ESSAYS ON THE IMPACTS OF CLIMATE CHANGE ON NORTH CAROLINA USING UNIQUE HOUSING AND FLOOD RISK DATA SETS

By

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ABSTRACT

Climate change is expected to introduce new challenges to communities in North Carolina and across the globe. However, our understanding of how and where losses from climate change will manifest is limited. This makes it difficult for policy makers to craft policies to meet these upcoming challenges. By combining novel flood risk data at the parcel level in North Carolina with transactional home sale data from Zillow, this research estimates a statistically significant, negative, and nonlinear impact of increased flood risk on a home's value. Based on projections of future flood risk, these results are extrapolated to provide parcel-level, real-dollar estimates of the impact of a changing climate on the housing stock value in North Carolina. Additionally, these estimated costs are shown to have disproportionate effects on different segments of the state and different demographic groups within the population.

This research adds context to the cost-benefit analysis of flood risk mitigation and adaptation policy in North Carolina. Given the large majority of North Carolina communities participating in the National Flood Insurance Program, a vast number of this state's citizens depend on its continued financial solvency. The distributional impacts of increased flood risk evidenced in this research should allow for a more robust policy regarding the allocation of resources. Furthermore, the estimated losses in property value can illuminate potential shortcomings in future property tax revenue which would affect public services such as education. Finally, the proliferation of the flood risk data in this research would provide additional price signals and allow property owners to make more well-informed decisions.

In Chapter 1, we combine a North Carolina subset of real estate transactions from the Zillow Transaction and Assessment Database (ZTRAX) with continuous flood probability metrics from the First Street Foundation Flood Lab in a hedonic model to estimate the premium of reduced flood risk beyond the impact of FEMA floodplain designation.

In Chapter 2, we extrapolate the results of our hedonic model to estimate parcel-level changes in housing stock value that are aggregated at the tract, county, and state levels using flood risk projections from the First Street Foundation for the years 2036 and 2051. We use these property value changes to estimate declines in annual property tax revenue. Additionally, we use regression analysis to investigate which socioeconomic and demographic groups will be most impacted by increases in flood risk.

In Chapter 3, we replicate the methodology from Chapters 1 and 2 except our hedonic model uses vigintile regression analysis to investigate the heterogeneous preferences between income groups using home value as a proxy.

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A Dissertation

Presented to the Faculty of the Department of Coastal Studies

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In Partial Fulfillment of the Requirements for the Degree

Doctor of Philosophy in Integrated Coastal Sciences

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Jason Kops

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DEDICATION

This dissertation is dedicated to my Wife and Mother.

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I cannot be more grateful for my wife, Mary Linton. She has provided moral and financial support throughout my academic journey, all while being an outstanding mother, pursuing her own professional goals, completing her own graduate degree, and literally saving lives. She leads by example and sets a high standard. I am extremely thankful for the decades of unconditional love and support provided by my Mother, who never failed to sacrifice anything and everything to provide a better life for me. I can never truly repay my debts to these two extraordinary women. I am also grateful for my children, who are always able to find the “funny” in a situation, even when I have difficulty doing the same. To the rest of my family and friends for all their support, thank you.

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Introduction

Our understanding of the economic costs of flooding to the residents of coastal and riverine communities is limited by maps of flood-prone areas that quickly become outdated. The potential benefits of more frequent updates would outweigh the costs (Henstra et al. 2019, Bakkensen & Ma 2020). The outdated and sometimes erroneous flood maps disrupt price signals and create market inefficiencies both inside and outside the FEMA-designated floodplains (Pollack et al. 2023). Most previous work on the link between flood risk and housing value looks at the impact of having a property in the 100-year or 500-year floodplain (Shilling et al. 1985, MacDonald et al. 1987, Donnelly 1989, Speyrer & Ragas 1991, Harrison et al. 2001, Bin & Polasky 2004, Bin et al. 2008b). The 100-year floodplain classification for a property is based on the maps provided by the Federal Emergency Management Agency (FEMA). Both the map areas and the costs estimates associated with them are likely to increase in the coming decades as development increases and climate-related flood events are expected to increase in frequency and magnitude (Mousavi et al. 2011, IPCC 2007, Konrad 2003, Shao et al. 2017, Gallagher 2021).

Moreover, current studies provide estimates of the discrete impact of a property being located in a floodplain. This paper develops models that account for the marginal effect of additional flood risk on housing prices based on a continuous measure of flood risk, the probability of a property flooding, in conjunction with the binary variable of residing in the FEMA 100-year floodplain. The key contribution of the paper is the estimated marginal change in the value of a parcel (based on actual transactions) associated with a marginal increase in the flood risk faced by the parcel, after controlling for structural and neighborhood characteristics. We additionally take steps to disentangle the disamenity of flood risk from the amenities provided by proximity to surface water. We do this by including an indicator variable for whether the property is within 1 kilometer of major surface water (lakes and rivers), providing for linear and quadratic terms for distance (within 1 km) to surface water, and by excluding properties within 1km of the coast.

We find that the continuous measures of flood risk from the First Street Foundation provide for a statistically significant and nonlinear impact on housing prices when controlling for FEMA floodplain designation. Specifically, higher flood risk decreases home value at a decreasing rate. This finding demonstrates that consumers possess some degree of flood risk knowledge beyond whether a property resides in a floodplain and appear to treat higher levels of flood risk as a disamenity.

Flood damage is one of the major costs to coastal communities and rising flood risks will impact at-risk communities both directly and indirectly (Pietrafesa et al. 2019, ABC11 2020, Weill 2022). Greater flood risks in one area can increase the cost of flood insurance more broadly, negatively impacting housing values and reducing residents' wealth (Daneil et al. 2009, Bin & Landry 2013). Lost housing values will in turn reduce property tax revenue that local governments heavily rely on to provide public services, specifically funding for education, to residents (Alm et al. 2011). Accurately estimating the direct and indirect economic costs of climate-related flooding can improve a community's ability to conduct an effective cost-benefit analysis when designing and implementing resiliency planning. However, assessing economic impacts of flooding through this housing value channel faces several challenges and requires combining large, diverse data sets.

The rest of the paper proceeds as follows. Section 2 provides a brief review of the relevant literature. Section 3 describes the data, its sourcing, and its management. Section 4 details the methodology of hedonic modeling, its potential functional forms, and its application to our data. Section 5 explores the results of our hedonic models and their economic interpretations. Section 6 concludes the paper by providing context for the results and possibilities for further research.

Literature

Hedonic modelling is an economic method of valuing differentiated products. In the housing market, the value of a property is comprised of the value of its utility-providing attributes or characteristics (Rosen 1974, Bishop et al. 2020, Guignet & Lee 2021). These characteristics typically include a wide array of structural aspects (number of bedrooms and bathrooms, square footage, etc.) as well as non-structural parcel-level characteristics and neighborhood characteristics. Hedonic modelling, first developed in the 1970s, is arguably the most widely applied revealed preference method of identifying and quantifying willingness-to-pay for marginal changes in structural attributes as well as in environmental amenities (Bishop et al. 2020). Preferences may change over time based on exogenous factors, but this change may be controlled for by analyzing a single market over several years or by using a larger dataset that encompasses a longer timeframe.

Hedonic theory suggests that the hedonic price equilibrium should be decreasing with disamenities such as risk (Jones-Lee 1974, MacDonald, Murdoch, & White 1987). Figure 1.1 illustrates this principle with $P(Z_i)$ representing the hedonic price curve for the level Z of the disamenity i, Θ representing indifference curves for the consumers with fixed incomes and utility and Φ representing the isoprofit curve for the sellers. In equilibrium, sellers and buyers sort themselves such that their indifference curves and isoprofit curves are tangent to the underlying hedonic price function. As such, the slope of the hedonic price curve simultaneously demonstrates the price which prospective buyers are willing to accept for marginal increases in flood risk as well as the potential return-on-investment for sellers of homes regarding their marginal cost of reducing flood risk (Rosen 1974, Bockstael & McConnell 2007). To estimate the underlying hedonic equilibrium value of flood risk changes, real parcel-level property transactions data must be combined with property location and structural characteristics as well as flood risk data.

Analyzing a larger geographic area and a longer timeframe poses unique challenges that can be resolved via flexibility in the model. For example, interacting dummies representing time and space can bolster the validity of the model and increase the probability that the "law of one price" remains applicable (Bishop et al. 2020). Omitted variable bias represents another hurdle for successful hedonic modeling, but recent advances in data collection and storage have produced datasets that are more exhaustive and accurate (Guignet & Lee 2021). Environmental qualities have proved prickly in the uneven nature of their recording, but the parcel-level flood risk data from the Flood Lab largely eliminates this problem in our application. The functional form of the hedonic model has been the center of debate for decades, with simpler regression models historically being favored over more complex models (Cropper et al. 1988). Again, advances in data quality have changed the status quo by providing more exhaustive property characteristics, resulting in improvements when using more flexible models (Kuminoff et al. 2010).

Shilling et al. (1985) theorize that the difference in housing prices between those within and those outside the floodplain should represent the present value of the future costs of the insurance premium, and explore the level of capitalization of flood insurance premia in housing prices by modelling sale price as a function of insurance premia and discount rates. They discovered that some property appraisers are making serious errors by not factoring in floodplain status in their evaluations.

MacDonald et al. (1987) investigate the effect of consumers' willingness-to-pay (WTP) for flood insurance to reduce flood risk exposure on housing prices by comparing communities participating in the National Flood Insurance Program and those that were not. They determined that in the absence of flood insurance, consumers' WTP to reduce flood risk was captured in the housing price and that in the presence of flood insurance, the increased insurance premiums and WTP to reduce flood risk were capitalized in the housing price. Donnelly (1989) models the discount applied to a property in the floodplain as proportional to the property tax liability. He found that consumers, on average, will spend about 12 percent less for a house residing in the floodplain. Speyrer and Ragas (1991) model not just the effect of flood risk on property value but also the effect of mandatory flood insurance premiums on the sale price of property. They determined that much of the decreased value of a home residing in the floodplain is attributed to mandatory insurance premiums and that repeated flooding does not reduce property values further.

Harrison et al. (2001) research the change in price differentials between properties within and outside of the floodplain since the passing of the National Flood Insurance Reform Act of 1994 and the accuracy of flood risk valuation by property tax assessors. They found that the price differential is smaller than the present value of future insurance premiums, that the differential grew larger following the passage of the National Flood Insurance Reform Act of 1994, and that property assessors have relatively overvalued properties within the floodplain. Bin & Polasky (2004) demonstrate a similar price differential between flood risk and flood insurance premiums that are both non-linear in relation to the probability of a property flooding. They discovered that this price differential grew significantly following Hurricane Floyd in 1999. Bin et al. (2008) also find a larger price discounts for homes in the floodplain in Pitt County, NC following Hurricane Floyd in 1999, but they determine that the price differential for flood risk and capitalized insurance premiums are nearly the same. All papers find evidence of a price discount for a properties located in the 100-year floodplain. The following section provides an overview of the data we use to test the impact of floodplain designation on home prices while simultaneously controlling for a more continuous measure of flood risk.

Data

Accurate hedonic analysis requires large data on property transactions that include detailed house and geospatial characteristics along with the sales price of each property. We utilize Zillow's Transaction and Assessment Database (ZTRAX), a large dataset compiled by the online real estate marketing company. The ZTRAX dataset is a panel of over 400 million real-world observations of real estate transactions spanning more than 20 years, including property characteristics and geographic information for over 150 million parcels in over 3,100 counties in the United States (Zillow 2022).

This paper focuses on the subset of ZTRAX housing transaction data for North Carolina occurring in the years 2000 through 2020, as the ZTRAX data on transactions is much sparser prior to 2000. Observations representing arms-length transactions of single-family properties are identified, and those that fail to meet this requirement are excluded. All sales prices are converted to January 2000 dollars using the Case-Shiller U.S. National Home Price Index. In addition, we remove any properties deemed outliers in their transaction price or structural characteristics as follows:

- Transactions for less than $5,000 or more than $2,000,000 (Case-Shiller adjusted)
- 0 bathrooms or greater than 5 bathrooms
- 0 bedrooms or greater than 5 bedrooms
- Fewer than 100 square feet or more than 6,000 square feet
- Structure age greater than 100 years
- More than 20 acres in lot size

After this data cleaning, 935,622 unique transactions of single-family homes remain.

One of the biggest challenges with estimating the disamenity value of flood risk is disentangling it with the amenity of coastal proximity (Moeltner et al. 2023, Bin & Kruse 2006, Bin et al. 2008a, Johnston & Moeltner 2019). In an attempt to capture amenities associated with proximity to surface water, the distance to the closest body of water was calculated using ArcGIS Pro software for each parcel in the dataset. Parcel proximity to the coastline was also calculated for each observation. Initial attempts to use these variables to separate coastal amenities from flood risk disamenities were judged to be insufficient, as such models still estimated positive and statistically significant marginal value to increased flood risk.

We then excluded all observations within one kilometer of the coastline. There are a total of 14,517 transactions within one kilometer of the coast, amounting to less than 2% of our data set. While one might worry that removing such properties would greatly reduce the flood risk makeup of our data, the geography of North Carolina largely allays these concerns. Much of eastern North Carolina is low-lying coastal plain with numerous areas that face significant flood risk while still being inland from coastal amenities. The percentage of homes that have non-zero flood risk in the entire dataset is 10.38% compared to 9.44% for homes more than 1km from the coast. Figure 1.2 shows the kernel densities of flood risk for all homes bearing a non-zero flood risk for both the entire sample and the sample excluding coastal properties. While it is true that homes within 1km of the coast have a higher rate of non-zero flooding probability, the distribution of flood risk for properties with non-zero flood risk is virtually identical with or without the observations of properties within 1km of the coast. The final dataset for analysis includes 921,105 unique transactions representing 676,798 unique parcels[1].

The ZTRAX data is then merged with flood zone and North Carolina flood risk data from the First Street Foundation's Flood Lab, obtained through East Carolina University's data sharing agreement with the First Street Foundation. The database contains contemporary flood risk evaluations based on a range of parcel-level flood risk measures using fluvial, pluvial, and storm surge flood models (First Street Foundation 2021). The contemporary flood risk data represents 2021 and, without access to flood risk assessments dating back to 2000, these values are used for all housing transactions in the ZTRAX data.

The First Street Foundation developed this dataset by partnering with 80 experts in hydrology, research, and data science to create the First Street Flood Model (FS-FM). These experts, from top institutions such as the Massachusetts Institute of Technology, University of California Berkeley, and Columbia University, leveraged their years of relevant research and modelling experience with data from government agencies such as FEMA, USGS, and NOAA to

[1] While our dataset contains 921,105 transactions, the regression models used smaller sample sizes as some observations were removed for being singleton observations. A singleton observation represents a single observation within a fixed effect group, such as a single transaction in a specific tract or month/year combination. The summary statistics provided in this paper include the entire sample.

create a high-resolution, nation-wide model for parcel-level flood risk. The FS-FM data has been used by researchers at numerous institutions such as the Massachusetts Institute of Technology, Harvard University, Johns Hopkins University, and the Wharton School of the University of Pennsylvania, among others. They continue to provide updates to their model according to updated climate projections (First Street Foundation 2020).

While First Street Foundation's Flood Lab includes a variety of flood risk metrics, we focus on flood risk probability. Each flood risk probability metric is specific to the footprint of each parcel in the data and is associated with three inputs: inundation depth, climate scenario, and year. These metrics represent the expected annual probability that flooding in excess of a specified inundation depth will occur in a given year according to a given climate scenario. The metric utilized in the hedonic model captures the percentage-chance of flooding exceeding 0 cm in 2021 given a medium climate scenario. In addition to this continuous flood risk metric, we control for the property residing in the FEMA-designated 100-year floodplain. Table 1.1 includes summary statistics for the Case-Shiller adjusted sales prices, the linear and nonlinear percentage-chance of flooding variables, and the FEMA dummy variable representing properties residing in the FEMA floodplain.[2]

[2] It has been argued that FEMA flood maps are inconsistently updated and may not be the most accurate measure of the 100-year floodplain (Pralle 2019, Henstra et al. 2019, Bakkensen & Ma 2020). The Flood Lab data provides the ability to construct a binary 100-year floodplain variable for all parcels whose probability of flooding is greater than or equal to 1%. Our data set contains a greater number of transactions within this 100-year floodplain than the FEMA designated floodplain. However, we elect to use the FEMA floodplain over the Flood Lab constructed floodplain in our hedonic models for two reasons. First, the FEMA floodplain designation is more highly visible to home sellers and prospective buyers than a potentially more accurate floodplain designation from the Flood Lab data. Second, as the previous literature has noted in this area, there are important insurance ramifications related to being in the FEMA floodplain that are not mirrored in the Flood Lab constructed floodplain. Homeowners residing in the FEMA floodplain are legally obligated to carry flood insurance by their mortgage provider if they have a government-backed mortgage, and mortgage lenders may require flood insurance despite residing outside of a floodplain (FloodSmart 2023). Furthermore, any homeowner that receives or has received federal disaster assistance because of flooding is required to maintain flood insurance on their property and inform subsequent owners of the continued obligation (FEMA 2022).

As reported in Table 1.1, the mean property price in our dataset is $128,128, which is slightly larger than the median price of $106,037. The latter number is very similar to the median NC home price reported in the 2000 decennial Census, $108,300 (U.S. Census Bureau n.d.). Most of the homes in our data have no flood risk as evidenced by the zero median values for flood risk probability and FEMA 100-year flood zone designation. The mean annual flood risk probability for the sample is 0.9%, and 1.81% of homes in the sample are located within a FEMA-designated 100-year flood zone. On average, homes in the sample have three bedrooms and just over two bathrooms, measuring 1,773 square-feet on roughly 0.66 acre (28,906 square-feet) lots. Roughly 20% of the sample is located within one kilometer of surface water suggesting there is sufficient need to disentangle the water proximity amenity from the flood risk disamenity. The empirical approach used to quantify these values is presented in the next section.

Methodology

Our hedonic model assumes that the sale price of a house is a function of the house and property characteristics, neighborhood and location characteristics, and flood risk metrics from the First Street Foundation. In its most basic form, sales price can be modeled using a semi-log ordinary least squares (OLS) equation represented by:

$$Ln(SP_{ijt}) = \Sigma_{ijt}\beta_{ijt}X_{ijt} + Risk_{ijt} + Risk^2_{ijt} + FEMA_{ijt} + p_j + \tau_t + \varepsilon_t \qquad (1.1)$$

Where ln(*SP)* represents the natural log of the sale price of the *i*th house in a spatial unit *j* and time period *t*, *X* represents a series of structural property characteristics up to fifth level polynomials and other controls, *Risk* and $Risk^2$ represent the Flood Lab estimated probability of a flood and the square of flood probability[3] respectively, *FEMA* is a binary variable indicating whether the property is in the FEMA 100-year floodplain, ρ_j and τ_t represent spatial and temporal fixed effects, respectively, and ε represents a random error term clustered by a unique longitudinal parcel identification number. Our preferred model utilizes month-year and zip-code fixed effects, though we also explore a variety of geographic levels (Census block, Census tract, and county) for our spatial fixed effects. Standard errors are clustered by parcel to control for properties appearing in the transactional dataset multiple times. A full set of independent variables is listed and described in Table 1.1.

Results

We first investigate whether our Flood Lab risk metric improves model fit relative to a model with only the FEMA floodplain designation. Given the widely demonstrated negative effect of a FEMA 100-year floodplain designation on sale price in the previous literature, each model is estimated both with and without the First Street Foundation flood risk variables. A comparison of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) demonstrates that models with both FEMA designation and Flood Lab metrics have superior goodness-of-fit relative to models with only FEMA designation. Table 1.2 shows that the AIC and BIC values are lower for all spatial fixed effects when including the percentage-chance of flooding in the hedonic models. Based on AIC, BIC, and overall statistical significance of the model estimates, the block-group fixed effect outperforms the other models with different spatial fixed effects. For the different geographic levels, variance in goodness-of-fit and the statistical significance of the estimated coefficients are both small. As the block-group and zip-code spatial

[3] Risk factor polynomials of a third order and higher lacked consistent statistical significance and were excluded from the model.

fixed effects create upper and lower bounds of flood risk impact, and as the block-group outperforms its spatial alternatives, we focus on these specifications in our analysis.

Tables 1.3 and 1.4 present our main results. Our full results with alternative fixed effect specifications are available in the appendix. When regressing the adjusted sale price against our quadratic flood risk variables and the FEMA floodplain designation with any spatial fixed effect, we find an overall negative effect of FEMA designation as well as a negative but diminishing effect of flood risk. For all spatial fixed effects, our FEMA variable and both flood risk variables are statistically significant at the 99.9% confidence level, except for the FEMA parameter estimate when using the block-group fixed effect and the non-squared flood risk parameter estimate with the county fixed effects. Their respective p-values are 0.004 0.013. The effect of FEMA floodplain designation is much larger than the combined effect of the nonlinear flood chance variables, which is not surprising given the visibility of the FEMA designation to consumers and the legally mandated insurance requirements of residing in the FEMA floodplain. Additionally, the coefficients of our structural characteristics in Tables 1.3 and 1.4 conform to our expectations and findings in the previous literature.

Figures 1.3 and 1.4 display the marginal effects and the cumulative effects, as a percentage of home sale price, of increasing flood risk for the block-group and zip-code fixed effects models, respectively. The marginal effect of a change from a zero percent chance of any flooding to a one percent chance of any flooding is clearly the most impactful, given that a one percent chance would place the property in a FEMA-designated floodplain. The marginal effect of increasing flood risk probability beyond 1% is also negative and cannot be explained by FEMA designation, thus showing that home values are sensitive to increases in flood risk beyond what can be explained by visible floodplain designation and increased insurance requirements.

The disamenity of flood risk rises at a diminishing rate, and our data finds that the marginal effect of increasing flood risk is no longer statistically significant at a flood probability of 10% for both the block-group and zip-code models. With flood risk below 10% for 96.21% of our sample, the vast majority of our data exhibit a statistically significant marginal flood risk. This finding of diminishing disamenity risk is intuitively appealing. At annual flood probabilities at or above 10%, one should expect the property to be flooded roughly three or more times over the course of a 30-year mortgage. When flooding occurs at such a high frequency, additional increases in risk may be far less salient and have less impact on the price of the house.

Conclusion

This paper combines a large dataset of North Carolina housing transactions with a novel parcel-level data set of estimates of joint flood risk from fluvial, pluvial, tidal and storm surge sources. We find that the inclusion of this risk metric adds information beyond what is captured in FEMA floodplain designation. Our analyses demonstrate that after controlling for FEMA 100-year floodplain designation, higher flood risk has a negative effect on housing transaction prices. These findings reinforce the conclusions from previous investigators that mandated NFIP insurance premiums are capitalized in the sale price of the home. The marginal effect is strongest at low levels of flood risk and diminishes at higher risk levels.

Despite using a multi-pronged approach to control for the amenity of proximity to water, our analysis is unlikely to be completely successful in disentangling this amenity from the disamenity of increased flood risk. This assumption of lingering entanglement is supported by the eventual upward bend and ultimately positive impact of the marginal effect curve at higher levels of flood risk. All things equal, an increase in flood risk for a house would lower its sale price compared to an identical house with less flood risk. Therefore, we believe the impacts of flood risk produced from our models could represent conservative estimates with the true cost being potentially higher.

Many avenues exist for extending this research. The flood risk data used in this paper is for the year 2021. Given the dynamic nature of flood risk, investigators with more experience in flood forecasting could devise a formula for reverse-forecasting to provide flood risk estimates for past years as our transactional housing data ranges from 2000-2020. Opportunities exist for expanding controls for water-based amenities that are not available in our data, such as the view from a property, the property's water quality, or sand quality, may further disentangle the amenity of close proximity to water with the disamenity of flood risk. Future investigators, may be able to include qualitative variables that are not available in our data, such as cultural importance of an area.

Regardless of potential research extensions, this paper offers a substantial improvement to estimates of the future costs of climate change for individuals and policy-makers at all levels. Climate change is expected to increase flood risk for many coastal areas due to an expected combination of increased hurricane intensity, sea level rise, and changing precipitation patterns. Our work suggests that this is likely to have a deleterious impact on the value of the housing stock even after controlling for FEMA floodplain designation.

The discount for increased flood risk beyond current FEMA floodplain designation should be considered by NFIP administrators in maintaining financial solvency. The cumulative premium for residing outside the floodplain should be considered in buyout offer valuations for repeat flood properties if the goal is to increase participation rates. The distributional impacts of increased flood risk should influence the allocation of flood risk mitigation efforts. The real dollar impact on the housing stock in North Carolina from increased flood risk will have significant ramifications for tax revenue, and thus public services, at the local, regional, and state levels. In Chapter 2, we estimate the parcel-level changes in home value from projected changes in flood risk, the related impact on property tax revenue, and the distributional impacts of these value changes among different demographic groups.

Tables and Figures

Figure 1.1: Hedonic Price Curve for a Disamenity

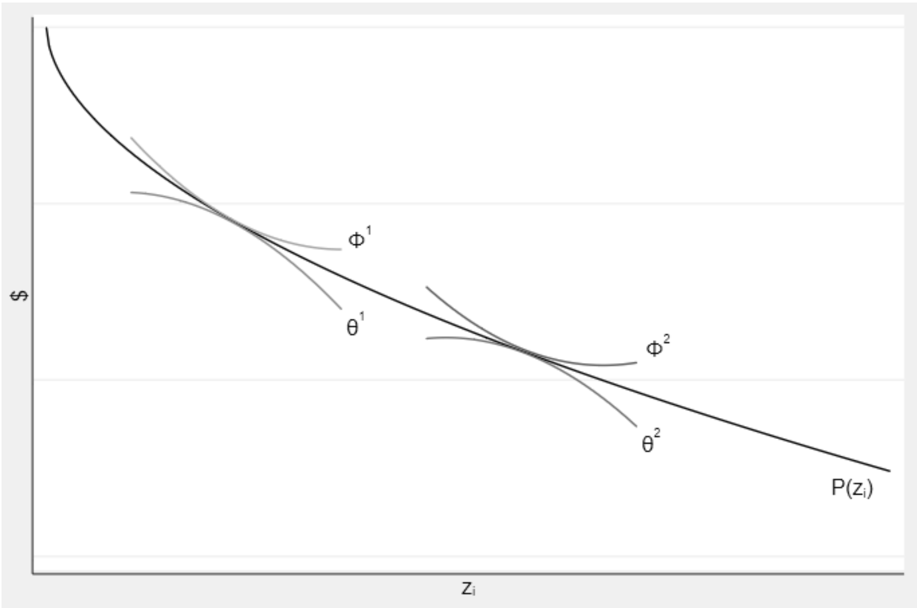


Figure 1.2: Kernel Density of Percentage Chance of Flooding

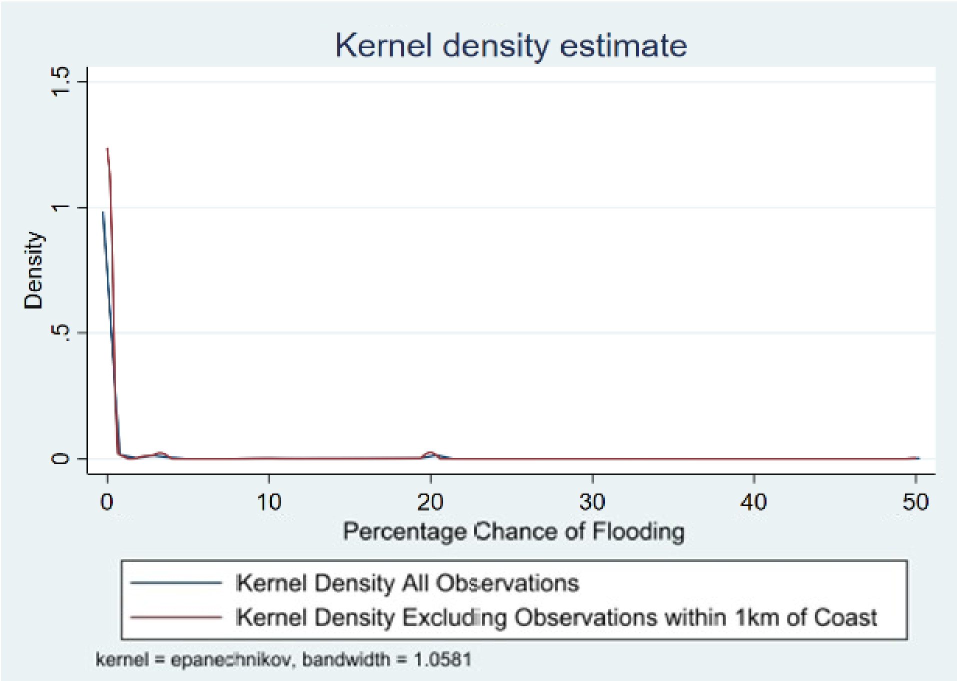


Table 1.1: Summary Statistics for Dependent and Independent Variables

Dependent Variable	**Description**	**Min**	**Max**	**Mean**	**Median**
Case-Shiller Adjusted Sale Price	The sale price of the property converted to year 2000 Case-Shiller Index dollars	$5,000	$1,996,973	$128,128	$106,037
Independent Variable	**Description**	**Min**	**Max**	**Mean**	**Median**
Percentage Chance of Flooding	The percentage chance of a property receiving any amount of flooding, provided by the First Street Foundation	0	50	0.9002368	0
Percentage Chance of Flooding Square	The percentage chance squared to capture the non-linear relationship (additional exponential powers prove statistically insignificant)	0	2,500	19.37159	0
FEMA 100-Year Flood Zone Designation	A dummy variable representing whether a property resides in the FEMA designated 100-year floodplain	0	1	0.0181185	0
Building Area	The size of the building in square feet	100	6,000	1,773.144	1,613
Lot Size	The size of the parcel in square feet	1	87,120	28,905.88	15,420.24
Bedrooms	The number of bedrooms on the property	1	5	3.216161	3
Bathrooms	The number of bathrooms on the property	0.5	5	2.301779	2.25
Age	The age of the structure on the property	2	100	33.26117	25
1km Water Proximity	A dummy variable representing whether a property resides within 1km of a body of water, calculated using GIS	0	1	0.2008069	0
Water Proximity*1km Water Proximity	An interaction between the 1km Water Proximity dummy and the property's proximity to water (in km)	0	0.9999908	0.0998493	0
Water Proximity*1km Water Proximity Squared	The proximity interaction variable squared to capture a nonlinear relationship (additional powers prove statistically insignificant)	0	0.9999816	0.0657428	0

Table 1.2: AIC and BIC Comparisons

	AIC		**BIC**	
	With Flood Risk	FEMA only	With Flood Risk	FEMA only
Block	1157415	1162371	1157732	1162665
Tract	1200704	1205634	1201020	1205927
Zip	1269150	1274088	1269467	1274382
County	1378128	1383017	1378445	1383311

Table 1.3: Mainline Regression Results for Block-Group Fixed Effect

	Observations:	918,389	**R^2:**	0.5704	**Adj. R^2:**	0.5682
	Variable	**Coefficient**		**P>|t|**	**95 CI Low**	**95 CI High**
Block	Mid Chance	-0.0018143	***	0.000	-0.0024925	-0.0011361
	Mid Chance Sq	0.0000889	***	0.000	0.0000651	0.0001126
	FEMA 100yr	-0.0165945	**	0.004	-0.027859	-0.0053301
	Building Area	-0.0005398	***	0.000	-0.000566	-0.0005135
	Building Area Square	0.0000005	***	0.000	0.0000004	0.0000005
	Building Area Cube	0.0000000	***	0.000	0.0000000	0.0000000
	Building Area Quartic	0.0000000	***	0.000	0.0000000	0.0000000
	Building Area Sursolid	0.0000000	***	0.000	0.0000000	0.0000000
	Lot Size	0.0000031	***	0.000	0.0000028	0.0000033
	Lot Size Square	0.0000000	***	0.000	0.0000000	0.0000000
	Lot Size Cube	0.0000000	***	0.000	0.0000000	0.0000000
	Lot Size Quartic	0.0000000	***	0.000	0.0000000	0.0000000
	Lot Size Sursolid	0.0000000	***	0.000	0.0000000	0.0000000
	Bedrooms	-0.3983052	***	0.000	-0.6091862	-0.1874241
	Bedrooms Square	0.2340437	***	0.000	0.1320818	0.3360055
	Bedrooms Cube	-0.0449017	***	0.000	-0.0659101	-0.0238934
	Bedrooms Quartic	0.0028364	***	0.000	0.0012736	0.0043992
	Bathrooms	0.2582301		0.075	-0.0259991	0.5424594
	Bathrooms Square	0.2618508	*	0.034	0.0199412	0.5037604
	Bathrooms Cube	-0.1576449	***	0.001	-0.2539883	-0.0613015
	Bathrooms Quartic	0.0325055	***	0.000	0.0143863	0.0506247
	Bathrooms Sursolid	-0.0023136	***	0.000	-0.0036094	-0.0010177
	Age	-0.0016349	***	0.000	-0.0017453	-0.0015245
	1km Water Prox	0.2988203	***	0.000	0.2867921	0.3108486
	Water Prox * 1km Water Prox	-1.0263778	***	0.000	-1.0708546	-0.981901
	Water Prox * 1km Water Prox Sq	0.8079525	***	0.000	0.7683993	0.8475058
	Intercept	10.8960609	***	0.000	10.6956061	11.0965158

**95% statistical significance*
***99% statistical significance*
****99.9% statistical significance*

Table 1.4: Mainline Regression Results for Zip-Code Fixed Effect

	Observations:	918,518	**R^2:**	0.5151	**Adj. R^2:**	0.5146
	Variable	**Coefficient**		**P>|t|**	**95 CI Low**	**95 CI High**
Zip	Mid Chance	-0.0019177	***	0.000	-0.0026189	-0.0012166
	Mid Chance Sq	0.0000835	***	0.000	0.0000593	0.0001077
	FEMA 100yr	-0.0338831	***	0.000	-0.0451788	-0.0225875
	Building Area	-0.0007218	***	0.000	-0.0007494	-0.0006943
	Building Area Square	0.0000006	***	0.000	0.0000006	0.0000007
	Building Area Cube	0.0000000	***	0.000	0.0000000	0.0000000
	Building Area Quartic	0.0000000	***	0.000	0.0000000	0.0000000
	Building Area Sursolid	0.0000000	***	0.000	0.0000000	0.0000000
	Lot Size	0.0000048	***	0.000	0.0000046	0.0000051
	Lot Size Square	0.0000000	***	0.000	0.0000000	0.0000000
	Lot Size Cube	0.0000000	***	0.000	0.0000000	0.0000000
	Lot Size Quartic	0.0000000	***	0.000	0.0000000	0.0000000
	Lot Size Sursolid	0.0000000	***	0.000	0.0000000	0.0000000
	Bedrooms	-0.5074338	***	0.000	-0.7385409	-0.2763266
	Bedrooms Square	0.2273063	***	0.000	0.1159437	0.3386689
	Bedrooms Cube	-0.0333211	**	0.004	-0.0562016	-0.0104405
	Bedrooms Quartic	0.0013903		0.109	-0.0003079	0.0030886
	Bathrooms	0.1336806		0.380	-0.1646798	0.4320411
	Bathrooms Square	0.5168808	***	0.000	0.2628657	0.7708958
	Bathrooms Cube	-0.2773681	***	0.000	-0.3785743	-0.1761619
	Bathrooms Quartic	0.0560384	***	0.000	0.0369967	0.07508
	Bathrooms Sursolid	-0.00399	***	0.000	-0.0053524	-0.0026276
	Age	-0.0016281	***	0.000	-0.0017255	-0.0015306
	1km Water Prox	0.3346595	***	0.000	0.3235049	0.3458141
	Water Prox * 1km Water Prox	-1.1959647	***	0.000	-1.2408012	-1.1511282
	Water Prox * 1km Water Prox Sq	0.9410368	**	0.000	0.9006105	0.981463
	Intercept	10.9421635	**	0.000	10.7254538	11.1588731

**95% statistical significance*
***99% statistical significance*
****99.9% statistical significance*

Figure 1.3: Census-Block Fixed Effect Marginal and Cumulative Effects of Flood Risk and FEMA Designation

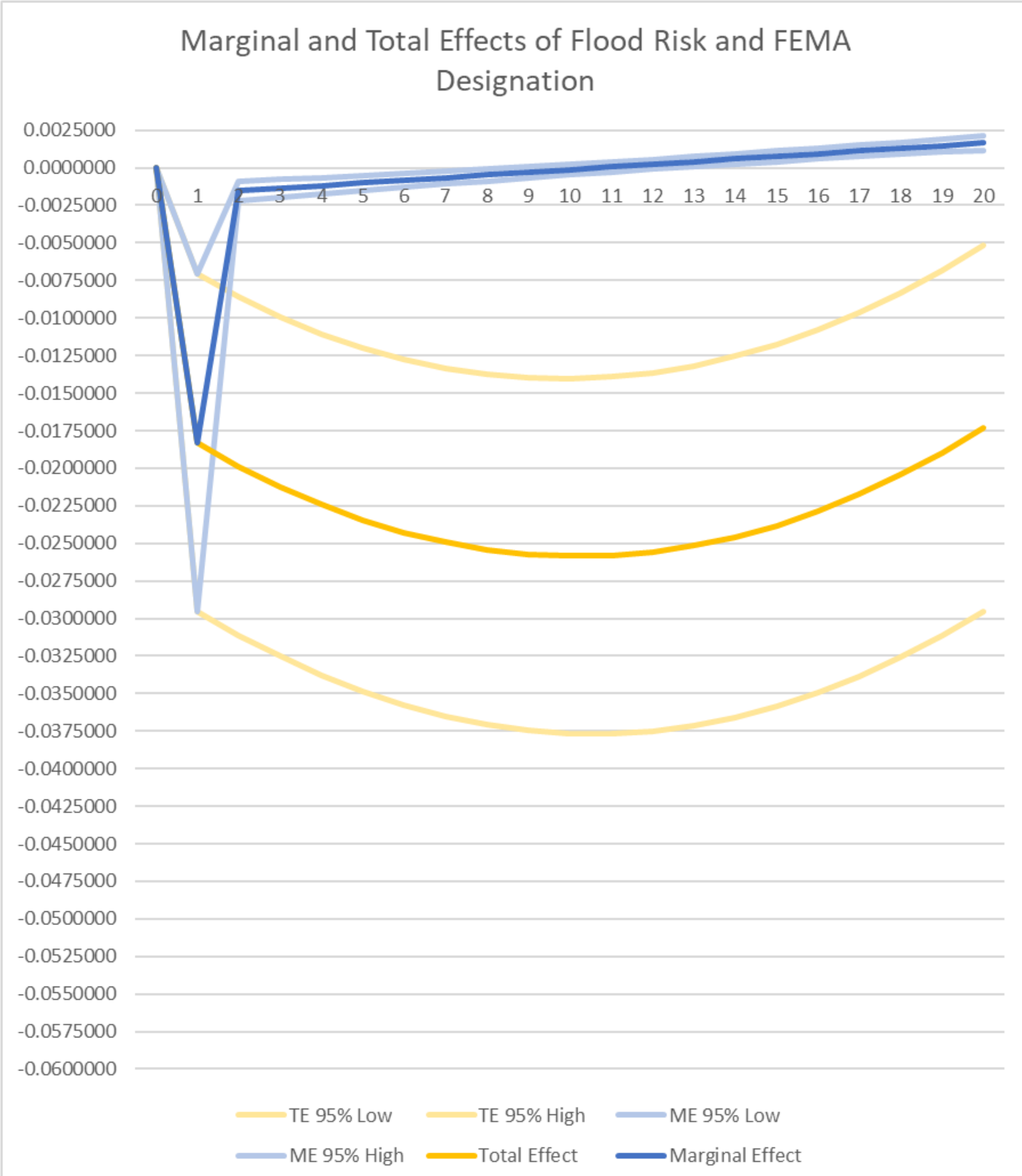
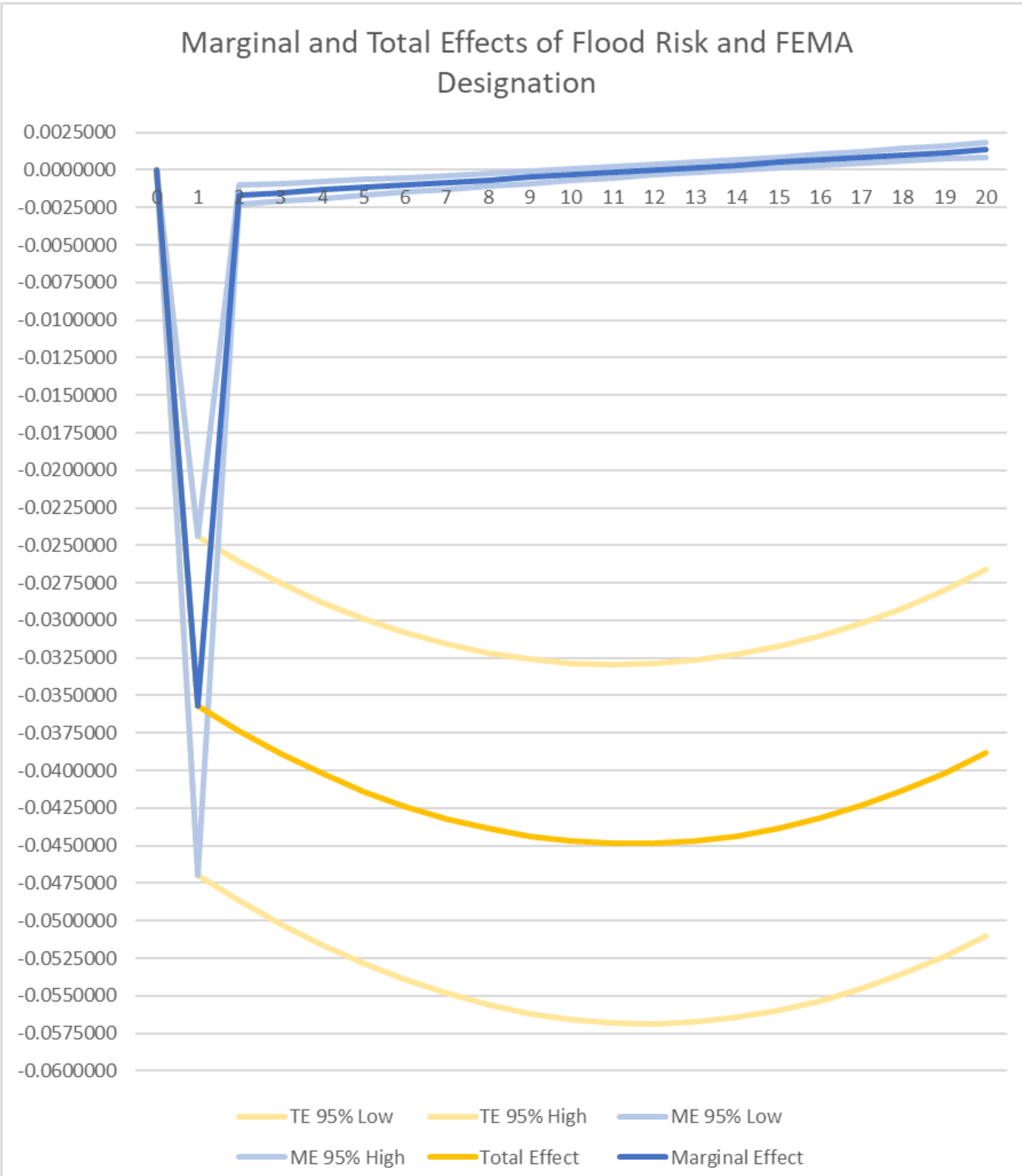


Figure 1.4: Zip-Code Fixed Effect Marginal and Cumulative Effects of Flood Risk and FEMA Designation



Chapter 2: Spatially and Demographically Heterogeneous Impacts of Climate-Related Flooding on Housing Value

Introduction

While coastal flooding is typically associated with storm surge flooding during extreme weather events, excessive rainfall and changing precipitation patterns can result in significant upstream flooding on coastal plains. In fact, fluvial and pluvial flooding can cause just as much, if not more, economic damage and loss of life as storm surge flooding (Pietrafesa et al. 2019). As climate change shifts precipitation patterns, the frequency and intensity of major flood-stage events are expected to increase over the next 50 years through a combination of fluvial, pluvial, tidal, and storm surge influences (Mousavi et al. 2011, IPCC 2007, Konrad 2003). Gradual sea-level rise can similarly magnify flood frequency and intensity in coastal regions, especially when coupled with increasing rainfall and upstream development (Vitousek et al. 2017). This rise in sea-level can compound flooding through storm surge-induced backwater effects at the coast during extreme weather events (Pietrafesa et al. 2019).

Kinston, NC, which lies about 80 river miles upstream of Pamlico Sound on the floodplain of the Neuse River, exemplifies this trend of increasing extreme flood events as it is already experiencing record-breaking floods. For instance, the three highest recorded river crests have occurred within the last 25 years, causing extensive flooding in and around Kinston. Such flooding events are increasing in frequency (NWS 2021). With this backdrop in mind, the purpose of this chapter is to investigate the economic impacts of rising climate change-induced flood risk on the state of North Carolina. Will Kinston prove to be a harbinger of flood events to come?

Estimating the true costs of climate change requires an integrated approach to compiling and analyzing the available data. Investigations from previous literature reveal heterogeneous impacts of increased flood risk both geographically and demographically (Bakkensen & Barage 2017, Ohba & Sugimoto 2019, Alcantara & Ahn 2021, Chakraborty et al. 2022, Yu et al. 2023). Impoverished and minority communities are expected to bear disproportionate burdens of increases in climate-change related flood-stage events (Maantay & Maroko 2009, Chakraborty et al. 2014, Moulds et al. 2021, Wing et al. 2022).

Maantay and Maroko (2009) focus on urban New York using the Cadastral-based Expert Dasymetric System (CEDS) model to disaggregate highly heterogeneous populations from tract-level data. We have parcel-level data and so can avoid the need to create estimates based on this type of disaggregation. Additionally, analyzing the entire state of North Carolina significantly minimizes or negates the need to disaggregate the tract-level Census data. Chakraborty et al. (2014) examine the Miami Metropolitan Statistical Area (MSA), which is one of the most diverse and hurricane-prone MSAs in the nation. While they provide distinctions between different levels of flood risk within the 100-year floodplain, they still utilize FEMA floodplain maps that are known to be outdated as opposed to our use of the novel parcel-level flood risk data from the First Street Foundation. Moulds et al. (2021) examine the relationship between formal and informal urban planning, the vulnerability of various socioeconomic populations, and the expected impact of flood risk. Wing et al. (2022) focus on the socioeconomic impact of expected damages from future flooding. Our approach differs from that of Wing, et al. because we isolate the loss in value from increased flood risk.

The nonlinear and heterogeneous effects of flood risk on property values have been thoroughly investigated in previous literature (Bin & Landry 2013, Petrolia et al. 2013, Eves &

Wilkinson 2014, Rajapaksa et al. 2017). In this paper, we take the approach one step further by combining the hedonic model results from Chapter 1, which use estimates of current flood risk, with the novel, parcel-level future flood risk projections for North Carolina provided by the First Street Foundation. This approach allows us to project changes in home values in North Carolina over the next fifteen and thirty years, given a range of climate scenarios (First Street Foundation 2021). We aggregate these parcel-level estimates of value change at the tract, county, and state level to provide estimates of expected property value loss attributable to climate change.[4] The tract level changes are aggregated using the updated Census tracts from 2020 as opposed to the 2010 Census tracts that the parcel-level data originally contained. The properties were spatially joined with the updated tract labels using GIS software. By combining the newly labelled tract aggregations with socioeconomic data from the 2020 Census, we were able to analyze whether the projected lost property value is uniformly or heterogeneously distributed across different income levels and demographic groups.

Estimated property value losses for the state by 2051 range between $334 million and $682 million (in 2021 dollars) depending on the climate scenario, and these numbers likely represent conservative estimates.[5] Some counties are estimated to lose as much as $84 million in single-family home property value, amounting to over 1% of the total value. Furthermore, we conservatively estimated annual losses in state property tax revenue in 2051 ranging between

[4] Logically, we must conclude that an increase in flood risk would not create a positive marginal effect on property value. Thus, we have replaced all risk levels having a positive marginal effect in our model with the impact of the last negative marginal effect. This has the effect of increasing the estimated costs of climate change, though the effect is relatively minor as it does not impact a large number of parcels.

[5] These estimates are conservative regarding projected economic costs, not just because of the correction for positive marginal effects of increased flood risk representing the lack of disentanglement between amenities and disamenities, but also because these estimates do not include any projected damages resulting directly from flooding. These estimates only include the change in property value from increased flood risk, which are biased upwards given the lack of disentanglement of the amenities and disamenities from proximity to surface water.

$1.8 million and $3.6 million, which would negatively impact the ability of localities to provide public services such as education. We stress that these numbers are not just conservative in estimating value loss but also in estimating the true financial costs of climate change. Impacted housing values will compose just a sliver of the realized costs related to climate change. These estimates do not provide a holistic analysis of expected or realized damages.

Combined with Census data, the value loss projections for North Carolina echo findings by previous investigators that the economic costs of increased flood risk will be disproportionately higher for lower-income households. Yet, in contrast to prior investigations, our analysis also demonstrates an outsized impact on White residents. More specifically, areas with White populations above the state average project to experience larger decreases in home values from climate change than areas with demographics equal to the North Carolina average.

The rest of the chapter proceeds as follows. Section 2 provides a synopsis of the related literature. Section 3 describes the data used and its management. Section 4 describes the methodology of the First Street Foundation flood risk forecasting and the integration of their projections with the hedonic model results and Census survey data. Section 5 details the results of our projections and the demographic impacts of increased flood risk as well as the heterogeneous increases in flood risk itself. Section 6 concludes the chapter by placing the results in a public policy context and providing avenues for further investigation.

Literature

While many unknowns remain regarding the economic costs of climate-related increases in flood risk exposure, numerous investigators have contributed to the literature that have broadened our understanding, however limited it remains, of the estimated financial impact of future flood events. In researching the impact of flood risk changes on housing value, many studies have estimated the economic costs in terms of structural damage to buildings. Elmer et al. (2012) calculated expected annual damages to residential buildings along the Mulde River basin in Germany. Their results demonstrate a decrease in the value of expected damages for the same level flood event as time progressed. Armal et al. (2020) integrated First Street Foundation flood risk data with depth-damage functions to predict annual damages to New Jersey residential properties from future flood events. They estimated a state-wide average increase of 41.4% in expected annual damages by 2050.

Pryce & Chen (2011) provide a meta-analysis of the impact of increased flood risk on the housing market, noting that, while a general consensus exists that increased flood risk provides downward pressure on housing prices, the available literature poses questions regarding the true impact. For example, many models, including ours, demonstrate a positive effect of increased flood risk to some degree. The authors contend that hedonic modelling often fails to account for heterogeneous impacts of amenities/disamenities based on the level of consumption. Furthermore, Pryce & Chen highlight the complicated relationships between flood risk, housing prices, supply and demand curves, and insurance and lending requirements. The impact on home value is of great importance given home equity has and continues to comprise a large majority of household wealth (Pearl & Frankel 1982, Kunreuther et al. 2019).

Estimating the true cost of increased flood risk is complicated further by the influence of knowledge and beliefs on risk assessment. Generally, a significant lag exists between the reality of flood risk and the perception of flood risk by residents (Gibson et al. 2017). Bakkensen and Barrage (2017) find evidence in Rhode Island that the underestimation of flood risk causes inflated property values upward of 13%. This lag can be explained in part by a lack of regular updating of FEMA floodplain maps and can be mitigated by releasing contemporary and accurate maps (Gibson & Mullins 2020, Pollack et al. 2023). When accurate maps are released to document an expanded floodplain, home prices have notably decreased in affected areas (Belanger & Bourdeau-Brien 2018, Gibson & Mullins 2020, Katz et al. 2022). Furthermore, Beltrán et al. (2018) discovered that temporal proximity to a major flood event affects the impact of flood risk on housing prices.

A substantial literature exists on the disproportionate impact of current and projected flood risk exposure on coastal regions globally (Reguero et al. 2015, Haigh & Nicholls 2017, Hsu et al. 2017, Toimil et al. 2017, Armal et al. 2020, Bevacqua et al. 2020). Additionally, investigators have noted that properties residing along rivers also face a disproportionate burden of increased flood risk (Alcantara & Ahn 2021, Yu et al. 2023). Due to myriad factors, different geographic areas will witness nonuniform increases in flood risk (Ohba & Sugimoto 2018). Specifically in North Carolina, both the Mountains and Coastal Plain regions will experience increased flood risk exposure relative to the Piedmont region (Wang & Sebastian 2021).

This increase in risk may be unevenly distributed across the population not just geographically but also demographically. Vulnerability to flood events is disproportionately higher in impoverished and minority communities who may not have the economic resources to relocate or rebuild following devastating floods (McCann 2006, Maantay & Maroko 2009, Chakraborty et al. 2014, Frank 2020, Moulds et al. 2021, Chakraborty et al. 2022, Wing et al. 2022). Extreme weather events can compound this problem by unequal wealth reduction (Kimsanova et al. 2024). Lower household wealth is associated with lower access to other resources and information, lower baseline health and education, and additional time necessary to recover from a disaster (Hallegatte et al. 2016). Whereas White communities currently bear a disproportionate amount of flood risk exposure in the U.S., the increase in expected flood risk for a community through 2050 is proportional to the percentage of the population that is Black. Furthermore, the estimated disproportionate vulnerability to flooding is expected to be exacerbated as climate change progresses (Wing et al. 2022).

This research contributes to the literature by analyzing the demographic burden of not just increases in flood risk exposure but also expected home value loss in real terms and as a percentage for all of North Carolina home value at the parcel, tract, county, and state levels. Additionally, we estimate future losses in property tax revenues based on these results.

Data

This paper incorporates three data sources. First, we utilize the hedonic model effects of flood risk on property values from Chapter 1 of this dissertation. Second, we use parcel-level data of current value assessments as well as current estimates and future projections of parcel flood risk from the First Street Foundation. The FS-FM currently uses the updated climate projection data from the Coupled Model Intercomparison Project Phase 6 (CMIP6) and Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (AR6). These climate projections are combined with the FS-FM to create multiple continuous metrics of flood risk for three climate scenarios based on fluvial, pluvial, storm surge, and tidal flood factors (First Street Foundation 2023).

Lastly, we incorporate tract-level data from the 2020 Census in North Carolina, and county-level property tax rates in North Carolina for the fiscal year 2023-24 (First Street 2021, USCB 2024, NCDOR 2024). The data from Chapter 1 includes parameter estimates for the nonlinear impact of flood probability and binary FEMA floodplain designation on home value

(Table 2.1). As we focus on the impact of changes in flood risk, we assume that all other structural and locational characteristics of each parcel remain unchanged over time. As a result, the remaining parameter estimates from our Chapter 1 model are not needed for our analysis in this work. We use the estimates from both the block and zip-code spatial fixed effect models as these represented upper and lower bound estimates from competing models.

The dataset used from the First Street Foundation contains parcel-level data on 5,363,329 single-family homes in North Carolina. Each observation, representing a single property, contains a unique identifier, latitude and longitude coordinates, an estimated property value, the property's FEMA-designated floodplain status, and the property's probability of flooding for years 2021, 2036, and 2051 in each of three climate scenarios (Low, Medium, and High). Combining pluvial, fluvial, storm surge, and tidal models with contemporary data on climate change patterns, the First Street Flood Model (FS-FM) provides flood risk analysis and projections at a 3m resolution across the United States (First Street Foundation 2023). The FS-FM has been featured in numerous peer-reviewed journal articles and plays a role in research at a significant number of major accredited universities (Liao & Mulder 2021, Bradt & Aldy 2022, Shu et al. 2023).

Flood probabilities are represented as integers for a simpler economic interpretation. Table 2.2 provides summary statistics for flood probabilities for each year and climate scenario. For all three climate scenarios, we see a similar increase in average flood risk across 30 years. The average flood risk probability in 2036 is roughly 10% higher than in 2021, and the average in 2051 is roughly 20% higher than in 2021.

Given our reliance on the FS-FM and the proven impact of floodplain designation (see Table 2.1 for evidence of the effect of FEMA floodplain designation on home value), it is impossible to make future value projections without making projections about how floodplain designation will evolve over time. To account for this issue, we normalized floodplain residency by converting property floodplain designation from FEMA-designated to FS-FM designated. Dummy variables were created representing 100-year floodplains constructed from the FS-FM flood probabilities for each year. A dummy variable value of 1 represents a property having a flood probability of 1% or greater in its respective year and climate scenario. Table 2.3 provides summary statistics for the FS-FM constructed floodplains. Originally, 248,769 properties (4.64% of the observations) were designated by FEMA as residing in the 100-year floodplain. Converting the floodplain designation based on the FS-FM probabilities more than doubles the number of properties residing in the floodplain regardless of the climate scenario. Put simply, this change isolates the damages from increased flood risk from climate change by altering present-day property value assessments so that the highly visible 100-year floodplain designation matches the FS-FM designation of which parcels face at least 1% annual risk of flooding. It is a necessary step, as failing to do so would lead to projections of flood risk changes that confound corrections to errors in the current FEMA flood map with changes in flood risk. This approach also creates a conservative estimate of the lost value to the housing stock between today and 2051, as it will not account for the real lost housing value that we project will occur as current inaccurate flood maps are updated to reflect present-day flood risk.

Given that the Census tract data for each parcel is based on 2010 Census boundaries, we plot the parcels in GIS software and spatially join each observation to shapefiles representing the updated 2020 tracts. Census tracts are created or removed to adjust for changes in population and to provide for a more homogenous population size between Census tracts (USCB 2021). From the 2020 Census, we gathered tract-level data on income levels and demographics for all of

North Carolina. Each observation, representing one Census tract, contains values for median income for households, mean income per capita, total number of households, total population size, population size by age group (under 18, under 5, 5 to 17, 18 to 64, 18 to 34, 35 to 64, 60 and older, and 65 and older), population size by race (White, Black, Asian, American Indian/Native Alaskan, Hawaiian/Pacific Islander, Other, and Two or More), population size by ethnicity (Hispanic or non-Hispanic), and poverty rates for not just the total population but also each subgroup. New variables were created by calculating the size of each subgroup as a percentage of the total population. These values were then demeaned using the state averages to provide economic meaning to the intercept estimate. In doing so, we subtract the state average for each variable from the tract-level value to create a new state-demeaned variable. The parameter estimate for each variable now represents deviation from the state-wide Census tract average per unit change in the variable. Summary statistics for these state-demeaned variables can be found in Table 2.4.[6]

The tax data sourced represent the property tax rates at the county level for all 100 counties in North Carolina for the fiscal year 2023-24 (the latest rates available). The mean county-level property tax rate in North Carolina is 0.64% (Table 2.5). We then combined these four datasets such that each observation represents a unique parcel with its corresponding flood risk metrics, tract-level socio-economic data, and county-level property tax rate.

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[6] Using state-demeaned averages provides economic meaning to the intercept parameter in each regression analysis. The intercept now represents the value of the dependent variable and the state averages for the independent variables (i.e. socioeconomic variables and demographics) for each model.

Methodology

The first step in estimating home value change based on future risk projections is to normalize the impact of crossing the 1% flood probability threshold. We accomplished this by adjusting current property value assessments to reflect the impact of the First Street floodplain designation as opposed to its FEMA designation. For example, a property with a FEMA floodplain designation that had less than a 1% chance of flooding according to the First Street data would see an increase in their property value proportional, as a percentage given the semi-log form of the hedonic model, to the parameter estimate of 100-year floodplain in the hedonic model. Conversely, a property that resides outside the FEMA floodplain but has at least 1% chance of flooding in the FS-FM is given a proportional decrease in property value. We performed this adjustment for estimates from both the Block and Zip-code models and for each climate scenario using the following formula:

$$APV_{ijc} = PV_i * [1 + \beta_j(FS_{ic} - FEMA_i)] \qquad (2.1)$$

Where *APV* represents the 2021 adjusted property value of the *i*th house using the spatial unit *j* hedonic model results for climate scenario *c*, *PV* represents the current property value estimate, β represents the parameter estimate for the effect of floodplain designation, *FS* represents the floodplain dummy constructed from the First Street probabilities, and *FEMA* represents the current FEMA floodplain designation for the property. By this formula, no adjustment is made for parcels where FEMA and FS-FM designations are in agreement. The adjusted property values serve as the basis for any estimated value changes resulting from changes in flood risk.

Second, we calculate the impact of the respective year's flood risk probability on property value (as a percentage):

$$PVI_{ijct} = \beta_1(FR_{ict}) + \beta_{2j}(FR^2_{ict}) + \beta_{3j}(FP_{ict}) \qquad (2.2)$$

Where PVI represents the impact of flood risk on the value of the ith house using the spatial unit j hedonic model results for climate scenario c in year t, β_1 represents the parameter estimate for the FS-FM flood risk probability (FR), β_2 represents the parameter estimate for the FS-FM flood risk probability quadratic term (FR^2), and β_3 represents the parameter estimate for the FEMA floodplain designation (FP). Intuitively, we know that, all things equal, increased flood risk cannot have a positive impact on home value. Given our inability to fully disentangle the amenities and disamenities associated with proximity to water, our models evidence an upward curve at a certain level of flood risk. This is likely an artefact of model fit (it applies to less than 4% of the observations in our Chapter 1 analysis), and to avoid the possibility of erroneously attributing positive value to increases in flood risk we have replaced all positive impacts from increased flood risk with the impact from flood probability that evidences the last negative marginal effect.[7] We then found the difference in property value impact from 2021 to 2036 and from 2021 to 2051. This difference is multiplied by the adjusted property value to estimate the loss in housing value attributed to increased flood risk over the 15- and 30-year intervals. The parcel-level adjusted property values and housing value losses are then aggregated at the tract, county, and state levels. We then calculated the value losses as a percentage of the total property values at the tract, county, and state levels. This will provide for meaningful analysis of the impact of climate change regardless of the value of the housing stock in any given area.

To go beyond a spatial analysis of climate change impacts and analyze the socioeconomic impacts of increased flood risk, both the absolute and percentage value losses at the tract level are regressed against the respective tract-level Census data using an ordinary least squares (OLS) equation:

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[7] When represented on a graph, this correction would create a flat line equal to the model curve's minimum value that replaces the upward curve of the parabolic model results.

$$PVL_{ijct} = Income_i + Poverty_i + White_i + Black_i + Asian_i + AmIndian_i + \varepsilon_{ijct} \quad (2.3)$$

$$DFR_{ijct} = Income_i + Poverty_i + White_i + Black_i + Asian_i + AmIndian_i + \varepsilon_{ijct} \quad (2.4)$$

Where PVL_{ijct} represents the average percentage value loss in 2021 dollars for the *i*th tract using the spatial effect *j* hedonic model results in climate scenario *c* for year *t*, DFR_{ijct} represents the average change (delta) in flood risk for the *i*th tract, $Income_i$ represents the state-demeaned average income per capita, $Poverty_i$ represents the state-demeaned percentage of the population in poverty, $White_i$ represents the state-demeaned percentage of the population that is white, $Black_i$ represents its respective state-demeaned percentage of the population, $Asian_i$ represents its respective state-demeaned percentage of the population, $AmIndian_i$ represents the state-demeaned percentage of the population that is American Indian, and ε represents a random error term. It is important to estimate models for both changes in flood risk and changes in housing value precisely because the disamenity of flood risk is highly nonlinear. As a result, it is possible that areas/groups experiencing the largest changes in flood risk are not necessarily the ones who experience the largest changes in property value.

Finally, we estimated the expected decreases in annual property tax revenue attributed to increased flood risk for 2036 and 2051. For each property, we multiplied the respective county property tax rate by the estimated value loss. These property tax revenue losses were then aggregated at the county and state levels.[8] These estimates are conservative given the additional local property taxes levied beyond county rates.

[8] We did not aggregate projected property tax losses at the tract level as property tax rates are generally not set or pooled at the tract level. Thus, such an aggregation would have little to no relevance towards policy-making.

Results

Property Value Change

Summary statistics for the parcel-, tract-, and county-level home value loss in real dollars and as a percentage of total housing stock value, shown in Tables 2.6-2.8, demonstrate the heterogeneous economic impacts of increase flood risk geographically. Given the two hedonic models and three climate scenarios, we evidence a wide range of value change. We theorize that this range, however large, represents a conservative estimate of expected losses given the yet discovered costs of increased flood risk. At both the tract and county levels, the most significant increases in flood risk exposure are heavily concentrated along the coast with a moderate increase in the mountains relative to the center of the state (Figures 2.1-2.6). While some parcels, tracts, and even one county witness some properties that increase in value attributable to reduced flood risk over time, the means for all geographic levels, models, and climate scenarios are negative. At the extremes, our model predicts that climate-change-related increases in flood risk exposure can decrease the value of an individual property by as much as 4.5%. Tracts and counties are projected to see reductions in housing stock value as high as 3.0% and 1.4% respectively. As one moves up in geographic scale, the projected value losses increasingly outweigh any projected gains.

When examining the ten most- and ten least-impacted tracts and counties, we witness a high amount of overlap regardless of the model, climate scenario, or projected year (Tables 2.17A-2.22A). Despite any variance in impacts, the results will be very predictable given the demonstrated trends. Of note, Currituck County has the highest frequency of being most-impacted both in terms of real dollar losses and losses as a percentage of property value. Conversely, Caswell County is estimated to be the least-impacted by climate-related changes in flood risk by almost any metric in this Chapter. As noted in the previous literature and in this paper, coastal communities will bear the brunt of the economic costs of increased flood risk probability.

Projected property losses aggregated at the state level, depending on the model and climate scenario, range from just over $200 million to about $533 million by 2036 (about 0.02-0.05% of total property value). By 2051, the estimates range from over $300 million to over double at nearly $700 million, representing a 0.03% to almost 0.07% loss in housing stock value respectively (Table 2.9).

All data point to a markedly smaller increase in value loss during the 2036-2051 period compared to 2021-2036. This may conflict with expectations, as most models suggest that the impacts of climate change will occur at an increasing rate over time. These tapering value losses represent the difference between changes at the extensive and intensive margins associated with increased flood risk. In this context, we view the extensive margin as going from essentially zero flood risk to one percent flood risk, while the intensive margin refers to increases in flood risk for parcels that already experience one percent or greater flood risk. The large value losses incurred by 2036 are heavily bolstered by the extensive margin of many homes crossing the 1% threshold, which bears a significant and outsize impact on value loss given the implications of floodplain designation. The more modest value losses from 2036 to 2051 represent the intensive marginal impact of increased flood risk from properties already exposed to it. Table 2.2 reinforces this conclusion given the nearly identical increase in mean flood risk between 2021-2036 and 2036-2051.

Demographic and Socioeconomic Impacts

Our regression analysis of the heterogeneous impacts on various demographic groups demonstrates trends counter to those found in the literature (Table 2.10). For example, our regression models demonstrate no statistically significant correlation between increased value loss as a percentage of property value and income or poverty rates. Furthermore, all models demonstrate a disproportionately large impact on White populations as opposed to all other examined races. These parameter estimates are statistically significant for the Asian, American Indian, and Hispanic percentages of the population.

When regressing changes in flood risk against these same socioeconomic variables, we again find that the White population is disproportionately and negatively impacted by changes in flood risk exposure compared to other demographic subsets (Table 2.11). Income and poverty levels continue to not have a statistically significant correlation to increased flood risk. These results suggest that the socioeconomic impacts of increased flood risk vary greatly by geography, thus aggregating these impacts at increasingly larger geographic levels can obfuscate the reality on the ground at more localized areas of study.

The cause for such disparities between the results of our investigation and of those prior remains an open question. North Carolina could simply be different from other states or the rest of the country, further demonstrating the spatial heterogeneity of impacts from increased flood risk. As the overwhelming majority of the state will be unaffected by increases in flood risk exposure, averaging the impacts across the entire population may obfuscate the effects on various demographics in the locations that are expected to see increases in flood probability. Low-income and minority populations may be more negatively impacted by increased flood risk in areas that witness increases, yet the majority of low-income and minority populations may reside in areas that will remain unaffected by climate-related increases in flood risk.

To investigate these possibilities, we performed the same analyses while including only the tracts most affected by increases in flood risk exposure.[9] The results tell a similar story albeit with a couple of distinct exceptions (Tables 2.12 & 2.13). In the new models with the more limited dataset, the correlation between percentage value change and average income per capita remains statistically insignificant and not confidently different than zero. However, the correlation between value change and the percentage of the population in poverty becomes positive, signifying that an increase in the percentage of the population below the poverty line correlates to a reduction in value loss. Higher-income brackets would face a heavier burden relative to the lowest-income brackets according to these models. The coefficients for the variable representing the percentage of the population that is Black reverse signs and become both negative and statistically significant, meaning that in the tracts most adversely affected by increased flood risk exposure, Black populations are disproportionately and negatively impacted compared to White populations. Regressing the change in flood risk against these socioeconomic variables produces some changes in positive and negative correlation when examining the high-risk tracts as opposed to all tracts. Yet, these changes in correlation lose statistical.

While our regression analyses of all North Carolina tracts in the dataset contradict previous investigations that find disproportionate impacts on minority and impoverished communities, both sets of conclusions can still remain true. Given the evidenced differences in extensive and intensive effects of increased flood risk, minority communities in North Carolina

[9] Tracts considered "most affected" are those that see a loss of value in the housing stock greater than 0.05% or an increase of flood probability greater than 1% depending on which dependent variable is being regressed (percentage value change delta flood risk respectively).

could face contemporary flood risk exposure substantially higher than majority communities and witness a smaller relative property value loss. Should majority communities witness a similar increase in flood probability as minority communities but cross the extensive margin threshold, the majority communities' value loss would be significantly higher than their minority counterparts if the minority communities only faced the less impactful intensive margin.

Property Tax Revenue

Given the difficulties of matching properties with precise property tax rates, we opted for estimating annual property tax revenue declines at the county level as well as aggregating these declines for state-wide totals. Our estimated declines in annual property tax revenue based on projected flood risk-induced property value loss follow the trend of representing conservative estimates for the economic impact. All estimated changes in revenue are negative, with a wide range of estimated impacts for counties both within the same model and between the various models and years (Table 2.14). For 2036, expected declines in county-level annual revenue range from $76 to just over $445,000 depending on the county, model, and climate scenario. For 2051, the range extends from about $235 to almost $470,000. When looking at the tails of revenue decline, we again witness a large overlap in the lists regardless of the model and climate scenario (Table 2.15). Currituck County and Caswell County again prove to be the relative loser and winner in terms of annual property tax revenue. At the state level, annual declines range from about $1 million to just over $3 million in 2036 and from $1.8 million to $3.6 million in 2051 (Table 2.16).

Conclusion

The estimates provided in this chapter are intended to provide further context for the cost-benefit analysis of proposed or potential flood risk mitigation and adaptation. By more deeply understanding the expected costs of climate change-related increases in exposure to flooding in the future, we can better plan and allocate resources in the present. One major shortcoming of the demographic portion of this analysis is the underlying assumption that people will not migrate in the face of changing flood risk. The demographic and socioeconomic composition of the Census tracts, and North Carolina as a whole, will continue to change as various subgroups of the population sort in and out of dynamic floodplains.

In allocating resources, policy-makers can make more-informed decisions regarding their distribution when cognizant of the disparate geographic and socioeconomic impacts. In choosing whether to participate in mitigation or buyout programs, property owners can also make more-informed decisions that help protect their wealth and livelihood. County officials can act now to head off projected revenue shortfalls that will potentially affect the financial viability of public services funded by property taxes.

Tables and Figures

Table 2.1: Relevant Hedonic Model Results from Chapter 1

	Variable	Coefficient		P>|t|	95 CI Low	95 CI High
Block	Mid Chance	-0.0018143	***	0.000	-0.0024925	-0.0011361
	Mid Chance Sq	0.0000889	***	0.000	0.0000651	0.0001126
	FEMA 100yr	-0.0165945	**	0.004	-0.027859	-0.0053301
Zip	Mid Chance	-0.0019177	***	0.000	-0.0026189	-0.0012166
	Mid Chance Sq	0.0000835	***	0.000	0.0000593	0.0001077
	FEMA 100yr	-0.0338831	***	0.000	-0.0451788	-0.0225875

Table 2.2: Summary Statistics for Flood Risk Probabilities by Year and Climate Scenario

Climate Scenario	Year	Mean	Median	Lower	Upper	Standard Deviation
Low	2021	1.6787	0	0	50	6.3479
	2036	1.8680	0	0	50	6.7448
	2051	2.0586	0	0	50	7.4302
Mid	2021	1.7146	0	0	50	6.3698
	2036	1.9208	0	0	50	6.7867
	2051	2.1285	0	0	50	7.5032
High	2021	1.7970	0	0	50	6.5546
	2036	2.0277	0	0	50	6.9843
	2051	2.2604	0	0	50	7.7928

Table 2.3: Summary Statistics for FS-FM-generated 100-year Floodplain

Climate Scenario	Year	Properties in Floodplain	Percentage of Total Properties	Percentage Increase
Low	2021	587,047	10.95	-
	2036	623,057	11.62	6.13
	2051	653,579	12.19	4.90
Mid	2021	591,186	11.02	-
	2036	659,299	12.29	11.52
	2051	659,073	12.29	-0.03
High	2021	632,624	11.80	-
	2036	691,521	12.89	9.31
	2051	705,705	13.16	2.05

Note: 5,363,329 parcels

Table 2.4: State-demeaned Summary Statistics for Tract-level Demographic Variables

Variable	State Average	Mean	Median	Lower	Upper	Standard Deviation
Average Income Per Capita	$32,305.05	-$204.08	-$4,088.55	-$32,305.05	$167,702.00	$15,180.85
% Population Poverty	13.9914	0.7744	-1.1661	-13.9914	86.0086	10.6968
% Population Black	21.1377	0.0990	-7.1634	-21.1377	76.9329	21.0805
% Population Asian	2.9901	-0.2463	-2.1558	-2.9901	52.0431	5.3119
% Population American Indian	1.1578	0.0206	-1.1578	-1.1578	92.7637	6.2125
% Population Other Race	6.9133	-0.3147	-1.9832	-6.9133	40.4041	6.0027
% Population Hispanic	10.9853	-0.5796	-3.1352	-10.9853	58.9716	8.2830

Note: 2,634 tracts

Table 2.5: Summary Statistics for County-level Property Tax Rates in North Carolina

	Mean	Median	Lower	Upper	Standard Deviation
Property Tax Rate	0.6448%	0.06560%	0.27%	1.045%	0.16282%

Table 2.6: Summary Statistics for Parcel-level Projected Value Change

Model	Climate Scenario	Year	Mean Parcel Value Change	Lower	Upper	Standard Deviation	Mean Parcel Value Change %	Lower	Upper	Standard Deviation
Block	**Low**	2036	-$37.49	-$72,580	$17,103	$409.60	-0.0176%	-2.5856	1.8053	0.1623
		2051	-$62.24	-$72,580	$18,035	$540.93	-0.0295%	-2.5856	2.5856	0.2164
	Mid	2036	-$60.39	-$72,580	$2,297	$543.07	-0.0286%	-2.5856	2.6669	0.2171
		2051	-$67.24	-$72,580	$21,341	$587.74	-0.0318%	-2.5856	2.5856	0.2348
	High	2036	-$56.54	-$85,928	$14,608	$518.19	-0.0269%	-2.5856	1.802	0.2098
		2051	-$72.93	-$85,928	$42,895	$622.24	-0.0346%	-2.5856	2.5856	0.2488
Zip	**Low**	2036	-$64.97	-$128,220	$33,463	$772.93	-0.0304%	-4.4894	3.545	0.3053
		2051	-$110.80	-$128,220	$34,434	$1,024.88	-0.0527%	-4.4894	4.4894	0.4102
	Mid	2036	-$109.45	-$128,220	$2,476	$1,032.90	-0.0520%	-4.4894	0.3340	0.4123
		2051	-$117.57	-$131,810	$37,976	$1,083.91	-0.0557%	-4.4894	4.4894	0.4329
	High	2036	-$99.41	-$150,435	$28,893	$979.36	-0.0475%	-4.4894	3.5421	0.3933
		2051	-$127.06	-$150,435	$76,546	$1,145.58	-0.0604%	-4.4894	4.4894	0.4582

Note: 5,363,329 parcels in each model

Table 2.7: Summary Statistics for Tract-level Projected Value Change

Model	Climate Scenario	Year	Mean Tract Value Loss	Lower	Upper	Standard Deviation	Mean Tract Value Loss %	Lower	Upper	Standard Deviation
Block	**Low**	2036	-$127,132	-$7,996,865	$5,393	$598,238	-0.0176%	-1.7242	0.0031	0.0774
		2051	-$202,630	-$10,956,127	$9,132	$825,522	-0.0298%	-1.7286	0.0026	0.0976
	Mid	2036	-$197,684	-$10,660,616	$65	$810,611	-0.0289%	-1.7075	0.0002	0.0972
		2051	-$220,137	-$11,908,236	$10,801	$895,355	-0.0321%	-1.7136	0.0150	0.1056
	High	2036	-$186,551	-$9,743,851	$11,005	$760,368	-0.0271%	-1.3543	0.0046	0.0926
		2051	-$236,695	-$11,587,450	$84,104	$911,548	-0.0349%	-1.3897	0.0498	0.1099
Zip	**Low**	2036	-$222,439	-$13,814,503	$15,851	$1,080,493	-0.0305%	-2.9886	0.0085	0.1402
		2051	-$361,194	-$19,796,998	$21,055	$1,491,387	-0.0531%	-3.0082	0.0058	0.1775
	Mid	2036	-$358,050	-$19,617,136	$96	$1,483,573	-0.0525%	-2.9700	0.0003	0.1786
		2051	-$384,716	-$21,150,682	$22,872	$1,585,537	-0.0563%	-2.9904	0.0186	0.1887
	High	2036	-$328,124	-$18,185,550	$28,176	$1,362,830	-0.0478%	-2.3488	0.0118	0.1680
		2051	-$411,696	-$20,358,512	$155,438	$1,600,368	-0.0610%	-2.4160	0.0921	0.1955

Note: 2,634 tracts in each model

Table 2.8: Summary Statistics for County-level Projected Value Change

Model	Climate Scenario	Year	Mean County Value Loss	Lower	Upper	Standard Deviation	Mean County Value Loss %	Lower	Upper	Standard Deviation
Block	**Low**	2036	-$2,226,262	-$32,124,082	$10,282	$4,941,022	-0.0178%	-0.5337	0.0005	0.0577
		2051	-$4,577,092	-$42,414,792	-$34,990	$7,174,511	-0.0301%	-0.7047	-0.0016	0.0786
	Mid	2036	-$4,382,772	-$44,403,560	-$28,078	$6,955,621	-0.0292%	-0.7380	-0.0013	0.0782
		2051	-$4,905,711	-$47,473,524	-$32,015	$7,844,069	-0.0325%	-0.7890	-0.0015	0.0856
	High	2036	-$3,866,412	-$38,815,312	-$41,492	$6,351,599	-0.0275%	-0.6457	-0.0019	0.0747
		2051	-$5,079,242	-$43,055,112	-$59,910	$8,490,183	-0.0355%	-0.7162	-0.0028	0.0905
Zip	**Low**	2036	-$3,619,621	-$55,970,084	-$11,752	$8,865,828	-0.0308%	-0.9331	-0.0005	0.1041
		2051	-$8,046,307	-$75,172,912	-$57,705	$1.27e^7	-0.0538%	-1.2537	-0.0027	0.1420
	Mid	2036	-$7,885,385	-$79,766,320	-$49,875	$1.26e^7	-0.0531%	-1.3312	-0.0023	0.1431
		2051	-$8,500,180	-$83,647,216	-$54,575	$1.36e^7	-0.0569%	-1.3958	-0.0025	0.1521
	High	2036	-$6,702,901	-$69,019,344	-$74,898	$1.11e^7	-0.0485%	-1.1538	-0.0035	0.1343
		2051	-$8,754,915	-$75,486,856	-$109,081	$1.47e^7	-0.0621%	-1.2619	-0.0051	0.1597

Note: 100 counties in each model

Figure 2.1: 2051 Tract-level Value Change as a Percentage per Climate Scenario and Model Fixed Effect

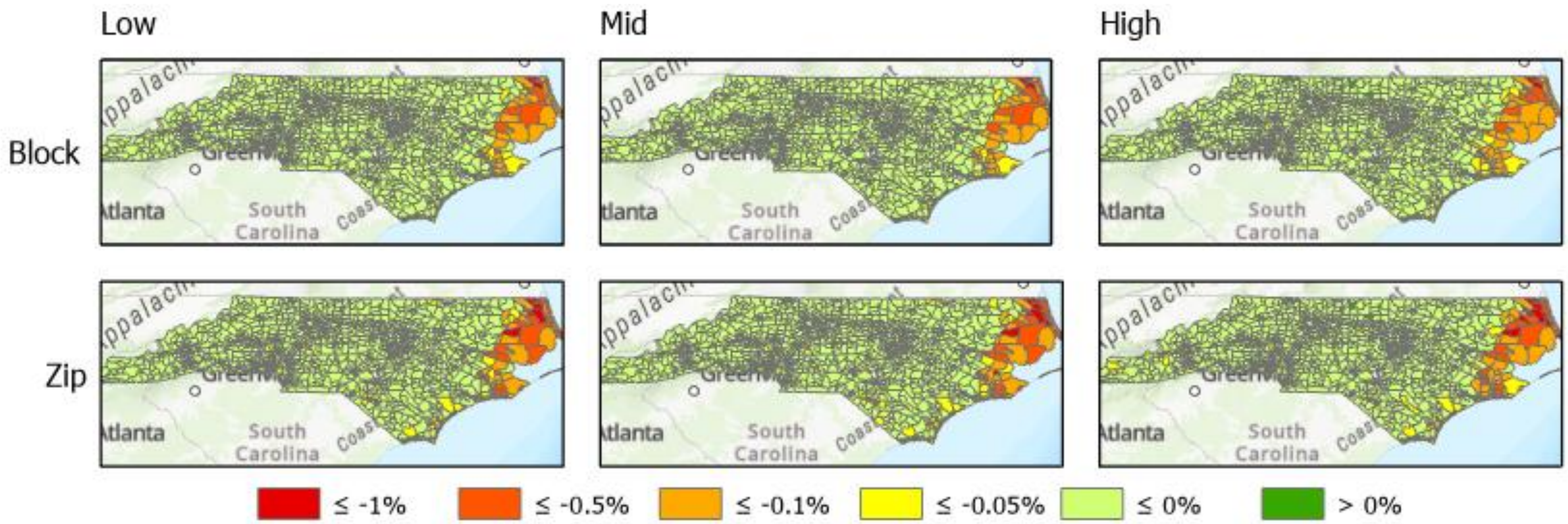

Figure 2.2: 2051 Tract-level Value Change in Dollars per Climate Scenario and Model Fixed Effect

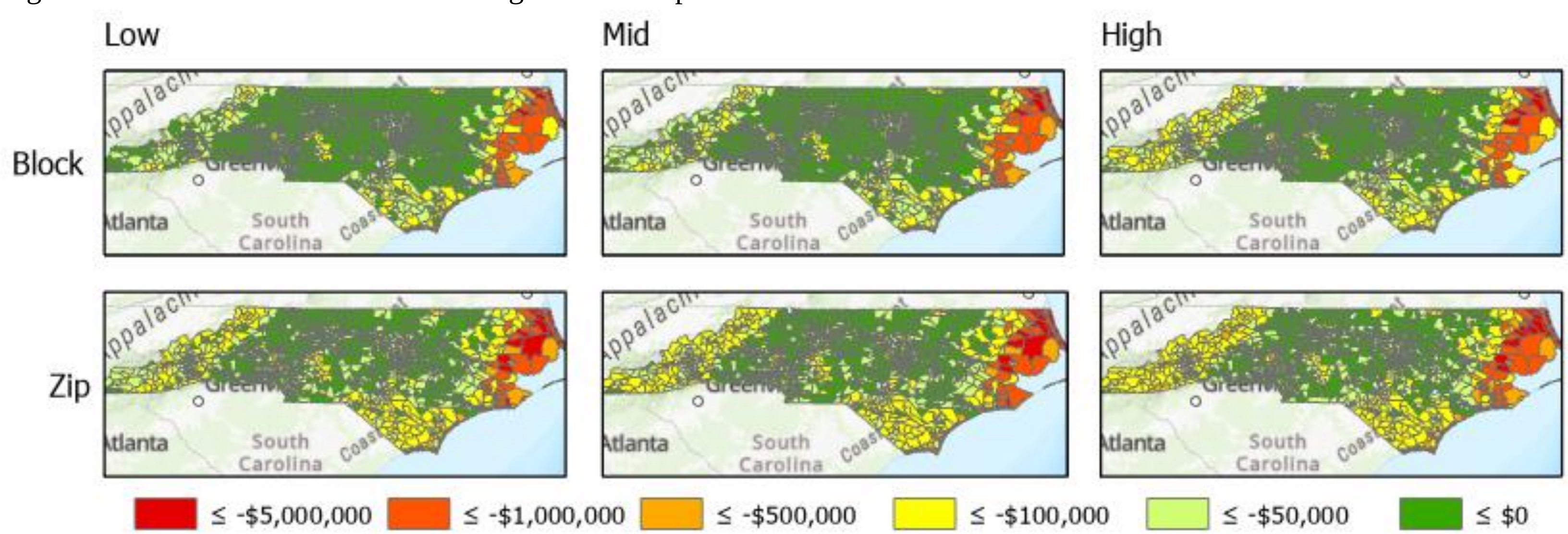

Figure 2.3: 2051 County-level Value Change as a Percentage per Climate Scenario and Model Fixed Effect

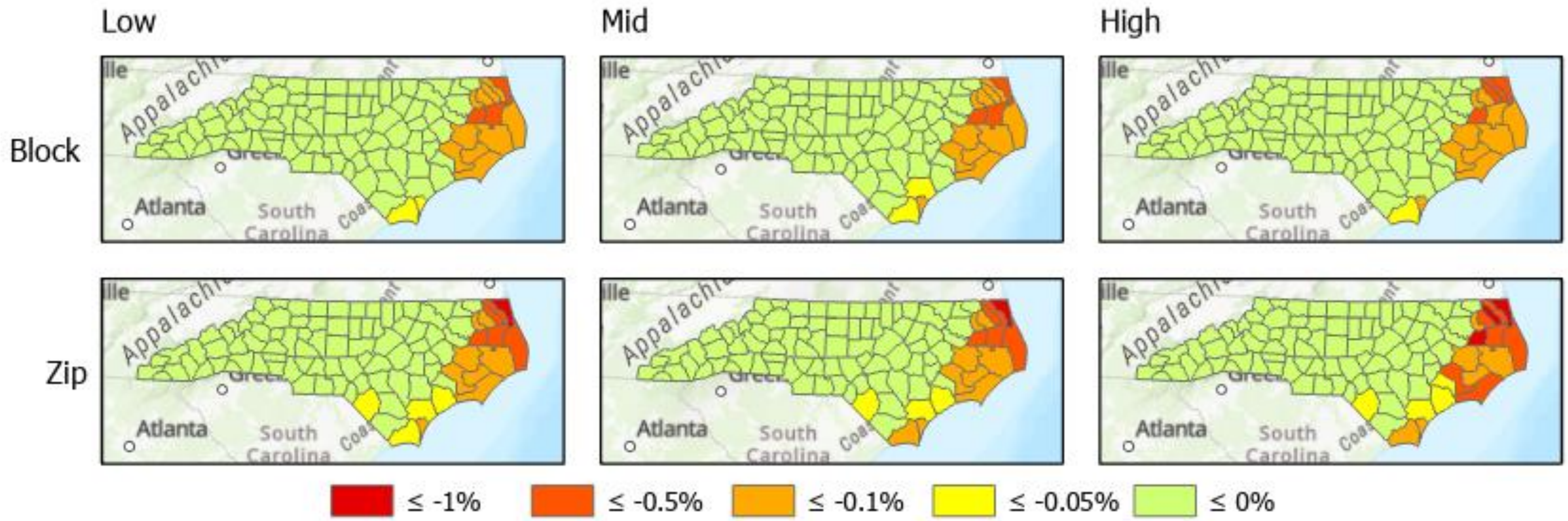

Figure 2.4: 2051 County-level Value Change in Dollars per Climate Scenario and Model Fixed Effect

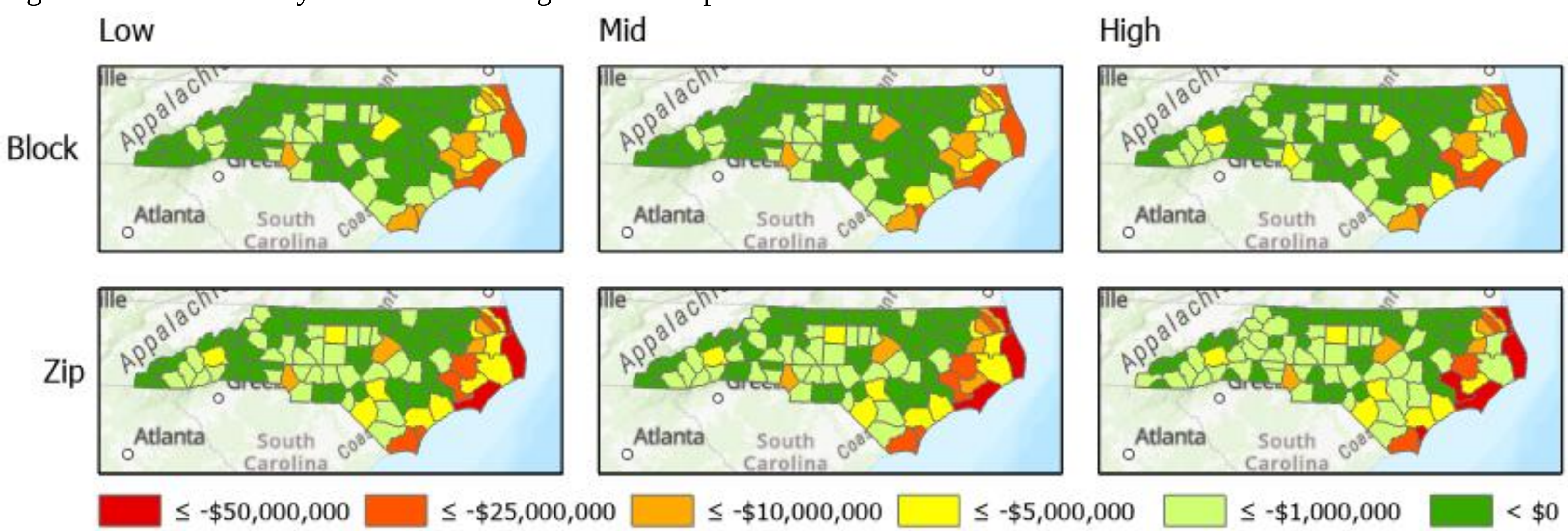

Figure 2.5: 2051 Tract-level Increases in Annual Percentage Flood Probability

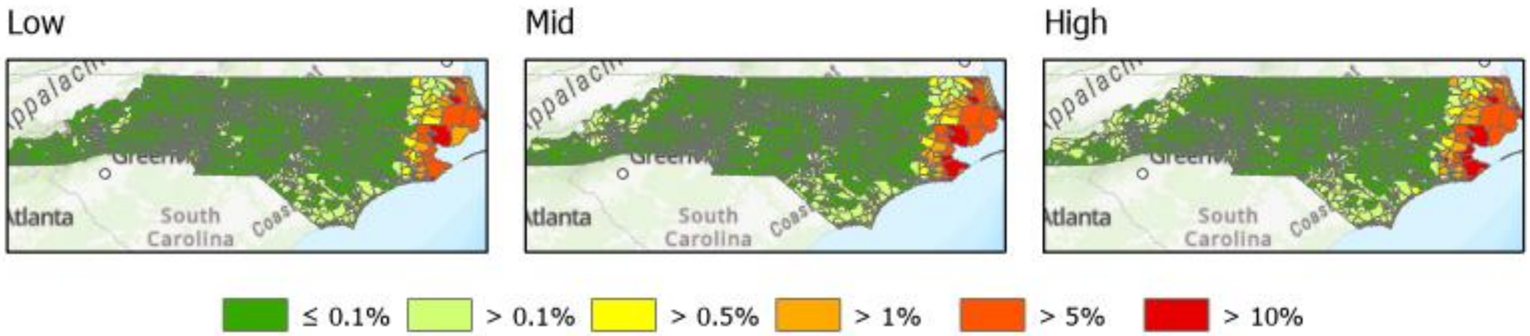

Figure 2.6: 2051 County-level Increases in Annual Percentage Flood Probability

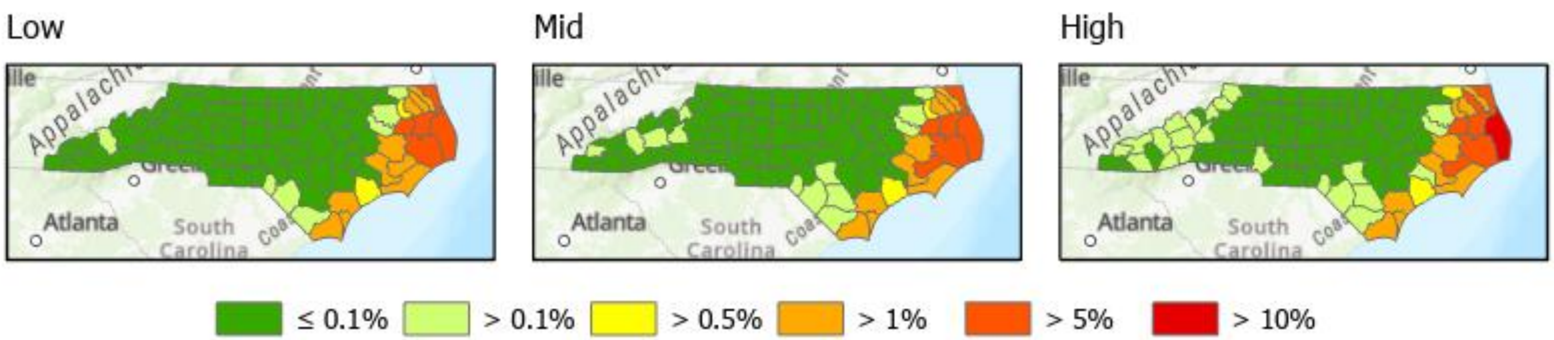

Table 2.9: Summary Statistics for State-level Projected Value Change

Model	Climate Scenario	Year	State Value Loss	State Value Loss %
Block	**Low**	2036	-$201,090,768	-0.0199%
		2051	-$333,828,352	-0.0331%
	Mid	2036	-$323,908,384	-0.0321%
		2051	-$360,634,624	-0.0358%
	High	2036	-$303,248,512	-0.0301%
		2051	-$391,142,272	-0.0388%
Zip	**Low**	2036	-$348,454,464	-0.0346%
		2051	-$592,277,184	-0.0590%
	Mid	2036	-$587,040,896	-0.0583%
		2051	-$630,589,056	-0.0626%
	High	2036	-$533,160,672	-0.0530%
		2051	-$681,469,376	-0.0677%

Table 2.10: Parameter Estimates for Percentage Value Change Regressed Against State-demeaned Variables Using OLS per Model and Climate Scenario

Model	Climate Scenario	Year	Mean Income Per Capita	% Poverty	% Black	% Asian		% American Indian		% Other Race	% Hispanic		Intercept	
Block	**Low**	2036	0.0000000	-0.0001743	0.0000656	0.0006353	***	0.0003152	***	0.0000487	0.0008299	***	-0.0133718	***
		2051	0.0000000	-0.0002008	0.0000751	0.0007992	***	0.0002056	*	-0.0001674	0.0011804	***	-0.0244184	***
	Mid	2036	0.0000001	-0.0001639	0.0000893	0.0007973	***	0.0002222	**	-0.0001696	0.0011851	***	-0.0233615	***
		2051	0.0000001	-0.0001779	0.0001065	0.0008913	***	0.0002417	**	-0.0002389	0.0013325	***	-0.0259885	***
	High	2036	0.0000001	-0.0001182	0.0001176	0.0006029	***	0.0003795	***	-0.0002024	0.0012003	***	-0.0217692	***
		2051	0.0000001	-0.0001923	0.0001512	0.0008187	***	0.0002777	**	-0.0003504	0.0015971	***	-0.0286628	***
Zip	**Low**	2036	0.0000000	-0.0003157	0.0001221	0.0011697	***	0.0006111	***	0.0001145	0.0015030	***	-0.0226384	***
		2051	0.0000001	-0.0003517	0.0001335	0.0014542	***	0.0003759	*	-0.0002863	0.0021295	***	-0.0433792	***
	Mid	2036	0.0000001	-0.0002971	0.0001574	0.0014610	***	0.0004030	**	-0.0003086	0.0021681	***	-0.0424000	***
		2051	0.0000001	-0.0003078	0.0001787	0.0015841	***	0.0004270	**	-0.0003966	0.0023486	***	-0.0455002	***
	High	2036	0.0000002	-0.0002023	0.0002102	0.0010407	**	0.0007034	***	-0.0003378	0.0021277	***	-0.0382736	***
		2051	0.0000002	-0.0003362	0.0002695	0.0014211	***	0.0004796	**	-0.0005888	0.0028074	***	-0.0501058	***

**95% statistical significance*
***99% statistical significance*
****99.9% statistical significance*
Note: 2,634 tracts per model

Table 2.11: Parameter Estimates for Flood Probability Increase Regressed Against State-demeaned Variables Using OLS per Climate Scenario

Climate Scenario	Year	Mean Income Per Capita	% Poverty	% Black		% Asian		% American Indian		% Other Race	% Hispanic		Intercept	
Low	2036	0.0017988	0.0000009	-0.0011898	*	-0.0068987	***	-0.0027478	***	-0.0004982	-0.0077647	***	0.1398271	***
	2051	0.0036096	0.0000019	-0.0023873	*	-0.0138138	***	-0.0054840	***	-0.0009305	-0.0155659	***	0.2807995	***
Mid	2036	0.0019007	0.0000009	-0.0014315	*	-0.0076088	***	-0.0030585	***	-0.0001251	-0.0087658	***	0.1511666	***
	2051	0.0038166	0.0000018	-0.0028720	*	-0.0152377	***	-0.0061015	***	-0.0001672	-0.0175750	***	0.3037235	***
High	2036	0.0021590	0.0000007	-0.0018119	**	-0.0083703	***	-0.0035951	***	0.0011287	-0.0103107	***	0.1710633	***
	2051	0.0043408	0.0000015	-0.0036290	**	-0.0167786	***	-0.0071923	***	0.0023444	-0.0207077	***	0.3439292	***

**95% statistical significance*
***99% statistical significance*
****99.9% statistical significance*
Note: 2,634 tracts per model

Table 2.12: Parameter Estimates for Percentage Value Change Regressed Against State-demeaned Variables for Tracts with a Percentage Value Change Less than -0.05%

Model	Climate Scenario	Year	Tracts	Mean Income Per Capita	% Poverty		% Black		% Asian		% American Indian		% Other Race	% Hispanic		Intercept	
Block	**Low**	2036	125	-0.0002138	0.0000022	*	-0.0023583		0.0112562	*	0.0071084		0.0064649	0.0023718		-0.1977981	***
		2051	172	0.0032732	0.0000028	*	-0.0027931		0.0086399	**	0.0118725	*	-0.0002682	0.0061356		-0.2175014	***
	Mid	2036	169	0.0043107	0.0000034	**	-0.0034683	*	0.0073417	**	0.0110771	*	0.0001126	0.0064816		-0.2228842	***
		2051	186	0.0031168	0.0000031	*	-0.0028806		0.0092777	***	0.0142964	*	-0.0024198	0.0084611	*	-0.2188258	***
	High	2036	157	0.0034040	0.0000021	*	-0.0043155	*	0.0037600		0.0171827	**	0.0006221	0.0034205		-0.2521339	***
		2051	202	0.0043116	0.0000023	*	-0.0026610		0.0015946		0.0031132	*	-0.0037714	0.0062637	*	-0.2613955	***
Zip	**Low**	2036	146	-0.0017709	0.0000012		-0.0046538	*	0.0143061	*	0.0256505	**	0.0081401	0.0000063		-0.3387467	***
		2051	309	0.0022142	0.0000038	**	-0.0002252		0.0074608	***	0.0042890	***	-0.0050131	0.0146066	***	-0.2408857	***
	Mid	2036	295	0.0028825	0.0000045	***	-0.0004598		0.0072800	***	0.0045032	***	-0.0074616	0.0173757	***	-0.2472697	***
		2051	323	0.0026290	0.0000046	***	0.0002025		0.0075643	***	0.0047351	***	-0.0058695	0.0162817	***	-0.2461933	***
	High	2036	235	0.0018697	0.0000039	*	-0.0023253		0.0049809	*	0.0162773	*	-0.0012917	0.0116530	**	-0.2770999	***
		2051	323	0.0036190	0.0000044	**	-0.0003454		0.0041766		0.0048443	***	-0.0023854	0.0152578	***	-0.2753490	***

**95% statistical significance*
***99% statistical significance*
****99.9% statistical significance*

Table 2.13: Parameter Estimates for Flood Probability Increase Regressed Against State-demeaned Variables Using OLS for Tracts with a Projected Increase Greater than 1%

Climate Scenario	Year	Tracts	Mean Income Per Capita	% Poverty	% Black	% Asian		% American Indian		% Other Race		% Hispanic	Intercept	
Low	2036	81	0.0362623	-0.0000056	-0.0120881	-0.1306957	*	-0.5334201	*	-0.1409312	*	0.1324413	2.8626275	***
	2051	115	-0.0336155	-0.0000016	0.0359038	-0.1446186		-0.7616662		-0.1378261		-0.0271697	3.6850305	***
Mid	2036	87	0.0132590	-0.0000093	-0.0046585	-0.1023154	*	-0.3499664		-0.1139922		0.0513029	2.7598603	***
	2051	123	-0.0435038	-0.0000023	0.0350849	-0.1829001	*	-0.8074188		-0.1107083		0.0408941	4.2079878	***
High	2036	101	-0.0013845	-0.0000030	0.0063776	-0.1461742	*	-0.2400219		-0.0628599		0.0998449	3.3417454	***
	2051	139	-0.0024940	-0.0000104	0.0139108	-0.2127733		-0.5537473		-0.0547701		0.1037561	4.9463654	***

**95% statistical significance*
***99% statistical significance*
****99.9% statistical significance*

Table 2.14: Summary Statistics for County-level Projected Declines in Property Tax Revenue in 2021 Dollars

Model	Climate Scenario	Year	Mean	Median	Lower	Upper	Standard Deviation
Block	**Low**	2036	-$10,631	-$1,221	-$179,895	-$76	$26,883
		2051	-$18,091	-$3,951	-$237,523	-$257	$36,304
	Mid	2036	-$17,555	-$3,730	-$248,660	-$206	$35,959
		2051	-$19,465	-$4,093	-$265,851	-$235	$39,444
	High	2036	-$16,294	-$3,387	-$217,366	-$305	$33,519
		2051	-$20,850	-$4,576	-$241,109	-$440	$40,925
Zip	**Low**	2036	-$18,322	-$1,624	-$313,322	-$86	$48,246
		2051	-$32,226	-$6,769	-$420,968	-$424	$64,976
	Mid	2036	-$31,851	-$6,628	-$446,691	-$367	$65,293
		2051	-$34,099	-$7,004	-$468,424	-$401	$69,513
	High	2036	-$28,694	-$5,900	-$386,508	-$551	$59,789
		2051	-$36,359	-$8,048	-$422,726	-$802	$71,820

Note: 100 counties

Table 2.15: Projected County-level Annual Property Tax Revenue Declines

Model	Climate Scenario	County	2036	County	2051
Block	**Low**	Currituck	-$179,895	Currituck	-$237,523
		Dare	-$123,722	Dare	-$158,621
		Beaufort	-$101,298	Beaufort	-$121,588
		New Hanover	-$75,029	New Hanover	-$111,089
		Carteret	-$68,359	Carteret	-$106,720
		-	-	-	-
		Greene	-$292	Graham	-$901
		Graham	-$265	Clay	-$680
		Polk	-$208	Greene	-$636
		Swain	-$160	Swain	-$457
		Caswell	-$76	Caswell	-$257
	Mid	Currituck	-$248,660	Currituck	-$265,852
		Dare	-$148,590	Dare	-$163,967
		Beaufort	-$114,660	Beaufort	-$123,366
		New Hanover	-$102,535	New Hanover	-$118,423
		Pasquotank	-$100,722	Carteret	-$115,998
		-	-	-	-
		Alleghany	-1,029	Yadkin	-$1,111
		Clay	-$812	Clay	-$825
		Greene	-$559	Greene	-$625
		Swain	-$534	Swain	-$554
		Caswell	-$206	Caswell	-$235
	High	Currituck	-$217,366	Currituck	-$241,109
		Dare	-$130,899	Dare	-$151,327
		Pasquotank	-$117,534	New Hanover	-$143,976
		Beaufort	-$114,284	Pasquotank	-$141,447
		New Hanover	-$93,808	Carteret	-$139,370
		-	-	-	-

		Swain	-$885	Davie	-$1,119
		Stokes	-$875	Clay	-$1,111
		Davie	-$861	Swain	-$1,094
		Yadkin	-$764	Yadkin	-$887
		Caswell	-$305	Caswell	-$440
Zip	**Low**	Currituck	-$313,322	Currituck	-$420,968
		Dare	-$224,160	Dare	-$284,461
		Beaufort	-$190,263	Beaufort	-$223,493
		New Hanover	-$131,436	New Hanover	-$192,850
		Carteret	-$123,271	Carteret	-$191,242
		-	-	-	-
		Alleghany	-$423	Graham	-$1,738
		Graham	-$368	Clay	-$1,275
		Polk	-$249	Greene	-$1,078
		Swain	-$204	Swain	-$813
		Caswell	-$86	Caswell	-$424
	Mid	Currituck	-$446,691	Currituck	-$468,424
		Dare	-$268,996	Dare	-$286,881
		Beaufort	-$215,363	Beaufort	-$224,427
		Pasquotank	-$190,286	New Hanover	-$203,234
		New Hanover	-$184,052	Pasquotank	-$202,063
		-	-	-	-
		Alleghany	-$1,829	Yadkin	-$1,953
		Clay	-$1,450	Clay	-$1,426
		Greene	-$1,003	Greene	-$1,078
		Swain	-$924	Swain	-$922
		Caswell	-$367	Caswell	-$401
	High	Currituck	-$386,508	Currituck	-$422,726
		Dare	-$228,785	Dare	-$257,724
		Pasquotank	-$216,145	New Hanover	-$250,780

Beaufort	-$213,234	Pasquotank	-$250,007
Carteret	-$162,342	Carteret	-$242,534
-	-	-	-
Swain	-$1,579	Clay	-$1,908
Stokes	-$1,568	Anson	-$1,898
Davie	-$1,390	Davie	-$1,844
Yadkin	-$1,319	Yadkin	-$1,505
Caswell	-$551	Caswell	-$802

Note 100 counties

Table 2.16: Projected State-level Annual Property Tax Revenue Declines

Model	**Climate Scenario**	**2036**	**2051**
Block	**Low**	-$1,063,054	-$1,809,093
	Mid	-$1,755,471	-$1,946,518
	High	-$1,629,400	-$2,084,950
Zip	**Low**	-$1,832,198	-$3,222,619
	Mid	-$3,185,121	-$3,409,940
	High	-$2,869,409	-$3,635,930

Chapter 3: Using Vigintile Regression Analysis to Examine Distributional Impacts of Climate-Related Increases in Flood Risk Exposure on Housing Values and Demographic Groups

Introduction

Chapters 1 and 2 of this dissertation have confirmed that impacts of flood risk across various spatial and socioeconomic spectrums are heterogeneous as the previous literature has found (Maantay & Maroko 2009, Bin & Landry 2013, Petrolia et al. 2013, Eves & Wilkinson 2014, Chakraborty et al. 2014, Bakkensen & Barage 2017, Rajapaksa et al. 2017, Ohba & Sugimoto 2019, Alcantara & Ahn 2021, Moulds et al. 2021, Chakraborty et al. 2022, Wing et al. 2022, Yu et al. 2023). To explore the heterogeneous impacts from another angle, this chapter allows for the effect of flood risk on home value to vary by the sales price of the property to analyze distributional effects. By using home values as a proxy for income levels, we can provide a more nuanced analysis of the impacts faced by income-stratified populations and the demographic groups within those strata.

We replicate the methodologies utilized in Chapters 1 and 2 but use vigintile regression analysis to estimate effects of nonlinear flood risk and floodplain designation on observations within each quantile based on home value instead of estimating the average effect across all observations. Individual counties may witness declines in aggregated single-home values as high as $86 million. As with the previous chapter, we assume these projections are conservative and underestimate the actual economic impact. Our vigintile regressions show that the average effects estimated in the mainline regressions from the previous chapter mask significant differences across the distribution of housing stock, with low-value and high-value homes exhibiting the largest negative impact of increases in flood risk.

In support of the findings of the previous chapter but in contrast to previous investigations, we estimate that White populations will face more deleterious economic impacts compared to other demographic subgroups. Overall, North Carolina will face an estimated loss in home stock value ranging from about $370 million to just over $621 million (in 2021 dollars) by 2051, depending on the severity of climate-related increases in flood risk. Additionally, we estimate declines in state-wide annual property tax revenue ranging between $1.8 and about $2.7 million by the year 2051. When compared to estimates based on the Chapter 1 mainline regression results, those generated from the vigintile hedonic models in this chapter appear to have, generally speaking, higher floors and lower ceilings.

The rest of the chapter proceeds as follows. Section 2 briefly summarizes the relevant literature. Section 3 revisits the datasets used from Chapters 1 and 2 while providing new context for this chapter. Section 4 explains the difference in hedonic model methodology between our mainline regression and vigintile regression analyses. Section 5 provides the updated estimates based on the vigintile hedonic models and a comparison to previous chapters. Section 6 provides context for the differences in estimates resulting from using the different hedonic models.

Literature

OLS regression analyses can produce results that do not accurately represent what occurs at the lower or upper tails of a dataset's distribution given the potential asymmetrical nature of observations around a mean (Koenker & Hallock 2001). Skewed distributions can undermine assumptions of normally distributed error terms, providing for biased and unreliable estimates

(Coad & Rao 2006). When analyzing continuous variables, a quantile regression analysis can better account for data points that skew the distribution and provide an outsized effect on the mean results generated by an OLS regression (Yu et al. 2003). Given the known success from using quantile regressions for salary and growth statistics, we believe home sale prices may benefit from a similar approach (Mello & Perrelli 2003, Wei et al. 2006, Coad & Rao 2008, Wiseman & Chatterjee 2010, Gilpin 2012, Porter 2014, Hsu et al. 2021).

In similar research that relates to flood risk, Bin et al. (2017) found that National Flood Insurance Program (NFIP) payouts for flood loss are progressive, and NFIP policy creates a net negative effect when controlling for income and insurance payouts. Zhang (2016) also used quantile regression analysis to assess the impact of flood risk on home value in the Fargo-Moorhead metropolitan area in North Dakota. While they found that lower-value homes faced outsized impacts, they estimated that higher-value homes were least affected. However, their findings were directly related to the impact on consumers from an extreme flood event in 2009.

In work that focuses on housing markets flood risk, Ziets et al. (2008) demonstrate that the variance in OLS regression estimates in the housing market can be solved by using quantile regression analysis that allows for heterogeneity in home characteristic preferences between income groups. Waltl (2016) similarly argues that quantile regression analysis can account for spatial variation in housing prices even within a single metropolitan area. We extend this line of research by estimating unconditional vigintile effects using the recentered influence function approach (Firpo et al. 2009).

Data

In this chapter we use the same final Zillow dataset from Chapter 1 with 921,105 unique transactions representing 676,798 unique parcels combined with the First Street Foundation 2021 flood risk metrics and FEMA floodplain designations. In estimating the property value changes for parcel-, tract-, county-, and state-level projections, we use the same final dataset from Chapter 2 that includes 5,363,329 parcels and their respective contemporary and future flood probability metrics. The same 2024 tax rates for North Carolina counties from Chapter 2 are used to estimate property tax revenue losses for years 2036 and 2051. The same Census data integrated in Chapter 2 is used here as well.

We provide summary statistics for the demographic data when observations have been isolated to represent each of the 19 partitions created, for the vigintile regression analysis (Tables 3.1-3.7). Note that the percentages of the population that are Black, Other Race, or Hispanic negatively correlate to average property value. Conversely, the percentage of the population that is Asian positively correlates to average property value. Intuitively, the percentage of the population below the poverty line negatively correlates to home value while the average income per capita positively correlates.

Methodology

First, we replicate the hedonic model specification from Chapter 1 except we estimate a vigintile regression analysis represented by the equation:

$$RIF[ln(SP_{iqjt})] = \Sigma_{iqjt}\beta_{iqjt}X_{iqjt} + Risk_{iqjt} + Risk^2_{iqjt} + FEMA_{iqjt} + \rho_j + \tau_t + \varepsilon_{iqjt} \quad (3.1)$$

where $RIF[ln(SP_{iqjt})]$ represents recentered influence function of the natural log of the Case-Shiller adjusted sale price of the *i*th house in the home value percentile *q* using a spatial unit *j* and time period t, X_{iqjt} represents a set of structural property characteristics up to fifth level polynomials and other controls, $Risk_{iqjt}$ and $Risk^2_{iqjt}$ represent the Flood Lab estimated probability of flood and the square of flood probability[10] respectively, $FEMA_{iqjt}$ is a binary variable indicating whether the property is in the FEMA 100-year floodplain, ρ_j and τ_t represent spatial and temporal fixed effects, respectively, and ε represents a random error term clustered by a unique longitudinal parcel identification number. V represents every 5th percentile (5, 10, 15…95) that creates 19 partitions for 20 equal quantiles (vigintiles). The recentered influence function provides for an unconditional quantile regression that controls for the influence of individual observations on the dependent variable's distributional quantile. Although unique parameter estimates are calculated for each quantile partition, the entire sample is used for each estimation. Our preferred models are the same as in Chapter 1, although we again explore other fixed effect specifications.

Second, we create 19 equal quantiles, based on property value, from the Chapter 2 dataset containing 5,363,329 parcels to which we can apply each of the 19 quantile partitions. As in the previous chapter, we adjust property values to reflect the difference in a property's floodplain designation between FEMA and the First Street model using the following formula:

$$APV_{iqjc} = PV_i * [1 + \beta_{qj}(FS_{ic} - FEMA_i)] \qquad (3.2)$$

where APV_{iqjc} represents the 2021 adjusted property value of the ith house in quantile q using the spatial unit j hedonic model results for climate scenario c, PV_i represents the current property value estimate for house i, β_{qj} represents the parameter estimate for the effect of floodplain designation for house i in climate scenario c, FS_{ic} represents the floodplain dummy constructed from the First Street probabilities, and $FEMA_i$ represents the current FEMA floodplain

[10] Risk factor polynomials of a third order and higher lacked consistent statistical significance and were excluded from the model.

designation for the house. This property value adjustment yields a normalized impact on home value from changes in flood risk exposure as the future floodplain designations are based on First Street projections.

Third, we calculate the percenteage impact of the respective year's flood risk probability on property value:

$$PVI_{iqjct} = \beta_{1qj}(FR_{ict}) + \beta_{2qj}(FR^2_{ict}) + \beta_{3qj}(FP_{ict}) \qquad (3.3)$$

Where PVI_{iqjct} represents the impact of flood risk on the value of the ith house in the home value quantile q using the spatial unit j hedonic model results for climate scenario c in year t, β_{1qj} represents the parameter estimate for the FS-FM flood risk probability (FR_{ict}), β_{2qj} represents the parameter estimate for the FS-FM flood risk probability squared (FR^2_{ict}), and β_{3qj} represents the parameter estimate for the FS-FM constructed floodplain designation (FP_{ict}). As in Chapter 2, we adjust the model such that flood risk values creating a positive marginal effect have been replaced with the value of flood risk that generates the last negative marginal effect at the minimum of each parabolic model curve. This prevents, all other things equal, any increase in flood risk from having a positive impact on home value. This process differs from Chapter 2 in that 19 sets of coefficients, depending on the home-value vigintile a parcel belongs to, are used to determine the impact as opposed to one set of coefficients for all parcels in the previous chapter.

As in the previous chapter, we multiply the difference in value impacts between the base year 2021 and years 2036 and 2051 by the adjusted property value to estimate the value changes for all parcels resulting from climate-related changes in flood risk. These parcel-level changes in property value are then aggregated at the tract, county, and state levels. Using the aggregations of the adjusted property values for each corresponding geographic area, we calculate the value change as a percentage at each respective spatial unit.

To further explore the distributional impacts of increased flood risk exposure, we perform the same OLS regression analyses from Chapter 2 of tract level value changes, both in absolute terms and as a percentage, against the socioeconomic and demographic data from the Census. In this case, the dependent variables have been calculated using the vigintile regression results but are still represented by the formulas:

$$PVL_{ijct} = Income_i + Poverty_i + White_i + Black_i + Asian_i + AmIndian_i + \varepsilon_{ijct} \qquad (3.4)$$

Where PVL_{ijct} represents the average percentage value loss in 2021 dollars for the ith tract using the spatial effect j hedonic model results in climate scenario c for year t, $Income_i$ represents the state-demeaned average income per capita for tract i, $Poverty_i$ represents the state-demeaned percentage of the population in poverty for tract i, $White_i$ represents the state-demeaned percentage of the population that is white for tract i, $Black_i$ represents its respective state-demeaned percentage of the population for tract i, $Asian_i$ represents its respective state-demeaned percentage of the population for tract i, $AmIndian_i$ represents the state-demeaned percentage of the population that is American Indian for tract i, and ε represents a random error term.

Finally, we replicate the estimated decreases in annual property tax revenue resulting from climate-related increases in flood risk exposure, but the decreases in revenue are based on the property value change estimates from the vigintile regression models. We again aggregated the property tax revenue declines at the county and state levels. Our methodology in this chapter replicates the combined methodology from Chapters 1 and 2 except for using vigintile hedonic regressions and their respective parameter estimates.

Results

Vigintile Regression Results

Tables 3.8 and 3.9 present the flood risk coefficients from our vigintile regressions, again using our preferred models with block-group and zip-code fixed effects. Statistical significance varies among the vigintiles and the fixed effects with the lowest- and highest-quantiles demonstrating estimates most statistically different from zero. As with the mainline regression results from Chapter 1, the zip-code fixed effect generally estimates a higher sensitivity to flood risk on home value relative to the block-group fixed effect. Why some vigintiles evidence a positive estimate for FEMA floodplain designation is an open question, yet these estimates have p-values beyond any reasonable threshold of significance. As a robustness test, we estimate and provide the regression results for the tract- and county-level fixed effects in the Appendix (Tables 3.19A and 3.20A).

Figures 3.1-3.6 illustrate the marginal effect of increasing flood risk from 0% to 1% through the continuous (First Street Foundation) metric channel, the FEMA floodplain designation channel, and the combined effect, respectively. Turning first to the continuous measure of flood risk, the upper and lower sale price vigintiles for both models evidence the strongest and most statistically significant negative effect, reflecting a parabolic relationship between the disamenity of flood risk and housing values. Put another way, we find greater evidence of sensitivity of housing prices to flood risk at the high-value and low-value portions of the housing stock, while the middle portion of the housing stock does not exhibit the same statistically significant effect.

By contrast, the marginal effect across vigintiles from FEMA floodplain designation demonstrate a larger sensitivity to floodplain designation for the highest-value homes. The low-value home price sensitivity varies between the block-group and zip-code models, though both demonstrate significantly larger confidence intervals than the higher vigintiles. For the block-group model, the lowest-value homes and some high-value vigintiles show a positive effect from floodplain designation, though this effect is not statistically significant. As in the mainline regression, the effect of FEMA floodplain designation is generally larger than the continuous and less visible flood risk measure.

Property Value Change

Tables 3.10-3.12 provide the summary statistics for the parcel-, tract-, and county-level home value loss in real dollars and as a percentage of total housing stock value based on the vigintile regression results. These tables evidence the distributional of impacts of climate change when accounting for heterogeneous effects of flood risk on different strata of home values. As in chapter 2, we maintain that these results represent conservative estimates of expected losses. Both the tract- and county-level estimates find significant increases in flood risk exposure in the Coastal Plain as well as the Mountain regions, especially relative to the Piedmont (Figures 3.7-3.10). In the worst-case scenario estimated by our models, some parcels will witness a decline in property value from increased flood risk as great as 12.6%. Individual tracts and counties could see declines in housing stock value as high as 2.4% and 1.0% of total property value respectively. While the variance in value change as a percentage at the parcel level is much higher with the vigintile regression analysis compared to the mainline regression analysis from Chapter 1, when aggregating these value losses, the extremes at the tract and county level are more tempered than those evidenced in Chapter 2.

Looking at the tails of county-aggregated property value losses among the different models, climate scenarios, and future projections, we witness trends similar to those in the previous chapter (Tables 3.21A-3.26A). Currituck County maintains a high frequency at the extreme of value loss regardless of the model, year, or scenario, but Dare and New Hanover Counties evidence a much higher frequency of having the highest value loss, both in absolute terms and as a percentage, compared to the Chapter 2 results. Caswell County maintains a relatively high frequency of being the least-impacted county, but Mecklenburg, Yadkin, and Wake Counties are more heavily represented. The story remains the same, however, in that coastal counties are the projected victims of the most extreme increases in flood risk exposure while more central counties fair best.

At the state level, aggregated property value loss estimates for 2036 range from just over $226 million to almost $511 million (about 0.02-0.05%) depending on the model and climate scenario. For 2051, we estimate a range of about $371 million to $621 million (about 0.04-0.06%). These estimates, evidenced in Table 3.13, have a higher floor but a lower ceiling than the state-level estimates using the original mainline regression models. Put another way, this more nuanced model moderates the more extreme optimistic and pessimistic estimates from our Chapter 2 analysis. As in the previous chapter, a significantly smaller increase in value loss occurs from 2036-2051 compared to the loss from 2021-2036. This difference again demonstrates the difference in impact between extensive and intensive changes in flood risk exposure.

Demographic and Socioeconomic Impacts

The results of our regression analysis examining how climate change will impact different socioeconomic groups support our findings in the previous chapter (Table 3.14). Asian, American Indian, and Hispanic populations maintain a statistically significant but lesser impact on percentage home value from increased flood risk compared to Non-Hispanic White populations. Black populations see a similar but smaller difference in home value impact. While not all models find statistical significance for the Black population parameter estimates, no coefficients evidenced statistical significance using percentage value change based on the mainline hedonic model results.

When looking at the income-related variables, the vigintile models evidence greater value loss given a higher percentage of the population in poverty while also demonstrating a greater value loss given a higher average income per capita. These findings are statistically significant at various levels whereas the parameter estimates from the non-vigintile models in the previous chapter lacked statistical significance Additionally, the correlation between value change and average income per capita became negative when using the vigintile analysis. These two parameter estimates support this chapter's marginal effect results in demonstrating that low- and high-income properties are most sensitive to increase in flood probability. While magnitude and statistical significance vary, the same story is told whether the regression analyses used the property value changes based on the mainline or vigintile hedonic models.

Overall, the regression results when isolating high-risk tracts tell a similar story where statistical significance remains, but much of the statistical significance is lost (Table 3.15).[11] Of note, the parameter estimates for average income per capita oscillate around zero but have lost all statistical significance. Where significance remains, the signs of the coefficients for the percentage of the population under the poverty line have reversed, positively correlating with value change and signifying that a higher percentage in poverty correlates with a reduction in

[11] As in Chapter 2, the high-risk tracts are those that see a loss of value in the housing stock greater than 0.05% or an increase of flood probability greater than 1% depending on which dependent variable is being regressed (percentage value change delta flood risk respectively).

value loss. The model results from isolating the high-risk tracts are very similar to those of the previous chapter.

Property Tax Revenue

Using the same methodology as the previous chapter but using the value change calculations based on the vigintile hedonic models, we estimate the projected tax revenue declines resulting from decreased values in the housing stock. The summary statistics found in Table 3.16 demonstrate a substantially greater average decline in property tax revenue compared to the findings in Chapter 2 despite the smaller magnitude of the extreme upper and lower bounds. This suggests that, when using the vigintile hedonic model results, more counties exist on the side of the spectrum most impacted by property value losses. In the year 2036, expected declines in county-level annual property tax revenue range from $0 to just over $300,000 depending on the county, model, and climate scenario. The year 2051 evidences a range in declines from $75 to about $387,000.

When identifying the counties most- and least-impacted by projected property tax revenue decline, we see similar trends not just between the different models and years but also between the results of this chapter and Chapter 2 (Table 3.17). Currituck, Dare, and New Hanover Counties remain the relative losers while Caswell, Swain, and Yadkin Counties continue to be relatively unimpacted. When estimated property tax revenue declines are aggregated at the state level, we see a range from just over $1.1 million to just under $2.7 million for 2036 and from about $1.9 million to almost $3.2 million in 2051 (Table 3.18).

Conclusion

Our findings, as opposed to those in Chapter 2, support the conclusions of previous investigators that low-income households will bear a disproportionately large burden of the costs of increased flood risk exposure. However, we discover that, as opposed to previous investigations including our own, high-income households will also face a disproportionately large burden. The impacts are in the tails of the distribution. Several factors may contribute to the parabolic impact of increased flood risk across the housing value spectrum. Insurance provided by the NFIP (and required for many properties residing in the FEMA 100-year floodplain) is capped at $250,000. Given a median sale price of $205,337 in the dataset, the insurance burden of higher flood risk is greatest (as a percentage of the value of the home) for lower value homes. Additionally, efforts to mitigate flood risk or otherwise adapt may prove prohibitively expensive for lower-income households.

Given the $250,000 insurance cap with the NFIP, more expensive homes may see increased capitalization of flood risk in the home value as the NFIP cap becomes an increasingly smaller percentage of the home value. As we assume the amenity of close proximity to water and the disamenity of flood risk are not fully disentangled in our models, our efforts to control for the effect of proximity to water could be more effective at higher home-value quantiles. While the disproportionate impact of increased flood risk on lower-value homes is well-documented in the literature, our work goes beyond the findings of previous papers in that we also find that increases in flood risk have an outsize impact on lower-value homes even after controlling for FEMA floodplain designation. As with Chapter 2, the analysis in this chapter is flawed by the underlying assumption that the demographic and socioeconomic composition of North Carolina and its Census tracts will remain the same.

Tables and Figures

Table 3.1: Summary Statistics for Percentage of Population in Poverty by Tract per Vigintile

Vigintile	Parcels	Mean	Median	Lower	Upper	Standard Deviation
1	282,383	20.8252%	19.4665	0	72.8140	10.9300
2	282,496	18.2892%	17.1221	0	72.8140	9.7802
3	281,953	17.6628%	16.6712	0	100	9.5645
4	284,176	16.8470%	15.8997	0	72.8140	9.2951
5	281,674	15.7117%	14.1934	0	72.8140	8.7526
6	281,374	15.0387%	13.8306	0	72.8140	8.8969
7	283,915	14.1129%	12.9926	0	100	8.4786
8	280,583	13.7225%	12.4975	0	100	8.4383
9	284,648	13.0065%	11.5301	0	100	8.5536
10	282,856	13.4681%	11.8246	0	72.8140	8.7162
11	279,964	13.5339%	11.9431	0	72.8140	8.7543
12	286,006	13.4745%	11.8391	0	72.8140	8.7223
13	277,088	13.4931%	11.7908	0	72.8140	9.0141
14	282,322	12.6545%	11.0485	0	72.8140	8.7801
15	286,906	13.2940%	11.4198	0	100	9.1581
16	284,902	12.3715%	10.6447	0	100	8.9532
17	274,538	11.5976%	9.2915	0	100	8.8524
18	282,174	9.4705%	6.8973	0	72.8140	8.1644
19	282,162	8.1066%	5.4530	0	100	7.9663

Table 3.2: Summary Statistics for Average Income per Capita by Tract per Vigintile

Vigintile	Parcels	Mean	Median	Lower	Upper	Standard Deviation
1	282,383	$23,558	$22,615	$4,453	$131,291	$7,675
2	282,496	$25,802	$24,244	$4,453	$129,331	$7,388
3	281,953	$25,670	$24,693	$3,320	$143,464	$7,593
4	284,176	$26,469	$25,280	$4,453	$200,007	$7,827
5	281,674	$26,836	$25,589	$926	$200,007	$7,649
6	281,374	$28,136	$26,585	$0	$200,007	$8,437
7	283,915	$29,156	$27,434	$0	$200,007	$8,775
8	280,583	$29,963	$28,065	$3,320	$200,007	$9,396
9	284,648	$31,345	$29,223	$831	$200,007	$10,286
10	282,856	$30,777	$28,670	$831	$200,007	$10,147
11	279,964	$31,034	$28,768	$831	$200,007	$10,807
12	286,006	$31,260	$28,903	$831	$200,007	$11,023
13	277,088	$31,710	$29,019	$4,453	$200,007	$12,038
14	282,322	$32,955	$30,315	$831	$200,007	$12,144
15	286,906	$32,214	$29,299	$0	$200,007	$11,908
16	284,902	$34,046	$31,078	$0	$200,007	$13,229
17	274,538	$35,656	$32,726	$0	$200,007	$13,796
18	282,174	$41,359	$39,996	$0	$200,007	$15,406
19	282,162	$51,875	$49,785	$0	$200,007	$22,374

Table 3.3: Summary Statistics for Black Percentage of Population by Tract per Vigintile

Vigintile	Parcels	Mean	Median	Lower	Upper	Standard Deviation
1	282,383	34.0023%	29.1630	0	98.0707	26.5591
2	282,496	27.3212%	20.8046	0	98.0707	24.5862
3	281,953	25.6187%	20.0756	0	98.0707	22.4390
4	284,176	23.9324%	18.7248	0	98.0707	21.0738
5	281,674	19.1993%	14.9437	0	98.0707	17.5097
6	281,374	21.6498%	15.9054	0	98.0707	19.6844
7	283,915	19.9135%	14.0731	0	98.0707	19.0165
8	280,583	18.3106%	12.6126	0	98.0707	18.1931
9	284,648	18.0693%	12.0744	0	98.0707	18.2789
10	282,856	17.1965%	10.8404	0	98.0707	18.1784
11	279,964	17.1248%	10.6082	0	98.0707	18.5458
12	286,006	15.9411%	9.3314	0	98.0707	18.0611
13	277,088	16.6995%	10.0917	0	98.0707	18.6394
14	282,322	15.8906%	9.5261	0	98.0707	17.6945
15	286,906	16.6390%	9.8742	0	98.0707	18.6009
16	284,902	15.7065%	9.3325	0	98.0707	17.8544
17	274,538	14.3318%	8.2773	0	98.0707	16.7032
18	282,174	11.3784%	6.7675	0	98.0707	13.5623
19	282,162	9.7505%	5.0881	0	98.0707	13.3312

Table 3.4: Summary Statistics for Asian Percentage of Population by Tract per Vigintile

Vigintile	Parcels	Mean	Median	Lower	Upper	Standard Deviation
1	282,383	1.4783%	0.2555	0	55.0333	3.0221
2	282,496	1.5660%	0.3252	0	55.0333	3.0633
3	281,953	1.5936%	0.3338	0	49.1571	3.1714
4	284,176	1.6518%	0.3554	0	55.0333	3.3174
5	281,674	1.6983%	0.5151	0	49.1571	2.9562
6	281,374	1.9031%	0.5741	0	55.0333	3.5317
7	283,915	1.8824%	0.5782	0	55.0333	3.4019
8	280,583	1.8596%	0.5410	0	49.1571	3.4023
9	284,648	2.1158%	0.6878	0	55.0333	3.9867
10	282,856	1.9169%	0.5151	0	55.0333	3.9142
11	279,964	1.8414%	0.4622	0	55.0333	3.8692
12	286,006	1.7546%	0.3997	0	55.0333	3.7786
13	277,088	1.8851%	0.4611	0	55.0333	4.0046
14	282,322	2.6998%	0.6413	0	55.0333	6.1947
15	286,906	2.0576%	0.5180	0	55.0333	4.3386
16	284,902	2.3717%	0.7245	0	55.0333	4.7272
17	274,538	2.6967%	0.8309	0	55.0333	5.3142
18	282,174	3.7560%	1.2948	0	55.0333	6.7103
19	282,162	4.4248%	1.8129	0	55.0333	7.1584

Table 3.5: Summary Statistics for American Indian Percentage of Population by Tract per Vigintile

Vigintile	Parcels	Mean	Median	Lower	Upper	Standard Deviation
1	282,383	0.7165%	0	0	93.9214	2.6101
2	282,496	1.0302%	0	0	93.9214	4.8983
3	281,953	2.5940%	0.0324	0	93.9214	10.2637
4	284,176	2.5152%	0.0577	0	93.9214	9.9615
5	281,674	1.2505%	0.0306	0	93.9214	5.5562
6	281,374	1.5039%	0	0	93.9214	6.8962
7	283,915	1.2045%	0	0	93.9214	5.7595
8	280,583	1.0813%	0	0	93.9214	5.3473
9	284,648	0.9539%	0	0	93.9214	4.7302
10	282,856	1.3236%	0	0	93.9214	6.4783
11	279,964	1.2823%	0	0	93.9214	6.0841
12	286,006	1.4858%	0	0	93.9214	7.1092
13	277,088	1.3296%	0	0	93.9214	6.3106
14	282,322	1.2205%	0	0	93.9214	6.2721
15	286,906	1.2849%	0	0	93.9214	6.4205
16	284,902	0.9839%	0	0	93.9214	5.2646
17	274,538	1.0057%	0	0	93.9214	5.3653
18	282,174	0.6476%	0	0	93.9214	3.6422
19	282,162	0.4894%	0	0	93.9214	2.5908

Table 3.6: Summary Statistics for Other Race Percentage of Population by Tract per Vigintile

Vigintile	Parcels	Mean	Median	Lower	Upper	Standard Deviation
1	282,383	7.6475%	6.1256	0	47.3173	6.3026
2	282,496	7.2740%	5.5718	0	47.3173	6.1347
3	281,953	7.1176%	5.4939	0	47.3173	6.0013
4	284,176	6.8467%	5.1379	0	47.3173	5.9186
5	281,674	7.0575%	5.0780	0	47.3173	6.3465
6	281,374	6.9093%	5.3414	0	47.3173	5.8826
7	283,915	6.5386%	5.0463	0	47.3173	5.6851
8	280,583	6.2113%	4.8056	0	47.3173	5.4750
9	284,648	5.8887%	4.4242	0	47.3173	5.2876
10	282,856	5.6874%	4.3344	0	47.3173	5.0552
11	279,964	5.4630%	4.0990	0	47.3173	4.9264
12	286,006	5.3523%	4.0531	0	47.3173	4.7910
13	277,088	5.5551%	4.1463	0	47.3173	5.0387
14	282,322	5.7844%	4.4588	0	47.3173	5.2117
15	286,906	5.4826%	4.0258	0	47.3173	4.9863
16	284,902	5.7014%	4.3344	0	47.3173	5.1401
17	274,538	5.3766%	4.1718	0	47.3173	4.7802
18	282,174	4.9604%	3.8391	0	47.3173	4.4182
19	282,162	4.5424%	3.5698	0	47.3173	4.1569

Table 3.7: Summary Statistics for Hispanic Percentage of Population by Tract per Vigintile

Vigintile	Parcels	Mean	Median	Lower	Upper	Standard Deviation
1	282,383	12.2340%	9.2455	0	66.6667	9.7052
2	282,496	11.2125%	8.5335	0.5485	69.9569	8.8273
3	281,953	10.8507%	8.3905	0	66.6667	8.4743
4	284,176	10.6099%	8.2254	0.5485	69.9569	8.3248
5	281,674	10.7244%	8.4401	0.5485	70.0412	8.0374
6	281,374	10.9085%	8.6836	0	69.9569	8.0303
7	283,915	10.4113%	8.3965	0	69.9569	7.7072
8	280,583	9.6925%	7.7689	0.5485	69.9569	7.3361
9	284,648	9.3352%	7.4524	0	69.9569	7.0641
10	282,856	8.7905%	6.8338	0	69.9569	6.7778
11	279,964	8.3778%	6.3800	0	69.9569	6.5830
12	286,006	8.1973%	6.2486	0	69.9569	6.6112
13	277,088	8.5020%	6.6182	0	69.9569	6.6525
14	282,322	8.5460%	6.6543	0	69.9569	6.6730
15	286,906	8.1583%	6.2580	0	70.0412	6.4147
16	284,902	8.6741%	6.6006	0	69.9569	6.8399
17	274,538	7.9357%	6.2034	0	69.9569	6.1153
18	282,174	7.2394%	5.9330	0	69.9569	5.4598
19	282,162	6.4095%	5.1245	0	69.9569	5.1821

Table 3.8: Vigintile Regression Results for Block-Group Fixed Effect

	Percentile	Percentage-Chance		Percentage-Chance Squared		FEMA 100-year	
Block	5	-0.003285		0.0001448	**	0.0035611	
	10	-0.0016333		0.0000838	**	-0.0063013	
	15	-0.0013492	*	0.0000659	**	-0.0263671	*
	20	-0.001217	*	0.0000468	**	-0.0223727	**
	25	-0.0008359	*	0.0000306	*	-0.0190702	**
	30	-0.0006658		0.0000255	*	-0.0153338	**
	35	-0.0005461		0.0000211	*	-0.0106572	
	40	-0.0003602		0.0000196		-0.0102661	
	45	-0.0004932		0.0000232	*	-0.0103902	*
	50	-0.0005188		0.0000296	**	-0.0067364	
	55	-0.0008403	**	0.0000418	***	-0.0055917	
	60	-0.00091	**	0.000045	***	-0.0019967	
	65	-0.0008891	*	0.0000504	***	0.0044408	
	70	-0.0009723	**	0.0000572	***	0.0066093	
	75	-0.0018941	***	0.0000962	***	0.0090847	
	80	-0.0023362	***	0.0001266	***	0.0097273	
	85	-0.0028939	***	0.0001623	***	0.0054074	
	90	-0.0038893	***	0.000207	***	-0.0282515	**
	95	-0.0057561	***	0.000279	***	-0.0795928	***

**95% statistical significance*
***99% statistical significance*
****99.9% statistical significance*

Table 3.9: Vigintile Regression Results for Zip-Code Fixed Effect

	Percentile	Percentage-Chance		Percentage-Chance Squared		FEMA 100-year	
Zip	5	-0.0026178		0.0001131	*	-0.0818856	**
	10	-0.0014826		0.0000763	**	-0.0696845	***
	15	-0.0014783	*	0.0000675	***	-0.0706941	***
	20	-0.0015793	***	0.0000532	***	-0.0481583	***
	25	-0.0011976	**	0.0000358	**	-0.0340541	***
	30	-0.0009022	*	0.0000259	*	-0.026023	***
	35	-0.0006756	*	0.0000178		-0.0185257	***
	40	-0.0003786		0.0000126		-0.0160429	**
	45	-0.0004405		0.0000138		-0.014525	**
	50	-0.0003765		0.0000185		-0.0099931	
	55	-0.0005433		0.0000259	*	-0.0100722	
	60	-0.000465		0.0000261	*	-0.0080125	
	65	-0.0003712		0.000032	**	-0.0022735	
	70	-0.000425		0.0000396	**	-0.0029902	
	75	-0.0014561	***	0.0000825	***	-0.0018922	
	80	-0.0022305	***	0.0001223	***	-0.0006542	
	85	-0.003123	***	0.0001628	***	-0.0046751	
	90	-0.0047904	***	0.0002224	***	-0.0316055	**
	95	-0.007281	***	0.0002892	***	-0.080053	***

**95% statistical significance*
***99% statistical significance*
****99.9% statistical significance*

Figure 3.1: Marginal Effect of Percentage-Chance Change from 0% to 1% Block Fixed Effect

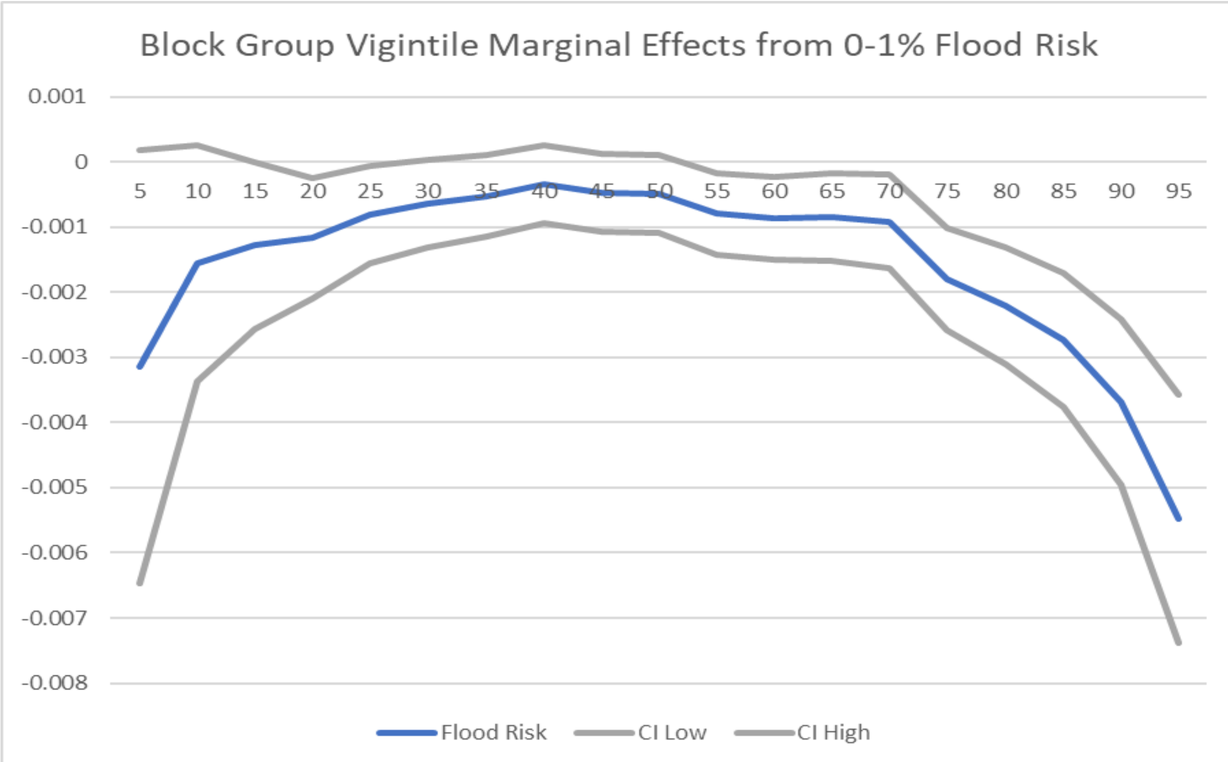

Figure 3.2: Marginal Effect of Percentage-Chance Change from 0% to 1% Zip Fixed Effect

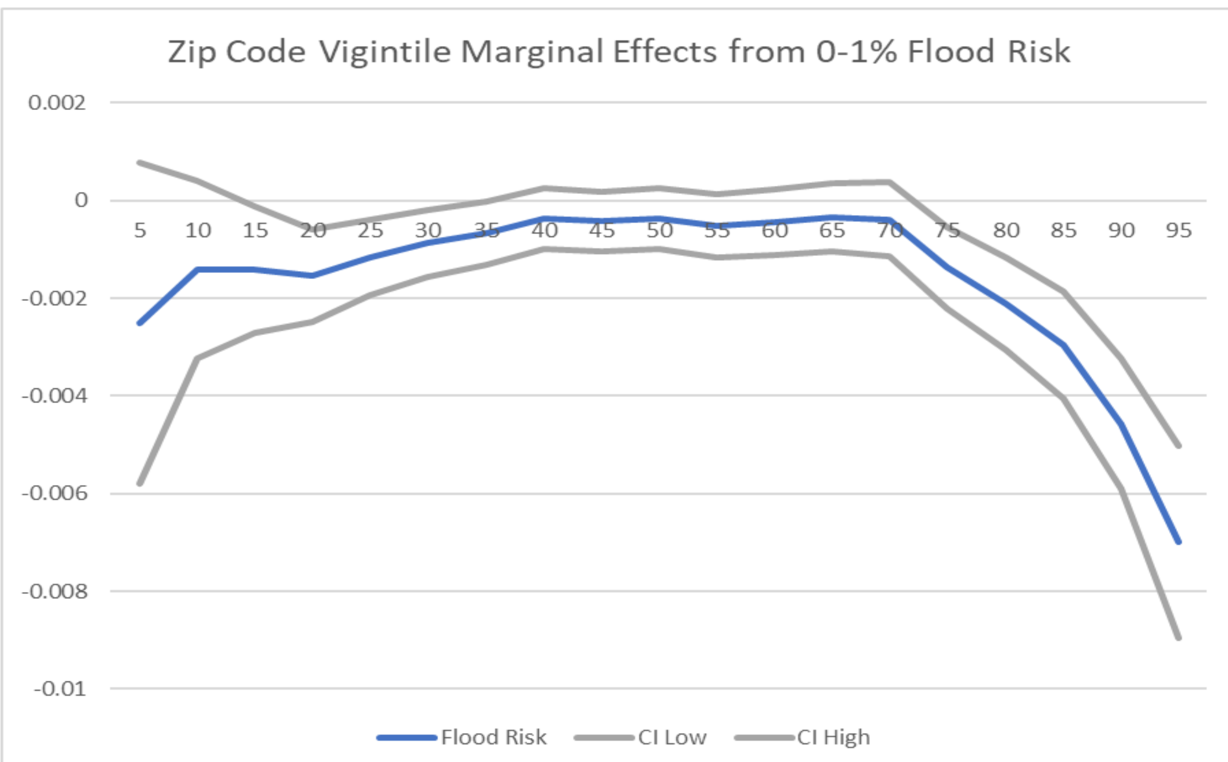

Figure 3.3: Marginal Effect of FEMA Floodplain Designation Block Fixed Effect

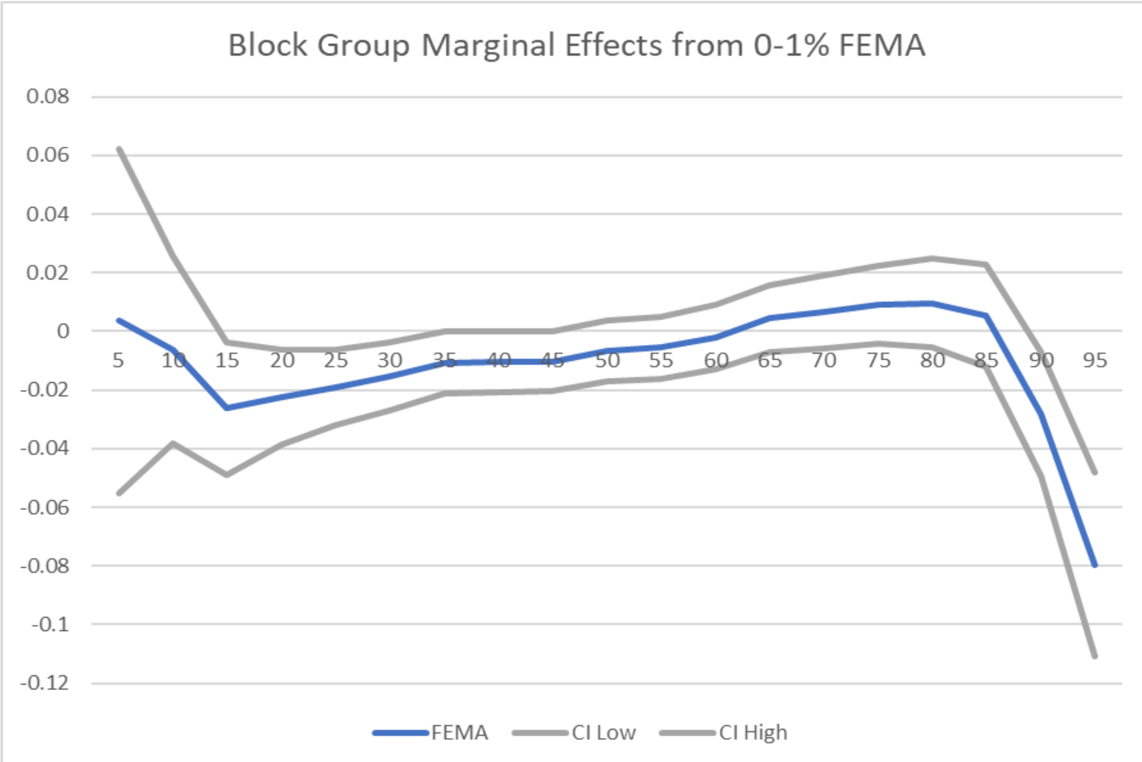

Figure 3.4: Marginal Effect of FEMA Floodplain Designation Zip Fixed Effect

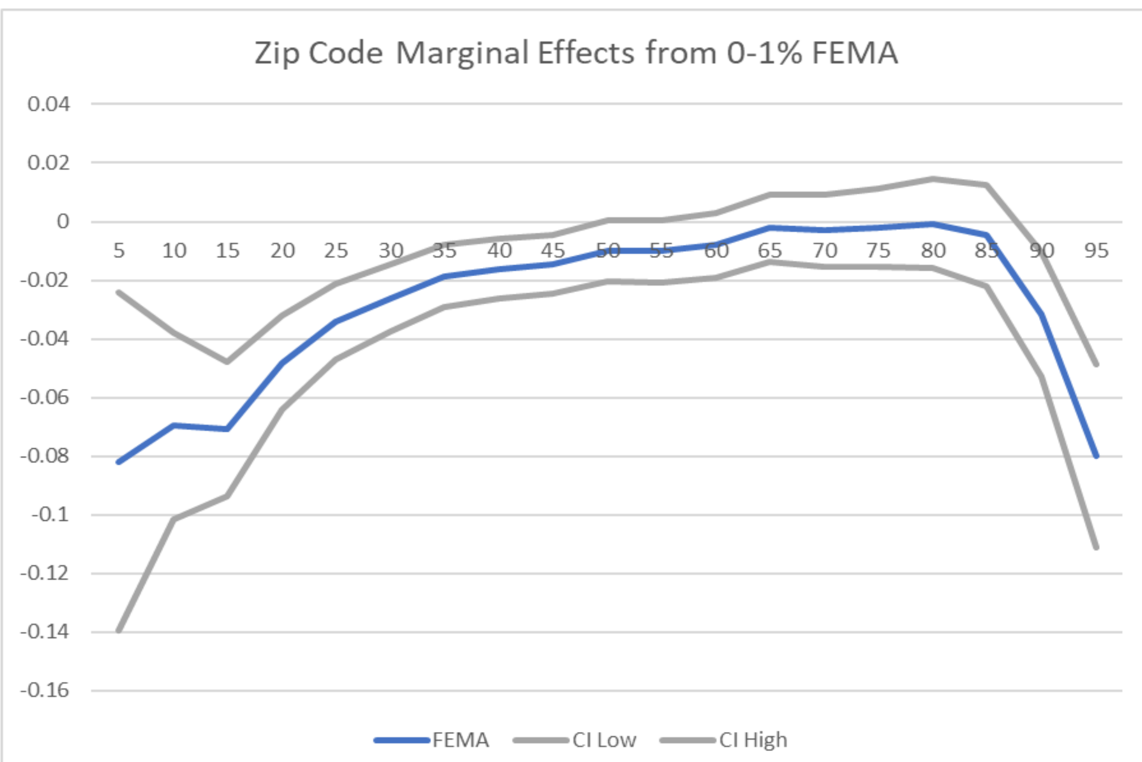

Figure 3.5: Combined Marginal Effects Block Fixed Effect

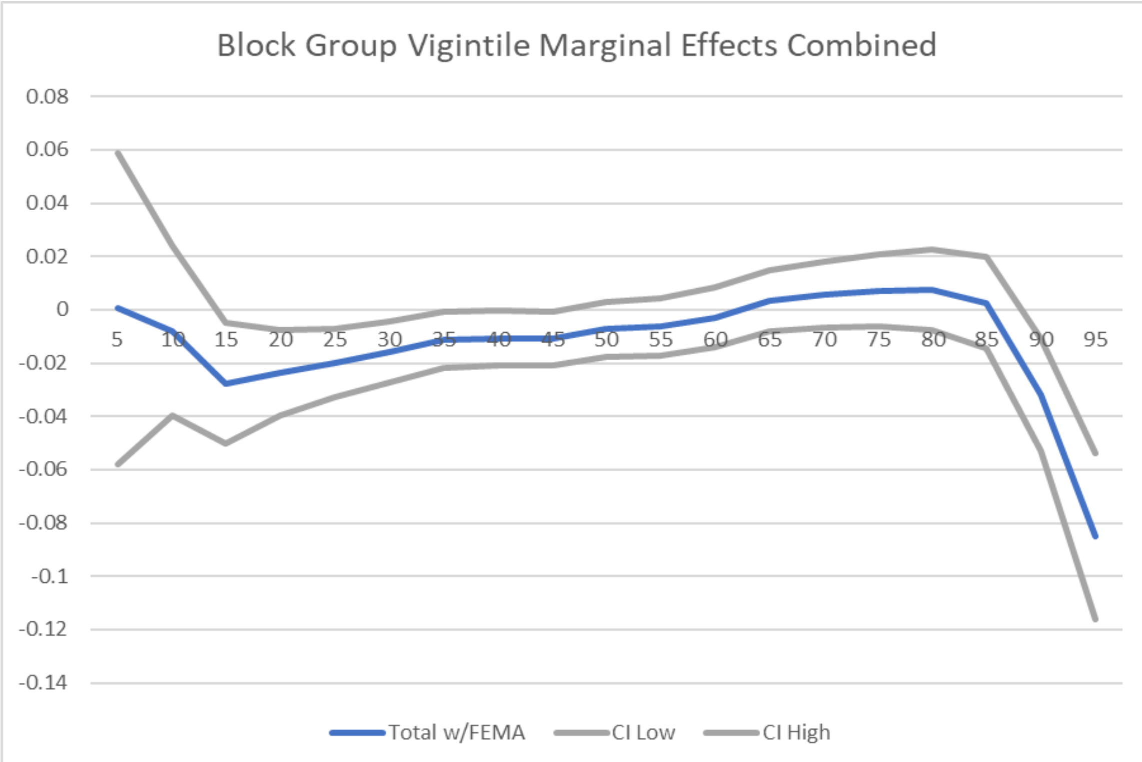

Figure 3.6: Combined Marginal Effects Zip Fixed Effect

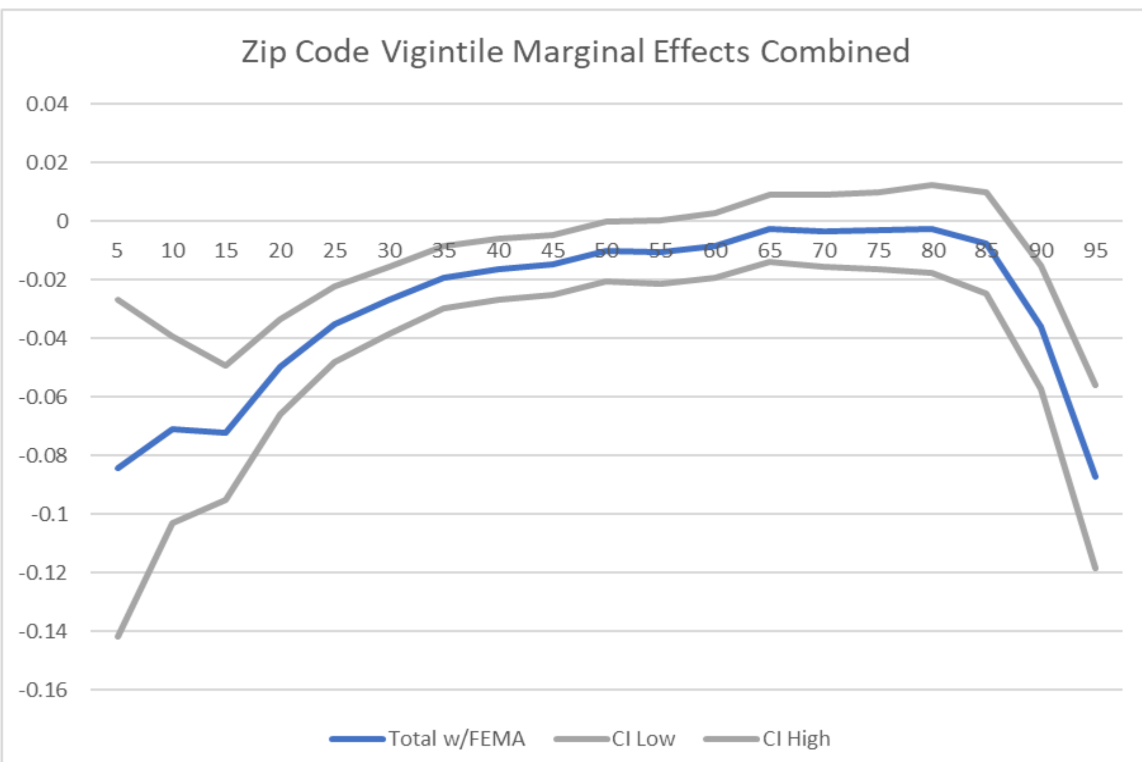

Table 3.10: Summary Statistics for Parcel-level Projected Value Change

Model	Climate Scenario	Year	Mean Parcel Value Change	Lower	Upper	Standard Deviation	Mean Parcel Value Change %	Lower	Upper	Standard Deviation
Block	**Low**	2036	-$42.16	-$310,194	$75,439	$1,212.88	-0.0128%	-10.9282	8.2457	0.2160
		2051	-$69.09	-$316,475	$78,208	$1,608.37	-0.0219%	-10.9282	10.9282	0.2883
	Mid	2036	-$66.17	-$310,194	$6,845	$1,626.87	-0.0198%	-10.9282	0.8683	0.2892
		2051	-$75.35	-$320,020	$88,053	$1,723.36	-0.0228%	-10.9282	10.9282	0.3067
	High	2036	-$60.74	-$365,108	$64,691	$1,448.45	-0.0188%	-10.9282	8.1790	0.2716
		2051	-$81.36	-$365,108	$184,529	$1,816.02	-0.0249%	-10.9282	10.9282	0.3248
Zip	**Low**	2036	-$59.66	-$356,069	$76,567	$1,311.90	-0.0224%	-12.5880	8.3732	0.3131
		2051	-$99.18	-$356,069	$80,085	$1,736.60	-0.0393%	-12.5880	12.5880	0.4301
	Mid	2036	-$95.19	-$356,069	$9,183	$1,737.88	-0.0381%	-12.5880	1.0221	0.4288
		2051	-$107.24	-$356,069	$93,170	$1,883.52	-0.0416%	-12.5880	12.5880	0.4533
	High	2036	-$87.54	-$419,892	$65,522	$1,622.97	-0.0348%	-12.5880	8.3987	0.4055
		2051	-$115.77	-$419,892	$211,344	$1,997.27	-0.0452%	-12.5880	12.5880	0.4809

Note: 5,363,329 parcels in each model

Table 3.11: Summary Statistics for Tract-level Projected Value Change

Model	Climate Scenario	Year	Mean Tract Value Loss	Lower	Upper	Standard Deviation	Mean Tract Value Loss %	Lower	Upper	Standard Deviation
Block	**Low**	2036	-$85,819	-$10,494,167	$36,750	$505,164	-0.0020%	-1.6638	0.0243	0.0668
		2051	-$140,612	-$14,801,922	$40,081	$678,414	-0.0249%	-1.6669	0.0252	0.0832
	Mid	2036	-$134,653	-$13,299,939	$29,166	$648,619	-0.0236%	-1.6423	0.0179	0.0814
		2051	-$153,348	-$14,745,569	$36,661	$730,741	-0.0268%	-1.6490	0.0480	0.0898
	High	2036	-$123,634	-$10,800,731	$30,139	$579,329	-0.0217%	-1.2241	0.0250	0.0750
		2051	-$165,610	-$15,157,888	$99,477	$782,643	-0.0295%	-1.3346	0.0523	0.0994
Zip	**Low**	2036	-$121,444	-$12,540,004	$32,817	$671,505	-0.0210%	-2.3302	0.0253	0.1000
		2051	-$201,854	-$17,330,416	$31,413	$897,250	-0.0382%	-2.3554	0.0315	0.1221
	Mid	2036	-$193,728	-$15,359,263	$1,288	$857,480	-0.0364%	-2.3056	0.0026	0.1193
		2051	-$218,261	-$17,689,028	$36,704	$970,187	-0.0405%	-2.3340	0.0800	0.1302
	High	2036	-$178,193	-$14,269,040	$16,338	$785,901	-0.0331%	-1.7511	0.0068	0.1123
		2051	-$235,649	-$17,868,872	$136,831	$1,028,896	-0.0444%	-1.7747	0.0811	0.1415

Note: 2,634 tracts in each model

Table 3.12: Summary Statistics for County-level Projected Value Change

Model	Climate Scenario	Year	Mean County Value Loss	Lower	Upper	Standard Deviation	Mean County Value Loss %	Lower	Upper	Standard Deviation
Block	**Low**	2036	-$2,260,949	-$38,257,800	-$9598	$6,613,287	-0.0280%	-0.4557	-0.0004	0.0723
		2051	-$3,705,775	-$49,880,568	-$11,551	$9,281,508	-0.0417%	-0.5927	-0.0003	0.0957
	Mid	2036	-$3,548,718	-$46,606,856	-$6,099	$8,834,972	-0.0406%	-0.6126	-0.0002	0.0940
		2051	-$4,041,312	-$53,688,424	-$14,599	$\$1.01e^{7}$	-0.0462%	-0.6767	-0.0004	0.1061
	High	2036	-$3,257,867	-$41,856,268	-$22,391	$7,981,594	-0.0386%	-0.5403	-0.0008	0.0877
		2051	-$4,363,693	-$66,961,896	-$30,074	$\$1.12e^{7}$	-0.0500%	-0.6220	-0.0008	0.1109
Zip	**Low**	2036	-$3,199,495	-$49,947,884	-$10,229	$8,964,742	-0.0441%	-0.6581	-0.0005	0.1123
		2051	-$5,319,470	-$64,964,780	-$59,121	$\$1.25e^{7}$	-0.0682%	-0.8657	-0.0028	0.1531
	Mid	2036	-$5,105,192	-$59,056,520	-$51,984	$\$1.19e^{7}$	-0.0670%	-0.8939	-0.0024	0.1515
		2051	-$5,751,688	-$69,610,592	-$55,700	$\$1.36e^{7}$	-0.0738%	-0.9756	-0.0026	0.1658
	High	2036	-$4,695,216	-$55,385,656	-$46,742	$\$1.09e^{7}$	-0.0623%	-0.7841	-0.0021	0.1400
		2051	-$6,208,880	-$86,047,088	-$69,351	$\$1.49e^{7}$	-0.0784%	-0.8930	-0.0021	0.1695

Note: 100 counties in each model

Table 3.13: Summary Statistics for State-level Projected Value Change

Model	Climate Scenario	Year	State Value Loss	State Value Loss %
Block	**Low**	2036	-$226,094,912	-0.0224%
		2051	-$370,577,472	-0.0368%
	Mid	2036	-$354,871,776	-0.0352%
		2051	-$404,131,168	-0.0401%
	High	2036	-$325,786,720	-0.0323%
		2051	-$436,369,280	-0.0433%
Zip	**Low**	2036	-$319,949,472	-0.0318%
		2051	-$531,947,008	-0.0528%
	Mid	2036	-$510,519,232	-0.0507%
		2051	-$575,168,832	-0.0571%
	High	2036	-$469,521,632	-0.0466%
		2051	-$620,887,936	-0.0616%

Figure 3.7: 2051 Tract-level Value Change as a Percentage per Climate Scenario and Model Fixed Effect

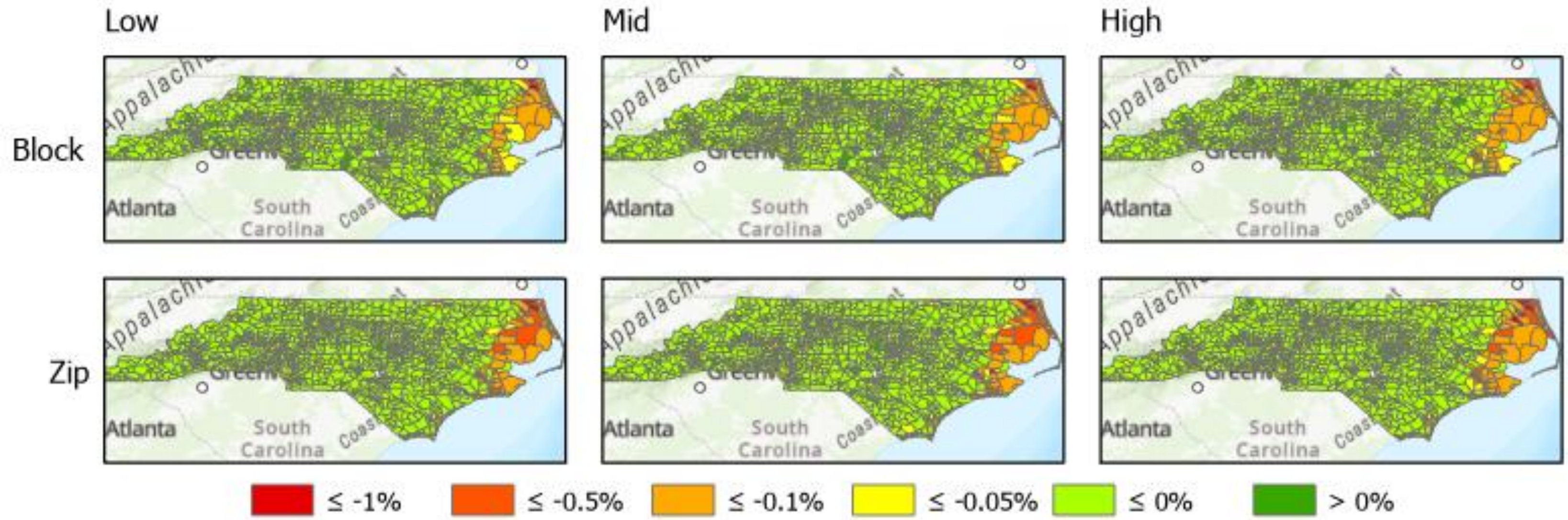

Figure 3.8: 2051 Tract-level Value Change in Dollars per Climate Scenario and Model Fixed Effect

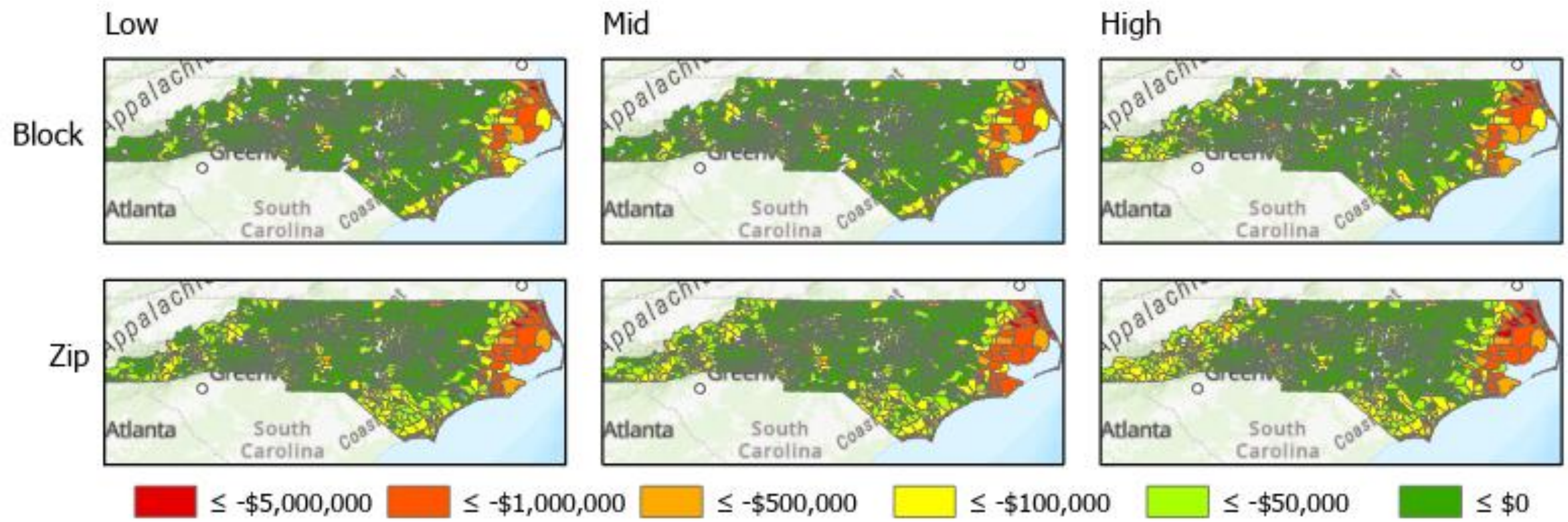

Figure 3.9: 2051 County-level Value Change as a Percentage per Climate Scenario and Model Fixed Effect

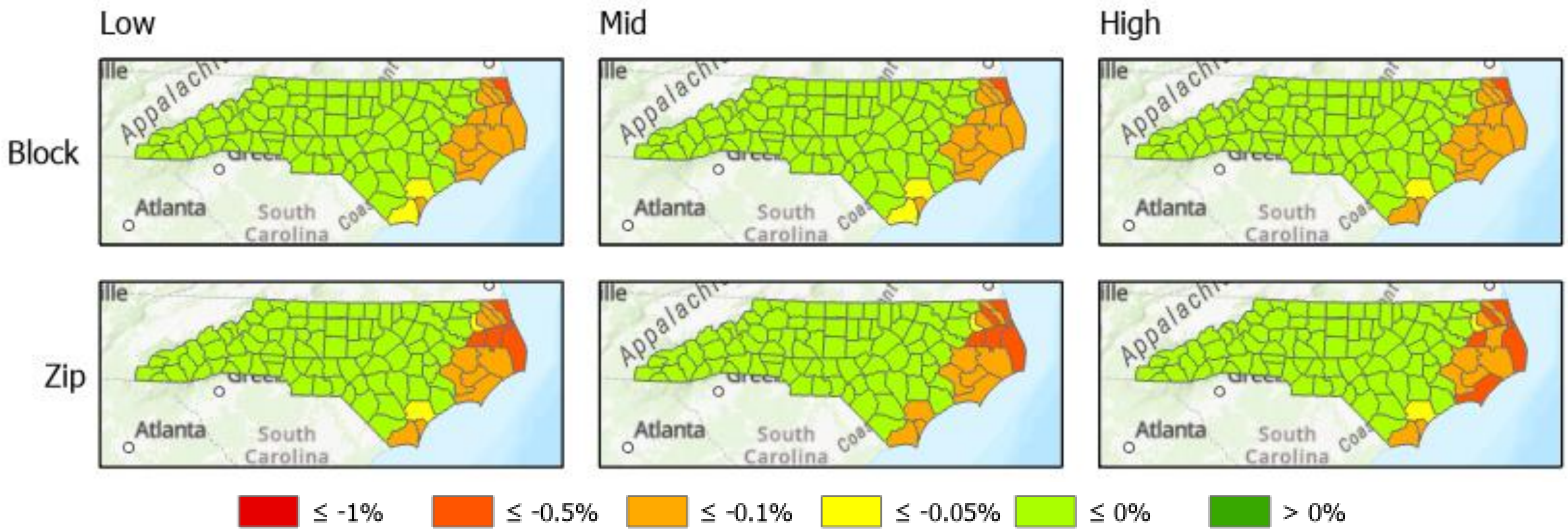

Figure 3.10: 2051 County-level Value Change in Dollars per Climate Scenario and Model Fixed Effect

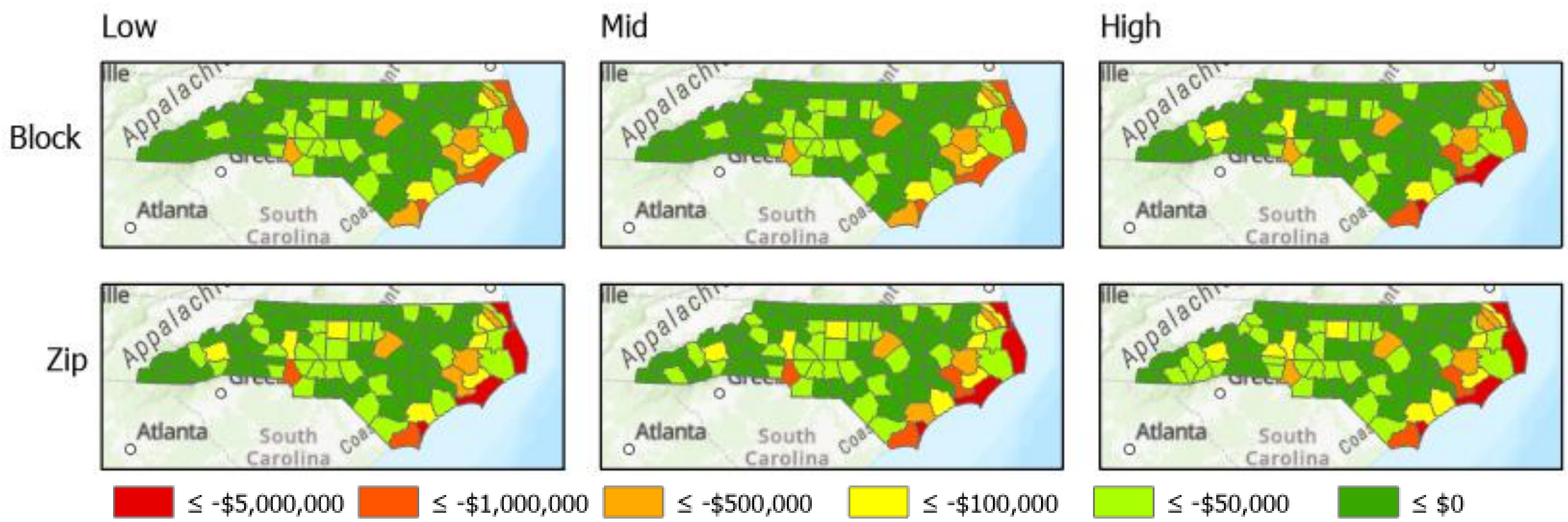

Table 3.14: Parameter Estimates for Percentage Value Change Regressed Against State-demeaned Variables Using OLS per Model and Climate Scenario

Model	Climate Scenario	Year	Mean Income Per Capita		% Poverty		% Black		% Asian		% American Indian		% Other Race	% Hispanic		Intercept	
Block	**Low**	2036	-0.0002139		-0.0000003	**	0.0000993	*	0.0007263	***	0.0002613	***	-0.0000362	0.0007517	***	-0.0136078	***
		2051	-0.0004947	**	-0.0000007	***	0.0001466	**	0.0008864	***	0.0002174	**	-0.0002108	0.0009541	***	-0.0240338	***
	Mid	2036	-0.0004569	*	-0.0000007	***	0.0001564	**	0.0008850	***	0.0002337	***	-0.0001586	0.0009281	***	-0.0226526	***
		2051	-0.0004916	*	-0.0000007	***	0.0001869	**	0.0010051	***	0.0002630	***	-0.0002391	0.0010873	***	-0.0258210	***
	High	2036	-0.0003025		-0.0000006	***	0.0001466	**	0.0007551	***	0.0002790	***	-0.0000826	0.0009342	***	-0.0209210	***
		2051	-0.0003901		-0.0000007	***	0.0002263	***	0.0009949	***	0.0002903	***	-0.0003976	0.0013652	***	-0.0284898	***
Zip	**Low**	2036	-0.0004645		-0.0000004	**	0.0000915		0.0009966	***	0.0004677	***	0.0000165	0.0012083	***	-0.0197633	***
		2051	-0.0008201	**	-0.0000008	***	0.0000994		0.0012218	***	0.0003036	*	-0.0003001	0.0015625	***	-0.0365920	***
	Mid	2036	-0.0007535	*	-0.0000007	***	0.0001101		0.0012065	***	0.0003220	**	-0.0002578	0.0015402	***	-0.0348366	***
		2051	-0.0008054	*	-0.0000008	***	0.0001528		0.0013859	***	0.0003601	**	-0.0003592	0.0017374	***	-0.0388246	***
	High	2036	-0.0005533		-0.0000006	**	0.0001428		0.0010049	***	0.0005110	***	-0.0002062	0.0015217	***	-0.0317691	***
		2051	-0.0007172	*	-0.0000008	**	0.0002174		0.0013399	***	0.0004276	***	-0.0005684	0.0021337	***	-0.0426280	***

**95% statistical significance*
***99% statistical significance*
****99.9% statistical significance*
Note: 2,634 tracts in each model

Table 3.15: Parameter Estimates for Percentage Value Change Regressed Against State-demeaned Variables for Tracts with Percentage Value Change Less than -0.05%

Model	Climate Scenario	Year	Tracts	Mean Income Per Capita	% Poverty		% Black	% Asian		% American Indian		% Other Race	% Hispanic		Intercept	
Block	**Low**	2036	126	-0.0015547	-0.0000018		-0.0013508	0.0092212	***	-0.0021309		0.0006654	0.0037537		-0.1918961	***
		2051	247	-0.0006700	0.0000010		0.0005616	0.0061799	***	0.0034163	***	-0.0029914	0.0066348	**	-0.1728175	***
	Mid	2036	236	0.0004535	0.0000012	*	0.0001475	0.0061834	***	0.0032145	***	-0.0027706	0.0064097	**	-0.1763585	***
		2051	259	0.0003224	0.0000013	*	0.0005082	0.0067687	***	0.0033256	***	-0.0040473	0.0073616	**	-0.1837615	***
	High	2036	197	0.0007318	0.0000008		-0.0006007	0.0062932	***	0.0038682		-0.0023783	0.0059558	***	-0.1857114	***
		2051	259	0.0006445	0.0000011		0.0008636	0.0066490	***	0.0046308		-0.0050586	0.0077280	***	-0.2015678	***
Zip	**Low**	2036	159	-0.0023238	0.0000003		-0.0028283	0.0126344	***	0.0183614	**	-0.0007709	0.0073773		-0.2344194	***
		2051	326	0.0004965	0.0000023	**	0.0008167	0.0078655	***	0.0044207	**	-0.0029700	0.0090636	**	-0.2094233	***
	Mid	2036	305	0.0008343	0.0000025	**	0.0005163	0.0079339	***	0.0048579	**	-0.0037407	0.0096366	**	-0.2117592	***
		2051	331	0.0012351	0.0000026	**	0.0007579	0.0090295	***	0.0044240	**	-0.0038705	0.0106641	***	-0.2220873	***
	High	2036	260	0.0004972	0.0000014		-0.0006445	0.0081502	***	0.0088099		-0.0022920	0.0091222	***	-0.2148081	***
		2051	336	0.0003000	0.0000020	*	0.0012694	0.0080597	***	0.0040978	***	-0.0058223	0.0126787	***	-0.2344124	***

**95% statistical significance*
***99% statistical significance*
****99.9% statistical significance*
Note: 2,634 tracts in each model

Table 3.16: Summary Statistics for County-level Projected Declines in Property Tax Revenue in 2021 Dollars

Model	Climate Scenario	Year	Mean	Median	Lower	Upper	Standard Deviation
Block	**Low**	2036	-$15,942	-$5,311	-$163,757	-$71	$28,900
		2051	-$39,200	-$15,235	-$223,815	-$75	$51,208
	Mid	2036	-$36,805	-$12,481	-$209,731	-$40	$48,566
		2051	-$41,181	-$14,118	-$241,598	-$95	$54,533
	High	2036	-$30,240	-$9,515	-$188,353	-$165	$40,573
		2051	-$39,263	-$15,568	-$301,329	-$195	$56,745
Zip	**Low**	2036	-$21,836	-$7,196	-$221,567	-$75	$38,680
		2051	-$52,499	-$22,192	-$291,546	-$335	$65,545
	Mid	2036	-$49,141	-$18,983	-$300,876	-$374	$61,554
		2051	-$55,076	-$20,961	-$328,377	-$405	$70,030
	High	2036	-$41,063	-$15,658	-$263,634	-$344	$53,454
		2051	-$53,414	-$21,258	-$387,212	-$510	$73,687

Note: 100 counties

Table 3.17: Tails of Projected County-level Annual Property Tax Revenue Declines

Model	Climate Scenario	County	2036	County	2051
Block	**Low**	New Hanover	-$163,757	New Hanover	-$223,815
		Currituck	-$153,645	Currituck	-$199,851
		Dare	-$153,223	Dare	-$199,772
		Carteret	-$86,402	Carteret	-$134,326
		Beaufort	-$59,309	Wake	-$115,251
		-	-	-	-
		Graham	-$171	Graham	-$358
		Yadkin	-$164	Greene	-$250
		Greene	-$159	Swain	-$182
		Swain	-$83	Caswell	-$164
		Caswell	-$71	Yadkin	-$75
	Mid	New Hanover	-$209,731	New Hanover	-$241,598
		Currituck	-$206,523	Currituck	-$228,108
		Dare	-$181,331	Dare	-$204,330
		Carteret	-$123,731	Carteret	-$148,276
		Wake	-$111,650	Wake	-$121,814
		-	-	-	-
		Hertford	-$293	Hertford	-$393
		Swain	-$211	Swain	-$251
		Greene	-$164	Greene	-$228
		Caswell	-$116	Caswell	-$141
		Yadkin	-$40	Yadkin	-$95
	High	New Hanover	-$188,353	New Hanover	-$301,329
		Currituck	-$182,030	Currituck	-$209,557
		Dare	-$145,761	Carteret	-$193,804
		Carteret	-$130,318	Dare	-$176,530
		Wake	-$87,602	Craven	-$128,505
		-	-	-	-

		Hertford	-$481	Stokes	-$546
		Greene	-$439	Swain	-$537
		Swain	-$394	Surry	-$503
		Yadkin	-$191	Caswell	-$288
		Caswell	-$165	Yadkin	-$195
Zip	**Low**	Currituck	-$221,567	Currituck	-$291,456
		New Hanover	-$207,274	New Hanover	-$289,049
		Dare	-$200,041	Dare	-$260,184
		Beaufort	-$128,343	Carteret	-$178,909
		Carteret	-$114,492	Beaufort	-$147,928
		-	-	-	-
		Graham	-$221	Graham	-$870
		Polk	-$208	Yadkin	-$717
		Greene	-$203	Greene	-$577
		Swain	-$80	Caswell	-$435
		Caswell	-$75	Swain	-$335
	Mid	Currituck	-$300,876	Currituck	-$328,377
		New Hanover	-$265,754	New Hanover	-$313,248
		Dare	-$236,206	Dare	-$265,951
		Carteret	-$163,653	Carteret	-$197,277
		Beaufort	-$142,783	Wake	-$151,579
		-	-	-	-
		Stokes	-$906	Stokes	-$948
		Yadkin	-$695	Yadkin	-$708
		Greene	-$511	Greene	-$577
		Caswell	-$382	Caswell	-$409
		Swain	-$374	Swain	-$405
	High	Currituck	-$263,634	New Hanover	-$387,212
		New Hanover	-$249,235	Currituck	-$300,243
		Dare	-$195,021	Carteret	-$250,785

Carteret	-$166,382	Dare	-$233,639
Beaufort	-$141,219	Craven	-$193,303
-	-	-	-
Greene	-$897	Stokes	-$989
Stokes	-$854	Swain	-$977
Swain	-$775	Surry	-$944
Yadkin	-$530	Yadkin	-$524
Caswell	-$344	Caswell	-$510

Note: 100 counties

Table 3.18: Projected State-level Annual Property Tax Revenue Declines

Model	Climate Scenario	2036	2051
Block	**Low**	-$1,125,723	-$1,890,694
	Mid	-$1,809,613	-$2,054,280
	High	-$1,646,417	-$2,177,294
Zip	**Low**	-$1,627,165	-$2,783,296
	Mid	-$2,676,257	-$2,991,892
	High	-$2,429,146	-$3,171,398

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APPENDIX

Table 1.5A: Mainline Regression Results for Other Geographic Fixed Effects

	Variable	Coefficient		95 CI Low	95 CI High
Tract	Mid Chance	-0.0017103	***	-0.0024069	-0.0010136
	Mid Chance Sq	0.0000837	***	0.0000596	0.0001078
	FEMA 100yr	-0.0062646		-0.0176172	0.005088
County	Mid Chance	-0.0008436	*	-0.001585	-0.0001021
	Mid Chance Sq	0.0000465	***	0.000022	0.000071
	FEMA 100yr	-0.025807	***	-0.038062	-0.0135521

**95% statistical significance*
***99% statistical significance*
****99.9% statistical significance*

Table 2.17A: Value Losses and Value Loss Percentages for the Mainline Block Model and Low Climate Scenario

	Tract-level Value Change Tails						**County-level Value Change Tails**			
Year	**Tract**	**County**	**Value Change**	**Tract**	**County**	**% Value Change**	**County**	**Value Change**	**County**	**% Value Change**
2036	1101.01	Currituck	$ (10,125,466.00)	1102.02	Currituck	-1.7176%	Currituck	$ (43,096,328.00)	Currituck	-0.7134%
	9702	Dare	$ (9,588,569.00)	1102.01	Currituck	-1.5670%	Dare	$ (35,488,284.00)	Washington	-0.4750%
	1102.02	Currituck	$ (7,992,052.50)	1103.02	Currituck	-1.0953%	Carteret	$ (26,803,594.00)	Tyrrell	-0.4580%
	1102.01	Currituck	$ (7,446,499.00)	9604	Pasquotank	-0.9599%	New Hanover	$ (21,872,908.00)	Camden	-0.4120%
	9704	Dare	$ (6,628,631.50)	9702	Dare	-0.8961%	Beaufort	$ (17,976,194.00)	Pasquotank	-0.3996%
	1103.02	Currituck	$ (6,024,599.50)	9502.01	Washington	-0.8383%	Brunswick	$ (16,876,184.00)	Dare	-0.3451%
	9202.02	Perquimans	$ (5,330,926.50)	9303	Beaufort	-0.7757%	Pasquotank	$ (15,533,892.00)	Perquimans	-0.2372%
	9607.01	Pasquotank	$ (5,161,297.50)	9607.01	Pasquotank	-0.7218%	Craven	$ (14,459,071.00)	Beaufort	-0.2308%
	9501.02	Camden	$ (5,118,781.50)	9602	Pasquotank	-0.6926%	Mecklenburg	$ (9,329,931.00)	Hyde	-0.2186%
	9701.01	Dare	$ (4,513,545.00)	9501.02	Camden	-0.6707%	Wake	$ (9,286,414.00)	Carteret	-0.1899%
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	53.08	Mecklenburg	$ -	31.09	Mecklenburg	0.0000%	Martin	$ (169,560.09)	Rockingham	-0.0046%
	56.09	Mecklenburg	$ -	56.09	Mecklenburg	0.0000%	Anson	$ (168,465.23)	Franklin	-0.0045%
	5	Onslow	$ -	5	Onslow	0.0000%	Alleghany	$ (164,354.39)	Greene	-0.0044%
	116.01	Orange	$ -	116.01	Orange	0.0000%	Stokes	$ (161,354.69)	Yadkin	-0.0041%
	116.02	Orange	$ -	116.02	Orange	0.0000%	Person	$ (158,063.75)	Chatham	-0.0039%
	9802	Swain	$ -	9802	Swain	0.0000%	Yadkin	$ (158,046.50)	Surry	-0.0039%
	9802	Wake	$ -	9802	Wake	0.0000%	Hertford	$ (150,424.23)	Stokes	-0.0035%
	16.07	Mecklenburg	$ 1.83	16.07	Mecklenburg	0.0000%	Swain	$ (134,965.52)	Person	-0.0035%
	13.03	Durham	$ 5.57	13.03	Durham	0.0000%	Greene	$ (73,680.55)	Granville	-0.0033%
	109	Guilford	$ 8.03	109	Guilford	0.0000%	Caswell	$ (29,713.35)	Caswell	-0.0014%
2051	1101.01	Currituck	$ (11,206,029.00)	1102.02	Currituck	-1.7210%	Currituck	$ (45,381,644.00)	Currituck	-0.7513%
	9702	Dare	$ (10,272,765.00)	1102.01	Currituck	-1.6039%	Dare	$ (38,537,772.00)	Washington	-0.5021%
	1102.02	Currituck	$ (8,007,889.00)	1103.02	Currituck	-1.1453%	Carteret	$ (31,175,368.00)	Tyrrell	-0.5005%
	1102.01	Currituck	$ (7,622,069.00)	9604	Pasquotank	-1.0181%	New Hanover	$ (25,024,838.00)	Camden	-0.4381%
	9704	Dare	$ (7,211,487.50)	9702	Dare	-0.9601%	Beaufort	$ (19,213,520.00)	Pasquotank	-0.4281%

1103.02	Currituck	$ (6,299,732.50)	9502.01	Washington	-0.8397%	Brunswick	$ (19,067,234.00)	Dare	-0.3748%
9202.02	Perquimans	$ (5,744,147.50)	9303	Beaufort	-0.8164%	Pasquotank	$ (16,642,819.00)	Perquimans	-0.2572%
9607.01	Pasquotank	$ (5,455,946.00)	9607.01	Pasquotank	-0.7630%	Craven	$ (16,045,107.00)	Beaufort	-0.2467%
9501.02	Camden	$ (5,420,150.50)	9602	Pasquotank	-0.7508%	Mecklenburg	$ (10,321,790.00)	Hyde	-0.2334%
9701.01	Dare	$ (5,137,128.00)	9501.02	Camden	-0.7102%	Wake	$ (9,889,634.00)	Carteret	-0.2209%
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9802	Swain	$ -	9802	Swain	0.0000%	Stokes	$ (176,652.72)	Rockingham	-0.0051%
9802	Wake	$ -	9802	Wake	0.0000%	Person	$ (170,587.14)	Greene	-0.0049%
109	Guilford	$ 15.90	109	Guilford	0.0000%	Alleghany	$ (169,291.28)	Franklin	-0.0049%
145.03	Guilford	$ 268.60	9706.06	Granville	0.0001%	Yadkin	$ (166,905.19)	Yadkin	-0.0043%
9706.06	Granville	$ 300.10	145.03	Guilford	0.0002%	Hertford	$ (156,402.53)	Surry	-0.0042%
19.27	Mecklenburg	$ 435.76	111.06	Orange	0.0006%	Clay	$ (154,727.28)	Chatham	-0.0042%
111.06	Orange	$ 1,259.62	165.05	Guilford	0.0006%	Graham	$ (152,654.13)	Stokes	-0.0039%
165.05	Guilford	$ 1,479.55	9304.01	Henderson	0.0015%	Swain	$ (126,961.62)	Person	-0.0038%
9304.01	Henderson	$ 4,020.48	525.05	Wake	0.0025%	Greene	$ (82,370.08)	Granville	-0.0036%
525.05	Wake	$ 9,132.43	19.27	Mecklenburg	0.0026%	Caswell	$ (34,990.09)	Caswell	-0.0016%

Table 2.18A: Value Losses and Value Loss Percentages for the Mainline Block Model and Mid Climate Scenario

	Tract-level Value Change Tails						County-level Value Change Tails			
Year	Tract	County	Value Change	Tract	County	% Value Change	County	Value Change	County	% Value Change
2036	1101.01	Currituck	$ (10,660,616.00)	1102.02	Currituck	-1.7020%	Currituck	$ (44,403,560.00)	Currituck	-0.7351%
	9702	Dare	$ (10,173,568.00)	1102.01	Currituck	-1.5618%	Dare	$ (37,101,040.00)	Washington	-0.4877%
	1102.02	Currituck	$ (7,919,237.00)	1103.02	Currituck	-1.1396%	Carteret	$ (28,823,550.00)	Tyrrell	-0.4802%
	1102.01	Currituck	$ (7,422,055.50)	9604	Pasquotank	-1.0077%	New Hanover	$ (22,785,666.00)	Camden	-0.4411%
	9704	Dare	$ (6,859,687.50)	9702	Dare	-0.9508%	Brunswick	$ (18,694,266.00)	Pasquotank	-0.4179%
	1103.02	Currituck	$ (6,268,362.50)	9502.01	Washington	-0.8159%	Beaufort	$ (18,345,564.00)	Dare	-0.3608%
	9202.02	Perquimans	$ (5,536,141.00)	9303	Beaufort	-0.7965%	Pasquotank	$ (16,245,440.00)	Perquimans	-0.2457%
	9501.02	Camden	$ (5,508,025.00)	9607.01	Pasquotank	-0.7579%	Craven	$ (15,169,304.00)	Beaufort	-0.2356%
	9607.01	Pasquotank	$ (5,419,430.00)	9602	Pasquotank	-0.7305%	Wake	$ (9,544,625.00)	Hyde	-0.2354%
	9701.01	Dare	$ (4,646,682.00)	9501.02	Camden	-0.7217%	Mecklenburg	$ (9,318,669.00)	Carteret	-0.2042%
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	9802	Swain	$ -	9802	Swain	0.0000%	Vance	$ (174,321.02)	Rockingham	-0.0046%
	310.01	Gaston	$ 3.15	310.01	Gaston	0.0000%	Anson	$ (166,157.14)	Franklin	-0.0046%
	19.23	Mecklenburg	$ 4.44	13.02	Onslow	0.0000%	Martin	$ (164,182.16)	Greene	-0.0043%
	13.02	Onslow	$ 4.86	19.23	Mecklenburg	0.0000%	Stokes	$ (160,084.97)	Yadkin	-0.0041%
	37.01	Mecklenburg	$ 7.62	9706.06	Granville	0.0000%	Yadkin	$ (159,806.80)	Chatham	-0.0038%
	38.08	Mecklenburg	$ 7.75	38.08	Mecklenburg	0.0000%	Person	$ (153,862.05)	Surry	-0.0037%
	110	New	$ 15.93	37.01	Mecklenburg	0.0000%	Swain	$ (148,365.38)	Stokes	-0.0035%
	9706.06	Granville	$ 20.47	110	New	0.0000%	Hertford	$ (147,108.72)	Person	-0.0034%
	19.27	Mecklenburg	$ 34.98	112.01	Guilford	0.0001%	Greene	$ (71,098.59)	Granville	-0.0034%
	112.01	Guilford	$ 64.91	19.27	Mecklenburg	0.0002%	Caswell	$ (28,077.87)	Caswell	-0.0013%
2051	1101.01	Currituck	$ (11,908,236.00)	1102.02	Currituck	-1.7081%	Currituck	$ (47,473,524.00)	Currituck	-0.7859%
	9702	Dare	$ (11,285,842.00)	1102.01	Currituck	-1.5990%	Dare	$ (40,940,504.00)	Tyrrell	-0.5264%
	1102.02	Currituck	$ (7,947,640.50)	1103.02	Currituck	-1.2215%	Carteret	$ (34,117,048.00)	Washington	-0.5215%
	1102.01	Currituck	$ (7,598,451.00)	9604	Pasquotank	-1.1066%	New Hanover	$ (26,316,332.00)	Camden	-0.4904%
	9704	Dare	$ (7,509,912.50)	9702	Dare	-1.0547%	Brunswick	$ (21,768,802.00)	Pasquotank	-0.4616%

1103.02	Currituck	$ (6,718,664.00)	9303	Beaufort	-0.8519%	Beaufort	$ (19,738,606.00)	Dare	-0.3981%
9501.02	Camden	$ (6,121,620.00)	9607.01	Pasquotank	-0.8304%	Pasquotank	$ (17,944,152.00)	Perquimans	-0.2697%
9202.02	Perquimans	$ (6,082,654.00)	9602	Pasquotank	-0.8186%	Craven	$ (17,126,902.00)	Hyde	-0.2598%
9607.01	Pasquotank	$ (5,938,018.50)	9502.01	Washington	-0.8174%	Wake	$ (10,424,900.00)	Beaufort	-0.2535%
9701.01	Dare	$ (5,264,801.00)	9501.02	Camden	-0.8021%	Mecklenburg	$ (10,344,087.00)	Carteret	-0.2417%
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112.01	Guilford	$ 120.68	112.01	Guilford	0.0001%	Clay	$ (191,804.36)	Franklin	-0.0051%
39.03	Mecklenburg	$ 383.19	9706.06	Granville	0.0002%	Anson	$ (184,447.42)	Rockingham	-0.0050%
111.06	Orange	$ 488.11	111.06	Orange	0.0002%	Martin	$ (177,414.05)	Greene	-0.0048%
9706.06	Granville	$ 513.57	39.03	Mecklenburg	0.0003%	Stokes	$ (174,887.44)	Yadkin	-0.0044%
145.03	Guilford	$ 780.02	145.03	Guilford	0.0006%	Yadkin	$ (170,991.17)	Surry	-0.0040%
19.27	Mecklenburg	$ 2,493.88	165.05	Guilford	0.0013%	Person	$ (164,011.73)	Chatham	-0.0040%
111.06	Orange	$ 1,259.62	165.05	Guilford	0.0006%	Graham	$ (152,654.13)	Stokes	-0.0039%
165.05	Guilford	$ 1,479.55	9304.01	Henderson	0.0015%	Swain	$ (126,961.62)	Person	-0.0038%
9304.01	Henderson	$ 4,020.48	525.05	Wake	0.0025%	Greene	$ (82,370.08)	Granville	-0.0036%
525.05	Wake	$ 9,132.43	19.27	Mecklenburg	0.0026%	Caswell	$ (34,990.09)	Caswell	-0.0016%

Table 2.19A: Value Losses and Value Loss Percentages for Mainline Block Model and High Climate Scenario

	Tract-level Value Change Tails						County-level Value Change Tails			
Year	**Tract**	**County**	**Value Change**	**Tract**	**County**	**% Value Change**	**County**	**Value Change**	**County**	**% Value Change**
2036	1101.01	Currituck	$ (10,904,761.00)	1102.01	Currituck	-1.4906%	Currituck	$ (42,933,980.00)	Currituck	-0.7108%
	9702	Dare	$ (10,288,256.00)	1102.02	Currituck	-1.4468%	Dare	$ (38,772,444.00)	Washington	-0.4878%
	9704	Dare	$ (7,090,384.50)	1103.02	Currituck	-1.0896%	Carteret	$ (30,618,070.00)	Tyrrell	-0.4819%
	1102.01	Currituck	$ (7,083,354.50)	9604	Pasquotank	-1.0842%	New Hanover	$ (24,205,352.00)	Camden	-0.4603%
	1102.02	Currituck	$ (6,732,171.00)	9702	Dare	-0.9615%	Brunswick	$ (19,923,820.00)	Pasquotank	-0.4578%
	1103.02	Currituck	$ (5,993,139.50)	9607.01	Pasquotank	-0.8242%	Beaufort	$ (18,558,408.00)	Dare	-0.3771%
	9607.01	Pasquotank	$ (5,893,487.50)	9602	Pasquotank	-0.7999%	Craven	$ (18,244,804.00)	Perquimans	-0.2490%
	9501.02	Camden	$ (5,685,154.50)	9303	Beaufort	-0.7930%	Pasquotank	$ (17,797,582.00)	Hyde	-0.2478%
	9202.02	Perquimans	$ (5,505,911.00)	9502.01	Washington	-0.7588%	Wake	$ (9,525,936.00)	Beaufort	-0.2383%
	9705.02	Dare	$ (5,340,446.00)	9501.02	Camden	-0.7449%	Mecklenburg	$ (9,432,492.00)	Carteret	-0.2169%
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	31.09	Mecklenburg	$ -	31.09	Mecklenburg	0.0000%	Martin	$ (179,036.27)	Vance	-0.0047%
	5	Onslow	$ -	5	Onslow	0.0000%	Vance	$ (176,862.58)	Franklin	-0.0047%
	9.02	Onslow	$ -	9.02	Onslow	0.0000%	Swain	$ (172,376.78)	Rockingham	-0.0046%
	116.01	Orange	$ -	116.01	Orange	0.0000%	Yadkin	$ (171,708.78)	Yadkin	-0.0044%
	116.02	Orange	$ -	116.02	Orange	0.0000%	Anson	$ (168,436.16)	Granville	-0.0039%
	9802	Swain	$ -	9802	Swain	0.0000%	Person	$ (162,439.78)	Chatham	-0.0039%
	109	Guilford	$ 5.42	9304	Caswell	0.0000%	Hertford	$ (157,631.27)	Surry	-0.0038%
	20.32	Durham	$ 6.19	109	Guilford	0.0000%	Stokes	$ (152,756.08)	Person	-0.0036%
	9304	Caswell	$ 9.31	20.32	Durham	0.0000%	Greene	$ (94,672.64)	Stokes	-0.0034%
	1.03	Mecklenburg	$ 116.66	1.03	Mecklenburg	0.0007%	Caswell	$ (30,729.07)	Caswell	-0.0014%
2051	1101.01	Currituck	$ (12,052,220.00)	1102.01	Currituck	-1.5242%	Currituck	$ (45,778,756.00)	Currituck	-0.7108%
	9702	Dare	$ (11,488,753.00)	1102.02	Currituck	-1.4522%	Dare	$ (42,593,184.00)	Washington	-0.4878%
	9704	Dare	$ (7,830,934.50)	9604	Pasquotank	-1.2329%	Carteret	$ (36,229,260.00)	Tyrrell	-0.4819%
	1102.01	Currituck	$ (7,243,034.50)	1103.02	Currituck	-1.1591%	New Hanover	$ (27,547,798.00)	Camden	-0.4603%
	1102.02	Currituck	$ (6,757,151.00)	9702	Dare	-1.0737%	Brunswick	$ (22,697,182.00)	Pasquotank	-0.4578%

9607.01	Pasquotank	$ (6,704,490.50)	9607.01	Pasquotank	-0.9376%	Pasquotank	$ (20,518,352.00)	Dare	-0.3771%
9501.02	Camden	$ (6,383,472.50)	9602	Pasquotank	-0.9306%	Craven	$ (20,502,244.00)	Perquimans	-0.2490%
1103.02	Currituck	$ (6,375,469.00)	9501.02	Camden	-0.8364%	Beaufort	$ (19,679,628.00)	Hyde	-0.2478%
9202.02	Perquimans	$ (6,043,028.50)	9609	Craven	-0.8103%	Wake	$ (10,404,215.00)	Beaufort	-0.2383%
9705.02	Dare	$ (5,510,225.50)	9303	Beaufort	-0.8066%	Mecklenburg	$ (10,087,366.00)	Carteret	-0.2169%
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22.02	Onslow	$ 2,748.03	312.04	Gaston	0.0015%	Martin	$ (195,065.09)	Vance	-0.0047%
9304.01	Henderson	$ 3,122.50	22.02	Onslow	0.0017%	Swain	$ (194,870.14)	Franklin	-0.0047%
525.05	Wake	$ 3,243.59	303.01	Gaston	0.0019%	Vance	$ (191,842.25)	Rockingham	-0.0046%
59.24	Mecklenburg	$ 3,957.00	58.29	Mecklenburg	0.0028%	Anson	$ (185,345.94)	Yadkin	-0.0044%
303.01	Gaston	$ 4,331.35	24	Mecklenburg	0.0032%	Person	$ (184,080.67)	Granville	-0.0039%
904.02	Duplin	$ 4,688.93	9301.01	Surry	0.0033%	Yadkin	$ (172,641.86)	Chatham	-0.0039%
9301.01	Surry	$ 6,270.77	523.05	Wake	0.0043%	Hertford	$ (161,677.19)	Surry	-0.0038%
59.21	Mecklenburg	$ 10,238.75	59.21	Mecklenburg	0.0043%	Stokes	$ (159,592.86)	Person	-0.0036%
24	Mecklenburg	$ 10,460.11	19.27	Mecklenburg	0.0137%	Greene	$ (107,672.81)	Stokes	-0.0034%
18	Onslow	$ 33,186.52	18	Onslow	0.0196%	Caswell	$ (32,433.48)	Caswell	-0.0014%

Table 2.20A: Value Losses and Value Loss Percentages for Mainline Zip Model and Low Climate Scenario

	Tract-level Value Change Tails						**County-level Value Change Tails**			
Year	**Tract**	**County**	**Value Change**	**Tract**	**County**	**% Value Change**	**County**	**Value Change**	**County**	**% Value Change**
2036	1101.01	Currituck	$ (19,036,254.00)	1102.02	Currituck	-2.9668%	Currituck	$ (78,356,752.00)	Currituck	-1.2972%
	9702	Dare	$ (18,663,808.00)	1102.01	Currituck	-2.7210%	Dare	$ (65,355,488.00)	Washington	-0.8736%
	1102.02	Currituck	$ (13,804,647.00)	1103.02	Currituck	-2.0364%	Carteret	$ (49,979,748.00)	Tyrrell	-0.8476%
	1102.01	Currituck	$ (12,930,641.00)	9604	Pasquotank	-1.8747%	New	$ (39,828,044.00)	Camden	-0.7964%
	9704	Dare	$ (12,197,076.00)	9702	Dare	-1.7442%	Beaufort	$ (34,050,836.00)	Pasquotank	-0.7701%
	1103.02	Currituck	$ (11,201,371.00)	9303	Beaufort	-1.5455%	Brunswick	$ (31,007,174.00)	Dare	-0.6356%
	9202.02	Perquimans	$ (10,310,828.00)	9502.01	Washington	-1.4332%	Pasquotank	$ (29,937,504.00)	Perquimans	-0.4473%
	9607.01	Pasquotank	$ (10,068,100.00)	9607.01	Pasquotank	-1.4080%	Craven	$ (27,393,052.00)	Beaufort	-0.4373%
	9501.02	Camden	$ (9,884,649.00)	9602	Pasquotank	-1.3286%	Wake	$ (16,922,188.00)	Hyde	-0.4110%
	9701.01	Dare	$ (8,141,707.00)	9501.02	Camden	-1.2952%	Mecklenburg	$ (16,568,455.00)	Carteret	-0.3541%
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	1.04	Mecklenburg	$ -	1.01	Mecklenburg	0.0000%	Anson	$ (304,808.53)	Vance	-0.0083%
	31.09	Mecklenburg	$ -	1.04	Mecklenburg	0.0000%	Alleghany	$ (302,323.13)	Franklin	-0.0082%
	53.08	Mecklenburg	$ -	31.09	Mecklenburg	0.0000%	Martin	$ (298,285.69)	Greene	-0.0078%
	5	Onslow	$ -	5	Onslow	0.0000%	Stokes	$ (294,303.94)	Yadkin	-0.0075%
	116.01	Orange	$ -	116.01	Orange	0.0000%	Yadkin	$ (289,669.09)	Chatham	-0.0069%
	116.02	Orange	$ -	116.02	Orange	0.0000%	Person	$ (274,419.88)	Surry	-0.0069%
	9802	Swain	$ -	9802	Swain	0.0000%	Hertford	$ (267,389.41)	Stokes	-0.0065%
	9802	Wake	$ -	9802	Wake	0.0000%	Swain	$ (241,724.89)	Person	-0.0061%
	13.03	Durham	$ 6.29	13.03	Durham	0.0000%	Greene	$ (130,438.57)	Granville	-0.0060%
	109	Guilford	$ 8.92	109	Guilford	0.0000%	Caswell	$ (51,536.00)	Caswell	-0.0024%
2051	1101.01	Currituck	$ (20,297,670.00)	1102.02	Currituck	-2.9845%	Currituck	$ (81,227,584.00)	Currituck	-1.3447%
	9702	Dare	$ (19,409,338.00)	1102.01	Currituck	-2.7929%	Dare	$ (68,833,856.00)	Washington	-0.9042%
	1102.02	Currituck	$ (13,886,874.00)	1103.02	Currituck	-2.0983%	Carteret	$ (55,821,828.00)	Tyrrell	-0.8975%
	1102.01	Currituck	$ (13,271,929.00)	9604	Pasquotank	-1.9376%	New Hanover	$ (43,540,972.00)	Camden	-0.8247%
	9704	Dare	$ (12,866,037.00)	9702	Dare	-1.8139%	Beaufort	$ (35,272,504.00)	Pasquotank	-0.8016%

1103.02	Currituck	$ (11,541,893.00)	9303	Beaufort	-1.5898%	Brunswick	$ (33,618,684.00)	Dare	-0.6694%
9202.02	Perquimans	$ (10,765,623.00)	9607.01	Pasquotank	-1.4532%	Pasquotank	$ (31,160,492.00)	Perquimans	-0.4700%
9607.01	Pasquotank	$ (10,391,040.00)	9502.01	Washington	-1.4347%	Craven	$ (29,091,682.00)	Beaufort	-0.4530%
9501.02	Camden	$ (10,210,729.00)	9602	Pasquotank	-1.3933%	Mecklenburg	$ (17,696,268.00)	Hyde	-0.4297%
9701.01	Dare	$ (8,878,130.00)	9501.02	Camden	-1.3379%	Wake	$ (17,545,926.00)	Carteret	-0.3955%
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523.05	Wake	$ 6.15	523.05	Wake	0.0000%	Stokes	$ (310,078.16)	Rockingham	-0.0088%
109	Guilford	$ 17.79	109	Guilford	0.0000%	Alleghany	$ (308,632.84)	Franklin	-0.0086%
9706.06	Granville	$ 509.28	9706.06	Granville	0.0002%	Yadkin	$ (295,709.38)	Greene	-0.0084%
39.03	Mecklenburg	$ 863.73	39.03	Mecklenburg	0.0007%	Graham	$ (294,625.63)	Yadkin	-0.0076%
19.27	Mecklenburg	$ 912.56	111.06	Orange	0.0009%	Clay	$ (289,703.22)	Surry	-0.0072%
111.06	Orange	$ 1,695.77	165.05	Guilford	0.0010%	Person	$ (286,370.47)	Chatham	-0.0071%
165.05	Guilford	$ 2,269.52	145.03	Guilford	0.0022%	Hertford	$ (264,571.19)	Stokes	-0.0068%
145.03	Guilford	$ 2,893.13	9304.01	Henderson	0.0029%	Swain	$ (225,972.09)	Granville	-0.0064%
9304.01	Henderson	$ 7,884.76	19.27	Mecklenburg	0.0055%	Greene	$ (140,140.34)	Person	-0.0063%
525.05	Wake	$ 21,055.15	525.05	Wake	0.0058%	Caswell	$ (57,704.52)	Caswell	-0.0027%

Table 2.21A: Value Losses and Value Loss Percentages for Mainline Zip Model and Mid Climate Scenario

	Tract-level Value Change Tails						County-level Value Change Tails			
Year	Tract	County	Value Change	Tract	County	% Value Change	County	Value Change	County	% Value Change
2036	1101.01	Currituck	$ (19,617,136.00)	1102.02	Currituck	-2.9503%	Currituck	$ (79,766,320.00)	Currituck	-1.3205%
	9702	Dare	$ (19,297,122.00)	1102.01	Currituck	-2.7160%	Dare	$ (67,164,944.00)	Washington	-0.8876%
	1102.02	Currituck	$ (13,727,687.00)	1103.02	Currituck	-2.0844%	Carteret	$ (52,263,236.00)	Tyrrell	-0.8718%
	1102.01	Currituck	$ (12,906,570.00)	9604	Pasquotank	-1.9263%	New	$ (40,900,368.00)	Camden	-0.8274%
	9704	Dare	$ (12,471,985.00)	9702	Dare	-1.8034%	Beaufort	$ (34,458,088.00)	Pasquotank	-0.7895%
	1103.02	Currituck	$ (11,465,222.00)	9303	Beaufort	-1.5691%	Brunswick	$ (33,054,100.00)	Dare	-0.6532%
	9202.02	Perquimans	$ (10,536,377.00)	9607.01	Pasquotank	-1.4457%	Pasquotank	$ (30,691,260.00)	Perquimans	-0.4569%
	9607.01	Pasquotank	$ (10,337,255.00)	9502.01	Washington	-1.4079%	Craven	$ (28,194,540.00)	Beaufort	-0.4425%
	9501.02	Camden	$ (10,297,720.00)	9602	Pasquotank	-1.3689%	Wake	$ (17,211,358.00)	Hyde	-0.4297%
	9501	Washington	$ (8,329,059.50)	9501.02	Camden	-1.3493%	Mecklenburg	$ (16,572,654.00)	Carteret	-0.3703%
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	9802	Swain	$ -	9802	Swain	0.0000%	Vance	$ (309,799.00)	Franklin	-0.0083%
	310.01	Gaston	$ 1.71	13.02	Onslow	0.0000%	Anson	$ (302,573.38)	Rockingham	-0.0083%
	13.02	Onslow	$ 2.28	310.01	Gaston	0.0000%	Stokes	$ (293,134.53)	Greene	-0.0077%
	19.23	Mecklenburg	$ 4.89	19.23	Mecklenburg	0.0000%	Martin	$ (292,396.19)	Yadkin	-0.0075%
	37.01	Mecklenburg	$ 8.35	38.08	Mecklenburg	0.0000%	Yadkin	$ (291,592.69)	Chatham	-0.0068%
	38.08	Mecklenburg	$ 8.50	37.01	Mecklenburg	0.0000%	Person	$ (270,282.09)	Surry	-0.0068%
	110	New Hanover	$ 17.40	110	New Hanover	0.0000%	Hertford	$ (264,054.34)	Stokes	-0.0064%
	19.27	Mecklenburg	$ 47.52	9706.06	Granville	0.0000%	Swain	$ (256,680.52)	Granville	-0.0061%
	112.01	Guilford	$ 70.94	112.01	Guilford	0.0001%	Greene	$ (127,656.72)	Person	-0.0060%
	9706.06	Granville	$ 95.75	19.27	Mecklenburg	0.0003%	Caswell	$ (49,875.04)	Caswell	-0.0023%
2051	1101.01	Currituck	$ (21,150,682.00)	1102.02	Currituck	-2.9706%	Currituck	$ (83,647,216.00)	Currituck	-1.3847%
	9702	Dare	$ (20,529,448.00)	1102.01	Currituck	-2.7876%	Dare	$ (71,630,680.00)	Tyrrell	-0.9306%
	1102.02	Currituck	$ (13,822,390.00)	1103.02	Currituck	-2.1839%	Carteret	$ (59,338,336.00)	Washington	-0.9275%
	1102.01	Currituck	$ (13,247,028.00)	9604	Pasquotank	-2.0344%	New Hanover	$ (45,163,012.00)	Camden	-0.8826%
	9704	Dare	$ (13,221,947.00)	9702	Dare	-1.9186%	Brunswick	$ (36,879,616.00)	Pasquotank	-0.8384%

1103.02	Currituck	$ (12,012,898.00)	9303	Beaufort	-1.6303%	Beaufort	$ (35,908,312.00)	Dare	-0.6966%
9202.02	Perquimans	$ (11,146,781.00)	9607.01	Pasquotank	-1.5263%	Pasquotank	$ (32,590,754.00)	Perquimans	-0.4843%
9501.02	Camden	$ (10,983,689.00)	9602	Pasquotank	-1.4682%	Craven	$ (30,384,200.00)	Beaufort	-0.4611%
9607.01	Pasquotank	$ (10,913,829.00)	9501.02	Camden	-1.4392%	Wake	$ (18,146,168.00)	Hyde	-0.4610%
9701.01	Dare	$ (9,061,843.00)	1104.04	Currituck	-1.4259%	Mecklenburg	$ (17,748,816.00)	Carteret	-0.4204%
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9706.06	Granville	$ 745.86	9706.06	Granville	0.0003%	Clay	$ (331,644.09)	Franklin	-0.0088%
111.06	Orange	$ 855.38	111.06	Orange	0.0004%	Anson	$ (323,032.88)	Rockingham	-0.0088%
530.11	Wake	$ 931.44	530.11	Wake	0.0005%	Stokes	$ (308,569.22)	Greene	-0.0082%
39.03	Mecklenburg	$ 2,670.34	165.05	Guilford	0.0017%	Martin	$ (305,254.69)	Yadkin	-0.0077%
19.27	Mecklenburg	$ 3,105.43	39.03	Mecklenburg	0.0021%	Yadkin	$ (300,516.16)	Surry	-0.0070%
145.03	Guilford	$ 3,454.50	145.03	Guilford	0.0026%	Person	$ (279,822.97)	Chatham	-0.0069%
165.05	Guilford	$ 3,891.17	9304.01	Henderson	0.0029%	Hertford	$ (259,223.70)	Stokes	-0.0068%
523.05	Wake	$ 6,400.35	525.05	Wake	0.0063%	Swain	$ (256,076.59)	Granville	-0.0066%
9304.01	Henderson	$ 7,813.72	523.05	Wake	0.0109%	Greene	$ (137,118.02)	Person	-0.0062%
525.05	Wake	$ 22,872.40	19.27	Mecklenburg	0.0186%	Caswell	$ (54,574.64)	Caswell	-0.0025%

Table 2.22A: Value Losses and Value Loss Percentages for Mainline Zip Model and High Climate Scenario

	Tract-level Value Change Tails						County-level Value Change Tails			
Year	**Tract**	**County**	**Value Change**	**Tract**	**County**	**% Value Change**	**County**	**Value Change**	**County**	**% Value Change**
2036	1101.01	Currituck	$ (19,864,068.00)	1102.01	Currituck	-2.6179%	Currituck	$ (77,448,312.00)	Currituck	-1.2821%
	9702	Dare	$ (19,322,208.00)	1102.02	Currituck	-2.5457%	Dare	$ (69,550,680.00)	Washington	-0.8840%
	9704	Dare	$ (12,776,660.00)	9604	Pasquotank	-2.0116%	Carteret	$ (54,034,016.00)	Tyrrell	-0.8739%
	1102.01	Currituck	$ (12,440,636.00)	1103.02	Currituck	-2.0080%	New	$ (42,576,836.00)	Camden	-0.8483%
	1102.02	Currituck	$ (11,845,167.00)	9702	Dare	-1.8058%	Brunswick	$ (34,790,256.00)	Pasquotank	-0.8356%
	1103.02	Currituck	$ (11,045,072.00)	9303	Beaufort	-1.5642%	Beaufort	$ (34,672,540.00)	Dare	-0.6764%
	9607.01	Pasquotank	$ (10,858,401.00)	9607.01	Pasquotank	-1.5186%	Pasquotank	$ (32,480,096.00)	Perquimans	-0.4610%
	9202.02	Perquimans	$ (10,504,606.00)	9602	Pasquotank	-1.4450%	Craven	$ (32,129,166.00)	Beaufort	-0.4453%
	9501.02	Camden	$ (10,460,709.00)	9501.02	Camden	-1.3706%	Wake	$ (17,043,908.00)	Hyde	-0.4436%
	9705.02	Dare	$ (8,485,260.00)	9609	Craven	-1.3499%	Mecklenburg	$ (16,171,768.00)	Carteret	-0.3828%
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	22.02	Onslow	$ 3,351.05	9605.03	Rutherford	0.0019%	Vance	$ (305,221.13)	Rockingham	-0.0081%
	411.04	Johnston	$ 4,346.94	59.24	Mecklenburg	0.0020%	Anson	$ (301,199.00)	Davie	-0.0081%
	58.29	Mecklenburg	$ 5,315.33	22.02	Onslow	0.0021%	Martin	$ (291,014.13)	Yadkin	-0.0073%
	152.02	Guilford	$ 5,452.41	904.02	Duplin	0.0022%	Yadkin	$ (283,496.16)	Surry	-0.0066%
	904.02	Duplin	$ 7,791.59	312.04	Gaston	0.0026%	Person	$ (280,426.41)	Chatham	-0.0066%
	59.24	Mecklenburg	$ 8,203.89	59.21	Mecklenburg	0.0043%	Swain	$ (276,138.13)	Greene	-0.0064%
	9301.01	Surry	$ 9,483.25	24	Mecklenburg	0.0048%	Hertford	$ (267,535.31)	Person	-0.0062%
	59.21	Mecklenburg	$ 10,280.63	9301.01	Surry	0.0049%	Stokes	$ (266,243.00)	Stokes	-0.0059%
	24	Mecklenburg	$ 15,642.35	58.29	Mecklenburg	0.0085%	Greene	$ (106,788.50)	Granville	-0.0056%
	18	Onslow	$ 27,365.33	18	Onslow	0.0162%	Caswell	$ (45,917.54)	Caswell	-0.0021%
2051	1101.01	Currituck	$ (21,304,246.00)	1102.01	Currituck	-2.6832%	Currituck	$ (81,065,032.00)	Currituck	-1.3420%
	9702	Dare	$ (20,664,886.00)	1102.02	Currituck	-2.5622%	Dare	$ (74,191,432.00)	Washington	-0.9339%
	9704	Dare	$ (13,779,280.00)	9604	Pasquotank	-2.1772%	Carteret	$ (61,586,008.00)	Tyrrell	-0.9288%
	1102.01	Currituck	$ (12,750,628.00)	1103.02	Currituck	-2.0917%	New Hanover	$ (46,588,624.00)	Pasquotank	-0.9157%
	1102.02	Currituck	$ (11,921,781.00)	9702	Dare	-1.9313%	Brunswick	$ (38,384,536.00)	Camden	-0.9133%

9607.01	Pasquotank	$ (11,785,723.00)	9607.01	Pasquotank	-1.6483%	Beaufort	$ (35,626,456.00)	Dare	-0.7215%
1103.02	Currituck	$ (11,505,257.00)	9602	Pasquotank	-1.5955%	Pasquotank	$ (35,595,016.00)	Perquimans	-0.4948%
9501.02	Camden	$ (11,251,540.00)	9303	Beaufort	-1.5526%	Craven	$ (34,568,232.00)	Hyde	-0.4718%
9202.02	Perquimans	$ (11,104,919.00)	9501.02	Camden	-1.4743%	Wake	$ (18,112,428.00)	Beaufort	-0.4575%
9501	Washington	$ (9,131,350.00)	9609	Craven	-1.4295%	Mecklenburg	$ (17,424,336.00)	Carteret	-0.4363%
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152.02	Guilford	$ 5,949.43	312.04	Gaston	0.0030%	Martin	$ (332,051.22)	Vance	-0.0087%
9304.01	Henderson	$ 6,964.89	22.02	Onslow	0.0036%	Anson	$ (327,491.44)	Rockingham	-0.0087%
303.01	Gaston	$ 8,411.21	303.01	Gaston	0.0036%	Vance	$ (325,992.06)	Davie	-0.0085%
525.05	Wake	$ 9,010.27	59.21	Mecklenburg	0.0058%	Swain	$ (311,445.19)	Yadkin	-0.0079%
904.02	Duplin	$ 9,440.37	24	Mecklenburg	0.0060%	Person	$ (310,124.59)	Granville	-0.0071%
59.24	Mecklenburg	$ 10,486.56	9301.01	Surry	0.0065%	Yadkin	$ (305,392.78)	Chatham	-0.0069%
9301.01	Surry	$ 12,416.90	58.29	Mecklenburg	0.0068%	Stokes	$ (278,974.16)	Person	-0.0069%
59.21	Mecklenburg	$ 13,811.79	523.05	Wake	0.0098%	Hertford	$ (277,208.47)	Surry	-0.0068%
24	Mecklenburg	$ 19,415.49	19.27	Mecklenburg	0.0172%	Greene	$ (176,430.34)	Stokes	-0.0061%
18	Onslow	$ 53,060.73	18	Onslow	0.0313%	Caswell	$ (52,599.20)	Caswell	-0.0024%

Table 3.19A: Vigintile Regression Results for Tract Fixed Effect

	Percentile	Percentage-Chance		Percentage-Chance Squared		FEMA 100-year	
Tract	5	-0.0050926	**	0.0001475	**	-0.0411948	
	10	-0.0030051	**	0.0000927	**	-0.0431736	**
	15	-0.0024043	**	0.0000716	**	-0.043299	**
	20	-0.0019662	**	0.000052	**	-0.0290883	**
	25	-0.0014627	**	0.0000371	**	-0.0174543	*
	30	-0.0011328	**	0.0000304	**	-0.0105204	
	35	-0.0009094	**	0.0000245	*	-0.0021446	
	40	-0.0006112		0.0000213	*	0.0017952	
	45	-0.0006488	*	0.0000229	*	0.00602	
	50	-0.000511		0.0000265	*	0.0126949	*
	55	-0.0006255		0.0000349	**	0.0170522	**
	60	-0.0004912		0.0000343	**	0.0221026	**
	65	-0.0002731		0.0000378	**	0.0296075	**
	70	-0.0001131		0.0000406	**	0.0328796	**
	75	-0.00082		0.0000761	**	0.0370816	**
	80	-0.0011352	*	0.0001074	**	0.040965	**
	85	-0.0014319	*	0.000141	**	0.0376234	**
	90	-0.0023847	**	0.0001909	**	0.0033099	
	95	-0.0039323	**	0.0002602	**	-0.0550042	**

**95% statistical significance*

***99% statistical significance*

Table 3.20A: Vigintile Regression Results for County Fixed Effect

	Percentile	Percentage-Chance		Percentage-Chance Squared		FEMA 100-year	
County	5	-0.0031076		0.0000776		-0.1481209	**
	10	-0.001667		0.0000546		-0.1109332	**
	15	-0.0013669		0.0000448	*	-0.091541	**
	20	-0.0013702	**	0.0000371	*	-0.0587876	**
	25	-0.0009852	*	0.0000239		-0.0371294	**
	30	-0.0006709		0.000016		-0.0254179	**
	35	-0.0003573		0.0000058		-0.0150317	*
	40	0.0000449		-0.0000025		-0.0094074	
	45	0.0000742		-0.0000039		-0.0050494	
	50	0.0003097		-0.0000036		0.0016429	
	55	0.0003792		-0.000001		0.0040589	
	60	0.0005956		-0.0000035		0.0091211	
	65	0.0008137	*	0.0000002		0.0165074	**
	70	0.0009852	*	0.0000025		0.0169291	*
	75	0.0002037		0.0000393	**	0.0195889	**
	80	-0.0003537		0.0000725	**	0.0238286	**
	85	-0.0008899		0.0001027	**	0.0222909	*
	90	-0.0019987	**	0.0001406	**	0.0007042	
	95	-0.0035242	**	0.0001759	**	-0.0275473	

**95% statistical significance*

***99% statistical significance*

Table 3.21A: Value Losses and Value Loss Percentages for Vigintile Block Model and Low Climate Scenario

	Tract-level Value Change Tails						County-level Value Change Tails			
Year	**Tract**	**County**	**Value Change**	**Tract**	**County**	**% Value Change**	**County**	**Value Change**	**County**	**% Value Change**
2036	9704	Dare	$ (10,494,167.00)	1102.02	Currituck	-1.6422%	Dare	$ (38,257,800.00)	Currituck	-0.4557%
	9701.01	Dare	$ (10,145,567.00)	1103.02	Currituck	-1.1678%	New Hanover	$ (36,390,440.00)	Dare	-0.3734%
	1102.02	Currituck	$ (7,722,790.00)	9609	Craven	-1.0930%	Currituck	$ (27,436,638.00)	Perquimans	-0.1865%
	1101.01	Currituck	$ (6,307,687.50)	122.03	New Hanover	-1.0452%	Carteret	$ (25,412,284.00)	Carteret	-0.1803%
	123	New Hanover	$ (6,275,626.50)	1102.01	Currituck	-0.9512%	Brunswick	$ (14,017,484.00)	Washington	-0.1734%
	122.03	New Hanover	$ (5,754,497.00)	9501.03	Pamlico	-0.7589%	Craven	$ (13,216,948.00)	Pasquotank	-0.1628%
	9709.04	Carteret	$ (5,045,465.50)	9704	Dare	-0.7176%	Beaufort	$ (9,489,497.00)	Hyde	-0.1559%
	9710.03	Carteret	$ (4,835,008.50)	9607.01	Pasquotank	-0.6371%	Pasquotank	$ (6,317,911.00)	New Hanover	-0.1454%
	1102.01	Currituck	$ (4,549,798.00)	1103.01	Currituck	-0.6364%	Mecklenburg	$ (6,200,659.00)	Tyrrell	-0.1424%
	1103.02	Currituck	$ (4,059,869.00)	9303	Beaufort	-0.6325%	Perquimans	$ (5,836,475.50)	Craven	-0.1319%
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	310	Caldwell	$ 1,070.69	616	Davidson	0.0029%	Yancey	$ (46,088.95)	Surry	-0.0011%
	9304.02	Cherokee	$ 1,771.44	325.06	Gaston	0.0036%	Alleghany	$ (42,415.59)	Duplin	-0.0011%
	201.04	Chatham	$ 4,655.21	36.02	Cumberland	0.0037%	Hertford	$ (32,398.44)	Swain	-0.0010%
	9202.02	Polk	$ 5,031.37	535.24	Wake	0.0038%	Polk	$ (32,330.55)	Cherokee	-0.0010%
	209	Edgecombe	$ 5,333.39	5.02	Mecklenburg	0.0064%	Granville	$ (31,350.04)	Stokes	-0.0010%
	210.13	Union	$ 5,632.44	38.1	Mecklenburg	0.0075%	Graham	$ (28,906.41)	Polk	-0.0008%
	620.01	Davidson	$ 5,808.25	535.16	Wake	0.0100%	Yadkin	$ (25,253.18)	Wilkes	-0.0007%
	9706	Macon	$ 10,698.88	58.54	Mecklenburg	0.0144%	Swain	$ (22,975.97)	Yadkin	-0.0007%
	39.03	Mecklenburg	$ 31,452.55	540.06	Wake	0.0155%	Greene	$ (20,192.37)	Granville	-0.0006%
	207.02	Chatham	$ 36,749.57	9803	Mecklenburg	0.0179%	Caswell	$ (9,598.19)	Caswell	-0.0004%
2051	9701.01	Dare	$ (10,145,567.00)	1102.02	Currituck	-1.6669%	Dare	$ (49,880,568.00)	Currituck	-0.5927%
	9704	Dare	$ (10,494,167.00)	9609	Craven	-1.1550%	New Hanover	$ (49,736,728.00)	Dare	-0.4868%
	1101.01	Currituck	$ (6,307,687.50)	1103.02	Currituck	-1.0830%	Carteret	$ (39,507,760.00)	Carteret	-0.2803%
	123	New Hanover	$ (6,275,626.50)	1102.01	Currituck	-0.9988%	Currituck	$ (35,687,596.00)	Pasquotank	-0.2631%
	9709.04	Carteret	$ (5,045,465.50)	122.03	New Hanover	-0.9888%	Brunswick	$ (24,188,632.00)	Tyrrell	-0.2313%

1102.02	Currituck	$	(7,722,790.00)	9704	Dare	-0.8039%	Mecklenburg	$	(21,264,384.00)	Perquimans	-0.2177%
122.03	New Hanover	$	(5,754,497.00)	9501.03	Pamlico	-0.7392%	Wake	$	(17,541,976.00)	Washington	-0.2116%
9710.03	Carteret	$	(4,835,008.50)	9701.01	Dare	-0.6735%	Craven	$	(15,641,838.00)	New Hanover	-0.1988%
1103.02	Currituck	$	(4,059,869.00)	9703.02	Dare	-0.6672%	Beaufort	$	(11,340,400.00)	Hyde	-0.1842%
9702	Dare	$	(3,969,892.00)	1103.01	Currituck	-0.6545%	Pasquotank	$	(10,209,380.00)	Camden	-0.1758%
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9302	Cherokee	$	11,518.44	535.24	Wake	0.0048%	Richmond	$	(97,183.37)	Surry	-0.0022%
535.24	Wake	$	12,420.31	201	Burke	0.0064%	Lenoir	$	(92,615.20)	Wilkes	-0.0021%
111.06	Orange	$	13,140.73	111.06	Orange	0.0067%	Madison	$	(87,243.41)	Lenoir	-0.0021%
58.54	Mecklenburg	$	14,093.60	38.1	Mecklenburg	0.0075%	Stokes	$	(68,230.63)	Hertford	-0.0020%
302	Caldwell	$	14,675.70	19.27	Mecklenburg	0.0113%	Graham	$	(60,656.98)	Granville	-0.0020%
535.16	Wake	$	20,197.93	535.16	Wake	0.0128%	Swain	$	(50,611.85)	Richmond	-0.0020%
207.02	Chatham	$	26,927.51	58.54	Mecklenburg	0.0161%	Hertford	$	(49,079.18)	Greene	-0.0019%
201	Burke	$	31,115.05	9803	Mecklenburg	0.0197%	Greene	$	(31,772.64)	Stokes	-0.0015%
39.03	Mecklenburg	$	32,628.82	540.06	Wake	0.0213%	Caswell	$	(22,279.47)	Caswell	-0.0010%
540.06	Wake	$	40,081.42	39.03	Mecklenburg	0.0252%	Yadkin	$	(11,550.61)	Yadkin	-0.0003%

Table 3.22A: Value Losses and Value Loss Percentages for Vigintile Block Model and Mid Climate Scenario

	Tract-level Value Change Tails						County-level Value Change Tails			
Year	**Tract**	**County**	**Value Change**	**Tract**	**County**	**% Value Change**	**County**	**Value Change**	**County**	**% Value Change**
2036	9701.01	Dare	$ (13,299,939.00)	1102.02	Currituck	-1.6422%	New Hanover	$ (46,606,856.00)	Currituck	-0.6126%
	1101.01	Currituck	$ (11,463,598.00)	1103.02	Currituck	-1.1678%	Dare	$ (45,276,060.00)	Dare	-0.4422%
	9704	Dare	$ (11,061,951.00)	9609	Craven	-1.0930%	Currituck	$ (36,879,108.00)	Pasquotank	-0.2645%
	1102.02	Currituck	$ (7,622,803.00)	122.03	New Hanover	-1.0452%	Carteret	$ (36,391,612.00)	Carteret	-0.2582%
	123	New Hanover	$ (7,483,753.50)	1102.01	Currituck	-0.9512%	Brunswick	$ (26,909,676.00)	Camden	-0.2198%
	122.03	New Hanover	$ (7,181,838.00)	9501.03	Pamlico	-0.7589%	Mecklenburg	$ (19,347,944.00)	Tyrrell	-0.2083%
	9710.03	Carteret	$ (6,898,675.50)	9704	Dare	-0.7176%	Wake	$ (16,993,950.00)	Perquimans	-0.2041%
	1103.02	Currituck	$ (6,412,359.50)	9607.01	Pasquotank	-0.6371%	Craven	$ (14,438,528.00)	Washington	-0.1989%
	9709.04	Carteret	$ (5,841,479.50)	1103.01	Currituck	-0.6364%	Beaufort	$ (10,560,578.00)	Hyde	-0.1882%
	9702	Dare	$ (5,818,225.00)	9303	Beaufort	-0.6325%	Pasquotank	$ (10,259,803.00)	New Hanover	-0.1863%
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	409.03	Johnston	$ 5,254.00	616	Davidson	0.0029%	Anson	$ (93,280.85)	Rockingham	-0.0022%
	59.21	Mecklenburg	$ 5,829.84	325.06	Gaston	0.0036%	Gates	$ (89,413.59)	Granville	-0.0018%
	532.05	Wake	$ 7,054.94	36.02	Cumberland	0.0037%	Richmond	$ (70,738.16)	Surry	-0.0016%
	38.1	Mecklenburg	$ 7,139.44	535.24	Wake	0.0038%	Lenoir	$ (66,914.97)	Lenoir	-0.0015%
	9516.01	Cleveland	$ 8,157.39	5.02	Mecklenburg	0.0064%	Swain	$ (58,722.27)	Hertford	-0.0014%
	9711	Richmond	$ 8,793.07	38.1	Mecklenburg	0.0075%	Stokes	$ (56,935.11)	Richmond	-0.0014%
	535.24	Wake	$ 9,796.59	535.16	Wake	0.0100%	Hertford	$ (34,852.51)	Greene	-0.0013%
	58.54	Mecklenburg	$ 12,645.93	58.54	Mecklenburg	0.0144%	Greene	$ (20,901.85)	Stokes	-0.0013%
	535.16	Wake	$ 15,878.24	540.06	Wake	0.0155%	Caswell	$ (15,743.94)	Caswell	-0.0007%
	540.06	Wake	$ 29,166.16	9803	Mecklenburg	0.0179%	Yadkin	$ (6,099.20)	Yadkin	-0.0002%
2051	9701.01	Dare	$ (14,745,569.00)	1102.02	Currituck	-1.6490%	New Hanover	$ (53,688,424.00)	Currituck	-0.6767%
	1101.01	Currituck	$ (13,254,450.00)	1103.02	Currituck	-1.2817%	Dare	$ (51,018,700.00)	Dare	-0.4983%
	9704	Dare	$ (12,190,768.00)	9609	Craven	-1.2115%	Carteret	$ (43,610,704.00)	Carteret	-0.3094%
	123	New Hanover	$ (8,601,224.00)	122.03	New Hanover	-1.1278%	Currituck	$ (40,733,528.00)	Pasquotank	-0.3044%
	9710.03	Carteret	$ (7,813,655.50)	1102.01	Currituck	-0.9886%	Brunswick	$ (31,701,294.00)	Camden	-0.2655%

122.03	New Hanover	$	(7,748,933.50)	9501.03	Pamlico	-0.8235%	Mecklenburg	$	(21,354,640.00)	Tyrrell	-0.2369%
1102.02	Currituck	$	(7,654,047.50)	9704	Dare	-0.7909%	Wake	$	(18,541,016.00)	Perquimans	-0.2275%
9702	Dare	$	(7,068,398.50)	9607.01	Pasquotank	-0.7158%	Craven	$	(16,668,262.00)	Washington	-0.2248%
1103.02	Currituck	$	(7,037,362.50)	9303	Beaufort	-0.6780%	Pasquotank	$	(11,810,121.00)	New Hanover	-0.2146%
9709.04	Carteret	$	(7,021,606.00)	9701.01	Dare	-0.6719%	Beaufort	$	(11,492,720.00)	Hyde	-0.2075%
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302	Caldwell	$	8,997.63	38.1	Mecklenburg	0.0047%	Gates	$	(104,018.67)	Rockingham	-0.0026%
535.16	Wake	$	9,534.05	165.05	Guilford	0.0050%	Graham	$	(102,787.27)	Lenoir	-0.0023%
31.06	Mecklenburg	$	9,813.70	111.06	Orange	0.0054%	Lenoir	$	(99,671.27)	Granville	-0.0022%
111.06	Orange	$	10,646.30	535.16	Wake	0.0060%	Richmond	$	(95,956.76)	Richmond	-0.0019%
165.05	Guilford	$	11,520.09	201	Burke	0.0062%	Swain	$	(69,595.65)	Hertford	-0.0019%
525.05	Wake	$	11,672.99	540.06	Wake	0.0086%	Stokes	$	(67,226.48)	Surry	-0.0019%
540.06	Wake	$	16,125.23	58.54	Mecklenburg	0.0096%	Hertford	$	(46,802.06)	Greene	-0.0017%
201	Burke	$	30,382.08	9803	Mecklenburg	0.0112%	Greene	$	(29,066.28)	Stokes	-0.0015%
207.02	Chatham	$	35,838.53	39.03	Mecklenburg	0.0283%	Caswell	$	(19,179.59)	Caswell	-0.0009%
39.03	Mecklenburg	$	36,660.60	19.27	Mecklenburg	0.0480%	Yadkin	$	(14,598.68)	Yadkin	-0.0004%

Table 3.23A: Value Losses and Value Loss Percentages for Vigintile Block Model and High Climate Scenario

	Tract-level Value Change Tails						County-level Value Change Tails			
Year	**Tract**	**County**	**Value Change**	**Tract**	**County**	**% Value Change**	**County**	**Value Change**	**County**	**% Value Change**
2036	1101.01	Currituck	$ (10,800,731.00)	1102.02	Currituck	-1.2241%	New Hanover	$ (41,856,268.00)	Currituck	-0.5403%
	9709.04	Carteret	$ (9,544,267.00)	9609	Craven	-1.1889%	Carteret	$ (38,328,964.00)	Dare	-0.3558%
	9701.01	Dare	$ (9,364,575.00)	1103.02	Currituck	-1.0147%	Dare	$ (36,394,732.00)	Pasquotank	-0.3087%
	9704	Dare	$ (7,288,891.50)	122.03	New Hanover	-0.8190%	Currituck	$ (32,505,310.00)	Carteret	-0.2722%
	123	New Hanover	$ (6,631,255.00)	1102.01	Currituck	-0.7944%	Brunswick	$ (22,762,402.00)	Perquimans	-0.2404%
	9702	Dare	$ (5,683,494.00)	9709.04	Carteret	-0.7053%	Craven	$ (19,555,032.00)	Camden	-0.2357%
	1102.02	Currituck	$ (5,668,578.50)	9607.01	Pasquotank	-0.7016%	Mecklenburg	$ (13,651,606.00)	Washington	-0.1980%
	9710.03	Carteret	$ (5,613,713.00)	9604	Pasquotank	-0.6732%	Wake	$ (13,333,650.00)	Craven	-0.1952%
	122.03	New Hanover	$ (5,591,580.00)	9303	Beaufort	-0.6258%	Pasquotank	$ (11,977,056.00)	Tyrrell	-0.1920%
	1103.02	Currituck	$ (5,565,278.00)	1103.01	Currituck	-0.6047%	Beaufort	$ (10,508,883.00)	New Hanover	-0.1674%
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	19.03	Cumberland	$ 8,678.40	540.16	Wake	0.0048%	Martin	$ (106,048.20)	Granville	-0.0024%
	20.23	Durham	$ 9,475.40	19.03	Cumberland	0.0051%	Rockingham	$ (93,892.14)	Hertford	-0.0024%
	59.21	Mecklenburg	$ 11,161.23	333.11	Gaston	0.0055%	Surry	$ (91,095.27)	Sampson	-0.0021%
	540.06	Wake	$ 11,767.73	20.23	Durham	0.0056%	Davie	$ (86,405.05)	Davie	-0.0019%
	57.2	Mecklenburg	$ 12,332.61	540.06	Wake	0.0063%	Stokes	$ (79,596.65)	Vance	-0.0018%
	12	Wayne	$ 15,814.95	407	Johnston	0.0065%	Vance	$ (68,911.65)	Stokes	-0.0017%
	407	Johnston	$ 18,456.54	9205.02	Pender	0.0072%	Hertford	$ (57,304.34)	Surry	-0.0014%
	9205.02	Pender	$ 23,023.21	38.1	Mecklenburg	0.0078%	Greene	$ (55,863.07)	Rockingham	-0.0013%
	540.16	Wake	$ 24,152.04	537.17	Wake	0.0114%	Yadkin	$ (29,356.68)	Caswell	-0.0010%
	537.17	Wake	$ 30,139.18	15.01	Durham	0.0250%	Caswell	$ (22,390.95)	Yadkin	-0.0008%
2051	9709.04	Carteret	$ (15,157,888.00)	9609	Craven	-1.3346%	New Hanover	$ (66,961,896.00)	Currituck	-0.6220%
	1101.01	Currituck	$ (13,330,298.00)	122.03	New Hanover	-1.3055%	Carteret	$ (57,001,236.00)	Dare	-0.4310%
	9701.01	Dare	$ (11,594,691.00)	1102.02	Currituck	-1.2307%	Dare	$ (44,077,276.00)	Carteret	-0.4048%
	122.03	New Hanover	$ (8,913,000.00)	1103.02	Currituck	-1.1219%	Currituck	$ (37,420,900.00)	Perquimans	-0.3755%
	123	New Hanover	$ (8,599,812.00)	9709.04	Carteret	-1.1202%	Brunswick	$ (32,482,668.00)	Pasquotank	-0.3744%

9704	Dare	$	(8,534,316.00)	9604.03	Craven	-0.9906%	Craven	$	(28,890,580.00)	Camden	-0.2908%
9710.03	Carteret	$	(7,944,749.50)	9201.02	Perquimans	-0.9316%	Mecklenburg	$	(16,500,911.00)	Craven	-0.2884%
9702	Dare	$	(7,203,180.50)	120.12	New Hanover	-0.8543%	Wake	$	(15,942,301.00)	New Hanover	-0.2679%
9709.03	Carteret	$	(7,192,072.00)	1102.01	Currituck	-0.8275%	Pasquotank	$	(14,523,948.00)	Washington	-0.2556%
120.12	New Hanover	$	(6,592,729.50)	9607.01	Pasquotank	-0.8188%	Beaufort	$	(12,040,957.00)	Tyrrell	-0.2171%
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122.01	Orange	$	31,867.24	15.01	Durham	0.0120%	Martin	$	(131,313.86)	Wayne	-0.0034%
58.29	Mecklenburg	$	32,884.18	24	Mecklenburg	0.0139%	Granville	$	(127,943.68)	Davie	-0.0032%
201	Burke	$	34,973.54	325.1	Gaston	0.0141%	Rockingham	$	(126,539.59)	Sampson	-0.0031%
59.21	Mecklenburg	$	35,354.71	36.02	Cumberland	0.0144%	Surry	$	(91,176.34)	Granville	-0.0023%
24	Mecklenburg	$	44,967.50	59.21	Mecklenburg	0.0148%	Hertford	$	(87,910.49)	Vance	-0.0023%
325.1	Gaston	$	48,437.76	19	Wayne	0.0372%	Vance	$	(85,024.07)	Caswell	-0.0018%
18	Onslow	$	66,643.32	18	Onslow	0.0394%	Stokes	$	(82,708.53)	Stokes	-0.0018%
19	Wayne	$	71,003.57	303.01	Gaston	0.0429%	Greene	$	(71,941.09)	Rockingham	-0.0018%
9708.02	Ashe	$	73,662.65	19.27	Mecklenburg	0.0450%	Caswell	$	(39,145.14)	Surry	-0.0014%
303.01	Gaston	$	99,477.06	58.29	Mecklenburg	0.0523%	Yadkin	$	(30,073.93)	Yadkin	-0.0008%

Table 3.24A: Value Losses and Value Loss Percentages for Vigintile Zip Model and Low Climate Scenario

	Tract-level Value Change Tails						County-level Value Change Tails			
Year	**Tract**	**County**	**Value Change**	**Tract**	**County**	**% Value Change**	**County**	**Value Change**	**County**	**% Value Change**
2036	9704	Dare	$ (12,540,004.00)	1102.02	Currituck	-2.3302%	Dare	$ (49,947,884.00)	Currituck	-0.6581%
	9701.01	Dare	$ (11,866,210.00)	1102.01	Currituck	-1.5110%	New Hanover	$ (46,060,848.00)	Dare	-0.4879%
	1102.02	Currituck	$ (10,800,692.00)	9303	Beaufort	-1.4344%	Currituck	$ (39,565,496.00)	Washington	-0.4348%
	1101.01	Currituck	$ (8,772,638.00)	9609	Craven	-1.3348%	Carteret	$ (33,674,088.00)	Tyrrell	-0.3370%
	123	New Hanover	$ (8,116,528.00)	9502.01	Washington	-1.2928%	Craven	$ (21,239,316.00)	Beaufort	-0.2646%
	1102.01	Currituck	$ (7,155,580.00)	1103.02	Currituck	-0.9964%	Beaufort	$ (20,534,908.00)	Pasquotank	-0.2637%
	9702	Dare	$ (6,646,542.00)	122.03	New Hanover	-0.8907%	Brunswick	$ (18,898,686.00)	Perquimans	-0.2624%
	122.03	New Hanover	$ (6,121,486.50)	9304	Beaufort	-0.8147%	Pasquotank	$ (10,215,344.00)	Hyde	-0.2567%
	9709.04	Carteret	$ (5,719,212.00)	9704	Dare	-0.8123%	Mecklenburg	$ (8,630,024.00)	Carteret	-0.2391%
	9710.03	Carteret	$ (5,612,625.00)	1103.01	Currituck	-0.8121%	Perquimans	$ (8,204,353.00)	Craven	-0.2122%
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	9304.02	Cherokee	$ 2,332.30	530.11	Wake	0.0007%	Alleghany	$ (50,856.07)	Lenoir	-0.0012%
	209.02	Burke	$ 2,795.88	410.02	Rockingham	0.0007%	Vance	$ (46,205.07)	Stokes	-0.0012%
	606.02	Franklin	$ 2,888.44	209.02	Burke	0.0010%	Polk	$ (38,903.95)	Duplin	-0.0011%
	126.11	Guilford	$ 2,943.01	9304.02	Cherokee	0.0010%	Yadkin	$ (37,596.79)	Surry	-0.0011%
	9605.01	Craven	$ 3,112.16	9605.01	Craven	0.0013%	Graham	$ (37,408.18)	Polk	-0.0010%
	410.02	Rockingham	$ 3,335.68	9202.02	Polk	0.0014%	Granville	$ (32,997.83)	Swain	-0.0010%
	9202.02	Polk	$ 6,074.09	126.11	Guilford	0.0031%	Hertford	$ (29,282.59)	Yadkin	-0.0010%
	303	Lee	$ 9,346.65	207.02	Chatham	0.0040%	Greene	$ (25,792.55)	Wilkes	-0.0008%
	207.02	Chatham	$ 31,596.39	303	Lee	0.0046%	Swain	$ (22,346.11)	Granville	-0.0006%
	39.03	Mecklenburg	$ 32,816.74	39.03	Mecklenburg	0.0253%	Caswell	$ (10,229.18)	Caswell	-0.0005%
2051	9701.01	Dare	$ (17,330,416.00)	1102.02	Currituck	-2.3554%	Dare	$ (64,964,780.00)	Currituck	-0.8657%
	9704	Dare	$ (14,940,007.00)	1102.01	Currituck	-1.5916%	New Hanover	$ (64,233,156.00)	Dare	-0.6346%
	1101.01	Currituck	$ (14,824,643.00)	9609	Craven	-1.4920%	Carteret	$ (52,620,344.00)	Tyrrell	-0.5787%
	123	New Hanover	$ (11,011,264.00)	9303	Beaufort	-1.4736%	Currituck	$ (52,045,728.00)	Washington	-0.5734%
	1102.02	Currituck	$ (10,917,597.00)	1103.02	Currituck	-1.4512%	Brunswick	$ (32,953,002.00)	Pasquotank	-0.4723%

9709.04	Carteret	$	(9,637,332.00)	9502.01	Washington	-1.2934%	Mecklenburg	$	(27,004,660.00)	Carteret	-0.3736%
9702	Dare	$	(9,589,957.00)	9604	Pasquotank	-1.1452%	Craven	$	(24,350,270.00)	Camden	-0.3333%
1103.02	Currituck	$	(7,967,557.00)	122.03	New Hanover	-1.0683%	Beaufort	$	(23,668,410.00)	Beaufort	-0.3049%
9710.03	Carteret	$	(7,703,351.00)	9704	Dare	-0.9677%	Wake	$	(21,846,140.00)	Perquimans	-0.3028%
1102.01	Currituck	$	(7,536,938.50)	9501.03	Pamlico	-0.9430%	Pasquotank	$	(18,291,472.00)	Hyde	-0.2994%
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62.22	Mecklenburg	$	843.15	62.22	Mecklenburg	0.0002%	Granville	$	(196,692.92)	Madison	-0.0051%
303	Lee	$	2,396.54	207.02	Chatham	0.0011%	Madison	$	(191,245.16)	Hertford	-0.0048%
19.27	Mecklenburg	$	5,238.37	303	Lee	0.0012%	Gates	$	(190,428.80)	Wilkes	-0.0047%
207.02	Chatham	$	8,378.14	31.06	Mecklenburg	0.0027%	Graham	$	(147,501.09)	Greene	-0.0044%
31.06	Mecklenburg	$	9,013.12	525.05	Wake	0.0056%	Stokes	$	(145,797.64)	Surry	-0.0043%
165.05	Guilford	$	18,958.66	201	Burke	0.0057%	Hertford	$	(115,406.93)	Swain	-0.0042%
525.05	Wake	$	20,220.04	165.05	Guilford	0.0082%	Yadkin	$	(110,328.77)	Granville	-0.0035%
111.06	Orange	$	25,993.14	111.06	Orange	0.0132%	Swain	$	(92,990.67)	Stokes	-0.0032%
201	Burke	$	27,581.95	39.03	Mecklenburg	0.0242%	Greene	$	(73,355.75)	Yadkin	-0.0028%
39.03	Mecklenburg	$	31,412.67	19.27	Mecklenburg	0.0315%	Caswell	$	(59,120.73)	Caswell	-0.0028%

Table 3.25A: Value Losses and Value Loss Percentages for Vigintile Zip Model and Mid Climate Scenario

	Tract-level Value Change Tails						County-level Value Change Tails			
Year	Tract	County	Value Change	Tract	County	% Value Change	County	Value Change	County	% Value Change
2036	1101.01	Currituck	$ (15,359,263.00)	1102.02	Currituck	-2.3056%	New Hanover	$ (59,056,520.00)	Currituck	-0.8939%
	9701.01	Dare	$ (15,186,684.00)	1103.02	Currituck	-1.5764%	Dare	$ (58,977,692.00)	Dare	-0.5766%
	9704	Dare	$ (13,420,473.00)	1102.01	Currituck	-1.5059%	Currituck	$ (53,727,828.00)	Tyrrell	-0.5531%
	1102.02	Currituck	$ (10,686,991.00)	9303	Beaufort	-1.4579%	Carteret	$ (48,133,188.00)	Washington	-0.5467%
	123	New Hanover	$ (9,649,959.00)	9609	Craven	-1.4008%	Brunswick	$ (36,177,980.00)	Pasquotank	-0.4760%
	9702	Dare	$ (9,596,704.00)	9604	Pasquotank	-1.2506%	Mecklenburg	$ (24,270,952.00)	Camden	-0.4207%
	1103.02	Currituck	$ (8,652,011.00)	9502.01	Washington	-1.1785%	Craven	$ (22,934,800.00)	Carteret	-0.3418%
	9710.03	Carteret	$ (8,114,221.50)	122.03	New Hanover	-1.1211%	Beaufort	$ (22,845,308.00)	Hyde	-0.3027%
	122.03	New Hanover	$ (7,704,916.00)	9501.03	Pamlico	-0.9568%	Wake	$ (21,054,072.00)	Beaufort	-0.2944%
	1102.01	Currituck	$ (7,130,960.00)	1103.01	Currituck	-0.9099%	Pasquotank	$ (18,433,464.00)	Perquimans	-0.2865%
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	37.01	Mecklenburg	$ 2.18	37.01	Mecklenburg	0.0000%	Graham	$ (220,837.61)	Richmond	-0.0052%
	19.23	Mecklenburg	$ 9.73	19.23	Mecklenburg	0.0000%	Martin	$ (197,481.77)	Franklin	-0.0050%
	13.03	Durham	$ 11.39	13.03	Durham	0.0000%	Gates	$ (182,377.45)	Swain	-0.0047%
	110	New Hanover	$ 12.38	525.09	Wake	0.0000%	Granville	$ (181,985.69)	Hertford	-0.0046%
	525.09	Wake	$ 41.88	13.02	Onslow	0.0000%	Stokes	$ (137,267.84)	Greene	-0.0039%
	13.02	Onslow	$ 48.58	110	New Hanover	0.0000%	Hertford	$ (110,844.46)	Surry	-0.0038%
	112.01	Guilford	$ 222.95	165.05	Guilford	0.0001%	Yadkin	$ (106,931.83)	Granville	-0.0033%
	165.05	Guilford	$ 339.62	112.01	Guilford	0.0003%	Swain	$ (104,007.84)	Stokes	-0.0030%
	19.27	Mecklenburg	$ 432.65	39.03	Mecklenburg	0.0010%	Greene	$ (65,019.63)	Yadkin	-0.0028%
	39.03	Mecklenburg	$ 1,287.61	19.27	Mecklenburg	0.0026%	Caswell	$ (51,984.15)	Caswell	-0.0024%
2051	1101.01	Currituck	$ (17,689,028.00)	1102.02	Currituck	-2.3340%	New Hanover	$ (69,610,592.00)	Currituck	-0.9756%
	9701.01	Dare	$ (17,443,688.00)	1103.02	Currituck	-1.7187%	Dare	$ (66,404,620.00)	Dare	-0.6493%
	9704	Dare	$ (14,902,100.00)	1102.01	Currituck	-1.5799%	Currituck	$ (58,638,684.00)	Tyrrell	-0.5814%
	123	New Hanover	$ (11,665,776.00)	9609	Craven	-1.5699%	Carteret	$ (58,022,756.00)	Washington	-0.5726%
	9702	Dare	$ (10,911,718.00)	9303	Beaufort	-1.5091%	Brunswick	$ (43,278,136.00)	Pasquotank	-0.5192%

1102.02	Currituck	$	(10,818,242.00)	9604	Pasquotank	-1.3280%	Mecklenburg	$	(27,158,202.00)	Camden	-0.4683%
9710.03	Carteret	$	(9,478,139.00)	122.03	New Hanover	-1.2247%	Craven	$	(25,403,988.00)	Carteret	-0.4120%
1103.02	Currituck	$	(9,432,925.00)	9502.01	Washington	-1.1793%	Beaufort	$	(23,744,048.00)	Hyde	-0.3257%
122.03	New Hanover	$	(8,416,595.00)	9501.03	Pamlico	-1.0352%	Wake	$	(23,071,458.00)	Perquimans	-0.3128%
9709.04	Carteret	$	(8,043,155.00)	9702	Dare	-1.0229%	Pasquotank	$	(20,105,336.00)	Beaufort	-0.3059%
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303	Lee	$	5,415.72	207.02	Chatham	0.0026%	Martin	$	(209,703.83)	Wilkes	-0.0057%
9605.01	Craven	$	6,606.44	303	Lee	0.0026%	Granville	$	(207,879.72)	Franklin	-0.0056%
31.06	Mecklenburg	$	10,426.40	9605.01	Craven	0.0027%	Gates	$	(195,886.83)	Swain	-0.0051%
19.27	Mecklenburg	$	13,300.45	31.06	Mecklenburg	0.0031%	Graham	$	(193,885.55)	Hertford	-0.0048%
207.02	Chatham	$	19,931.29	201	Burke	0.0056%	Stokes	$	(143,677.14)	Greene	-0.0044%
165.05	Guilford	$	19,980.98	525.05	Wake	0.0063%	Hertford	$	(115,617.54)	Surry	-0.0040%
111.06	Orange	$	22,545.08	165.05	Guilford	0.0087%	Swain	$	(112,477.38)	Granville	-0.0037%
525.05	Wake	$	22,899.31	111.06	Orange	0.0114%	Yadkin	$	(108,858.60)	Stokes	-0.0032%
201	Burke	$	27,348.27	39.03	Mecklenburg	0.0283%	Greene	$	(73,376.42)	Yadkin	-0.0028%
39.03	Mecklenburg	$	36,704.12	19.27	Mecklenburg	0.0800%	Caswell	$	(55,700.38)	Caswell	-0.0026%

Table 3.26A: Value Losses and Value Loss Percentages for Vigintile Zip Model and High Climate Scenario

	Tract-level Value Change Tails						**County-level Value Change Tails**			
Year	**Tract**	**County**	**Value Change**	**Tract**	**County**	**% Value Change**	**County**	**Value Change**	**County**	**% Value Change**
2036	1101.01	Currituck	$ (14,269,040.00)	1102.02	Currituck	-1.7511%	New Hanover	$ (55,385,656.00)	Currituck	-0.7841%
	9709.04	Carteret	$ (11,183,064.00)	9609	Craven	-1.5223%	Carteret	$ (48,935,784.00)	Pasquotank	-0.5447%
	9701.01	Dare	$ (11,076,499.00)	9303	Beaufort	-1.4460%	Dare	$ (48,694,408.00)	Washington	-0.5010%
	9704	Dare	$ (9,270,798.00)	9604	Pasquotank	-1.3759%	Currituck	$ (47,077,412.00)	Dare	-0.4767%
	9702	Dare	$ (9,189,069.00)	1103.02	Currituck	-1.3686%	Brunswick	$ (30,692,724.00)	Tyrrell	-0.4520%
	123	New Hanover	$ (9,037,213.00)	1102.01	Currituck	-1.2794%	Craven	$ (29,906,336.00)	Camden	-0.4281%
	1102.02	Currituck	$ (8,090,125.50)	9602	Pasquotank	-1.0157%	Beaufort	$ (22,594,974.00)	Carteret	-0.3479%
	1103.02	Currituck	$ (7,498,439.00)	9502.01	Washington	-0.9952%	Pasquotank	$ (21,089,648.00)	Perquimans	-0.3290%
	9607.01	Pasquotank	$ (7,025,287.50)	9607.01	Pasquotank	-0.9900%	Mecklenburg	$ (17,674,684.00)	Craven	-0.2990%
	9710.03	Carteret	$ (6,802,892.00)	122.03	New Hanover	-0.9032%	Wake	$ (16,876,698.00)	Beaufort	-0.2912%
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	536.15	Wake	$ 213.75	9311.01	Halifax	0.0003%	Rockingham	$ (200,399.23)	Harnett	-0.0046%
	1.03	Mecklenburg	$ 215.12	61.05	Mecklenburg	0.0004%	Anson	$ (191,054.09)	Hertford	-0.0045%
	9311.01	Halifax	$ 591.46	30.03	Forsyth	0.0005%	Martin	$ (185,816.67)	Sampson	-0.0043%
	61.05	Mecklenburg	$ 878.72	19.27	Mecklenburg	0.0012%	Davie	$ (167,087.47)	Davie	-0.0037%
	30.03	Forsyth	$ 1,242.75	1.03	Mecklenburg	0.0013%	Surry	$ (166,894.78)	Granville	-0.0037%
	402	Rockingham	$ 3,528.04	402	Rockingham	0.0015%	Stokes	$ (129,424.64)	Stokes	-0.0028%
	407	Johnston	$ 6,851.65	407	Johnston	0.0024%	Greene	$ (114,071.62)	Rockingham	-0.0028%
	57.2	Mecklenburg	$ 11,742.41	12	Wayne	0.0032%	Hertford	$ (108,501.31)	Surry	-0.0026%
	12	Wayne	$ 12,311.44	57.2	Mecklenburg	0.0043%	Yadkin	$ (81,474.00)	Caswell	-0.0022%
	59.21	Mecklenburg	$ 16,337.51	59.21	Mecklenburg	0.0068%	Caswell	$ (46,742.09)	Yadkin	-0.0021%
2051	9709.04	Carteret	$ (17,868,872.00)	1102.02	Currituck	-1.7747%	New Hanover	$ (86,047,088.00)	Currituck	-0.8930%
	1101.01	Currituck	$ (17,622,624.00)	9609	Craven	-1.7492%	Carteret	$ (73,760,192.00)	Pasquotank	-0.6313%
	9701.01	Dare	$ (14,081,557.00)	9604	Pasquotank	-1.5039%	Dare	$ (58,336,880.00)	Washington	-0.6091%
	123	New Hanover	$ (11,850,454.00)	1103.02	Currituck	-1.5009%	Currituck	$ (53,614,868.00)	Dare	-0.5711%
	9702	Dare	$ (10,864,790.00)	9303	Beaufort	-1.4509%	Brunswick	$ (44,395,696.00)	Carteret	-0.5245%

9704	Dare	$	(10,848,207.00)	122.03	New Hanover	-1.4453%	Craven	$	(43,458,368.00)	Tyrrell	-0.4968%
122.03	New Hanover	$	(9,866,507.00)	1102.01	Currituck	-1.3463%	Beaufort	$	(24,745,862.00)	Perquimans	-0.4921%
9710.03	Carteret	$	(9,692,031.00)	9709.04	Carteret	-1.3211%	Pasquotank	$	(24,443,320.00)	Camden	-0.4898%
9709.03	Carteret	$	(8,702,808.00)	9607	Craven	-1.2641%	Mecklenburg	$	(21,594,026.00)	Craven	-0.4345%
1103.02	Currituck	$	(8,223,654.00)	9604.03	Craven	-1.2523%	Wake	$	(20,202,684.00)	New Hanover	-0.3445%
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111.06	Orange	$	18,007.61	57.2	Mecklenburg	0.0076%	Martin	$	(250,897.72)	Harnett	-0.0068%
58.29	Mecklenburg	$	19,180.85	9301.01	Surry	0.0088%	Davie	$	(237,401.20)	Sampson	-0.0068%
57.2	Mecklenburg	$	20,637.51	111.06	Orange	0.0091%	Anson	$	(217,544.67)	Richmond	-0.0062%
201	Burke	$	30,006.39	24	Mecklenburg	0.0159%	Granville	$	(208,139.66)	Davie	-0.0052%
24	Mecklenburg	$	51,224.27	59.21	Mecklenburg	0.0278%	Hertford	$	(182,747.98)	Granville	-0.0037%
9708.02	Ashe	$	57,622.34	58.29	Mecklenburg	0.0305%	Surry	$	(171,057.39)	Rockingham	-0.0035%
19	Wayne	$	58,226.42	19	Wayne	0.0306%	Stokes	$	(149,801.44)	Stokes	-0.0033%
59.21	Mecklenburg	$	66,320.71	303.01	Gaston	0.0478%	Greene	$	(140,053.56)	Caswell	-0.0032%
303.01	Gaston	$	110,753.70	19.27	Mecklenburg	0.0758%	Yadkin	$	(80,625.02)	Surry	-0.0027%
18	Onslow	$	136,831.19	18	Onslow	0.0811%	Caswell	$	(69,351.13)	Yadkin	-0.0021%