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AMENITIES, RISK, AND FLOOD INSURANCE REFORM

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ABSTRACT

This paper provides the first, comprehensive evidence on the question of whether the subsidized flood insurance rates are needed to meet the affordability goal of the National Flood Insurance Program. We use IRS records at the zip code level from 2009 to 2016 to compare the real median incomes of homeowners in areas subject to flooding risks to those homeowners in neighboring zip codes. Our analysis includes all of the Gulf Coast states and over 1000 other communities around the United States containing FEMA designated Special Flood Hazard Areas (SFHA). There are clear patterns of positive income stratification for coastal locations in Florida, New Jersey, and New York. We also find lower income for coastal locations in California, North Carolina, as well as the shoreline along rivers identified as in SFHA in Delaware, and Virginia fit this pattern.

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1. Introduction

Last year, 2017, was estimated to be the most costly for hurricane damage in the U.S. to date, causing over $306 billion in losses. Significant storms in Florida and North Carolina this past fall suggest the pattern is continuing. Indeed, the Federal Emergency Management Agency's (FEMA) 2018 third quarter *Watermark* report estimates over $40 billion as the probable maximum annual loss. This pattern of flood and hurricane related damage is not news. A number of authors have recognized the rising toll of extreme weather events (see Kousky [2017], Kousky and Lingle [2017], Bin et al. [2017], and Walls et al. [2018] as a few examples). While several analyses of the effects of climate change suggest that an increase in severe, coastal storms is one likely outcome (Emanuel [2005] and Knutson and Tuleya [2004]), people's decisions in selecting places to live are also contributing factors influencing the damages from these storms. In understanding these decisions there are at least three elements to be considered: (a) households are attracted to coastal amenities; (b) their perceptions of the risks associated with coastal hazards may not be accurate; and (c) the incentives created by government policies can induce misguided responses.

The last of these, policy, is especially important as Congress has continued to postpone reforms to federal flood insurance[1]. The federal government has been responsible for this insurance through the National Flood Insurance Program (NFIP) for 50 years and the insurance rates for protection often bear little relationship to the flood risks. The Congressional Budget Office [2017] (CBO) estimated that 85% of the policies in the highest risk areas (Zone V) were subsidized and that the average subsidy was 40% of rates that would be set on actuarial basis[2].

[1] The most recent of three short term re-authorizations took place on 12/21/2018 and extends the program in its current form to 5/31/2019.

[2] See CBO [2017] figure 4 on page 17. In addition, after a storm is declared a presidential disaster, the Federal Emergency Management Agency (FEMA), the Small Business Administration (SBA), and the Department of

The magnitude of the "grandfathered" subsidies differs by flood zone, elevation conditions for the properties involved, and whether those properties received federal assistance in the past[3]. Popular opinion editorials (Siguad [2018] for example) have raised concerns that these subsidies primarily go to wealthy homeowners. All of these comparisons, including the recent FEMA [2018] affordability analysis, are based on summary statistics for samples subject to selection effects. That is, they generally compare income of policyholders with those who have chosen not to buy insurance. More importantly, they provide an incomplete picture of the population actually facing flood risks and the key policy questions associated with them, namely, is the affordability goal motivating public subsidies needed, and, if it is, how should it be met? This conclusion follows from Kousky and Lingle [2018] recent analysis of the geographic distribution of the NFIP residential policies using data from February 2018. They found that 3% of all US counties account for 75% of the policies and that these are concentrated along the Gulf and Atlantic coasts. These authors also note in the last decade every state has experienced a damaging flood.

This paper provides the first, comprehensive, national evidence on the question of whether the affordability of flood insurance rates is relevant to those households facing these risks. We use IRS records at the zip code level from 2009 to 2016 to compare the real median incomes of homeowners in areas subject to flooding risks to those homeowners in neighboring zip codes. By exploiting geography we use this comparison as a partial control for other characteristics likely to also be important to locational decisions such as access to employment, local public services, and other local conditions (i.e. climate, state and local taxes, etc.). Our analysis includes all of the Gulf Coast states and over 1000 other communities around the United States in FEMA designated Special Flood Hazard Areas (SFHA).

Housing and Urban Development (HUD) have a variety of programs with grants to homeowners (regardless of whether they have insurance), subsidized loans, and other funds that are intended to reduce the time for local communities to return to normal conditions, but which have the added effect of creating counterproductive incentives. Kousky, Michel-Kerjan, and Raschky [2017] found, for the case of Florida, that these types of assistance reduce average insurance coverage. A dollar increase in the average aid grant reduced the average insurance coverage by about six dollars.

[3] Zone V designates a coastal area where the velocity of wave action adds at least 3 feet to the water level that is reached in a 100year flood. Zone A designates a 100year floodplain or on in which there is at least a 1 percent annual probability of flooding and not designated as Zone V. Zone X is any mapped area not inside a 100 year floodplain. See Appendix B of the Congressional Budget Office [2017] report for discussion NFIP subsidies.

Three important insights emerge from our assessment. The first stems from a recognition that extensions to the Tiebout [1956] sorting logic (Kuminoff et al. [2013]) would imply that strong preferences for coastal amenities tend to induce income stratification, with high amenity areas having a greater proportion of high income households than those areas with low coastal amenities. Our findings suggest that once risk is introduced into this framework the predictions are not always upheld. The effects of proximity depend on the resource that is the source of the coastal or water related amenities and the characteristics of the surrounding area. Second, the character of the income distribution, as reflected in the real median income, for areas with water-based amenities compared to nearby locations is remarkably consistent over time. High income areas remain that way regardless of the history of floods involved over the period of our analysis. The same is true for areas where we don't find stratification by income for locations adjoining water-based resources. Third, and finally, the geographic comparison group used as a control to gauge the effects of amenity and risk can matter in judging the estimated incidence of flood policy and the associated conclusions about affordability. So in contrast to some of the popular criticisms of the NFIP there is not one answer to the affordability question when it is considered simply on the basis of location.

We begin this description of the conceptual and empirical dimensions of our research in the next section with summaries of the time profile for real median incomes in Florida and Louisiana. These comparisons highlight why the research design we adopted to describe the incidence of the NFIP program is so important. After that, in section 3, we describe the implications of the single crossing property for sorting outcomes with amenities and risk. This section also outlines the connection between our research design and Musgrave's [1959] definition of incidence for judging the distributional effects of policies. We adapt his definition to reflect Hendren's [2018] logic for evaluating policies involving risk. Section 4 describes our data and models. Five summarizes the results. Section 6 relates our findings to other recent research on the affordability issue and the NFIP. The last section summarizes the research and comments on its policy implications.

2. Setting the Stage

Three figures introduce and illustrate the importance of understanding the effects of sorting and its persistent impact on which households benefit from the current NFIP policies. Figures 1, 2, and 3 plot the real median income (in 2015 dollars) for coastal and adjoining interior zip codes for the Gulf Coast of Florida, the Gulf Coast of Louisiana, and the Atlantic Coast of Florida each year from 2009 to 2016. These income measures are developed using administrative data constructed at the zip code level from the IRS income tax returns.

Figures 1 and 2 use the IRS income measures at the zip code level for Florida and Louisiana. To construct measures for the real median incomes we used the conditional income distributions reported by zip code for intervals of adjusted gross income associated with those households who took a mortgage interest deduction.[4] The IRS records for the Gulf Coast of Florida and Louisiana are also consistent with the HMDA records[5]. When we use a model with a constant effect for coastal locations compared to adjoining interior zip codes the estimates imply a $12,545 *positive*, and significant, difference in real median incomes for the Gulf Coast of Florida, a positive and significant difference of $17,916 for the Atlantic Coast of Florida, and a *negative* and significant $12,960 difference for Louisiana. The findings from these models are discussed in more detail below.

Each of the figures plots three curves. The top dashed line for the Florida Gulf and Atlantic zip codes is the real median income for the coastal locations. The solid line immediately below it (with "dots" identifying years) is the real median income for the adjacent interior locations. The bottom solid line is the real median income for all households in the US in real terms ($2015). It does not attempt to distinguish homeowners from renters and thus we would expect it to be below our estimates for those claiming the mortgage interest deduction. This pattern reverses for Louisiana with the dashed line associated with shoreline zip codes appearing below the solid line for the real median incomes based on IRS records. Here the interior adjacent zip codes have higher median incomes than coastal locations. Each of these estimates is derived as a conditional

[4] The limits used to define the income distributions remained fixed from 2009 to 2016. They are: under $25,000; $25,000 to $50,000; $50,000 to $75,000; $75,000 to $100,000; $100,000 to $200,000; and over $2000,000. We used the Stata command gdsum, developed by Daniel Klein, University of Bamberg, daniel1.klein@gmx.de to estimate the median and did not set an upper maximum for the open ended top interval in these distributions. The median, m. is estimated as follows: $m = l + \frac{(n/_2 - cf)}{n_{mc}} * (\mu - l)$. with $l =$ lower bound of the median class, $\mu =$ the upper bound of the median class, $n_{mc} =$ the number of observations in the median class (mc), $n =$ the number of observations, and $cf =$ cumulative frequency in the class prior to the median class.

[5] See Kahn and Smith [2018] for more details on the comparison for results at the county and zip codes level using data from mortgage applications available thru the Home Mortgage Disclosure Act of 1975 (HMDA).

median estimated separately with regressions for coastal and non-coastal zip codes. The national estimates are taken from reports by the Federal Reserve Bank of Minneapolis.

All these areas have been subject to hurricanes over the time span in our sample and the differences in income levels remained consistent. These results imply locational sorting is more complex than a simple story would imply. Of course, the ability to avoid flood risks depends on the geography of each area. The nature of the coastal amenity is also exceptionally different between the Florida locations and the majority of Louisiana's coastal locations which are primarily wetlands[6].

For now, our takeaway message is that there is clear evidence consistent with the positive income stratification implied by the sorting hypothesis when there are high levels of amenities. However, the locations involved are recognized as having *both* high levels of coastal amenities and high risks of storms and flooding related damage that would be covered by the NFIP. Thus, it would seem the attraction of the amenities outweighs the risks and that for these cases affordability may be less of an issue. On the other hand, for other areas (Louisiana) there is equally consistent evidence implying the risks seem to outweigh any amenity effect of coastal locations. As a result, it is reasonable to ask whether these patterns are "typical" for different regions covered by the NFIP and, if so, what do the differences imply for reform of its affordability mandate?

These differences alone imply that the current NFIP policy which sets insurance rates based on the dates of flood maps in relationship to the construction date for all homes in all locations cannot be justified as required to assure affordability of the insurance. The results for these two Gulf Coast states imply, for example, that in the case of Florida this policy seems to be subsidizing wealthier households. By contrast, one would not necessarily draw this conclusion for the case of Louisiana. It is reasonable to ask are these two examples special? We return to this question in the remainder of the paper. First, we describe, in the next section, why the real

[6] A recent report by the US Geological Survey (Covillion et al. [2011]) indicated that 1.2 million acres of land has been lost in Louisiana between 1992 and 2010 and the majority of the land loss in this report is composed of tidal wetlands. Recently Louisiana's Coastal Protection and Restoration Authority [2017] released a Master Plan predicting continued and more significant land loss than previously expected. As part of the Plans' effort to inform the public, it includes an interactive online mapping capability (http://cims.coastal.louisiana.gov/masterplan/) that displays, among other elements, the land change, flood risks, and composition of coastal vegetation in locations throughout the state. According to this resource, all of the coastal areas of the state are composed of marsh or wetlands.

median income for homeowners, independent of decisions to purchase flood insurance, is an incidence measure consistent with both Musgrave and Hendren. In developing our remaining empirical analysis we will confine the modeling to the IRS records because they offer a consistent income measure and are more uniformly available for all the zip codes we consider.

3. Sorting and Incidence Analysis

a. Background on Sorting

Equilibrium sorting models have their origins in Tiebout's [1956] description for how households can select a preferred bundle of local public and private goods by moving. Given that communities differ in the housing available, employment opportunities, and other local public goods, these models maintain that a household selects their preferred community and in the process reveals aspects of their preferences. When household income is assumed exogenous, housing prices will reflect the effects of local public goods. Epple et al. [1984] demonstrate how the single crossing property implies income stratification[7]. This property describes how the slope of each indifference curve in the plane defined by a housing price and the measure of local public goods changes with income. If all households have the same preferences, then increases in this slope with income will imply positive income stratification.

It is reasonable to assume households may have different tastes for local public goods. This type of extension has been used to develop strategies for estimating household preferences based on how the distribution of tastes and income contributes to the degree of stratification[8]. Here we simply consider whether the presence of coastal amenities and storm risks would change the basic expectations in this type of model. Using a simple expected utility framework with two outcomes – storm damage reducing income and no storm damage – together with the assumption that the probability of a storm's damage increases with the amount of coastal amenities the composite of amenity and risk does not offer unambiguous predictions. Depending on the strength of preferences for amenities and the properties we assume for the marginal utility

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[7] Nechyba [1997] provides a formal demonstration of existence and properties of the equilibrium.

[8] See Sieg et al.[2004] for an example and Kuminoff et al.[2013] for a review of the alternative formulations of sorting models.

of income it is possible to overturn the income stratification prediction. Appendix A outlines the logic for this conclusion in formal terms. We find that with other reasonable assumptions the predictions would be maintained. However, the predictions for market equilibria are not clear (as we explain below) and the importance of these tendencies will depend on the differences in risk perceptions across individuals and locations, the heterogeneity in tastes for coastal amenities (and more generally water based amenities), incomes, as well as market responses. Thus, as one might expect, there are good reasons that would explain incomplete income stratification. Unfortunately it is not possible to use the properties of a structural model to fully characterize the market equilibrium once risk is introduced. This conclusion follows because amenities contribute to preferences directly and also affect the nature of the risks. Moreover, current flood insurance policy influences which areas and homes would face the full implications of damages from storms. The composite of these factors undermines our ability to establish clear expectations for whether an observed equilibrium would satisfy the ascending bundles property used in estimating structural models[9]. As a result, we propose to describe what can be observed –namely the income distributions across location and time in areas with coastal or water related amenities and subject to flood risks compared to nearby areas hypothesized to have comparable conditions in other respects.

b. Incidence

Our research design combines insights from two earlier contributions. The first of these by Hendren [2018] considers how the modeling of individual behavior influences the role of uncertainty in characterizing the willingness to pay for insurance; and the second, by Musgrave [1959] 60 years ago provides a general equilibrium definition of the incidence of policies on the distribution of income. Musgrave's definition for incidence provides a straightforward strategy for evaluating the relevance of the affordability goal in the setting of rates under the National Flood Insurance Program. His framework would measure incidence of a policy through the change in the distribution of real income as a result of that action. It recognizes that policy, whether involving taxes, subsidies, public expenditures, or regulations have effects on

[9] See Kuminoff et al.[2013] for a discussion of how the property is used to establish this condition and used in estimation of the vertical form of these models.

individuals through changes in the amounts and sources of their income as well as through changes in the relative prices. These prices affect each household's expenditures on market goods and services as well as their labor-leisure choices and, at a market level, are determined by the composite of all these responses. Thus, his assessment of the incidence of a policy requires consideration of the *net* effects of all of these adjustments after it has been implemented so that they are captured in the resulting distribution of real income.

We will use this concept of incidence a bit differently here. We evaluate the income distributions for households directly affected by the risks associated with their location in coastal or shoreline zip codes (or in zip codes associated with Special Flood Hazard Areas that adjoin the source for the flooding risk -- either a river or lake if these locations are not coastal areas). These distributions are then compared to adjacent (interior) zip codes. We do not distinguish policyholders from non-policyholders. Following Hendren's argument, using the choice to have insurance as part of the criteria used to select the households considered in judging affordability amounts to accepting the household choices that affect what is *actually* at risk. While Hendren's argument is associated with measuring the willingness to pay for insurance, it is also relevant to an analysis of incidence. That is, when people have some knowledge of the risk they face before the insurance decision, then in his case their willingness to pay for insurance will typically be less than in cases without that information[10]. The same is true in judging incidence. Once a decision is made to purchase insurance, the policyholder knows the financial consequences of flooding.

In our case, people have accepted an implicit amenity/risk trade-off in selecting a place to live. They do not know if a storm will actually damage their properties. This situation is the analog to his example of a cancer patient's willingness to pay for insurance compared to someone's value for insurance before knowing her health state. Our estimates for the income distributions include policyholders and non-policyholders in different locations. As a result, they deal with incidence for households who have accepted different risks. This conclusion follows from our design which distinguishes them based on their locations. The households do not know what the damage they might experience for any particular storm. By comparing distributions across locations with different risks we evaluate whether the incidence is differentially imposed

[10] Hendren [2018] makes this point in footnote #1 and attributes it to Hirshleifer [1971].

on those less able to afford insurance. In this respect, then, it is a measure of incidence that attempts to construct an analog reflecting the concerns raised by Hendren's proposed adaptation of measures of the willingness to pay for insurance.

c. NFIP Subsidies

Federal flood insurance under the NFIP is available to homeowners and communities that agree to enact local floodplain ordinances and building codes. Homes built before 1968 or before a flood insurance rate map was completed (pre-FIRM) are eligible for subsidized insurance. This process means that homes eligible for the subsidy in the high risk zones V and A face a chargeable rate for insurance that is significantly below the NFIP's risk based rate[11].

Communities voluntarily join the program. To join they must adopt a set of minimum floodplain management regulations associated with the 100 year flood risk designation. With community participation, the NFIP creates flood insurance rate maps (FIRMs) and sets rates. These maps describe the floodplain in each community and the associated risks. FEMA has developed these maps for more than 20,000 communities. Rural areas with low levels of development have maps that are constructed with approximate methods that show an outline of areas where a flood has at least a one percent annual risk. Detailed maps are made for areas with higher levels of development. They use a variety of models that take account of drainage area, flood durations, structures, amount of impermeable surface, etc. Nonetheless, the process is not forward-looking. It does not attempt to anticipate changes in the risks faced in these areas due to climate change or likely future modifications to land uses that would affect flood risks.

When the annual base flood risk is one percent or higher for a location, the area is designated a Special Flood Hazard Area (SFHA). For communities that are or have participated in the NFIP, homeowners in a mapped SFHA are required to purchase flood insurance as a condition for receiving a federally backed mortgage. After the first year of a mortgage the compliance with this requirement has not been closely monitored.[12] The rates for NFIP insurance

[11] The insurance rate under the subsidy system is called the chargeable rate. It is a flat rate across all structures, risk zones, and communities. See Szmurlo [2018] for more details.

[12] Michel-Kerjan, de Forges and Kunreuther [2012] estimate, using 2001 data that by 2009 only about 20% of the NFIP policies remained in place. These policies were acquired for a federally backed mortgage. The attrition was higher in Florida and Louisiana with declines to under 20% by 2008.

are the same across the country for the areas with the same risk zone designations defined based on each location's FIRM.

In 2012 Congress recognized the need for reform in the rates for the NFIP and passed the Biggert Waters Flood Insurance Reform and Modernization Act. The core principle of this legislation was to move the NFIP toward a risk-based set of premiums "… that better reflected expected losses from floods at insured properties"[13]. This revision eliminated pricing at subsidized rates (the pre-FIRM rates) and grandfathering. Unfortunately, as the recent National Research Council [2015] report on the NFIP program indicated, shortly after its passage, a large number of communities expressed concerns with this legislation. Their concerns related to the effects of the new higher insurance rates on home prices and on the program's goal of expanding the take-up rates for flood insurance. As a result, in 2014, Congress passed the Homeowner Flood Insurance Affordability Act which changed the process associated with removing pre-FIRM subsidized rates and reinstated grandfathering.

This legislation also directed FEMA to develop an affordability framework that proposed "programmatic and regulatory changes that address the affordability of flood insurance" (FEMA [2018], p.2). Section 9 of the legislation proposed five criteria for this assessment:

1. Accurate communication to consumers of the flood risk associated with their properties;

2. Targeted assistance to flood insurance policyholders based on their financial ability to continue their participation in the NFIP;

3. Individual or community actions that mitigate or lower the cost of flood insurance;

4. The impact of increases in risk premium rates upon participation in the NFIP;

5. The impact flood insurance rate map updates will have on the affordability of flood insurance.

[13] National Research Council [2015] p.51

Unfortunately the fifth element in these criteria appears to assume affordability requires adjusting rates for all homeowners in high risk areas whenever there are new or revised FIRMs. Our findings, as previewed in section 2, confirm that this "blanket" approach is the wrong strategy for addressing affordability as a means to allow households to more easily adapt to new information about the flood risks they may face.

4. Data and Model

There are two components of the samples we use in evaluating the incidence of flood risks for different income groups and gauge the relevance of the NFIP's affordability criteria. The first includes all Gulf Coast, shoreline zip codes in Alabama, Florida, Louisiana, Mississippi, and Texas. We also added the Atlantic coast of Florida as another high risk area. We match the zip codes to the interior zip codes with adjacent boundaries to these coastal locations. We assembled the IRS administrative data providing zip code tabulations for the adjusted gross income from 2009 to 2016 for those returns that took the mortgage interest deduction as a proxy for homeownership. This period was selected because 2016 is the most recent year reported and in the years prior to 2009 the reports altered the income distributions used to define the conditional income distributions. In 2008, the tabulations did not report the counts for the returns taking the mortgage interest deduction.

The second component of our sample uses a set of zip codes providing a broader representation of areas subject to flood risks adjoining other types of water resources that are included in SFHA's. To develop this sample of communities that meet the needs of our incidence analysis, we use an early study of compliance with the building requirements associated with the NFIP by Mathis and Nicholson [2006]. In 2002, under contract from FEMA, the American Institute for Research (AIR) sought to assess the percentage of post-FIRM buildings with and without flood insurance in SFHAs that were in compliance with floodplain management regulations. To develop this assessment the report selected 10 cluster areas. They were:

Washington/Baltimore (Loudoun Co., VA)	Coastal North Carolina (Dare Co., NC)
Florida West Coast (Tampa, FL)*	Mid-Atlantic (New Castle Co., DE)

Florida Panhandle (Escambia Co., FL)*	Northern California (Contra Costa Co., CA)
Louisiana (New Orleans, LA)*	Mississippi River (St. Louis, MO)
Coastal Texas (Galveston, TX)*	Southwest (Maricopa Co., AZ)

For our analysis here we omit areas that overlap with the Gulf Coast (indicated in the list above with an asterisk). For each of these clusters, AIR delineated communities within a 100 mile radius of each cluster's central node. They were screened using FEMA's information system to identify those locations with a detailed FIRM[14]. This analysis was further refined to select communities with a significant number of buildings built after January 1, 1990 to allow sampling for the compliance study. We did not impose this last restriction on our sample and instead used all the communities who participated in the NFIP with detailed FIRM maps and were identified as having areas with SFHAs in 2003. Our data do not provide a balanced panel (eight yearly observations for each zip code) for all areas included. For some years, the IRS does not report tabulations for some zip codes. Maricopa County, Arizona has the largest number of these incomplete zip codes. Illinois and Maryland also have at least one zip code with a missing year[15].

Table 1 summaries all the communities considered in the AIR analysis. Column one lists the number of communities in each cluster. As we noted, we used all the communities for clusters that did not overlap with the Gulf Coast sample. Within each community, we assembled the zip code areas and classified them based on their relationship to a water source (i.e. coastal area, river, or lake). We identified those with a shoreline boundary within the zip code, those interior zip code that adjoin the zip codes with shoreline boundaries. We also selected a set of interior zip codes separated from the shoreline zip codes by at least one adjoining zip code area. These are labeled "nearby". For the adjacent zip codes, our sample allows the analysis of each type of water body to be conducted separately because the adjacent zip codes are distinguished by water

[14] See Appendix A in Mathis and Nicholson [2006] for a complete listing. Supplemental material in the form of Excel worksheets report the specific zip codes for the areas in each state that were used as part of our analysis.

[15] This was confirmed with Ms. Emily Gross of IRS Statistics of Income Division (11/26/2018). Her e-mail explained that the IRS Disclosure Protection Procedures likely implied that the zip code did not meet the minimum number of returns for that year.

body type. For the other zip codes we do not attempt to “attach” them to a specific waterbody. They are “nearby” but a formal definition of proximity given the size of the spatial units and the geographic expanse of the water resources would be somewhat arbitrary. Thus, to evaluate the effects of geography, we focus on states with only one type of waterbody to consider the effects of comparing our estimates for median incomes for shoreline zip codes versus other “nearby” locations.

These types of distinctions may be especially important for the flood zones that are not along the coast. In these cases, the geography of local floodplains, as well as the spatial distribution of landscape amenities likely affects the relative impact of the amenity/risk trade-off and the incidence of flood policy. Unfortunately, the spatial resolution of the IRS data does not allow us to distinguish these effects at a finer spatial scale. Earlier analysis (Kahn and Smith [2018]) used HMDA data for all Gulf Coast states at the county and zip code levels. Both analyses were consistent with the results using the IRS income tabulations. The IRS administrative records data provide the more reliable measures of income. As a result, we confine our summary here to the IRS records. Real income uses the national CPI (for urban households) and presents all income measures in 2015 dollars.

Our test is conducted by considering each state separately and pooling our estimates for the real median income across the zip codes in each community over time. We allow the treatment to enter our simple model in two separate ways –a more restrictive form that assumes the effect of the increased risk associated with a shoreline location is constant over time and a specification that allows it to vary. Equation (1) provides the more general model. The restrictive version replaces the interaction terms with a single fixed effect identifying the shoreline zip codes. Our test for the general case evaluates the joint null hypothesis that the coefficients for these interaction terms are all simultaneously zero for all time periods ($i.e.\ \gamma_t = 0$ for all t) represented in our sample.

$$(1) \quad y_{it} = \sum_t \beta_t l(t)_{it} + \sum_t \gamma_t l(t)_{it} \cdot C(i)_{it} + \varepsilon_{it}$$

where: y_{it} is the measure of the income distribution in year *t* for zip code i*;*

$l(t)_{it}$ is an indicator variable =1 when the estimated measure of the income distribution for year *t* and zip code *i* corresponds to year *t* and 0 otherwise (i.e. a dummy variable for the year of the application).

$C(i)_{it}$ is an indicator variable =1 when the estimated measure for the income distribution for zip code i corresponds to one with shoreline of a water resource (ocean, river or lake) and 0 otherwise (i.e. a dummy variable identifying the areas with shoreline).

ε_{it} is a random error

For all the states with coastal or resource specific (i.e. rivers or lakes) designations for the SFHAs flood zones, each of our tests is conducted using the adjacent zip codes as the control locations. For Arizona, Maryland, Missouri, Virginia, and West Virginia, with only one type of water body potentially responsible for flooding, we consider two alternative definitions for the control zip codes – adjacent and interior, “nearby” zip codes. We hypothesize that in these cases the differences in the sources of flood risk and the associated topography may impact the reliability of adjacent zip codes as controls. This simple alternative definition is roughly similar to the more careful logic of the “doughnut” approach to defining instruments in other spatial analyses of household choices of residential locations (see Bayer et al. [2016]).

5. Results

Tables 2 and 3 summarize our primary findings. In Table 2 we present our analysis for the Gulf Coast states and the Atlantic coast of Florida. The first column of estimates reports the test of the joint null hypothesis that all shoreline interaction coefficients are zero and the second a test when these effects are treated as constant over time. Figures 1 thru 3 plot the estimated coefficients for the shoreline and adjacent zip codes from the model that allows the effect of shoreline to vary over time. After that in the second column, we report also the estimated income difference between shoreline and interior adjacent zip codes when the estimated effect is assumed constant. In parentheses below each estimate we report the p-value for the test of significance. Three of the six estimated difference in medians are significant. Of these, two are positive for the Florida Coast and one negative for Louisiana, as we noted in section 2.

The remaining six columns in the table relate to separate models for the income classes used to estimate the medians. Each column reports the test for a separate model using the proportion of returns in each income category as the dependent variable and testing the joint null hypothesis that the coefficients for the interaction terms with the shoreline dummy variable and year fixed effects are simultaneously zero. The definitions for the IRS income bins remain unchanged from 2009 to 2016. The models (i.e. separate effects of shoreline by year, constant effect of shoreline for all years, and the count measures for income bins) for coastal zip codes in Florida, considering the Gulf and the Atlantic coasts, generally provide strong support the hypothesis of positive income stratification. Only one model, for the lowest income bin, fails to reject the null hypothesis of no association with the Gulf Coast and two with the Atlantic coast of Florida. By contrast, Louisiana's models indicate significant negative income stratification. These tests simply mirror what we reported at the outset in section 2 with figures 1, 2, and 3. As noted above, these figures plot the estimated coefficients by year for shoreline and adjacent interior zip codes using the medians derived from the IRS tabulations. The difference in real median income is comparable in absolute magnitude for Florida and Louisiana. In the case of Florida Gulf shoreline zip codes, the difference is $12,545 *higher* for the real median income associated with the shoreline zip codes while for Louisiana the shoreline zip codes have real median incomes that are $12,960 *less* those that are interior and adjacent.

The models using shares of the returns in each of the income bins rely on nominal incomes for each bin. Because the micro records are confidential, we cannot convert the intervals into real terms and re-bin the records. As noted, for Florida and Louisiana the results using the income bins are generally consistent with those for the medians suggesting shifts in the income distributions toward higher incomes for shoreline locations in Florida and higher incomes for the interior adjacent locations in Louisiana. Two of the other Gulf States (Alabama and Mississippi) do not reveal any significant patterns. Plots of their estimated shoreline and adjacent interior coefficients are provided in Appendix B. The results for Texas indicate significant differences in the share of returns for lowest (under $25,000) and the highest income (over $200,000) bins. The Gulf Coasts in Florida and Texas include well recognized coastal amenities that are significant recreational resources[16]. The situation is less clear for Louisiana[17] and somewhat more mixed for Alabama and Mississippi.

Overall then, our analysis of the Gulf Coast states provides only limited support for income stratification. It suggests based on the Gulf Coast of Florida with clear coastal amenities the incidence of insurance subsidies is likely to be tilted to wealthier households. The same judgement would apply for the Atlantic coast of Florida. In the case of Louisiana, the flood risk/insurance situation is more complex because of the geography involved. Kousky and Lingle [2018] identify Jefferson Parish Louisiana for example is one of the counties with more than 100,000 residential flood insurance policies[18]. This parish includes both shoreline and adjacent zip codes. Some of the shoreline areas in Louisiana are coastal wetlands and don't have zip codes. Thus, our evidence indicating higher median incomes for interior zip codes is more difficult to interpret within the reduced form framework of our model.

The second component of our sample, designed to match the Mathis and Nicholson national sample of communities in SFHAs, was selected to offer more resolution on whether the diversity in results observed for the Gulf States applies to all of the regions covered by the NFIP. Table 3 summarizes these results. We report tests for each state and type of resource with flood risks that are identified here as zip codes with shoreline locations (ocean, lake, and river resources). The results for four separate models are presented in the table. Columns one and two identify the state and type of resource. Columns three and five provide the test results for the flexible specification allowing the shoreline effect to change with the year in three and the constant effect across years in column five. When the estimated difference between shoreline and adjacent zip codes for the constant effect model is significant, we report the magnitude of the difference in real median income between shoreline and adjacent interior zip codes in column four.

Fourteen of the nineteen potential estimates using the constant effect of a shoreline specification are significant. They are evenly divided between situations indicating positive

[16] Of the ten protected national seashores two are in Florida (Canaveral and Gulf Islands) and one in Texas (Padre Island) Commercial web sites identify numerous beaches on the gulf coast –primarily in Florida (see https://vacationidea.com/beaches/best-gulf-coast-beaches.html as an example). These sites also highlight Galveston Island State Park in Texas.

[17] See footnote #6 above for details

[18] The other areas these authors identify with than 100,00 policies include Florida and Texas. Five of the counties are in Florida and one in Texas.

stratification (7 models – California/river, Delaware/ocean, Maryland/ocean, New Jersey/ocean, New York/ocean, New York/river, and Pennsylvania/lake) compared to negative stratification (7 models –Arizona/river, California/ocean, Delaware/river, Illinois/river, North Carolina/ocean, North Carolina/river, and Virginia/river).

Understanding the reasons for these different results would require a detailed evaluation of the specific attributes of each community and areas adjoining the flood zone areas. This is beyond our scope here[19]. These findings do confirm our basic argument. Household behavior in choosing where to live affects the residential component of the damages. In some cases the attraction of the amenities is sufficient to outweigh the risks of flooding. In others, the reverse is at work. So a judgment about the need for subsidized flood insurance rates based on geography or the age of a structure does not fit the income distributions we observe in a national sample of communities with SFHA. Efforts to assure affordable rates need to be based on the circumstances of each household. This strategy would also allow the insurance rates to serve one of their intended roles – as signals of the risks associated with locating in flood prone areas.

To evaluate the sensitivity of our results to the selection of control zip codes we also considered a different comparative standard when the location responsible for flooding risk was associated with only one type of resource. These results are for Arizona, Maryland, Missouri, Virginia, and West Virginia. In these cases the control zip code is not the adjacent location. We select locations separated by at least the adjacent zip code. They are in the state and close to the zip codes that are closest to the source of the flood risk. We have labeled them as “nearby”. This strategy is an approximate attempt to parallel the use of a “doughnut” structure that has served as an effective strategy in defining instruments in the estimation of sorting models. Column seven, eight and nine report these estimates for the flexible and constant effect models. In the cases of Arizona (Maricopa County) and Virginia our general conclusions would be comparable to what was learned using the adjacent zip codes as controls. Both indicate lower incomes in areas close to the risk. The magnitude of the estimated constant differential varies with the control selected. For Arizona the difference is larger and for Virginia it is smaller in absolute magnitude. For Maryland and West Virginia the results reverse the judgement about the direction of

[19] The online appendix provides a complete listing of all the zip codes included in our analysis of the AIRS sample. Appendix C provides graphs of the estimated real median incomes by year for shoreline and adjacent interior zip codes for each state.

stratification with the selection of the control and the statistical support for a differential is stronger.

We don't want to over interpret these differences. Zip codes are defined by the postal service for one set of objectives. There are many spatial boundaries that can be used as proxy measures for services conveyed to households because of their locations. Local communities have different public services and tax rates; school districts can affect the conditions of access to different types of schools; sub-divisions and HOAs also affect what homeowners have access to and are expected to pay for. So comparisons across zip codes don't allow us to control these other dimensions. Indeed, when we consider all of these details it is remarkable that the effects of sorting are so clear-cut in the coastal locations as well as in some of the other SFHA locations.

Given the aggregate nature of our data source (IRS tabulations) and the limited ability to exercise spatial control due to confidentiality limitations on our ability to isolate below the zip code level, we conclude that these results offer compelling support for recognizing how spatial sorting can influence the incidence of policies to provide affordable flood insurance that are defined based on location and age of a structure rather than on income. In the next section, we discussed how these findings contrast with the existing literature and why the differences in our result are important to reforming the NFIP.

6. Discussion

Previous research on the welfare impacts of policy changes and how they are evaluated emphasizes two points: (a) the importance of accounting for behavioral responses to a change in policy and the role of income and substitution effects in influencing the marginal willingness to pay for the "full" incremental costs of what is being evaluated (Hendren [2016]); and (b) the implications of how behavioral decisions affect the risk actually experienced for policies involving subsidies or mandates for insurance (Hendren [2018]). We argued that the same concerns arise in judgments being made about the affordability of flood insurance. Musgrave anticipated the importance of behavior in proposing what amounts to a general equilibrium perspective in judging the incidence of policies. That is, he wanted measures of income distributions before and after a policy change was made in order to judge incidence. His reasoning was not as fully developed as what Hendren offers in his discussion of what he labels as the "policy elasticity", but the connection is direct.

Judgments about affordability of flood insurance should take this *ex ante* perspective. In evaluating the incidence of any benefits attributed to assuring affordable insurance rates to protect against floods we want to know the income distribution for those households who *could* face flood risks. This perspective is important in judging the affordability of rates. A subsidized set of insurance rates policy affects both where they locate and whether they purchase insurance. Of course, defining a counterfactual that is consistent with an *ex ante* perspective is a tall order, especially in the face of a continuously changing landscape of policy and storm events. One way to address these issues is with a structural model for the sorting behavior of households. Recently Walls et al. [2018] have used a simulation framework with an agent-based model to evaluate who would bear the effects of increased storm frequency in a setting that is parameterized to mimic the mid-Atlantic region of the US. Their framework assumes agents are risk neutral and trade-off expected damage, coastal amenities, and housing costs. In this setting, price effects induce poor households to locate in high risk areas. With changes in their model's parameters or how they treat storm related damages, we should expect very different results[20].

We adopted an empirical perspective and take advantage of the variations in geography to characterize the counterfactuals in our analysis of incidence. By considering eight years of experience that overlap hurricanes and flooding events in risk prone areas we allow for changes that should lead households to update their perceptions of risks. We do not attempt to distinguish policyholders from non-policyholders and only identify households likely to be eligible for flood insurance through our focus on those claiming the mortgage interest deduction.

Our approach which focuses on eligibility for insurance and exposure to risk contrasts with all the past evaluations of affordability. The past analyses have largely focused on the distinctions between policyholders and non-policyholders. These evaluations overlook the importance of Hendren's [2018] argument[21]. The behavioral choice of insurance affects what is actually at risk for each type of household –those choosing to purchase insurance and those who

[20] The simple outline of the effects of single crossing assumption in our expected utility model in Appendix A is one example of how these changes could influence their findings. Our unambiguous reduced form results supporting positive income stratification for coastal locations in Florida is another.

[21] He also credits Hirshleifer's [1971] much earlier work with similar insights.

do not. As a result, it will affect any judgment about the incidence of these policies for different income groups. An *ex ante* perspective for judging incidence and affordability requires we consider the income distributions for households under conditions that ignore their insurance status in an attempt to mimic the situation before these choices are made. Our analysis of aggregate records that does not distinguish those who have flood insurance policies is one way to meet this objective

Some examples of the recent literature attempting to address affordability illustrate the potential problems. The new FEMA study created a unique database for assessing affordability by linking the NFIP policy information with household income and housing cost information from the American Community Survey (ACS). The 4.5 million active NFIP policy holders as of 2015 were matched by identity to the ACS households in the survey for that year. Over 64,000 matches were developed. Using census weights, the report compares incomes of policy holders to non-policy holders inside and outside SFHAs. The design of the FEMA affordability analysis is directly tied to the structure of the NFIP. Table 4 here reproduces Table 2.6 from the report. It compares median income by housing tenure, mortgage status, policy status, and location (i.e. inside and outside SFHAs). The median incomes are lower inside SFHAs regardless of the tenure and policy status compared to those outside. However, for those without mortgages, where there is no requirement to purchase insurance, the median income difference is relatively small. It appears more substantial with aggregation. For example, elsewhere in the report (taken from Table 2.3) when households are aggregated over tenure and mortgage status the difference in median incomes for policy holders and non-policy holders is more dramatic –77k for policy holders and 40k for non-policy holders inside SFHAs. The “take away” message of this assessment appears to be that once again lower income households face higher flood risks.

All of the other past efforts also confound distinct issues. These issues amount to different types of selection effects as to who is in and out of the sub-samples being evaluated. For example, another recent study by Bin et al. [2017] examined premiums to coverage and claims to coverage at the zip code level. These data were summarized in comparison to summary statistics for census tract income also summarized to the zip code level. Their analysis finds that premiums per unit of coverage decline with income. However, they are cautious in interpreting these findings and conclude calling for the need to consider the relationship between income and the receipt of a pre-FIRM price discount. More specifically they note: "We are unable to determine with this data, however, whether this is because higher income zip codes are less risky on average than lower zip codes, so they are able to purchase more coverage for the same price, or if this finding is driven by correlations between income and pre-FIRM discounts or other pricing structures of the NFIP" (Bin et al [2017] p.6).

Our analysis finds that judgments about affordability of flood insurance are more nuanced than either the popular accounts of subsidizing millionaires or these the FEMA concern that poor households are driven by housing costs to opt out of safe locations into areas prone to flood risks and without place based subsidies could not afford insurance. Households' behavior in response to coastal amenities, risk, and local housing markets, together with current policy, lead in some areas (notably the Gulf and Atlantic Coasts of Florida, coastal locations in New Jersey, and both coastal and river locations in New York) to outcomes where current policy might be judged as providing *subsidies to higher income households*. In other cases, however, such as the coastal locations in California, North Carolina, as well as the shoreline along rivers identified as SFHA in Delaware, and Virginia, the lower income households are indeed in the higher flood risk areas. These findings did not require the assumptions associated with a formal structural model of sorting behavior and are robust across model specifications.

7. Summary and Implications

After the National Flood Insurance Program's authorization expired in 2017, the program received several short-term extensions. The current temporary reauthorization has the program expiring in May 2019. FEMA's fourth quarterly *Watermark* report noted a goal that the NFIP will transform, over time, to a more fiscally sustainable program and expand the private market for insurance. In the interim, the agency has recommended that Congress authorized the NFIP to establish a *means-tested* affordability program that allows low income policyholders to maintain discounted rates. The report is not specific about what the rates would be in high risk areas compared to those for others. Concerns about the transition between the current system and one where rates reflect actuarial conditions have in the past prompted the continuation of subsidies. Our results support an approach that is directed at requiring affordability based rates to be linked to a *means test* using the income levels to evaluate those households judged as eligible. To our knowledge, our assessment offers the most comprehensive evaluation of the incidence of the

NFIP to date, both in terms of the geographic scale of the coverage of flood related resources, and the time span considered. We found that there are clear patterns of positive income stratification in some regions where the amenity levels likely outweigh the flood risks. Coastal locations in Florida, New Jersey, and New York seem consistent with the predictions of a Tiebout sorting model in attracting higher income households. So insurance subsidies under the current NFIP system based on place and timing of construction of houses would tend to favor these high income groups. At the same time, we find the program in other areas would benefit some lower income households. Thus, if one of the program's goals is to assure affordability through subsidies, this objective requires targeting with a means test for eligibility.

Table 1: Summary of the Communities from the AIR Study in Current Sample

Cluster	Participating Communities with Detailed SFHAs	Participating Communities with Only Approximate Zone A SFHAs	Participating Communities without Maps	Non-Participating Communities with Maps	Non-Participating Communities without maps	Undetermined[1]	Total
California-North	129	18	27	0	12	22	208
Coastal North Carolina/ Virginia	84	17	5	0	34	16	156
Florida Panhandle*	69	33	3	2	25	1	133
Florida-West Coast*	92	10	3	0	19	11	135
Louisiana*	126	47	12	0	28	13	226
Mid-Atlantic	364	51	13	0	72	26	526
Mississippi River	218	77	30	5	182	9	521
Southwest	47	2	1	0	2	0	52
Texas-Coastal*	132	27	7	0	10	3	179
Washington Baltimore	243	63	13	2	67	13	401

[1] The undetermined category includes communities with identified discrepancies between the 44 CFR §60.3 ordinance level. Source: Mathis and Nicholson [2006].

Table 2: Difference in Real Median Income and Measure of Income Distributions for Shoreline and Adjacent Interior Zip Codes:

Gulf and Atlantic Coast of Florida and Gulf Coast States -2009-2016

State		**Median**	**Constant**	**$1 to $25K**	**$25k**	**$50k**	**$75k to**	**$100k to**	**Over**
Source			**Effect Difference**		**to $50k**	**to $75k**	**$100K**	**$200k**	**$200k**
Alabama									
IRS									
	Zip code 2009-2016	**0.10**	**1,511**	**0.48**	**0.88**	**0.91**	**0.57**	**0.37**	**0.17**
n=241		**(p=0.99)**	**(p=0.76)**	**(p=0.87)**	**(p=0.53)**	**(p=0.51)**	**(p=0.81)**	**(p=0.94)**	**(p=0.99)**
Florida-Gulf									
IRS									
	Zip code 2009-2016	**18.09**	**12,545**	**1.61**	**11.4**	**4.1**	**4.08**	**3.38**	**30.5**
n=1872		**(p=0.00)**	**(p=0.00)**	**(p=0.12)**	**(p=0.00)**	**(p=0.00)**	**(p=0.00)**	**(p=0.00)**	**(p=0.00)**
Florida-Atlantic									

IRS									
	Zip code 2009-2016	31.4	17,916	0.99	25.83	11.02	5.13	1.21	50.21
n=2240		(p=0.00)	(p=0.00)	(p=0.44)	(p=0.00)	(p=0.00)	(p=0.00)	(p=0.29)	(p=0.00)
Louisiana									
IRS									
	Zip code 2009-2016	5.97	-12,960	2.23	0.71	2.38	2.14	4.18	2.56
n=536		(p=0.00)	(p=0.00)	(p=0.02)	(p=0.68)	(p=0.02)	(p=0.03)	(p=0.00)	(p=0.01)
Mississippi									
IRS									
	Zip code 2009-2016	0.14	-1,767	0.72	0.14	0.31	2.14	0.38	1.94
n=176		(p=0.99)	(p=0.37)	(p=0.67)	(p=0.99)	(p=0.96)	(p=0.03)	(p=0.93)	(p=0.06)
Texas									
IRS									
	Zip code 2009-2016	0.12	-598	1.98	0.83	0.89	0.53	1.17	1.93
n=832		(p=0.99)	(p=0.68)	(p=0.05)	(p=0.58)	(p=0.53)	(p=0.83)	(p=0.31)	(p=0.05)

Table 3: Test of Stratification with Real Median Income 2009-2016 at Zip Code Level: SFHA Areas in US

			Adjacent Control				"Nearby" Control				Sample	
			Model				Model				Sizes	
State	**Resource**	**Constant**	**Difference**	**Year Specific**		**Constant**	**Difference**	**Year Specific**		**Adjacent**		**"Nearby"**
Arizona	**River**	N (0.00)	-5,757	N (NS)		N (0.00)	-20,305	N (0.00)		391		492
California	**Ocean**	N (0.00)	-10,571	N (0.09)						864		
California	**River**	P (0.02)	6,197	P (NS)						368		
Delaware	**Ocean**	P(0.00)	6,128	P(NS)						160		
Delaware	**River**	N (0.00)	-26,075	N (0.00)						112		
Illinois	**River**	N (0.00)	-4,573	N (NS)						578		
Illinois	**Lake**	P (NS)		P (NS)						144		
Maryland	**Ocean**	P (0.01)	7,631	P (NS)		N (0.00)	-21,080	N (0.00)		369		569
Missouri	**River**	P (NS)		P (NS)		N (0.07)	-4,578	N (NS)		864		672
North Carolina	**Ocean**	N (0.04)	-5,423	N (NS)						424		
North Carolina	**River**	P (NS)	-4,700	P(NS)						128		
New Jersey	**Ocean**	P (0.01)	11,620	P (NS)						552		
New Jersey	**River**	N (NS)		N (NS)						608		
New York	**Ocean**	P (0.00)	11,006	P (0.00)						528		
New York	**River**	P (0.00)	23,744	P (0.01)						64		
Pennsylvania	**Lake**	P (0.00)	17,624	P (0.01)						112		
Pennsylvania	**River**	N(NS)		N (NS)						872		
Virginia	**River**	N (0.00)	-28,316	N (0.02)		N (0.00)	-13,516	N (NS)		152		288
West Virginia	**River**	N (NS)		P (NS)		P (0.00)	11,737	P (0.00)		104		256

Table 4: FEMA's 2018 Summary of Income Status of NFIP Policy Holders and Non-Policy Holders

		Policy Holders		Non-Policy Holders	
		In SFHA	Out SFHA	In SFHA	Out SFHA
Homeowners	With Mortgage	$85,000	$104,000	$66,000	$83,000
		(1.1 M)	(1.0 M)	(661000	(41.5 M)
	Without Mortgage	$70,000	$74,000	$40,000	$49,000
		(388000	(657000	(1.0 M)	(23.8 M)
Renters	Pay Rent	$52,000	$61,000	$34,000	$36,000
		(253000	(191000	(1.5 M)	(33.8 M)
	Not Pay Rent	$36,000	$40,000	$25,000	$28,000
		(22000	(20000	(103000	(1.9 M)
Total Households		**(1.76 M)**	**(1.89 M)**	**(3.26 M)**	**(101.0 M)**

SOURCE: FEMA analysis of NFIP policyholder data and Census ACS data.
NOTE: Data weighted using ACS sample weights; median income rounded to nearest $1,000; number of households rounded to nearest 100,000; M = millions
The numbers in parentheses correspond to the number of households

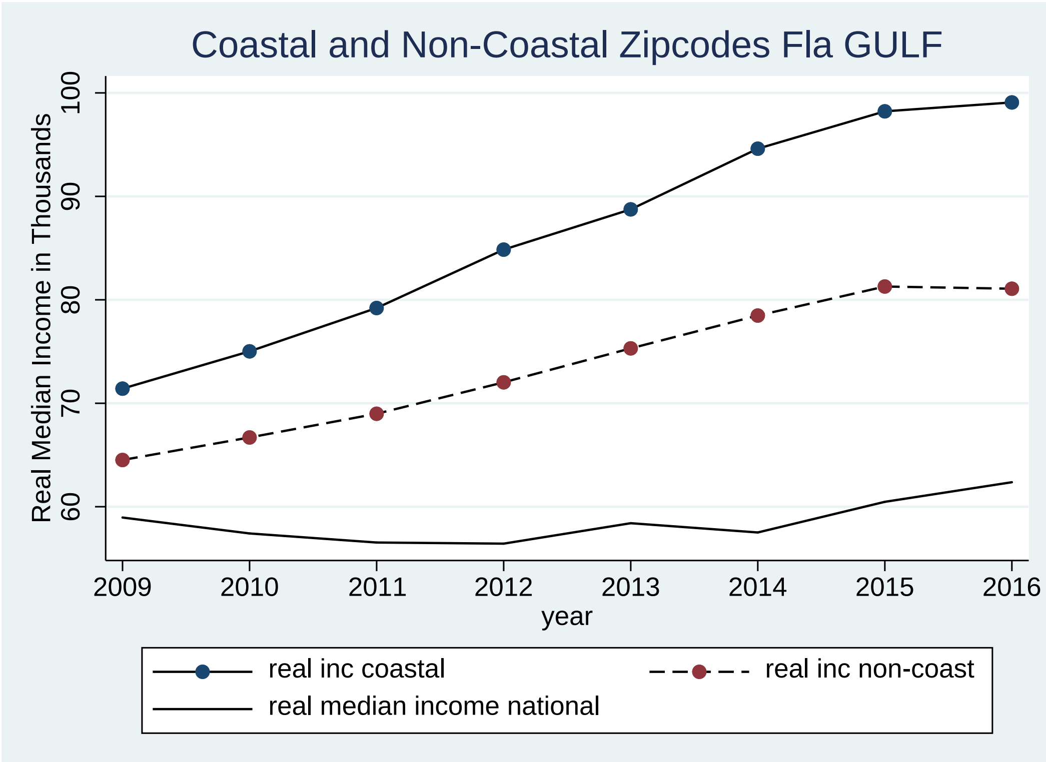

Figure 1: Real Median Income (2015$) from IRS Zip code Summaries: Florida Gulf Coast

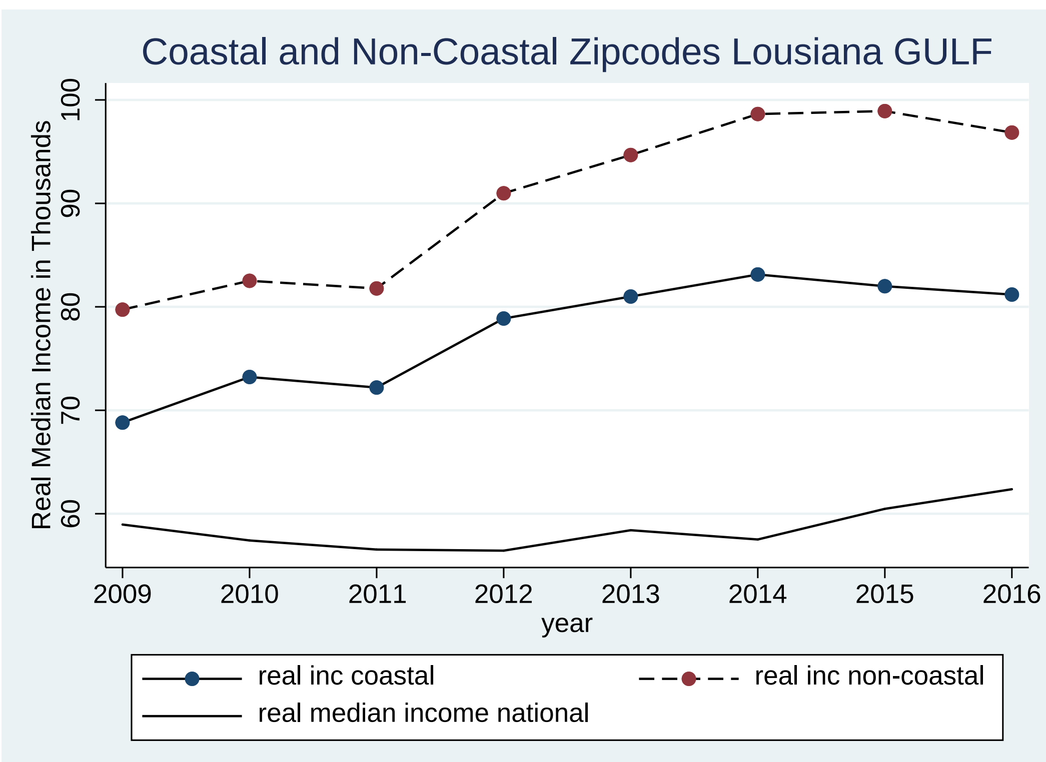

Figure 2: Real Median Income (2015$) from IRS Zip code Summaries: Louisiana Coast

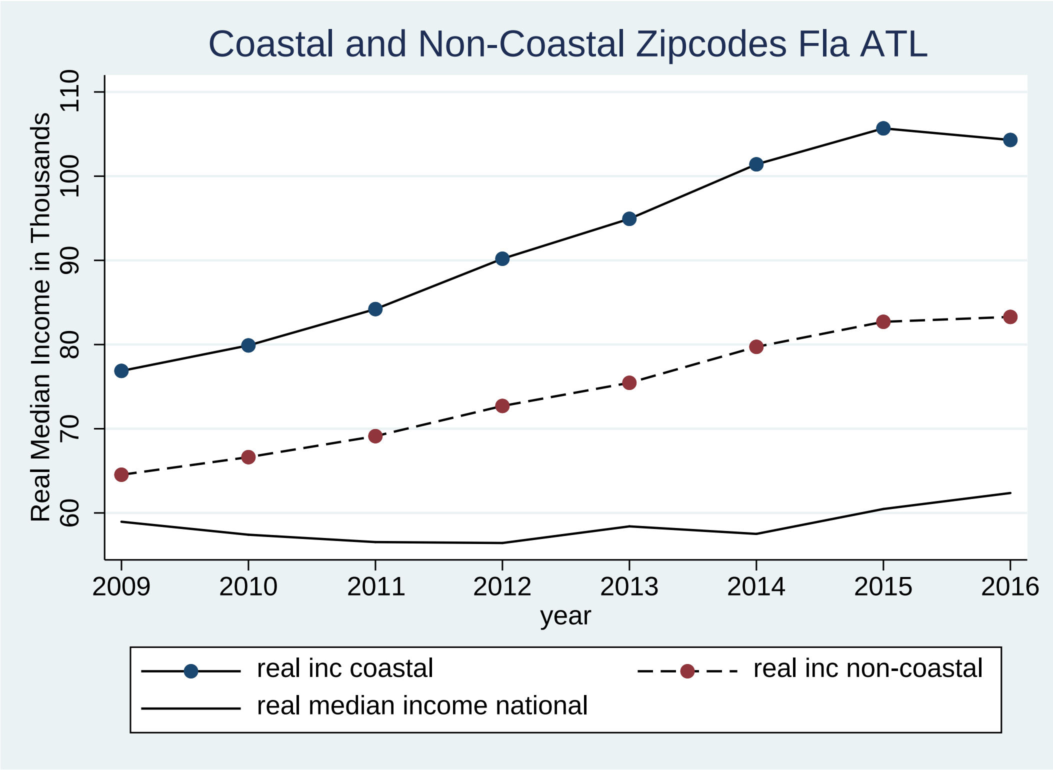

Figure 3: Real Median Income (2015$) from IRS Zip code Summaries: Florida Atlantic Coast

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Appendix A

The purpose of this Appendix is to summarize one approach to explaining how the single crossing property would imply income stratification within an expected utility framework. We assume a household can be represented with a single preference function.

Let $V(p, m, q)$ be the household's indirect utility function with p the rental price of housing, m household income and q a measure of coastal or water based amenities. We assume other prices are fixed and thus omit them from the function. The function is also assumed to well behaved, derived from a quasi-concave direct utility function assuming utility maximization subject to a budget constraint. In a sorting model, households select a community based on housing prices and local public goods. So that in these applications p and q would be indexed by community.

We use a static framework and assume the probability of flood damage is π. The effects of a flood are assumed to lead to income loss, represented here as D. This treatment is an important restriction. Our objective here is simply is illustrate one way in which sorting could lead to income stratification. Modifying the assumptions for how flood damage affects preferences or introducing parameters to allow for differences in tastes (see Sieg et al.[2004]) would imply incomplete stratification. And this is one of the primary motivations for the empirical analysis in this paper. Our goal here is to illustrate what would be needed for a structural model that would be consistent with tendencies for income stratification.

Expected utility is given as follows:

$$(1)\quad EU = \pi V(p, m - D, q) + (1 - \pi) V(p, m, q)$$

The maintained assumptions underlying our analysis imply that selecting a coastal location (or near a water body subject to flooding) for the water based amenities increases the risk of flood related damage. To introduce this logic into the model we assume the probability of damage is a function of q. This treatment implies (1) can be re-written as:

$$(2)\ \ EU = \pi(q)V(p, m-D, q) + \big(1-\pi(q)\big)V(p,m,q)$$

The single crossing property in this setting asks how the tradeoff between *p* and *q*, along a constant expected utility locus (and thus in *ex ante* terms) changes with income. In terms of this simple framework this is given by:

$$(3)\ \ \frac{\partial}{\partial m}\left(\frac{dp}{dq}\right) = \frac{\partial}{\partial m}\left(-\frac{EU_q}{EU_p}\right)$$

We develop this expression step by step.

$$(4a)\ \ EU_q = \pi' V(p, m-D, q) - \pi' V(p,m,q) + \ \pi V_q(p, m-D, q)$$
$$+ (1-\pi)V(p,m,q)$$

$$(4b)\ \ EU_p = \ \pi V_p(p, m-D, q)\ + (1-\pi)V_p(p,m,q)$$

So $\frac{\partial}{\partial m}(\frac{dp}{dq})$ in the *ex ante* case can be expressed as follows:

$$-\frac{\left(\pi'\big(V_m(p, m-D, q) - V_m(p,m,q)\big) + \pi V_{qm}(p, m-D, q) + (1-\pi)V_{qm}(p,m,q)\right)}{\pi V_p(p, m-D, q) + (1-\pi)V_p(p,m,q)}$$

$$+\frac{(\pi'\left(V(p,m-D,q)-V(p,m,q)\right)+\ \pi V_q(p,m-D,q)+(1-\pi)V_q(p,m,q))*(\pi V_{pm}(p,m-D,q)+(1-\pi)V_{pm}(p,m,q))}{(\pi V_p(p,m-D,q)+(1-\pi)V_p(p,m,q))^2}$$

The sign of these terms could be positive or negative, depending on plausible assumptions. More specifically, consider the first expression, the denominator is negative and we would expect the terms in the numerator are likely to have the same signs -- $(\pi'\left(V_m(p,m-D,q)-V_m(p,m,q)\right)$ is likely positive (diminishing marginal utility of income) and $\pi V_{qm}(p,m-D,q)+(1-\pi)V_{qm}(p,m,q)$ is positive. So the overall sign (including the leading negative sign) is positive. The second expression has a positive denominator. The first term in the numerator $((\pi'\left(V(p,m-D,q)-V(p,m,q)\right))$ is negative. The second term $(\pi V_q(p,m-D,q)+(1-\pi)V_q(p,m,q))*(\pi V_{pm}(p,m-D,q)+(1-\pi)V_{pm}(p,m,q))$ is positive for normal goods. That is, assuming $V_{pm}>0$. As a result, we need to consider first whether the second term is negative and then the net effect. If it is negative we need to consider the size of this effect in relationship to the first term to assess whether the single crossing property holds. It depends on the relative magnitude of these effects.

Appendix B – Gulf Coast Graphs

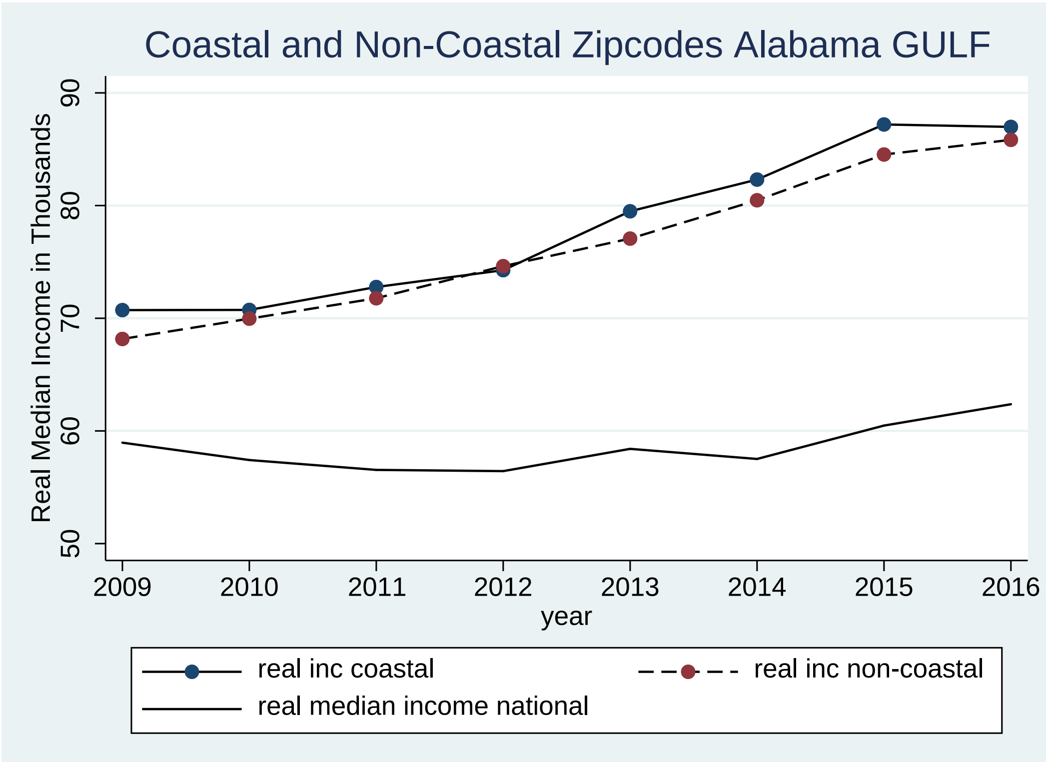

Figure 1b: Real Median Income (2015$) from IRS Zip code Summaries: Alabama Coast

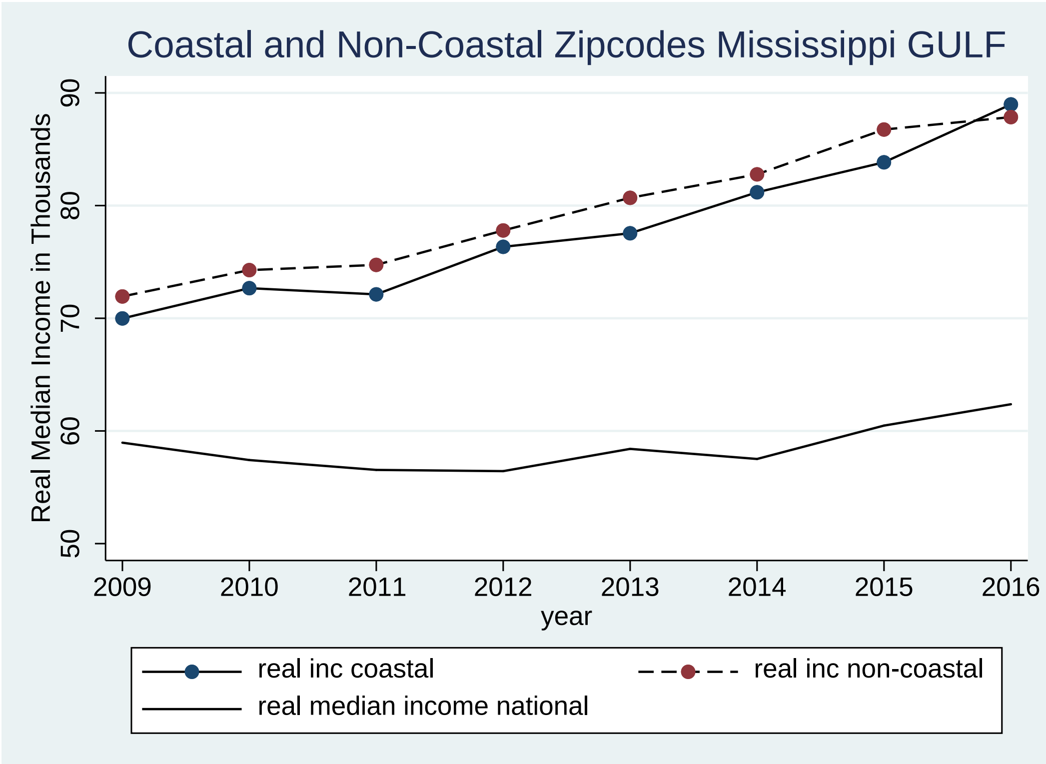

Figure 2b: Real Median Income (2015$) from IRS Zip code Summaries: Mississippi Coast

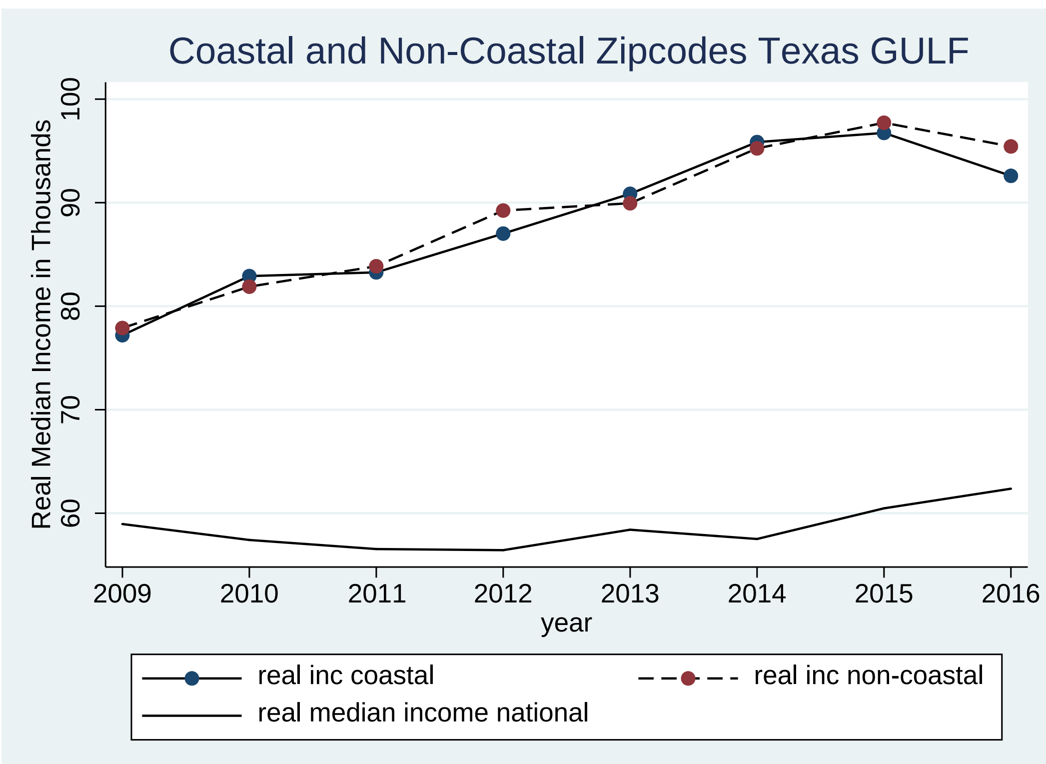

Figure 3b: Real Median Income (2015$) from IRS Zip code Summaries: Texas Coast

Appendix C - SFHA Graphs

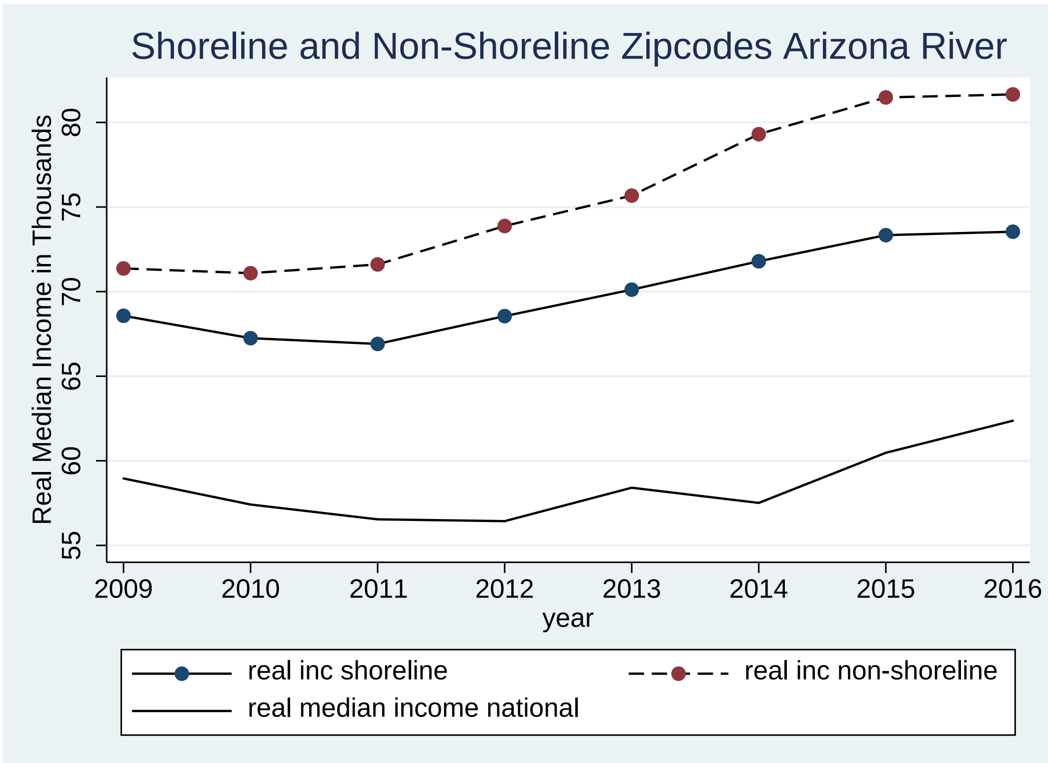

Figure 1c: Real Median Income (2015$) from IRS Zip code Summaries: Arizona River and Adjacent

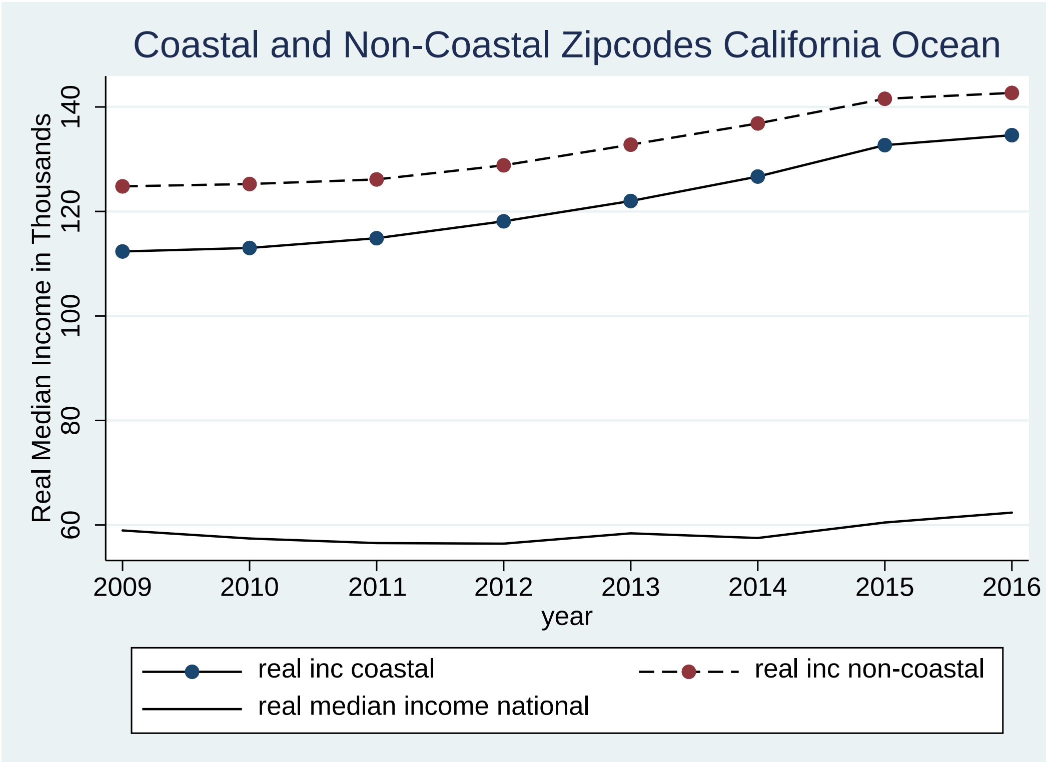

Figure 2c: Real Median Income (2015$) from IRS Zip code Summaries: California Ocean and Adjacent

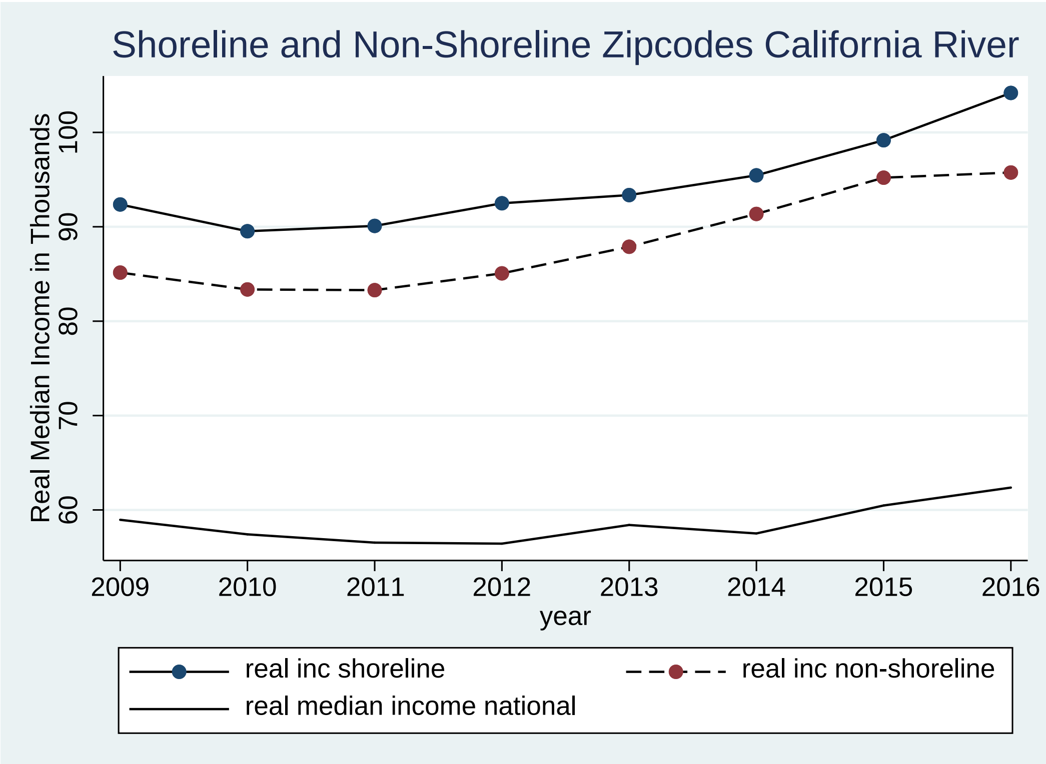

Figure 3c: Real Median Income (2015$) from IRS Zip code Summaries: California River and Adjacent

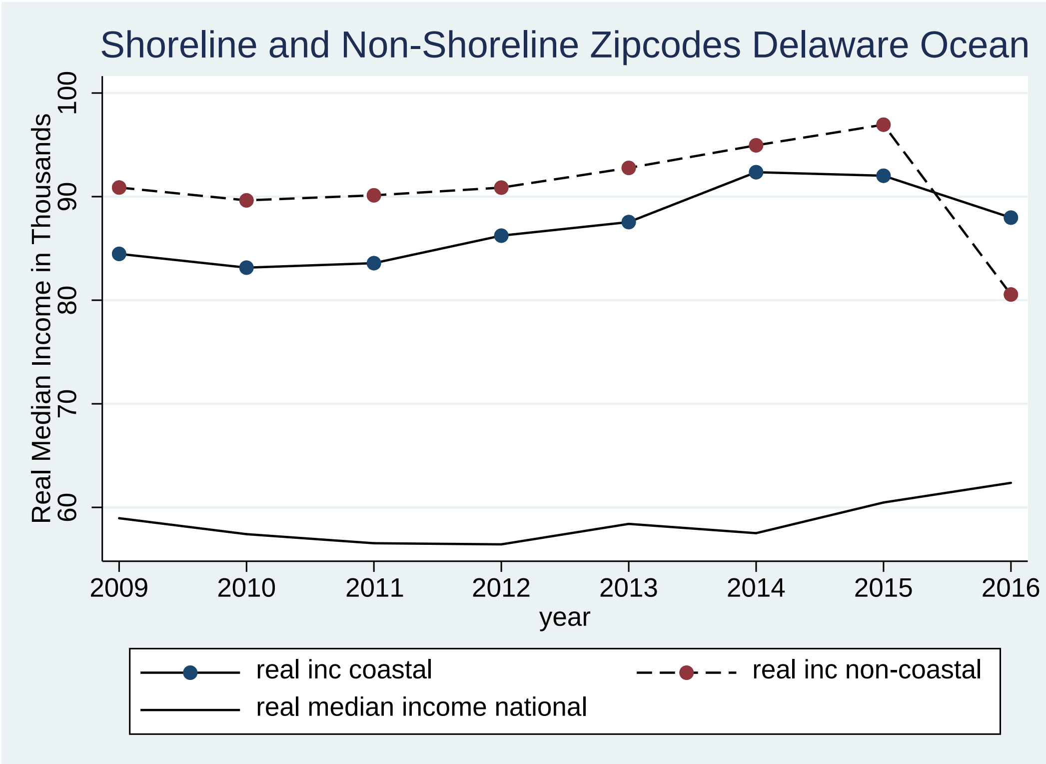

Figure 4c: Real Median Income (2015$) from IRS Zip code Summaries: Delaware Ocean and Adjacent

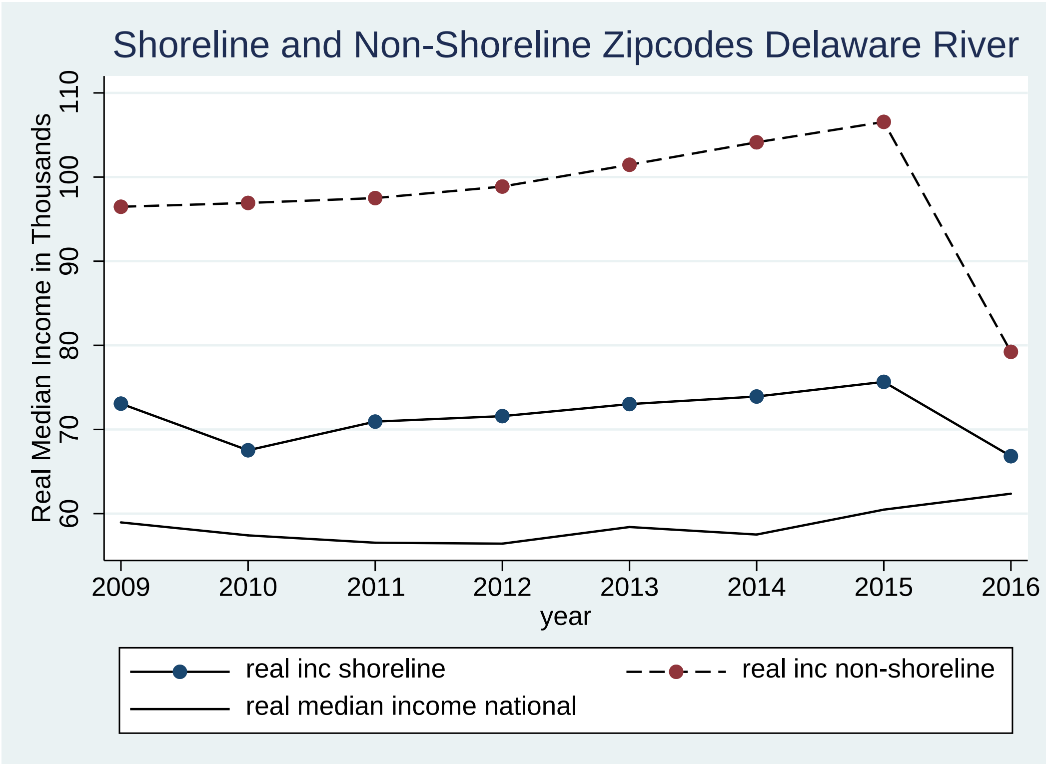

Figure 5c: Real Median Income (2015$) from IRS Zip code Summaries: Delaware River and Adjacent

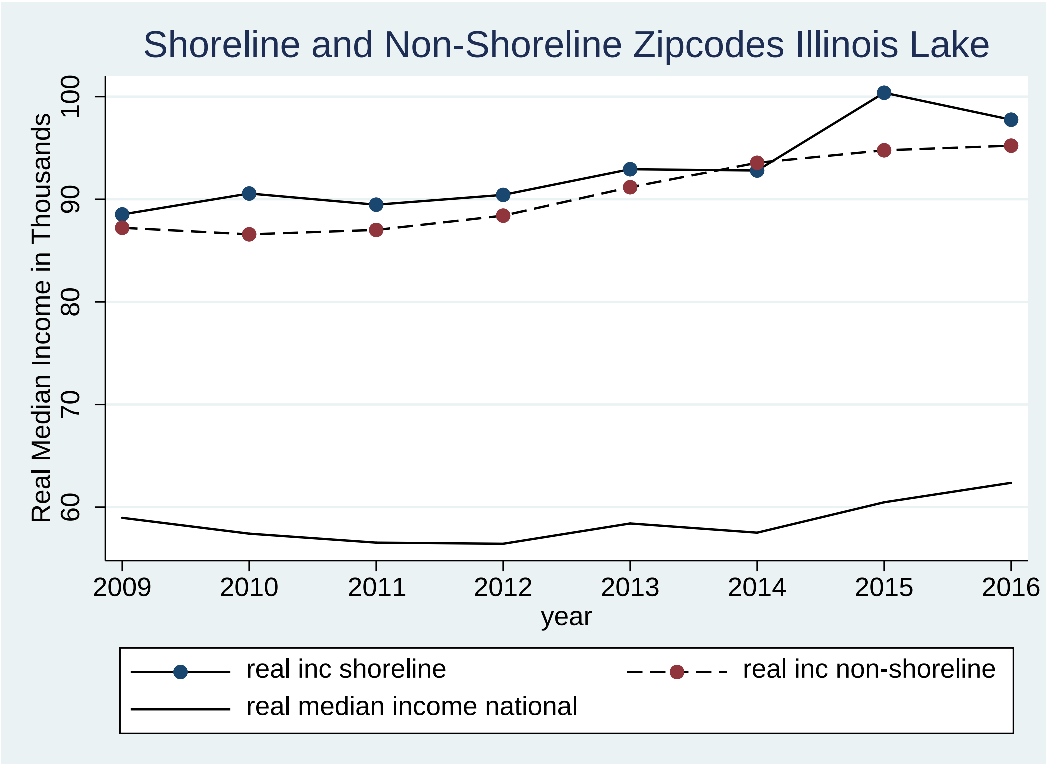

Figure 6c: Real Median Income (2015$) from IRS Zip code Summaries: Illinois Lake and Adjacent

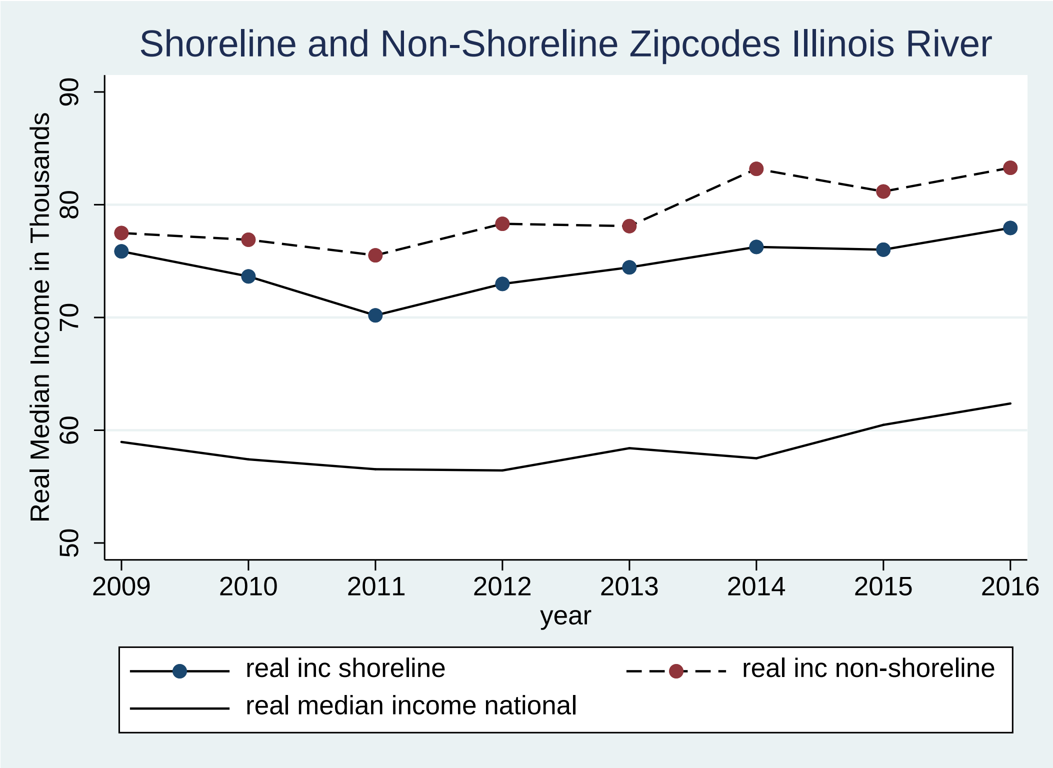

Figure 7c: Real Median Income (2015$) from IRS Zip code Summaries: Illinois River and Adjacent

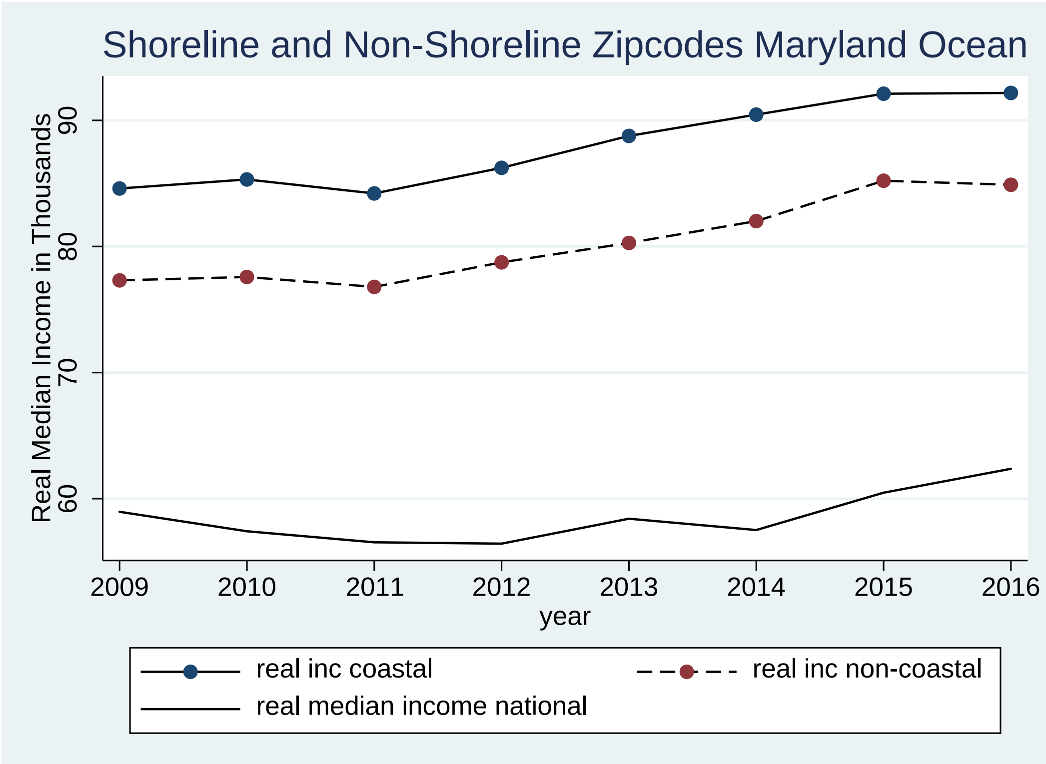

Figure 8c: Real Median Income (2015$) from IRS Zip code Summaries: Maryland Ocean and Adjacent

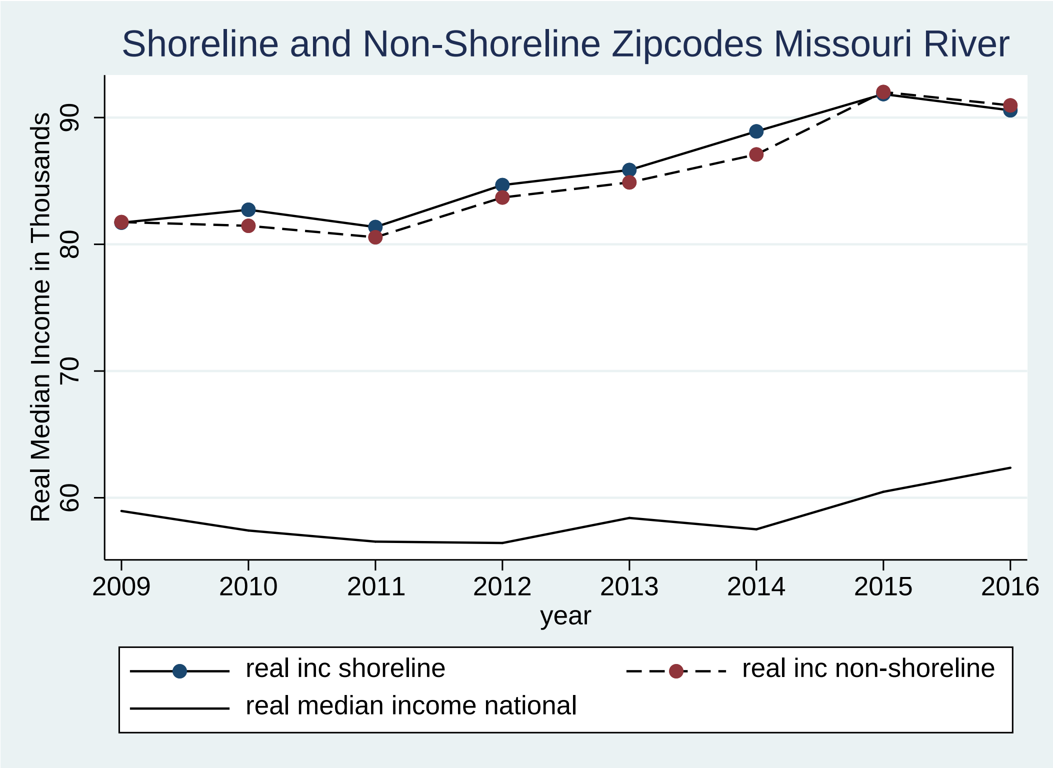

Figure 9c: Real Median Income (2015$) from IRS Zip code Summaries: Missouri River and Adjacent

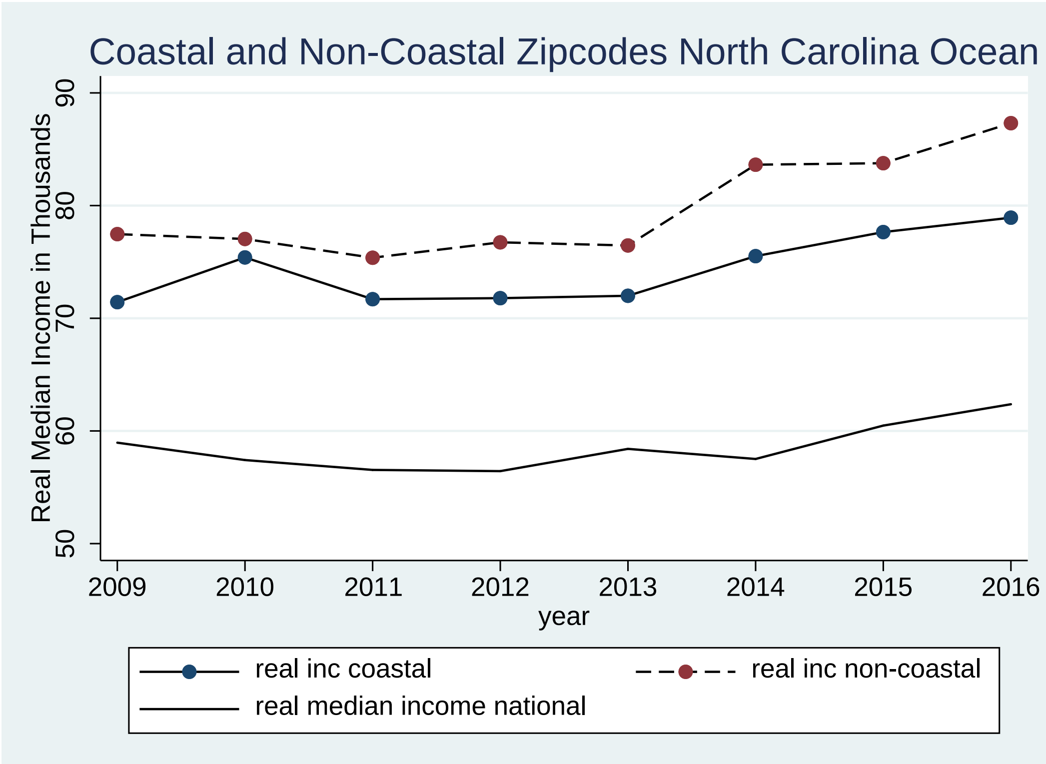

Figure 10c: Real Median Income (2015$) from IRS Zip code Summaries: North Carolina Ocean and Adjacent

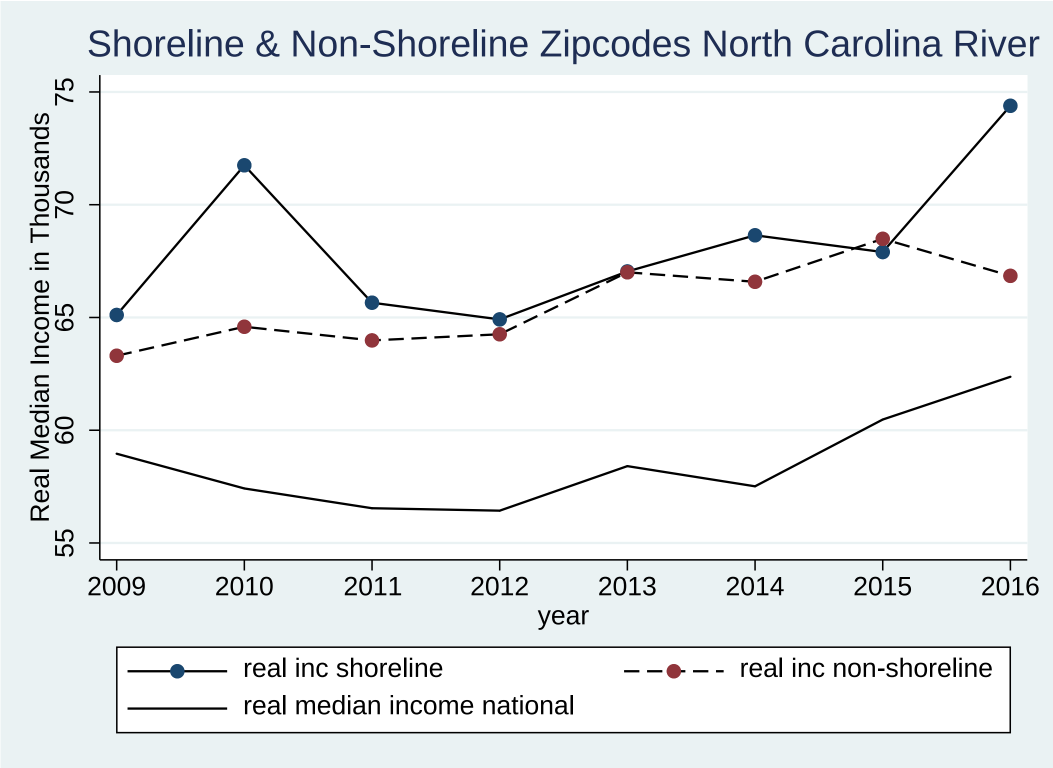

Figure 11c: Real Median Income (2015$) from IRS Zip code Summaries: North Carolina River and Adjacent

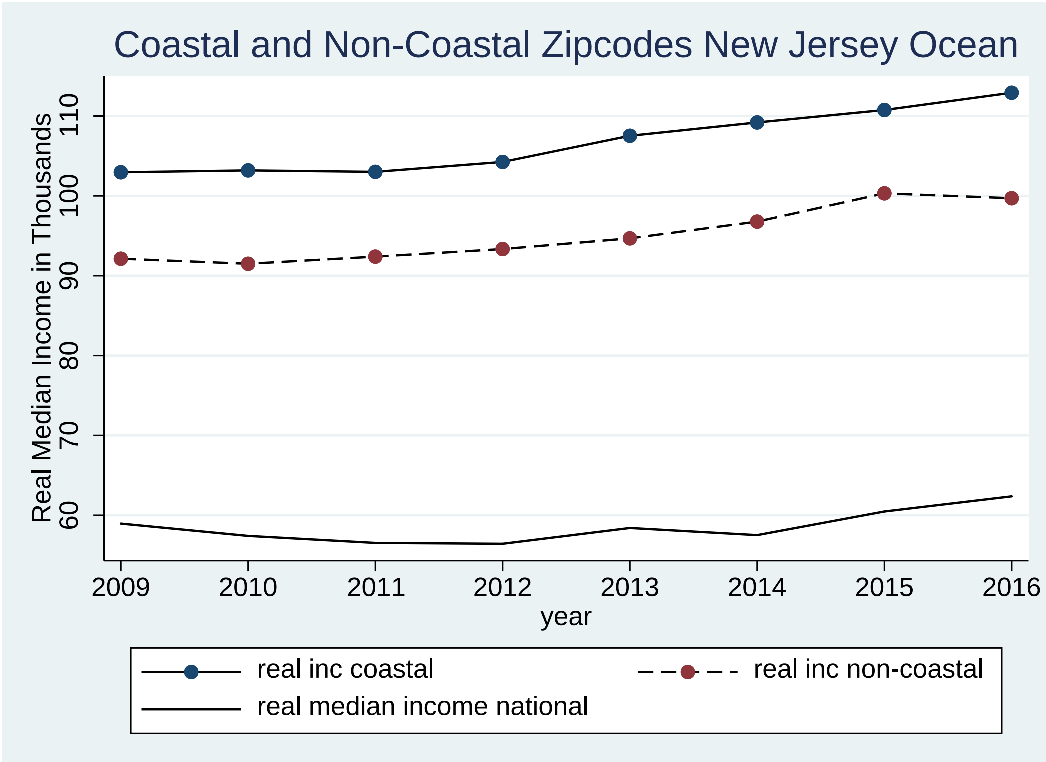

Figure 12c: Real Median Income (2015$) from IRS Zip code Summaries: New Jersey Ocean and Adjacent

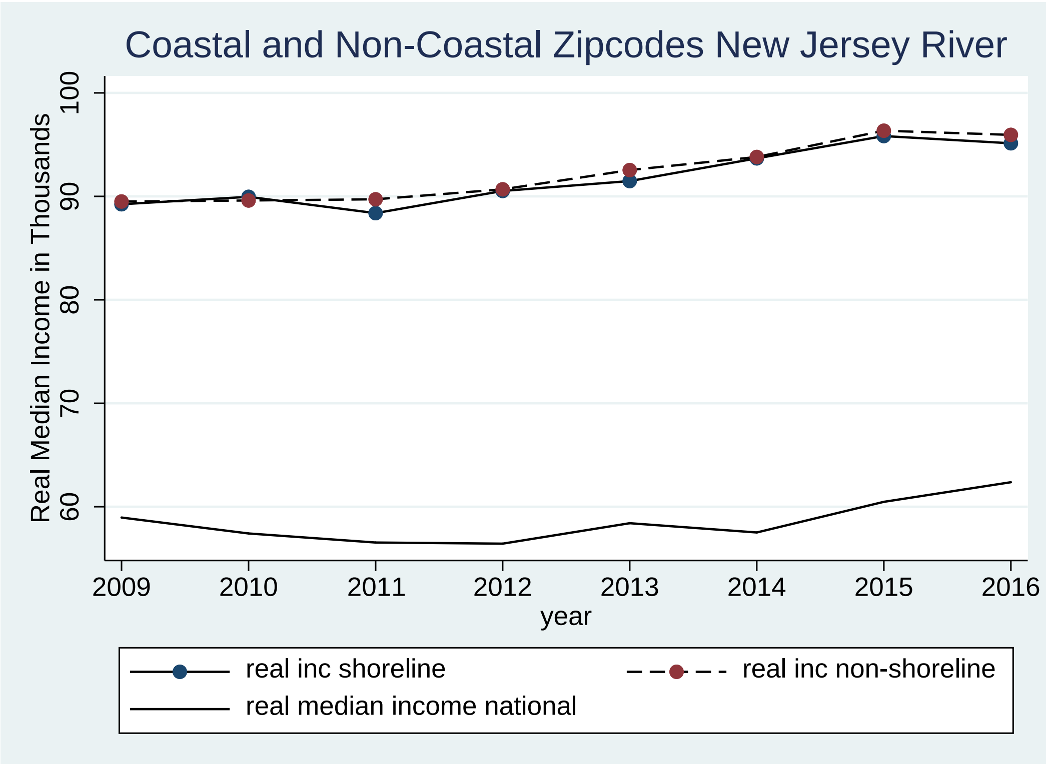

Figure 13c: Real Median Income (2015$) from IRS Zip code Summaries: New Jersey River and Adjacent

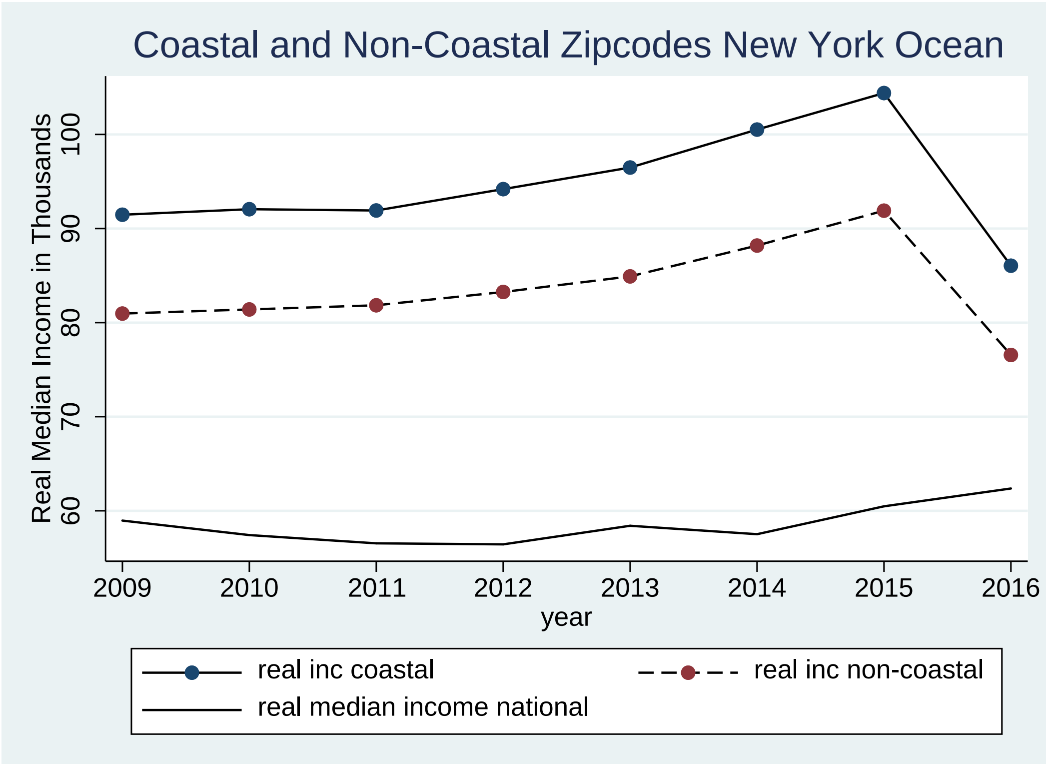

Figure 14c: Real Median Income (2015$) from IRS Zip code Summaries: New York Ocean and Adjacent

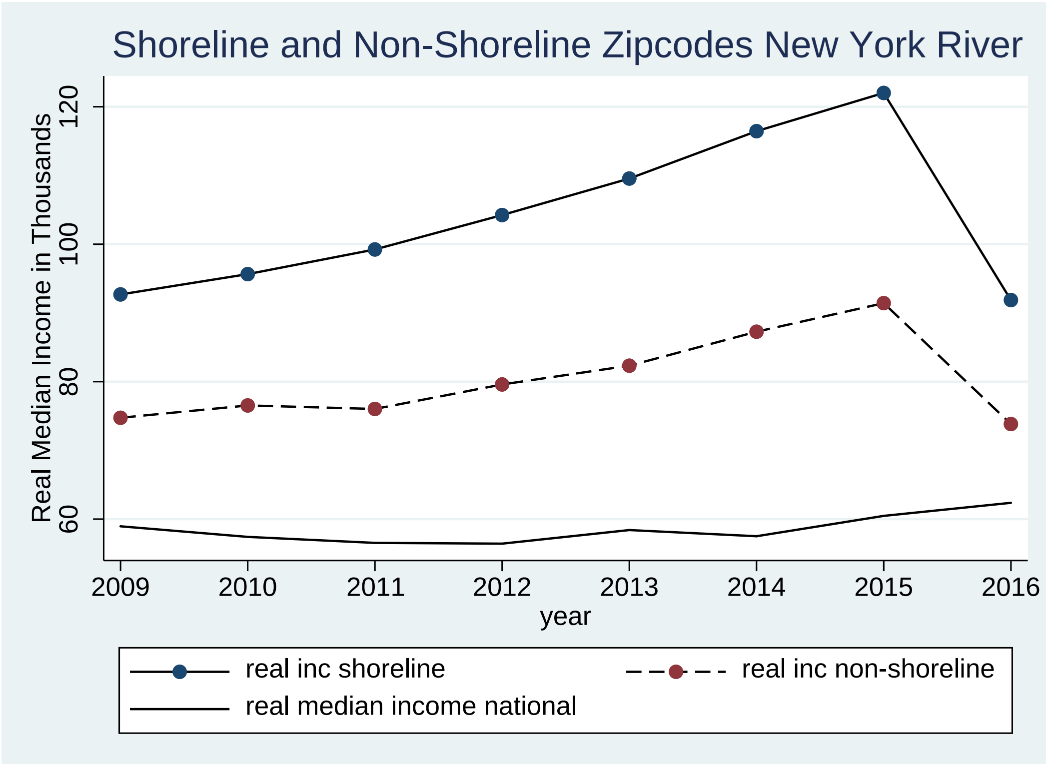

Figure 15c: Real Median Income (2015$) from IRS Zip code Summaries: New York River and Adjacent

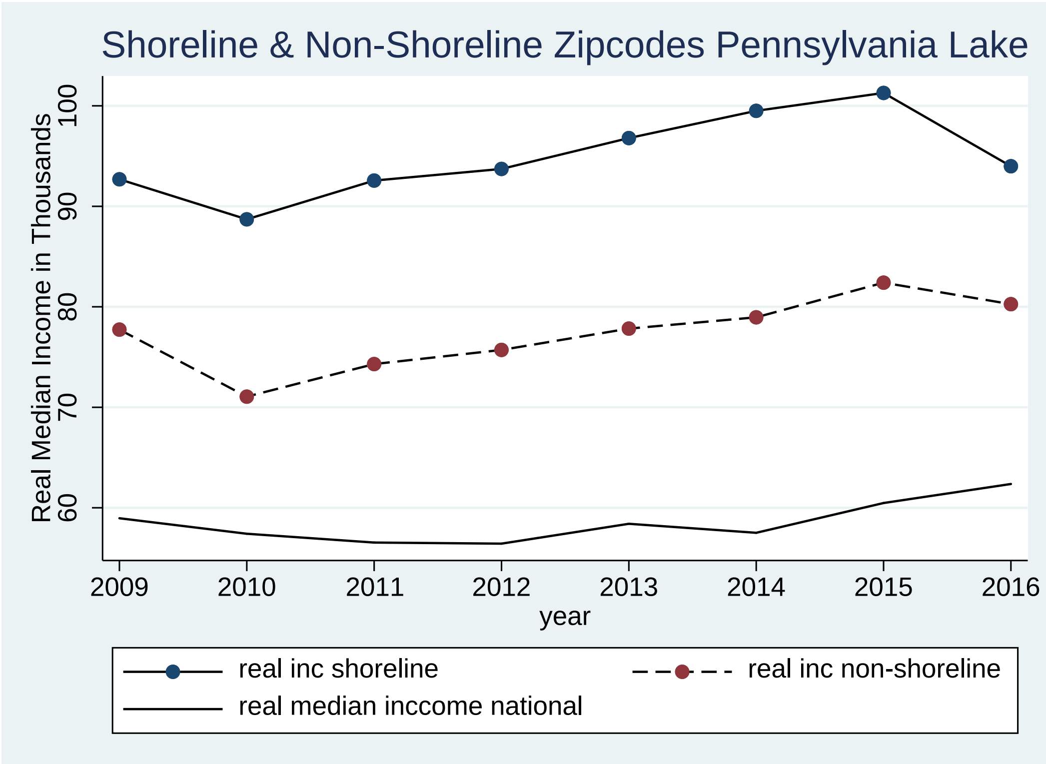

Figure 15c: Real Median Income (2015$) from IRS Zip code Summaries: Pennsylvania Lake and Adjacent

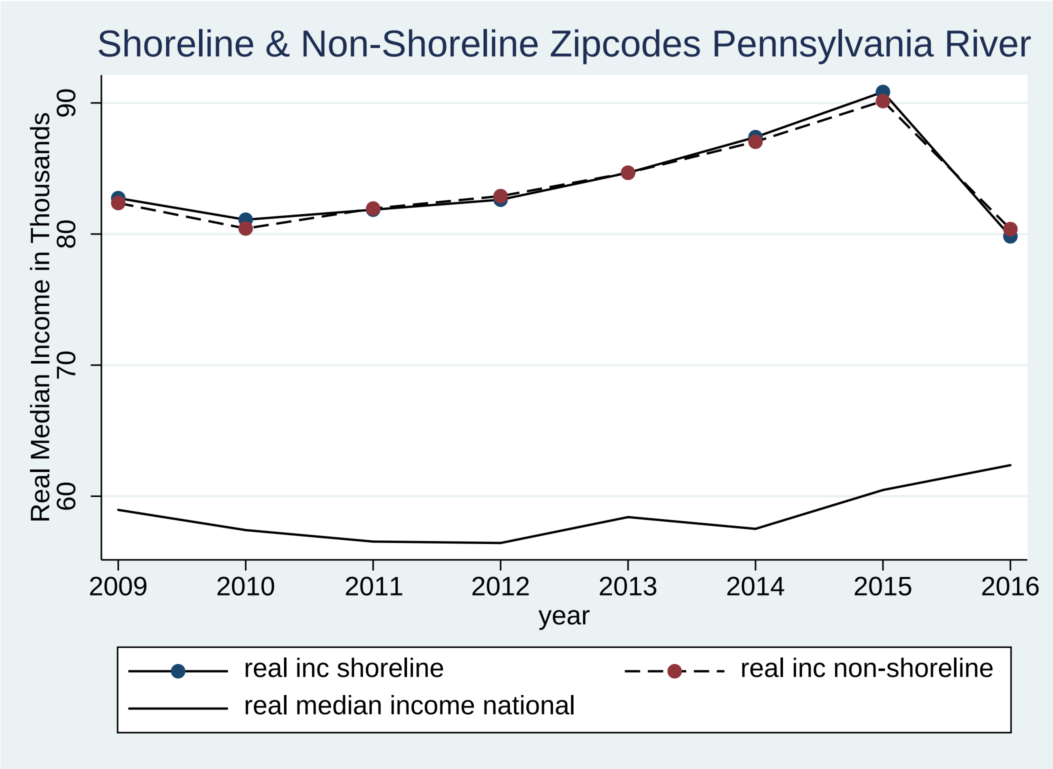

Figure 16c: Real Median Income (2015$) from IRS Zip code Summaries: Pennsylvania River and Adjacent

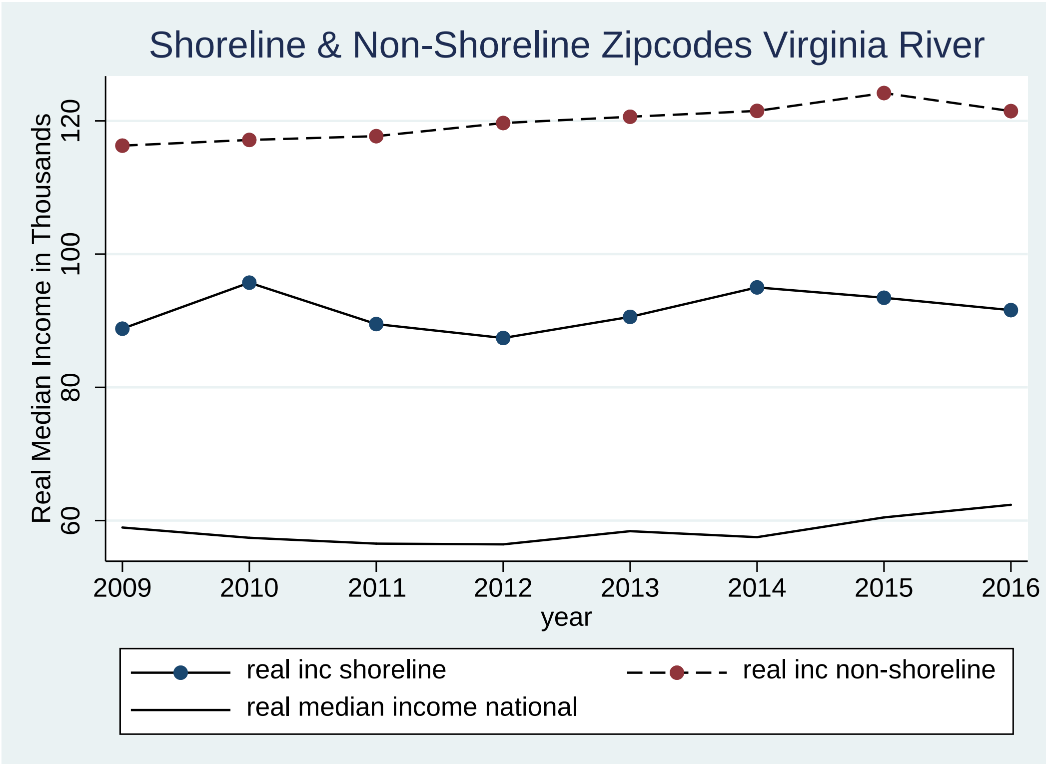

Figure 17c: Real Median Income (2015$) from IRS Zip code Summaries: Virginia River and Adjacent

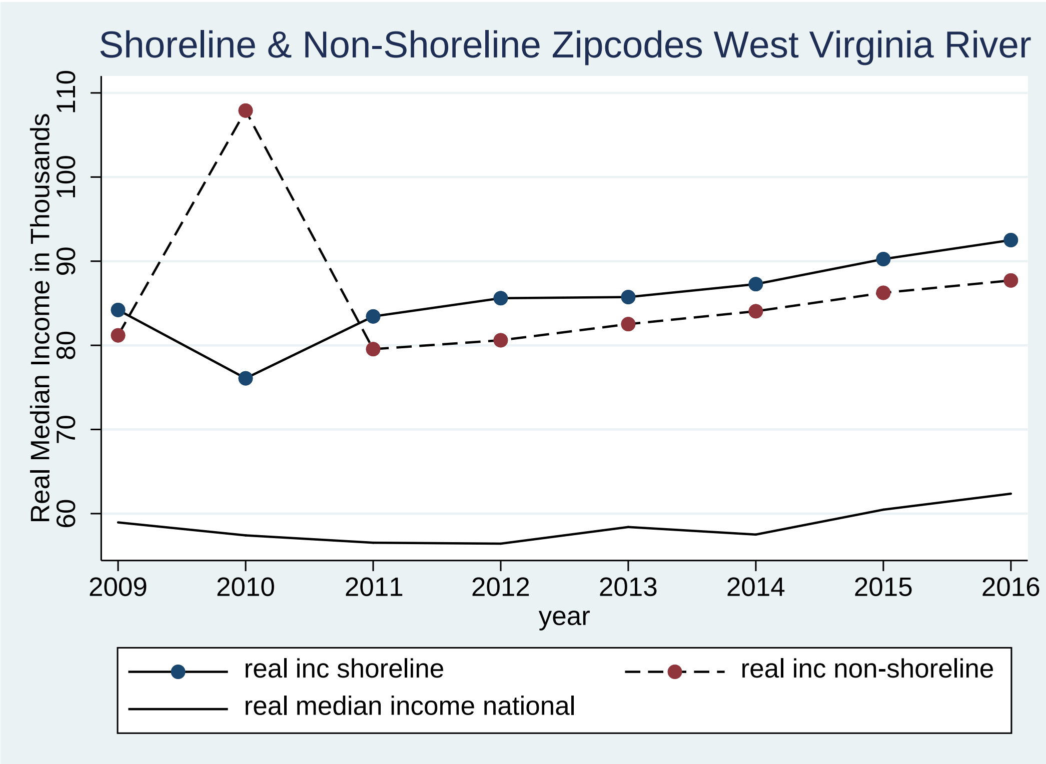

Figure 18c: Real Median Income (2015$) from IRS Zip code Summaries: West Virginia River and Adjacent