSA-specific variables (J = 281)					
High risk flood zone	The area of high risk flood zone in square miles	163.4	253.03	0	1735.2
CRS 300	CRS 300 credit score	148.5	178.19	0	674
CRS 400	CRS 400 credit score	192.1	282.68	0	1510
CRS 500	CRS 500 credit score	97.71	158.27	0	1337
CRS 600	CRS 600 credit score	40.35	62.26	0	392
CRS total	CRS total credit	520.6	669.8	0	3887
Dams	Number of flood control dams	2.18	9.48	0	110
Annual snowfall (in)	Annual snowfall (inches) from (NCDC)	17.97	23.59	0	115.6
High precip days	Annual days of precipitation with daily maximum over 1 inch from 1991 to 2000 (NCDC)	10.03	4.76	1	23
July Humidity (morning %)	July humidity (morning monitoring value in %)	86.48	11	28	100
Cultural establishments	Total number of establishments in business patterns such as arts, entertainment& recreation/land are (square miles) (U.S. Census)	0.14	0.31	0	4.23
Water area (square miles) (00s)	Water area (area in square miles/100) (U.S. Census)	2.47	5.13	0	39.55
Ln (Construction wage) ($000s)	Natural log of construction wage ($000s) (BLS)	3.46	0.19	2.9	3.95
Ln(production wage) ($000s)	Natural log of production wage ($000s) (BLS)	3.24	0.25	0.9	3.77
Ln(service wage) $000s	Natural log of service wage ($000s) (BLS)	3.44	0.12	3	3.92
Household demographics (I = 1,820,691)					
Estimated income in natural log term $	Estimated income for the head of household i possibly living in one of the MSA j	10.46	0.75	6.2	12.79
Whether j is out of i's birth macro region	Whether MSA j is out of individual i's birth macroregion (Yes = 1; No = 0)	0.75	0.42	0	1
Coast high	Individual i was born in gulf coast and east coast high risk region (Yes = 1; No = 0)	0.5102	0.4999	0	1
CA high	Individual i was born in west coast high risk region (California) (Yes = 1; No = 0)	0.0741	0.2619	0	1
Inland high	Individual i was born in inland high risk region (Yes = 1; No = 0)	0.1755	0.3804	0	1
Inland moderate	Individual i was born in inland moderate risk region (Yes = 1; No = 0)	0.1589	0.3656	0	1
Low	Individual i was born low risk region (Yes = 1; No = 0)	0.0813	0.2733	0	1
White	Race is white (Yes=1; No=0)	0.884	0.3202	0	1
Black	Race is black (Yes=1; No=0)	0.085	0.2795	0	1
Hispanic	identifies persons of Hispanic/Spanish/Latino origin and classifies them according to their country of origin when possible	0.035	0.1848	0	1
Age above 65	Whether individual I is over 65 years old (Yes = 1; No = 0)	0.17	0.38	0	1
College graduates	Whether individual I is college graduate	0.34	0.47	0	1

Table 2: Estimated Results of the 1st Stage Sorting Model

variables	Model 1 CRS total	Model 2 Series 300	Model 3 Series 400	Model 4 Series 500	Model 5 Series 600
	(1)	(2)	(3)	(4)	(5)
ln(predicted income)	1***	1***	1***	1***	1***
	(0.0072)	(0.0072)	(0.0073)	(0.0073)	(0.0072)
Age 65 –x- high risk flood zone	-0.0002***	-0.0001***	-0.0001***	-0.0001***	-0.0002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age 65 –x- CRS credit points	0.0002***	0.0005***	0.0003***	0.0006***	0.0022***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
College graduate –x- high risk flood zone	0.0001***	0.0001***	0.0001***	0.0002***	0.0001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
College graduate –x- CRS total credit	0.0001***	0.0004***	0.0002***	0	0.0009***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
White –x- high risk flood zone	0	0	0	0	0
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
White –x- CRS total credit	-0.0002***	-0.0005***	-0.0004***	-0.0004***	-0.0011***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black –x- high risk flood zone	0.0001***	0	0	0	0.0001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black –x- CRS total credit	-0.0004***	-0.0009***	-0.0006***	-0.0011***	-0.0027***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Hispanic –x- high risk flood zone	0.0004***	0.0003***	0.0004***	0.0002***	0.0004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Hispanic –x- CRS total credit	0	0.0001***	-0.0003***	0.0009***	-0.0005***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CA high -x-high risk flood zone	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Coast high-x-high risk flood zone	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Low-x-high risk flood zone	0.0006***	0.0006***	0.0006***	0.0006***	0.0006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Inland moderate-x-high risk flood zone	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MSA out of birth micro region	-2.03***	-2.0954***	-2.1142***	-2.093***	-2.0966***
	(0.0017)	(0.0017)	(0.0017)	(0.0016)	(0.0016)

* p<0.05, ** p<0.01, *** p<0.001; robust clustered standard errors in parenthesis; omitted region: inland high risk region

Table 3: Estimated Results of the 2nd-Stage Sorting Model

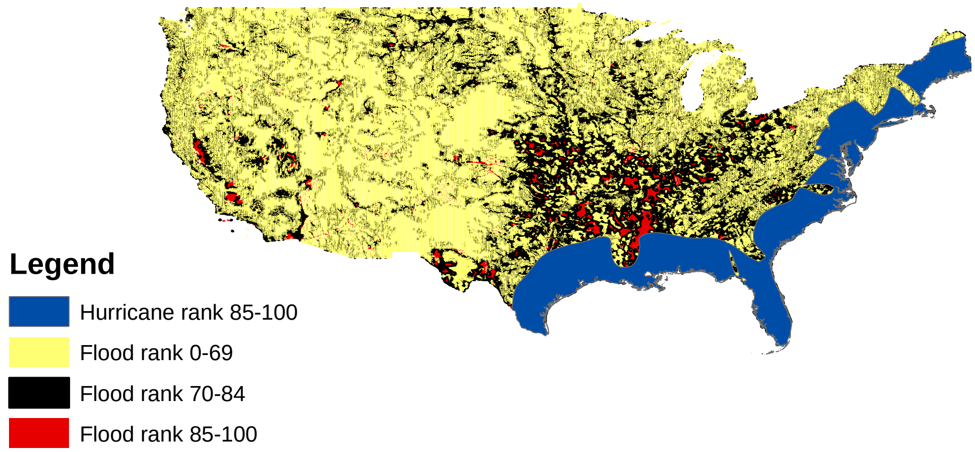
	Model 1 CRS total		Model 2 CRS series 300		Model 3 CRS series 400		Model 4 CRS series 500		Model 5 CRS series 600	
	(1)		(2)		(3)		(4)		(5)	
	OLS	IV with region dummies	OLS	IV with region dummies	OLS	IV with region dummies	OLS	IV with region dummies	OLS	IV with region dummies
High precip. days	0.0025	-.0492*	0.0038	-0.0456	0.0026	-.0597*	0.0051	-0.0452	0.0041	-0.0246
	(.0118)	(.0287)	(.0119)	(.02997)	(.0118)	(.0345)	(.0121)	(.0377)	(.0120)	(.0255)
Ln(construction)	0.2305	1.0233	0.1959	0.9377	0.1910	0.7871	0.211	1.2769	0.2411	.9685*
	(.3558)	(.6563)	(.3620)	(.6902)	(.3583)	(.7137)	(.3581)	(.9097)	(.3548)	(.5430)
Ln(production)	0.4520***	.5690*	.5038***	1.0247**	.4169***	0.3303	0.4297***	.8047*	.4501***	.5717**
	(.1192)	(.3272)	(.1242)	(.4023)	(.1168)	(.3632)	(.1284)	(.4644)	(.1194)	(.2608)
Ln(service)	2.0436***	1.3904*	1.9900***	1.0381	2.0416***	1.5235*	2.1501***	1.9763*	1.995***	1.3929*
	(.5451)	(.8231)	(.5494)	(.9099)	(.5482)	(.8951)	(.5835)	(1.0705)	(.5665)	(.7617)
Annual snowfall (in)	-0.0009	0.0016	-0.0011	0.0025	-0.0012	-0.0009	-0.00197	0.0026	-0.0013	0.00296
	(.0025)	(.0043)	(.00245)	(.0046)	(.0025)	(.0048)	(.0025)	(.00584)	(.0024)	(.0035)
Water area -x- CRS Series 300	-0.00003	-.0004**	-0.00005	-.0006**	-0.00002	-.0004**	0.000019	-.0005*	-0.000012	-0.0002
	(.00005)	(.00018)	(.00005)	(.00025)	(.00005)	(.0002)	(.00006)	(.00026)	(.00005)	(.0002)
Water area (sq. miles)	0.0514***	.1069***	.0538***	.1219***	.05088***	.1064***	0.0456***	.1031***	.04809***	.0670**
	(0.01501)	(.0299)	(.0152)	(.0364)	(.0149)	(.0332)	(.01477)	(.0390)	(.01485)	(.0266)
Cultural establishments	0.3914*	0.2098	.3849*	0.2056	.3915*	0.1813	0.3701*	0.1754	.38290*	.3922*
	(.212422)	(.3076)	(.2154)	(.3266)	(.2116)	(.3430)	(.2058)	(.4174)	(.2075)	(.2294)
July Humidity (morning %)	-.0174***	0.0038	-.0187***	0.0004	-.0176***	0.0067	-0.0216***	0.00091	-.0197***	-0.0073
	(.00520)	(.01181)	(.0052)	(.0119)	(.0052)	(.0139)	(.00536)	(.01515)	(.0053)	(.0117)
High risk flood zone (sq. miles)	0.00018	-0.0001	0.0002	-0.0001	0.0002	0.0002	0.00023	-0.00029	0.0002	0.00002
	(.00019)	(.0003)	(.0002)	(.0004)	(.0002)	(.0140)	(.0002)	(.00049)	(.0002)	(.0003)
CRS Credit Points	.0004***	.0020***	.00142***	.0084***	.0009***	.0052***	0.0006*	.01035**	.00271***	0.0122
	(.00007)	(.0006)	(.0003)	(.0030)	(.00016)	(.0019)	(.00034)	(.004759)	(.00392)	(.0099)
# of flood control dams	0.0197***	.01741**	.01984***	.0149*	.02024***	.01977**	0.02088***	.01822*	.02045***	.0176***
	(0.0039)	(.0079)	(.0037)	(.0085)	(.0039)	(.0087)	(.00388)	(.01062)	(0.0042)	(.0060)
R-square	.0.4998		0.4902		0.4980		0.4591		0.4724	

* p<0.05, ** p<0.01, *** p<0.001; robust clustered standard errors in parenthesis

Table 4: Marginal Willingness to Pay

		Region of Birth (0/1)					Retiree	College	Race			Income
Individual characteristics	Sample Mean	A	B	C	D	E	F	G	White H	Black I	Hispanic J	K
CA high	0.0741	1	0	0	0	0	0	0	0	0	0	0
Coast high	0.5102	0	1	0	0	0	0	0	0	0	0	0
Low	0.0813	0	0	1	0	0	0	0	0	0	0	0
Inland moderate	0.1589	0	0	0	1	0	0	0	0	0	0	0
Inland high	0.1755	0	0	0	0	1	0	0	0	0	0	0
Age above 65	0.1726	0	0	0	0	0	1	0	0	0	0	0
College graduates	0.3410	0	0	0	0	0	0	1	0	0	0	1
White	0.8840	0	0	0	0	0	0	0	1	0	0	0
Black	0.0854	0	0	0	0	0	0	0	0	1	0	0
Hispanic	0.0354	0	0	0	0	0	0	0	0	0	1	0
Household income (annual $1000)	34.718	35	35	35	35	35	35	35	35	35	35	70
	Marginal Willingness to Pay ($)											
Additional credit point in crs series 300	230	230	230	230	230	230	312	308	277	263	298	616
Additional credit point in crs series 400	170	170	170	170	170	170	192	188	167	160	171	377
Additional credit point in crs series 500	348	348	348	348	348	348	383	362	348	324	394	767
Additional credit point in crs total credit	66	66	66	66	66	66	78	75	64	57	71	150

Appendix A



Note: gulf coast and east coastal high (TX, LA, MS, AL, FL, GA, SC, NC, VA, MD, Washington DC, DE, NJ, CT, MA, RI, NH, ME, PA, NY, VT); west coastal high (CA); inland high risk (OK, AR, TN, KY, OH, IN, MO, KS, NV); inland moderate risk (MT, ND, SD, NE, WI, MN, IA, IL, WA, OR, WV); low risk (WY, ID, UT, AZ, CO, NM, MI)

Appendix B

Table B.1: Description of Variables Used for Income Regression

Variable	Obs	Mean	Std. Dev.	Min	Max	Description
age	3428583	45.13687	16.08084	15	93	Age
hsdrop	3428583	0.0197822	0.1392512	0	1	High school dropout
hsgrad	3428583	0.4506824	0.4975619	0	1	High school graduate
coll	3428583	0.418351	0.4932885	0	1	Completed some college (not four year degree)
collgrad	3428583	0.1111844	0.3143604	0	1	College graduate
male	3428583	0.5275276	0.4992417	0	1	Male
age_sq	3428583	2295.93	1569.715	225	8649	Age square
married	3428583	0.629698	0.4828856	0	1	Married or not
white	3428583	0.8693475	0.33702	0	1	Race = white
black	3428583	0.089607	0.2856179	0	1	Race = black
native	3428583	0.0048227	0.069278	0	1	Race = American Indian or Alaska Native
asian	3428583	0.0064881	0.080287	0	1	Race = Asian
other	3428583	0.0297347	0.1698546	0	1	Other race
manage_pro~n	3428583	0.2991472	0.4578845	0	1	Managerial and Professional occupation
tech_sales~n	3428583	0.29909	0.4578594	0	1	Technical, Sales, and Administrative occupation
service	3428583	0.1065846	0.3085844	0	1	Service occupation
farm_fores~h	3428583	0.0128584	0.1126634	0	1	Farming, forestry, and fishing occupation
production	3428583	0.0941733	0.2920697	0	1	Precision Production, Craft, and Repairers occupation
operatives~s	3428583	0.0992812	0.2990393	0	1	Operatives and Laborers occupation
other_occ	3428583	0.0888653	0.2845492	0	1	other occupation
Inc	3428583	37117.43	46356.83	4	680000	include wage income, business income (if self-employed), and retirement income)
Lninc	3428583	9.943536	1.236206	1.386294	13.42985	natural log of income

Table B.2: Estimated Results of Income Regression

Variables	Estimate	Std. Err.	T
Dependent variable: ln(income)			
Age	0.1458083	0.0001817	802.52
Age2	-0.0014907	1.97E-06	-758.19
Male (0/1)	0.5472341	0.0011467	477.23
HS grad or higher (0/1)	0.2073457	0.0039559	52.41
College, 1, 2, 3, 4 years of college (0/1)	0.5482908	0.0040278	136.13
College graduate or higher 5+ years of college (0/1)	0.8154107	0.0043296	188.34
Black (0/1)	-0.0976465	0.0019529	-50
Native American (0/1)	-0.1178957	0.007783	-15.15
Asian (0/1)	-0.1526193	0.0067441	-22.63
Misc. race (0/1)	-0.0629044	0.0032476	-19.37
Technical/Sales employee (0/1)	-0.2341183	0.0014967	-156.42
Service employee (0/1)	-0.6231083	0.002064	-301.9
farm_forest_fish	-0.7065591	0.0049102	-143.9
Production	-0.1549971	0.0022003	-70.44
operatives_laborers	-0.3228336	0.0021818	-147.96
other_occupation	-0.3764964	0.0027089	-138.98
Observation: 3,428,583			
R-square: 0.9902			

Appendix C

Table C: Housing Price Regression Results

Dependent Variable: ln(house value in $)		
Variables	Coefficient	Std. Err.
acre_9	0.2293447	0.0011204
acre_10	0.484376	0.0024098
room2	0.2601556	0.013702
room3	0.3645938	0.013633
room4	0.3399202	0.0138909
room5	0.4874492	0.0139123
room6	0.6201583	0.0139388
room7	0.7581641	0.0139573
room8	0.8844172	0.0139831
room9	1.094642	0.0140053
bed2	-0.0730917	0.0089261
bed3	0.0277223	0.0091637
bed4	0.0868816	0.0092378
bed5	0.1580952	0.0093004
bed6	0.2489188	0.0094754
unit2	-0.0357068	0.0128017
unit3	1.270124	0.0018044
unit4	1.116853	0.0023586
unit5	1.304594	0.0036758
unit6	1.289461	0.0044703
unit7	1.159725	0.0047681
unit8	1.129175	0.0054227
unit9	1.274372	0.0054686
unit10	1.418334	0.0044319
Noplumb	-0.1511751	0.0083232
Nokitch	-0.1768996	0.0095663
yr1 (0-1 year-old dwelling)	0.5237983	0.0026198
yr2 (2-5 year-old dwelling)	0.4621991	0.0016635
yr3 (6-10 year-old dwelling)	0.3713441	0.0016547
yr4 (11-20 year-old dwelling)	0.2462994	0.0013837
yr5 (21-30 year-old dwelling)	0.1101696	0.0013366
yr6 (31-40 year-old dwelling)	0.0707313	0.0013979
yr7 (41-50 year-old dwelling)	0.0487925	0.0013637
Constant	9.3902	0.0147
Observation: 1,820,691	R-square: 0.9981	

Appendix D

Table D: CRS Series Creditable Activities.

Activity	**Maximum possible points**
300 Public Information Activities	
310 Elevation Certificates	162
320 Map Information Service	140
330 Outreach Projects	380
340 Hazard Disclosure	81
350 Flood Protection Information	102
360 Flood Protection Assistance	71
400 Mapping & Regulatory Activities	
410 Additional Flood Data	1,346
420 Open Space Preservation	900
430 Higher Regulatory Standards	2,740
440 Flood Data Maintenance	239
450 Storm water Management	670
500 Flood Damage Reduction Activities	
510 Floodplain Management Planning	359
520 Acquisition and Relocation	3,200
530 Flood Protection	2,800
540 Drainage System Maintenance	330
600 Flood Preparedness Activities	
610 Flood Warning Program	255
620 Levee Safety	900
630 Dam Safety	175

Source: Coordinator's Manual FIA 15/2007; National Flood Insurance Program Community Rating System.

Appendix E

Table E: CRS Credit Points and Premium Reduction

Credit points	Class	Premium reduction SFHA[6]
4500+	1	45%
4,000-4,499	2	40%
3,500-3,999	3	35%
3,000-3,499	4	30%
2,500-2,999	5	25%
2,000-2,499	6	20%
1,500-1,999	7	15%
1,000-1,499	8	10%
500-999	9	5%
0-499	0	0

Source: Federal Emergency Management Agency (FEMA)

[6] SFHA—special flood hazard area