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Quantifying the Impact of Remapping Floodplains on Residential Property Values in Snohomish County, Washington: A Hedonic Approach

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QUANTIFYING THE IMPACT OF REMAPPING FLOODPLAINS ON RESIDENTIAL PROPERTY VALUES IN SNOHOMICH COUNTY, WASHINGTON: A HEDONIC APPROACH

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ABSTRACT

QUANTIFYING THE IMPACT OF REMAPPING FLOODPLAINS ON RESIDENTIAL PROPERTY VALUES IN SNOHOMISH COUNTY, WASHINGTON: A HEDONIC APPROACH

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Flood events are the most common and costly natural disasters. The Federal Emergency Management Agency (FEMA) quantifies flood risks in the form of Flood Insurance Rate Maps (FIRMS). These FIRMS delineate flood risks and are used to set flood insurance premiums. Changes in land use, the augmentation of the natural environment, is threatening the validity of the Nation's FIRMS. Therefore, Congress has approved remapping programs to update these FIRMs ensuring that current flood risks are known. This remapping presents another issue, specifically for properties that are remapped into a flood zone. Current literature suggests that properties within flood zones are discounted 5-13% compared to homes outside a flood zone. Therefore, the switching of flood zone status should negatively impact property values. To explore how the switching of flood zone status, as indicated by the remapping of FIRMs, impacts property values, a fixed effects hedonic pricing model will be estimated. We look to add to the limited literature related to revealing the impact of switching flood zone status through time and expand upon it by investigating consumer behavior towards the release of updated preliminary flood zones. Results suggest that properties who are remapped into a flood zone are initially valued higher during the release year, but one year after the

remapping their prices converge with properties who have always been within a flood zone.

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INTRODUCTION

Background

Flood events are the most common and costly natural disasters in the U.S., affecting millions of individuals each year (Pralle, 2019). According to the National Weather Service (NWS), in 2014, the U.S. witnessed over $2.8 billion in flood damages (National, 2014). Flood damages are expected to increase annually as the effects of climate change, population growth, and land use change are predicted to augment flood risks (Berndtsson et al., 2019; Pachauri et al., 2015).

The unpredictable nature of flooding events and their variety of possible damages creates difficulties when attempting to accurately quantify the risk a specific property is exposed to. This discouraged private insurance companies from offering flood related policies, eventually leaving the market in 1928 (Knowles & Kunreuther, 2014; Pralle, 2019; & Brilly et al., 2014). Without insurance, homeowners were exposed to potential flood damages with no financial mechanism to assist them if an event were to occur except for federal disaster relief funds. This led to increase demands for federal disaster relief funds placing an expanding debt on taxpayers. Finally, in 1968 the U.S. Government created the National Floodplain Insurance Program (NFIP), requiring all homeowners who live in a floodplain and have a federally backed mortgage to purchase government-administered flood insurance (Horn & Webel, 2019).

The Federal Emergency Management Agency (FEMA) was tasked with the responsibility to facilitate the NFIP. Before a county is eligible to participate the NFIP they first must have their 100-year floodplains (i.e., areas with at least a 1% annual probability of flooding) mapped. These areas are known as Special Flood Hazard Areas (SFHAs) (Horn & Webel, 2019; Pralle, 2019; Knowles & Kunreuther, 2014). To ensure that insurance premiums are relative to the amount of risk a property is exposed to, FEMA creates Flood Insurance Rate Maps (FIRMs) to delineate flood risks for a given community. These SFHAs and FIRMs are the only resources available to identify which homeowners are at risk and are required to purchase flood insurance and at what rate. FIRMs are also used at the county level by land use managers to regulate development within floodplains ensuring building is only occurring in appropriate areas.

By the year 2000, all counties participating in the NFIP had their FIRMs created but they had not been revised since the 1980s. This was problematic because floodplains change over time due to upstream land use change, increased construction of impermeable surfaces, and greater intensity of rainfall caused by climate change (Pralle, 2019; Pachauri et al., 2015; Du et al., 2015; Scholz, 2013; Poelmans et al., 2010; Ungaro et al., 2014; Berndtsson et al., 2019). If floodplains have changed since these FIRMs were created, then they do not accurately depict risk. Therefore, development may be occurring in inappropriate areas, insurance premiums are not set at an efficient rate, and homebuyers/owners are subjected to asymmetric information.

To address this, in 2003, Congress authorized the Map Modernization Program (i.e., Map Mod), with the goal to update these flood maps and increase their availability of by providing digital access (Federal Emergency Management Agency [FEMA], 2019a; Department of Homeland Security, 2005; FEMA, 2006). In 2009, FEMA received additional funds from Congress to develop a new remapping program that would build on the success of Map Mod. This led to the creation of the Risk Mapping, Assessment, and Planning program (i.e., Risk MAP) (Horn & Webel, 2019).

Problem

FEMA has been remapping the nation's floodplains for about two decades now, but there has been no analysis exploring how this remapping of risk has impacted residential property values. Identified literature relevant to home values suggest that the correction of flood risk will affect the values of homes because the homebuyer will account for the future insurance premium payments and potential of damage. Multiple peer reviewed articles have found that homes that are located within a flood zone are discounted approximately 5-13% compared to an equivalent home outside the flood zone (Samarasinghe & Sharp, 2010; Atreya et al., 2013; Bin & Landry, 2013; Shr & Zipp, 2019; Posey & Rogers, 2010; Bin et al., 2008; Zhang & Leonard, 2018; Bin & Polasky, 2004; Rambaldi et al., 2013).

Therefore, the updating of flood risk information throughout the nation has impacted many individuals' most valuable investment. Only one study has analyzed how the switching of flood zone status impacts the value of the property: Shr and Zipp (2019). They found that a property who switches into a flood zone sells for, on average, 11% less than an equivalent home outside the flood zone, however, homes that switched outside did not see a rebound in value.

Furthermore, there have been no studies that focus on or control for the release of preliminary flood zones. During each remapping event FEMA releases preliminary maps to communicate the updating of risks. However, these maps are not considered "official" and therefore are not used for the management of floodplains. The purpose of these preliminary maps is to allow the community to contest the changes made before they decide to accept them as official. This is similar to producing a draft map and then working collaboratively to edit it at a finer scale. Theoretically, this release of preliminary information could also impact the value of a property, however, this has not been directly investigated before.

FEMA states that the updating of flood risk is beneficial because it allows individuals to make informed decisions with the current risk metrics. Logically this holds true, and we could assume that an individual would behave in such a way. However, there is no empirical consensus on how individuals respond to a property that switches flood zone status or the impact from the release of preliminary flood maps.

Snohomish County, Washington, is one such area that has been subjected to the remapping of their floodplains because of their susceptibility to annual inundation events and large population densities. The county's high level of risk makes them a priority for flood zone remapping, but just as in other communities that have been remapped, there has been no assessment on how this impacted property values. The remapping of Snohomish County's flood zones provides an opportunity to further investigate how individuals respond to the remapping of flood risks. Additionally, as part of the remapping process FEMA released the county's preliminary flood zones in 2010. However, they were subjected to an extended preliminary period due to significant debate over how to address the treatment of levees. This resulted in a 10-year long period where updated preliminary information was released but management decisions were still being made with the outdated "official" maps from 1999. This allows another opportunity to explore how consumers react to the release of preliminary flood information and how this impact may change over time.

Purpose

The purpose of this study is to add to the limited literature on the impact of switching flood status by estimating a hedonic pricing model in Snohomish County, Washington from the years 2000 to 2020. Additionally, I use temporal analysis to identify if this impact decays over time as suggested by other researchers. To accomplish this research I outline the following objectives: 1) Utilize spatial analysis methods, through a Geographic Information System (GIS), to identify properties that have changed floodplain status as a result of the remapping process; 2) estimate fixed effects hedonic model to econometrically analyze the housing market in Snohomish County from 2000 to 2020; 3) econometrically compare the value of properties that switched flood zone statuses to explore how their values changed relative to homes that did not switch; 4) index property values for homes that switched statuses to identify how this impact changed through time.

Significance

The literature relevant to the simple presence of flood risk and home values has found that this potential for loss results in the discounting of property values between 6-13% when compared to an equivalent home not at risk. Therefore, homeowners within Snohomish County that have been remapped into a flood zone will have suffered a large financial loss. Theoretically, the remapping process can benefit specific property owners if they were previously within a floodplain but were remapped out. However, only one peer reviewed article has analyzed how the switching of flood zone status impacts residential property values: Shr and Zipp (2019). Therefore, this thesis will add to the limited literature and provide our estimates of the impact of changing floodplain status. Also, it is currently unclear how the financial impacts of changing flood zone status evolve through time. Therefore, this article will address this literary gap as well. This study estimates the total burden placed on homeowners in Snohomish County due to remapping flood zones, which can be used to inform current and future homebuyers as well as local government personnel. Finally, the study can contribute empirical insight into how consumers react to the release of preliminary flood information and how this impact may change over time. This will provide a new discussion topic within the current literature and allow future research opportunities.

CHAPTER II

LITERATURE REVIEW

NFIP History

From 1895 to 1928 private insurance companies were the only agencies that provided policies to cover potential losses caused by flooding events (Knowles & Kunreuther, 2014). The Mississippi floods of 1927 and other major inundation events in 1928 dramatically increased payments for damages. This caused these insurance companies to conclude it was not economical to cover flood damages and left the market altogether (Knowles & Kunreuther, 2014; Horn & Webel, 2019). Therefore, homeowners were left with no outlets to temporally spread the financial burden caused by damage from 1928 to 1968, when the NFIP was enacted.

Before the NFIP, the U.S.'s flood policy was strictly reactive, relying post-disaster relief funds to provide relief for homeowners spreading the costs of a few, who choose to be in high risk areas, to taxpayers. However, during the 1950s and 1960s flood damages were steadily increasing because population growth caused more development within floodplains (Knowles & Kunreuther, 2014; Pralle, 2019). Finally, severe flooding from hurricane Betsy in 1965, the U.S.'s first $1 billion natural disaster, and other inundation events caused the U.S. to realize that their post-disaster relief approach was not sustainable (Pralle, 2019).

Congress initiated a study to mitigate flood damages and reduce the burden on the Government and its taxpayers. This study suggested that offering federal flood insurance, investing in risk protection projects, and managing development in floodplains would all be effective strategies. After multiple failed attempts to change national flood policy, Congress only acted when costs to the government were too significant to ignore any longer. This led to the passing of the National Flood Insurance Act of 1968, the act responsible for tasking FEMA with creating and facilitating the NFIP.

NFIP Today

The NFIP's stated purpose is twofold: 1) to provide access to federally subsidized flood insurance to distribute the cost of flooding both spatially and temporally and 2) reduce the nation's flood risk through implementation of floodplain management standards (Horn & Webel, 2019). To accomplish these goals, the NFIP requires communities who participate in the program to work collaboratively with FEMA to employ flood risk mitigation strategies and develop FIRMs. Flood risk mitigation strategies include requiring special permits to build within the 100-year floodplain, elevating the lowest floor of residential buildings above the base flood elevation (BFE), restricting development in floodways, and using certain flood resistant construction material and designs (Horn & Webel, 2019). FIRMs are used to identify areas with varying levels of flood risk to communicate flood risk to homeowners and set insurance rate premiums.

These FIRMs have multiple categories defining different levels of flood risk setting boundaries at the 100 and 500-year floodplains. The most important of these is the SFHA which delineates the 100-year floodplain, which are high-risk areas that have a flood risk of 1% or greater annually (Horn & Webel, 2019). The NFIP requires all homes within these areas who have a federally backed mortgage to purchase flood insurance. Furthermore, FIRMs can be categorized by three broad zones A, V, and B. Zone A is defined as a SFHA or areas within 100-year floodplains, zone V are also identified as SFHAs but are subject to tidal/coastal floods, and zone B are areas between the 100 and 500-year floodplains or areas of moderate risk (Horn & Webel, 2019). These flood zones must accurately represent the flood risk to identify homes that are required to purchase insurance, set insurance rate premiums, and communicate flood risk to the public. The biggest threat to the validity of FIRMs is the inevitable changing of flood risk over time.

To address this, Congress passed the Map Mod and Risk MAP remapping programs. Part of the NFIP's mission is to work collaboratively with local communities to efficiently manage their flood zones. Therefore, FEMA provides each community with a preliminary map that contains the results of their hydrologic models to communicate the potential changes in flood risk. Then, they work with to community to further refine these maps by allowing what is known as Letters Of Amendment (LOAs). These LOAs provide homeowners the opportunity to officially contest the updating of flood risks. FEMA must then look into the concerns stated within these LOAs and make the appropriate adjustments. This process is repeated until all LOAs have been addressed and the community agrees to accept the updated flood maps provided by FEMA.

Changing Flood Risk

Risk is a function of natural hazard and vulnerability (Burndtsson et al., 2013). Natural hazards are risks caused by the environment, and in the case of flooding are the frequency and magnitude of inundation events. Vulnerability is the amount of assets or capital at risk of damage, for example, the value of homes within a floodplain. Natural hazards are derived from environmental conditions and are therefore more difficult to manage. Vulnerability, on the other hand, can more easily be managed through the regulation of development.

Models used to identify areas of high flood risk assume static river and watershed conditions. However, variable peak flows are increasingly observed and changes in sediment supply are known to alter the probability and magnitude of flooding events

(Call et al, 2017). Identified literature on drivers of changing flood risk outline two major contributors: augmented precipitation patterns caused by climate change, and urbanization.

Inundation events are largely determined by regional precipitation patterns, which in the future will be altered due to the effects of climate change. Climate change will alter the global water cycle and is predicted to shift global weather patterns. It is unclear exactly how each specific small-scale region will be impacted, but the Intergovernmental Panel on Climate Change (IPCC) has described likely trends for large-scale regions. The IPCC predicts that high latitude regions will likely experience an increase in their yearly average rainfall by 2100 (Pachauri et al., 2015). Additionally, mid-latitude regions can expect that extreme precipitation events will become more intense and frequent (Pachauri et al., 2015). Therefore, parts of the U.S. will have their precipitation patterns changed and it is likely that they will experience increased rainfall and frequency of extreme weather events. With climate change's forecasted impact on local weather patterns, it is likely that the flood risks for the U.S. will be altered in the near future.

Urbanization and its associated increase in development of impermeable surfaces has been identified as a main driver of changing flood risks. The replacement of permeable for impermeable surfaces dramatically changes regional water cycles by decreasing infiltration, evapotranspiration, runoff time, and increasing total runoff into streams/rivers (Scholtz, 2013; Poelmans et al., 2010; Ungaro et al., 2014; Berndtsson et al., 2019). Each of these alterations significantly alter flood risks because they cause severe peak flows by allowing more water to get to streams faster. Impermeable surfaces do not allow water to pass through them, so all the rainfall that would have been recharged into the ground is converted to runoff. Additionally, they decrease surface friction allowing this increased runoff to travel into a river faster (Scholtz, 2013; Ungaro et al., 2014; Berndtsson et al., 2019). Increasing the amount of surface covered with impermeable material will dramatically increase peak flows and therefore flood risks (Scholtz, 2013; Berndtsson et al., 2019).

With climate change threatening to alter global weather patterns and the continual need to develop urban areas, flood risks will certainly change if not increase in the future. Therefore, localized flood risk analysis and management should account for the probability of increased peak flows in the future. One way to address this is to periodically remap flood risks to efficiently protect those at risk.

Remapping Programs

By the 1980s, FEMA had constructed FIRMs for most counties participating in the NFIP. However, by the early 2000s there was growing concern about the accuracy of these maps (FEMA, 2019b). Stakeholders were skeptical that the inaccuracy of flood maps would lead to inefficient decision making at the county and individual homeowner levels (FEMA, 2006; FEMA, 2019a; FEMA, 2019b). In 2003, Congress approved a five-year funding initiative to create the Map Modernization Program (Map Mod) which would be carried out by FEMA (FEMA, 2006).

Map Mod’s purpose was to update the nation’s FIRMs and increase the availability of flood risk information by converting FIRMs to a digital format (FEMA, 2006). FEMA prioritized the highest populated census blocks at risk within counties first and then progressed to less populated areas (FEMA, 2006). Map Mod had a lofty goal to have digital FIRMs that cover 92% of the population and 65% of the U.S.’ land area. However, after five years of progress, only 39% of the population and 15% of the land area were remapped (FEMA, 2006). Map Mod ended after its 5-year budget came to an end, but in 2009 Congress requested that FEMA continue updating flood maps under the Risk Mapping, Assessment, and Planning (Risk MAP).

Soon after, Congress revised the NFIP with the passing of the Biggert-Waters Flood Insurance Reform Act of 2012 (BW-12), which formally created the Risk map program (FEMA, 2020). Risk MAP has the same purpose as Map Mod but is an ongoing program with no specific end date. However, as part of the BW-12 FEMA is required to analyze community flood maps every five years to determine if a community should have their flood map updated (FEMA, 2019b). In attempt to protect citizens from flood risk, Congress requested FEMA to update flood maps. However, they did not assess how this would impact residential housing prices.

Home Valuation

A home can be viewed as a bundle of goods and, therefore, its value is a function of the attributes which it possesses, such as number of bedrooms, total square footage, number of bathrooms, age, and view (Rosen, 1974). These attributes can extend past the home's property boundary though. For example, unique local neighborhood characteristics have been found to impact the value of a home (Nguyen-Hoang, 2011). This is a well understood phenomenon, with ample literature available that describes the impact local characteristics have on home values around the U.S. and internationally. Examples of specific local aesthetics that effect property values include proximity to high quality schools, community air quality, proximity to natural hazards, proximity to noise pollution, and proximity to environmental amenities (Nguyen-Hoang, 2011; Li et al., 2016; Toke et al., 2014; Clark, 2006; Sander & Zhao, 2015). Additionally, it has been found that proximity to these attributes affects the magnitude of their impacts on home values. It was found that as distance increase the magnitudes of their impacts decrease (Clark, 2006). Since flood risk is a natural hazard a property's exposure to risk will be capitalized into property values.

Hedonic Models

The hedonic model offers a framework through which the relationship between a dependent variable and multiple independent variables can be estimated through statistical regression analysis (Rosen, 1974). It functions based on the hedonic hypothesis which states a good's value is derived from its utility bearing attributes. Specifically, this framework compares differentiated products, in a competitive market, to reveal the implicit prices of these attributes. There are many types of regression analysis, but the hedonic model most commonly utilizes the multivariate Ordinary Least Squares (OLS) or similar variations to accommodate for different data types.

Regression analysis estimates relationships of two variables by graphing and creating a best fit line. Typically, the dependent variable is on the y-axis and the independent variable on the x-axis. For example, home values would be the dependent and number of rooms would be the independent variable. Once the data is plotted, the OLS statistical methods are applied to create a best fit line: Ordinary Least Squares simply means that when constructing the best-fit-line, the sum of squared residuals (i.e., distance from the best fit line and each data point) are minimized to estimate the most efficient representation of the relationship between the two variables (Wooldridge, 2013).

It is important to note here that because only two variables can be graphed at a time, the other variables must be held constant when estimating the target variables relationship or else the results may be inaccurate (Wooldridge, 2013). This is a key concept of regression analysis known as *ceteris paribus*, which is Latin for holding all other else equal (Wooldridge, 2013).

To achieve *ceteris paribus*, all other attribute values are replaced with the average value, calculated from the data, while estimating the OLS relationship (Wooldridge, 2013). The hedonic model's ability to reveal these implicit prices makes it ideal to analyze housing markets and reveal how home buyers value structural, neighborhood, and environmental characteristics.

Hedonic Model and Flood Risk

The ability of the hedonic model to estimate correlation measurements between a dependent variable and multiple independent variables makes it the tool of choice to further explore relationships within property transactions. Environmental economists have long used the hedonic model to estimate how the presence of different types of natural hazards/risks impact property values. A growing subsection of this literature focuses on investigating how flood risk affects property values. All existing literature relevant to flood risk and property values have used variations of the hedonic model. Each study utilizes the same functional form (natural log) of the dependent variable (sale price) and similar independent variables (property attributes). All studies correct for spatial autocorrelation by using two different approaches: either by using spatial lag models with weight matrices in the error and independent terms, or by using fixed effects controls with clustered errors. Some studies quantify flood risk differently, for example, authors have used flood risk maps or areas effected by past inundation events to identify properties at risk. Additionally, select articles analyze how time after an event impacts the flood risk effects. No matter the authors' methods/focus, the literature has revealed a discount associated with being in a high-risk flood area ranging from 5.7% to 13%

(Samarsinghe & Sharp, 2010; Posey & Rogers, 2010; Bin et al., 2008; Rambaldi et al., 2013; Atreya et al., 2013; Zhang & Leonard, 2018; & Shr & Zipp, 2019).

Studies that focused purely on analyzing how location within a high flood risk area, i.e. areas with a 1% or greater probability of flooding annually, have revealed similar discounts. Samarasinghe and Sharp (2010) utilize a spatial lag hedonic model in North Shore City, New Zealand. This study utilizes the release of flood maps and defines homes as being located within the 100 and 500-year floodplains. The authors reveal that, on average, a home located inside a flood zone is discounted 6.2% when compared to an equivalent home outside a flood zone. Posey and Rogers (2010) employ a similar model in St. Louis County, Missouri. Since this study takes place in the U.S. where flood insurance is mandatory, the authors expect to reveal a discount less than or equal to the value of the required insurance premium. The authors estimate for inland counties the flood risk discount is equal to 8.6% when compared to an equivalent home not at risk. Another study in the U.S., Bin et al. (2008) examine the effects of flood hazard on coastal properties in Carteret County, North Carolina. The authors estimate a 7.3% discount for homes that are located within the 100-year floodplain. Finally, Rambaldi et al. (2013) estimate a hedonic model in Brisbane, Australia. This study utilizes flood risk maps to identify homes at risk of flooding. This study is unique because it does not measure flood risk in 2-D horizontal distance but vertical distances from the Base Flood Elevation (BFE) level. The authors reveal that a home at or below the BFE level is discounted by 5.5% compared to an equivalent home above the BFE.

Other studies have estimated flood risk discounts but primarily focus on revealing what happens to these discounts after an actual inundation event. Atreya (2013) utilize a hedonic model with Difference-In-Difference specifications to estimate how flood risk discounts are impacts from an inundation event in Dougherty County, Georgia. The authors revealed that before the flood event homes within a flood zone were valued, on average, 9% less than an equivalent home not in the flood zone, but after the event there was a 35% discount. Furthermore, they estimated that this post-flood discount decayed over time allowing these homes to return to their pre-event values within 4-9 years. Similarly, Bin and Polasky (2004) employ a similar model to investigate pre- and post-event by analyzing homes in Pitt County, North Carolina, a county severely impacted by Hurricane Floyd in 1999. They estimated a 2.5% flood risk discount for pre-flood transaction but after Hurricane Floyd the discount more than doubled to 5.7%. Bin and Landry (2013) repeat the study above with the same data but improve their model to reduce omitted variable bias and identify how the magnitude of an event changes the risk discount. They utilize Hurricane Fran (1996) as a small event and Hurricane Floyd (1999) as a large event. The authors reveal no flood risk discount prior to Hurricane Fran but a 5.7% after. Additionally, after Hurricane Floyd they found an 8.8% discount, which decays with time and disappears 5-6 years after the event. Finally, Zhang and Leonard (2018) investigate how different control groups' sizes and times after an event impact flood risk discount estimates. They authors reveal that one year after an inundation event discounts increased to 13%, however, this decreases significantly every year after. Additionally, when the control groups contain homes further from the floodplain the discount increases. This indicates that flood risk is not dichotomous and contained only within a floodplain, but homes that are near flood zones are exposed to some risk and are discounted accordingly.

As the flood risk literature grew, authors become increasingly more specific in their research questions to reveal new relationships between flood risk and property values. The first articles simply focused on revealing how being located within a high-risk flood area discounted property values. The next step in the literature was to identify how actual flood events altered these discounts. Authors found that after an inundation event, homeowners are shocked and decrease values perhaps more than they should be. Then, studies identified that after an event these discounts decay and return to pre-event rates. Within the last year, the literature has progressed and expanded research boundaries to identify how remapping flood risk zones can impact property values. Specifically, Shr and Zipp (2019) investigate how the correction of asymmetric flood risk information, in the form of outdated FIRMs, impacts home values who are newly mapped into or outside of a 100-year flood zone. They utilize a fixed effects model with repeat property sales to reduce omitted variable bias. The authors estimate that properties who were outside a floodplain but were remapped into a flood zone are discounted by 11%. However, they find no statistically significant discount associated with being mapped out of a flood zone.

There are no additional articles to our knowledge that research how remapping flood zones and switching flood zone status impacts property values. Therefore, there is no research to validate Shr and Zipp's (2019) results. Furthermore, there has yet to be a study that researches how the effects of correcting flood risk information react over time. To address these gaps in the literature, this study will either reinforce Shr and Zipp's study or offer new results on how values of homes who are remapped into and out of a floodplain react and analyze the effect through time.

CHAPTER III

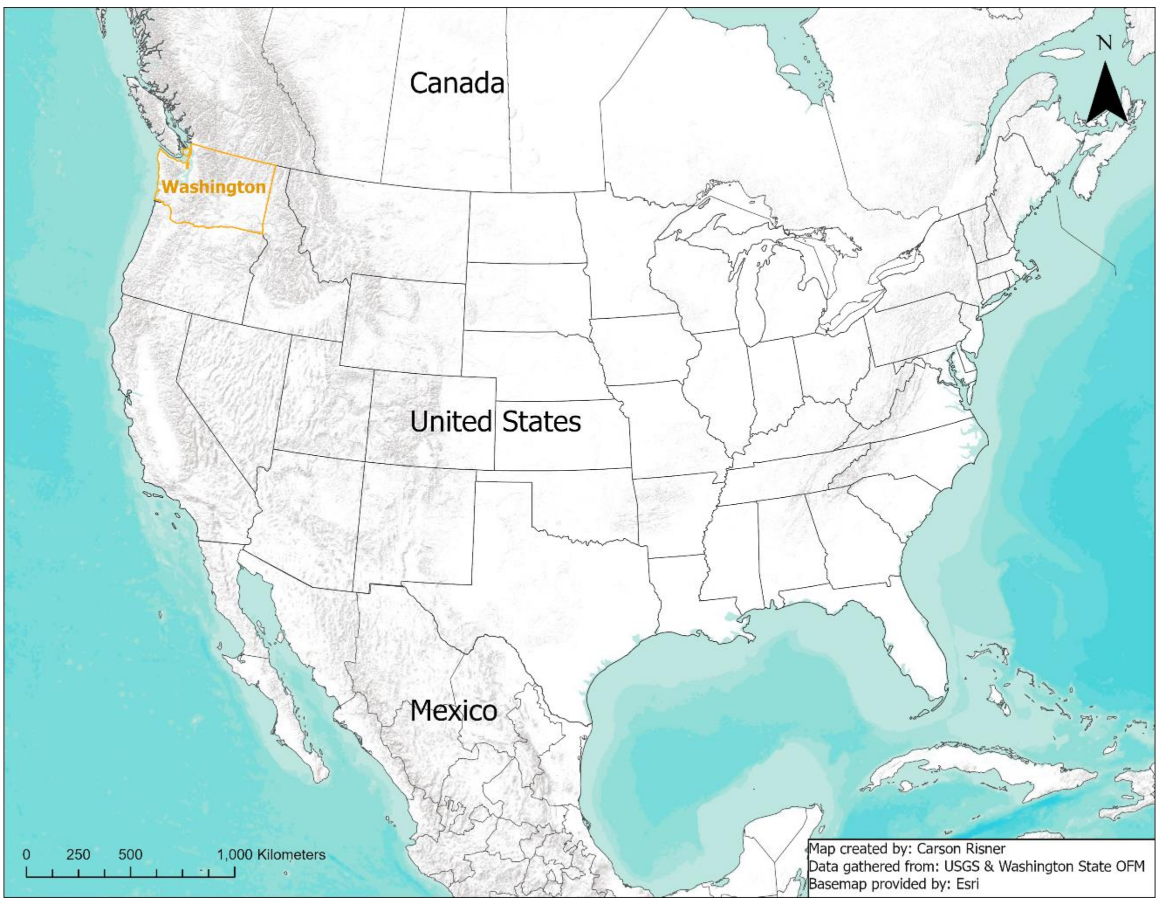
STUDY AREA

Location

The study area is geographically defined as the jurisdiction of Snohomish County, a local municipality in the Northwest corner of the United States, specifically in the State of Washington. Washington State is geographically the 13th largest state in the U.S. and is known for its agricultural production and diverse landscape. Located on the Pacific Coast, western Washington offers a temperate climate, saltwater beaches, lowlands, dense forests, and rugged mountains (see Figure 1).

Figure 1

Small scale map of the United States



Snohomish County is located in the western half of Washington State just north of Seattle, situated between the Cascade Mountains and Puget Sound. It is bordered by King County to the south, Island County to the west, Skagit County to the north, and Chelan County to the east: see Figure 2. The county is the 13th largest in terms of total land area within Washington State, covering 3,534 square kilometers. Snohomish County is geographically restricted by the Cascade Mountains and Puget Sound, forcing the majority of urban development to take place in the western lowlands. Major cities within Snohomish County include Everett, Snohomish, Marysville, Arlington, Monroe, and Stanwood.

Figure 2

Snohomish county within Washington State

Demographics and Economy

In 2019, Snohomish County had a population of 786,620, making it the third most populous county within Washington State. The county's education rate is above the national average with 92.2% of individuals with a high school diploma or higher. This can be further broken down: 23.8% of the population possess a high school diploma, 26% have some college experience, 10.6% with an associate's degree, 21.8% have a bachelor's degree, and 10% possess a graduate degree (U.S. Census Bureau, 2019). Snohomish County is known as a bedroom community, meaning that a significant portion of population lives within the county but work in another county. This is largely because of the county's proximity to King County and specifically the City of Seattle, which offers a significant amount of economic opportunities.

Snohomish County also supports its own variety of economic opportunities ranging from manufacturing, trade, agriculture, and forestry. In 2019, Snohomish County had a total of 291,836 jobs with a total payroll of $18.5 billion (Vance-Sherman, 2021). The largest employer within the county is the Boeing Company, a large aerospace manufacturing company, who as of 2019 supported 41,000 full time positions within the county (Vance-Sherman, 2021). In 2019, Snohomish County had a labor force participation rate of 65% with an average annual income of $69,615about $10,000 more than the national average (Washington State Employment Security Department, 2021; Vance-Sherman, 2021). The unemployment rate for the county fluctuated between 2.5-4% in 2019 (Washington State Employment Security Department, 2021). Snohomish County has a poverty rate of 8.1%, about 4% under the national average (Vance-Sherman, 2021). The county's housing market shows a 66.8% ownership rate with a median home value of $371,600, around $100,000 more than the national average (U.S. Census Bureau, 2019).

Topography

Snohomish County has varied topography ranging from sea level in the western portion of the county to over 3,050 meters in the mountainous east. The western part of the county touches Puget Sound forming saltwater beaches. Progressing east, to the midwest portion of the county, there are lowlands that support most of the county's activity including agricultural production, industrial manufacturing, commercial trade, and residential development. Further east, the lowlands increase in elevation turning into rolling hills. Here, there are rural communities and limited forestry activities. Finally, the eastern portion of the county shifts into a section of the Cascade Mountains containing mostly alpine wilderness. The topography of the county determines where different land uses can occur. For example, 68% of the county is forested, the majority of which is in the eastern portion. Eighteen percent is rural occurring in the central part of the county, 9% is urban and 5% is agriculture both of which occur in the lowlands of the western portion (Snohomish, 2019).

Weather and Climate

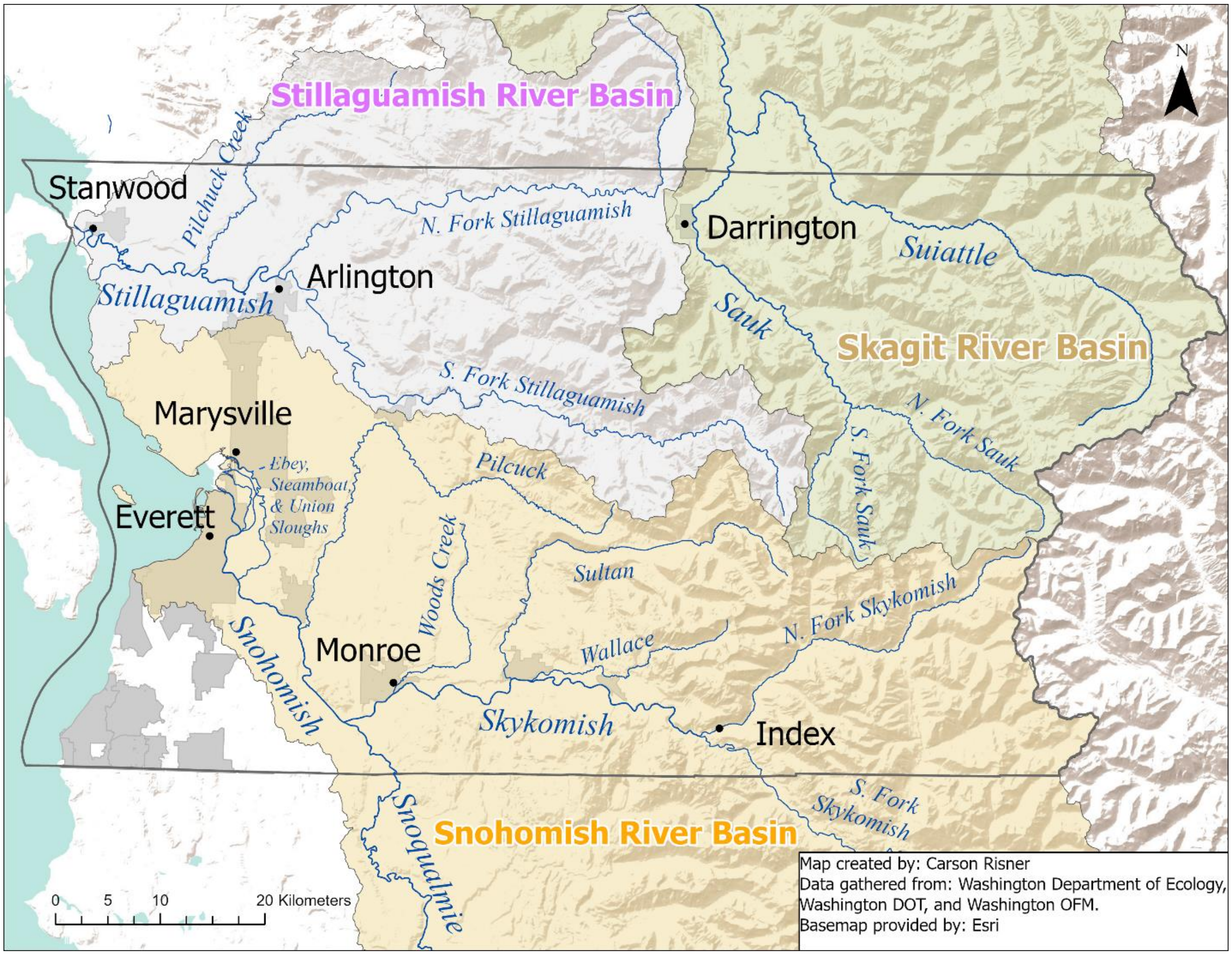
Snohomish County maintains a moderate climate and experiences average temperatures ranging from 24 degrees Celsius in the summer to 1.5 degrees in the winter (Snohomish, 2019). Temperatures have been known to exceed both the lower and upper bounds but on rare occasions. The average annual precipitation varies throughout the county from 89 centimeters in the lowlands to over 457 centimeters in the mountainous east (FEMA, 2005).

The extreme difference of precipitation between the lowlands and mountains can be explained by the process known as orographic lifting. Air masses are forced upward from elevated terrain causing the temperature of the air to dramatically decrease leading to precipitation. Snohomish County is subject to a significant number of rainstorms throughout the year caused by weather systems originating from the Pacific Ocean. The majority (75%) of precipitation occurs between the months of October to March (FEMA, 2005). These rainstorms produce high amounts of precipitation in a short amount of time causing sharp increases in river peak flows resulting in annual flood events. Average snowfall also varies throughout the county, the lowlands receive around 25-50 centimeters and the mountains receive 114 centimeters annually.

River Basins

Figure 3

Snohomish County rivers and river basins



Stillaguamish River Basin

The Stillaguamish River Basin consists of the main channel of the Stillaguamish River and its two tributaries: The North and South Forks, which meet to form the main river channel (refer to Figure 3). The tributaries start within the Cascade Mountains between 4,000 to 6,000 feet in elevation and drain approximately 684 square miles of land (FEMA, 2005). The North Fork starts near Darrington and meets with the South

Fork to form the Stillaguamish River. The South Fork starts near the town of Silverton and flows to its confluence with the North Fork near the city of Arlington.

The confluence of the North and South Forks creates the main channel of the Stillaguamish River. The main channel then travels through the lowlands and empties into Puget Sound. Near the coast the Stillaguamish divides into three tributaries to form a delta: Hat Slough, South, and West Passes. The upper river valleys are narrow but widen as they decrease in elevation. At the confluence of the North and South Forks the river valley is around one to one and a half miles wide but at the mouth of the river the valley widens to approximately two miles.

Snohomish River Basin

The Snohomish River Basin drains around 1,780 square miles and incorporates the Snohomish River and its two tributaries: the Skykomish and Snoqualmie Rivers. The Skykomish River begins near the town of Index and flows west to its confluence with the Snoqualmie River, near the city of Monroe, to form the Snohomish River. The Skykomish River is fed by its three tributaries: the Wallace River, near the town of Startup; the Sultan River, near the town of Sultan; and Woods creek, near the city of Monroe.

The Snoqualmie River originates in King County near Snoqualmie Pass. The Snohomish River begins where the Skykomish and Snoqualmie rivers join and empties into Puget Sound. The Snohomish river valley are also narrow at higher elevations and increase width in the lowlands. The lowlands are flat with a wide valley, allowing for flood waters to easily spread effecting more land. Near the mouth of the Snohomish River the main channel splits into three tributaries: Ebey, Steamboat, and Union Sloughs.

Principal Flood Problems

Flood events within Snohomish County are attributed to rainstorms mainly between the months of October to March and changes in land use (Snohomish, 2019). These storms typically last for 24 hours but it is not uncommon for them to experience two or more consecutive storms. These rainstorms are moderate in magnitude but consistent, with precipitation rates usually not exceeding one inch per hour (FEMA, 2005).

Flooding in the urban areas of the county is result of smaller tributaries and storm water systems being overwhelmed by the increased runoff. These events are characterized by sharply rising river levels and high magnitude peak flows. In fact, it is not uncommon to see peak flows double or triple on these occasions (FEMA, 2005; Snohomish, 2010). These flood events are typically smaller in scale, when compared to events for the larger rivers in the county, and only last between a few hours to a day.

The Stillaguamish, Snohomish, and Skykomish rivers are the watershed’s arterial drainage system, meaning that the precipitation that occurs in the mountains to the east of the county is funneled to these rivers. Therefore, flooding for these rivers is mainly caused by intense rainfall and land use change in the mountains (Snohomish, 2010). Often these inundation events are augmented by snowmelt or rain on snow events. Rain on snow (ROS) flooding events are of particular concern in Snohomish County. The eastern portion of Snohomish County contains a section of the Cascade Range, these higher elevations have typically accumulated 45 inches of snow per year. When rain contacts this snowpack, the temperature of the rain melts the snow and dramatically increases runoff (Beniston & Stoffel, 2016). This increased runoff causes extreme peak flows and overwhelms the local river systems causing large inundation events that can last up to a few days (Surfleet & Tullos, 2013; Snohomish, 2010).

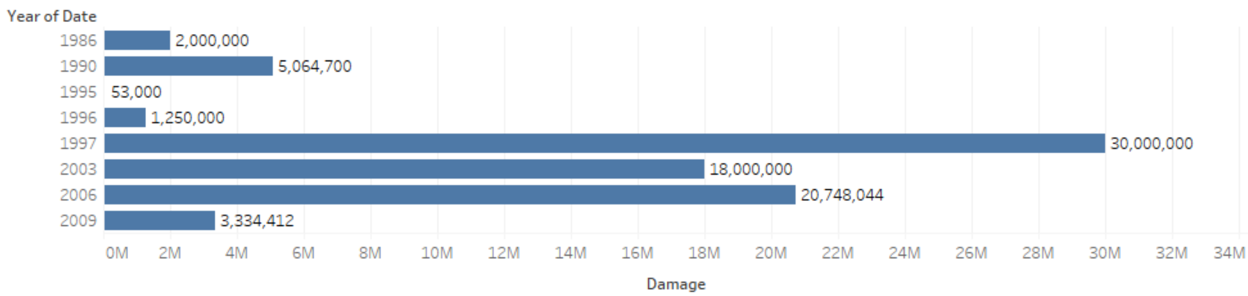
Development and Flood History

After World War II the country saw increased birth rates (a phenomenon known as the Baby Boomer generation) which eventually raised the demand for housing. Like other communities, before the enactment of the NFIP Snohomish County had little concern over the management of development in or near the flood plains. This increasing demand for the construction of new homes and no development regulations caused many homes to be built in high-risk flood areas. Without regulation these homes were built with no consideration of surrounding environmental hazards causing increases in annual damages and repetitive loss structures. This pattern continued up until the county decided to participate in the NFIP in 1984 (Snohomish, 2010). Since then Snohomish County has dramatically increased their flood resiliency by mapping their flood plains, constructing flood defense infrastructure, and, most importantly, regulating development.

Even with these precautions and defenses flooding remains a costly natural hazard for the county. As stated earlier, flooding events mainly occur in the winter season because of increased precipitation and snow melt. Between 1984 and 2010 Snohomish County was subjected to 11 different inundation events, nine of which caused enough damage that the county was eligible for federal assistance (Snohomish, 2009). Figure 4 shows the total estimated damages from flood events in each year they occurred.

Figure 4

Snohomish County nominal flood damages from 1984-2009



Flood damages have remained an issue for the county even after their adoption of the NFIP. This is the most recent flood damage estimation, though there have been more flooding events since 2009. Specifically, there have been six more inundation events taking place in 2010, 2011, 2014, and 2015. These events were smaller in scale and isolated geographically, however, there is no data available on their associated damages. None of these inundation events caused significant damage to the county as a whole and were not eligible for federal emergency relief funds.

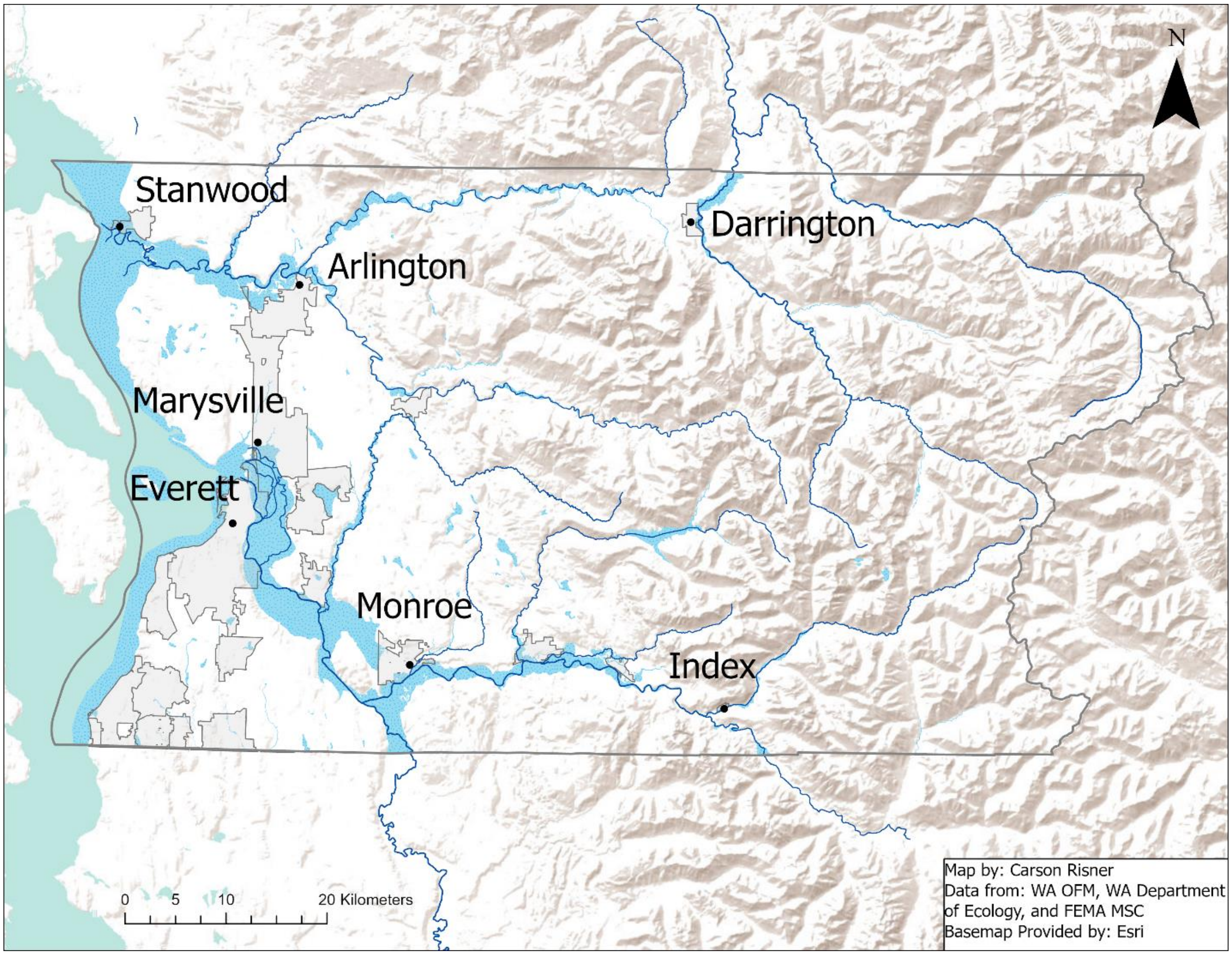
Remapping History

Snohomish County first had their flood zone remapped by FEMA in 1999. This was after the passing of the Map Mod program and because the County's high population densities and flood risk made them a priority for remapping. This remapping project was county wide and updated all relevant FIRMs. In accordance to Map Mod, five years later Snohomish County's flood zones were analyzed to determine if another remapping was necessary. In 2005, it was determined that portions of the County's FIRMs required updating and were remapped. This remapping only occurred in high population density areas such as portions of Everett and Snohomish. Therefore, a majority of the County did not have their flood zones remapping in 2005. The flood zone boundaries released at this time were not readily available in a digital format.

Five years later, the entire County's FIRMS were recommended for remapping again. A County wide remapping project was completed in 2010 and preliminary FIRMs were released delineating the new suggested areas of risk. These adjustments caused public scrutiny leading to the questioning of the authenticity of their results. Many homeowners filed (LOA) to assert that their properties were not at risk. A significant portion of this public commotion was caused by the treatment of levees within the hydrology model used to replicate the County's potential flood risks. The model revealed that certain levees would be ineffective against a contemporary 100-year flood and therefore all properties behind the levee were now at risk. However, the complaints and LOAs filed by homeowners within the county caused a 10-year debate about flood risks within Snohomish County. Finally, in June 2020 the all disputes had been settled and the official FIRMs were released. Figure 5 shows the preliminary flood zones that were released in 2010 and accepted in June 2020.

Figure 5

Snohomish County 100-year flood zones

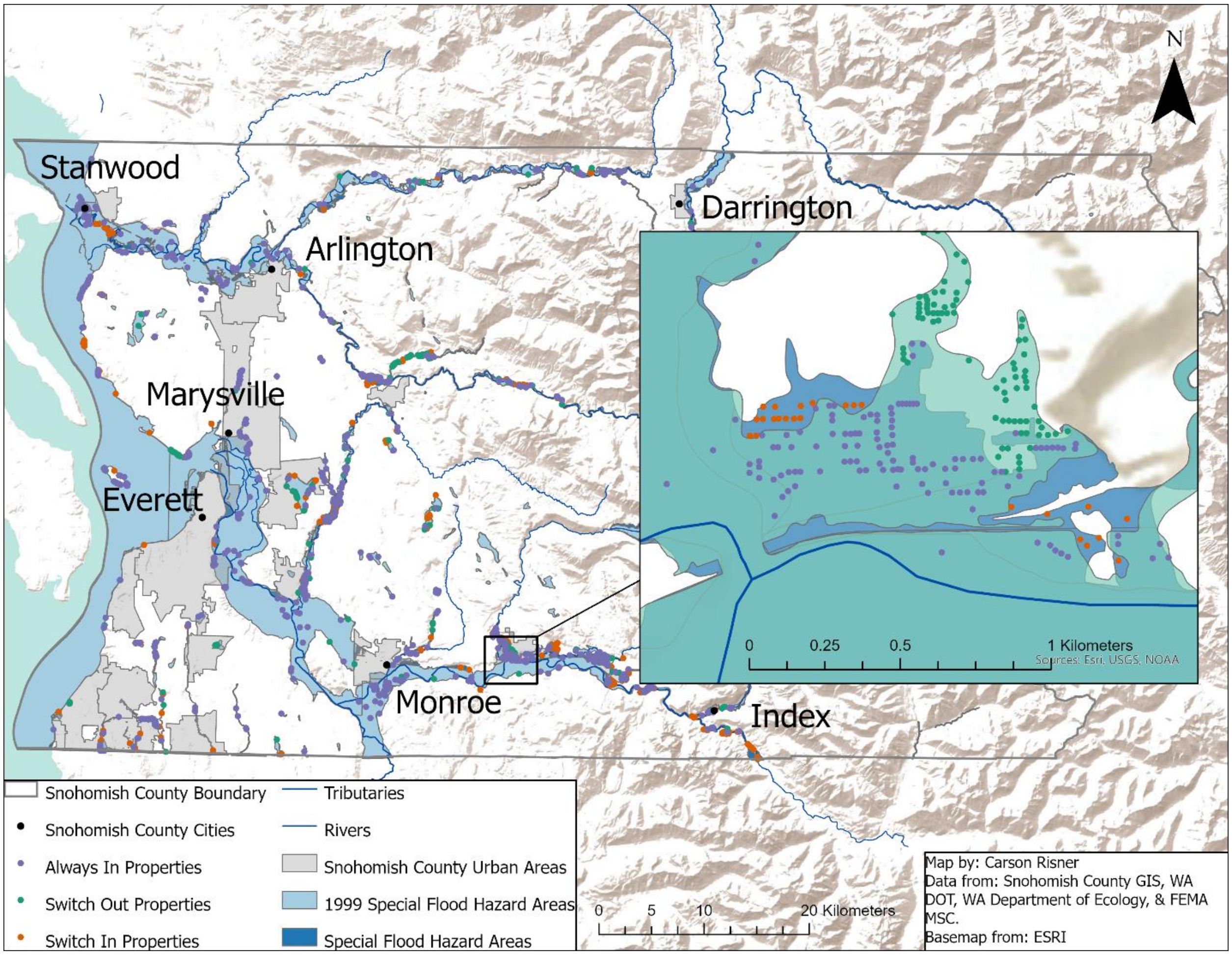


Note. Updated 100-year flood zones released in 2010.

Figure 6shows all homes that have been in a flood zone at some point in time and further specifies which properties either switched in or out as result of the remapping process. This map shows the impact of the remapping done in 2010 and visually represents the treatment that this research explores. There are 447 observation that were remapped into a flood zone and 405 observations that were remapped out of a flood zone.

Figure 6

Snohomish County properties flood status through time



CHAPTER IV

DATA

The primary dataset used was an Excel file that contained information on every home that was sold within Snohomish County between January 2000 and June 2020. This dataset was obtained from the Snohomish County Assessor's office. The dataset had 250,945 residential and mobile home observations. Each observation contained the home's address, structural attributes, assessed quality score, nominal purchase value, year built, and year sold.

First, all mobile home sales were removed by filtering and deleting observations by their home type code, indicating if a home was a mobile or structural home. Then, all observations that contained an attribute value of zero or displayed obvious data entry errors, such as homes with 30 bedrooms but only 2000 square feet of living space, were removed. There were multiple occasions where a development of multiple homes was aggregated and sold together as a single group transaction. Each home within the development was recorded as a unique sale, but the total sale value of all the homes was used for each observation's nominal sale value. Therefore, there were numerous homes that had significantly inflated sales values. To prevent bias caused by incorrectly recording the sale price of these homes, all aggregated home sales were removed from the dataset manually. After removing the outlined observations, the dataset contained 228,143 home sale observations. Since I will be comparing sales prices through time I must adjust for inflation. At this point, I standardized all nominal sales values to the year 2020 by creating a new column and utilizing the U.S. Bureau of Labor Statistics Consumer Price Index (CPI).

Next, homes that are closer to the flood zones are more likely to be more similar to homes in flood zones, in terms of both structural and neighborhood attributes, than homes further away. Therefore, comparing homes within flood zones to homes nearby will reduce the probability/severity of omitted variable bias, but will still have enough variance to provide robust results. Therefore, I identify census block groups that contain homes in floodplains and remove all transactions that occurred outside these block groups. The dataset now contains the structural and property characteristics for 55,210 property transactions.

Lastly, to remove any outliers, I utilize the Mahalanobis Distance Outlier Detection method. This approach is ideal for multivariate data since it utilizes the covariance of multiple independent variables, rather than removing observations based on a single attribute. Conceptually, Mahalanobis Distance calculates the distance, similar to the number of standard deviations, an observation is from the center of the sample distribution. Then, a chi squared cutoff value is used to identify which observations are considered outliers based on a predefined confidence level.

I utilize the Mahalanobis Distance for the Sale Price, Bedrooms, Acres, Distance, Total Square Feet, and Year Built to indicate the presence of outliers. Therefore, an observation's distance from the correlated mean of these variables are calculated. Then, I utilize the 95% confidence level for a chi square distribution with five degrees of freedom as the cutoff distance. Any observations further away than the cutoff distance are then removed from the dataset. In total 4,584 observations were removed. Finally, upon visual inspection it was found that the dataset still contained a few outliers. To remove these observations, I removed the upper 0.1% of the dataset. The summary statistics for the final dataset can be seen in Table 1.

Table 1

Summary statistics for primary dataset

Variable	Sample Size	Mean	Standard Deviation	Min.	Max.
Real Sale Price ($2020)	50,626	380,321	185,916	21,741	1,269,051
Flood	50,626	0.056	0.23	0	1
Switch In After	50,626	0.006	0.075	0	1
Switch Out After	50,626	0.005	0.067	0	1
Bedroom	50,626	3.22	0.733	1	6
Total Square Feet	50,626	1,967	729.262	508	5,058
Year Built	50,626	1988	22.896	1899	2020
Acres	50,626	0.975	1.879	0.045	20.7
Distance (Meters)	50,626	507.5	499.198	0	2733.5
Urban	50,626	0.463	0.498	0	1
Quality Grade	50,626	44.6	6.289	15	75

Note. Transaction data between January 1st, 2000 to June 1st, 2020.

CHAPTER V

METHODS

GIS Methods

The hedonic model is a powerful tool that can be used to statistically infer causality and relationships between multiple independent variables and a dependent variable through the comparison of differentiated products in a competitive market. However, the model is highly data dependent, meaning that reliable results rely heavily on the presence of a comprehensive dataset. Ideally, the dataset would include sufficient details on every factor that could impact an individual's subjective valuation of the good, so that the entire market variability in prices could be explained. Therefore, the more relevant independent attributes included within the model, the more variance within a market can be explained.

In housing markets, many variables have been shown to statistically impact the value of a property such as structural, neighborhood, and environmental characteristics. Rosen (1974) suggested that value is constructed by the utility bearing attributes a good possesses. Utility can loosely be defined as attributes that provide some type of use or benefit to the consumer. Putting aside the exact metrics through which consumers assign value, it is apparent that value is subjectively fabricated through the individual's specific life experiences and decision heuristics. Since value is constructed by the individual, and a market is collection of individuals, it is typically impractical to collect the level of information required to fully describe each consumer's preference. There will always be variation within a market that we cannot explain which, if unaddressed, can render some empirical issues. For example, if a model excludes an independent variable that is correlated with property values, then the model is compromised by what is known as omitted variable bias and it will not accurately estimate relationships. Therefore, many times researchers must combine multiple sources of data to create their own comprehensive dataset to best capture the variability of consumer preference within a market.

To ensure that environmental and neighborhood attributes were included in this study, I utilized Esri's ArcGIS Pro software to join proxy variables to the home sale points dataset based on their shared spatial relationship. The following sub-sections describe the methods employed to map the home sale points and join environmental and neighborhood attributes. To ensure spatial accuracy and alignment between datasets each shapefile was projected to Washington State Plane North (Meters) before joining.

Geocoding

To associate a geographic location with each home sale, I used the Geocode Addresses tool to match each observation to the center (centroid) of parcel polygons obtained from the Snohomish County File Transfer Protocol (FTP) website. The parcel shapefile delineates all property boundaries within the county and contains a unique parcel ID. To create the centroid point from the parcel polygons the Feature to Point tool was used. Both the home sales data and parcel centroid points contain unique parcel IDs which were used to match each home sale observation to parcel centroid point.

Each home sale observation was matched to its associated parcel centroid point and could be mapped in a GIS. This allowed me to join environmental and neighborhood variables onto the home sale points and create a comprehensive dataset. The following section will overview how other variables were joined to the home sales points.

Spatial Joins

The Spatial Join tool combines the observations from two data tables to a single dataset based on their shared spatial relationship. The first variable joined to the home sale points was the census block group IDs. This allows us to control for neighborhood characteristic differences through the fixed effects method.

Fixed effects models allow for a regression equation to control for omitted differences between observations by making *within* group comparisons (Allision, 2009). It is assumed that all observations within a census block group share similar neighborhood characteristics and are therefore controlled for when compared with other observations in the same block group further limiting the model's exposure to omitted variable bias. This was done for each census block group to isolate the treatment. Then, the correlation estimates for each block group are averaged revealing the Average Mean Effect (AME) of the treatment variable.

I obtained the 2020 census block group polygons from the Washington State Office of Financial Management (OFM). The Spatial Join tool was then used to join the census block ID that each home sale point was located *within*. The output shapefile contained all home sales points with their associated census block IDs and structural attributes.

The next variable that was joined was a binary variable that identifies if a home sale point is within a current 100-year flood zone or not. First, I gathered FEMA's National Flood Hazard Layer (NFHL) geodatabase for Washington State from Map Service Center (MSC) portal. The MSC is an interactive online archive that houses all of FEMA's current geographic flood zones data. This geodatabase can be filtered by geographic place names, such as states or counties, to define what community's flood zone boundaries should be downloaded. I obtained Washington States flood zones and then clipped Snohomish County's 100 and 500-year flood zones.

Since this research focuses on the SFHAs, I use Select by Attributes function to select all 100-year flood zones and export them to a separate shapefile. I then added a new field to the Snohomish County 100-year flood zone shapefile and set it equal to one to create a flood zone binary variable. The Spatial Join tool was then used to add the flood zone binary field to the home sales points. All homes sale points within the 100-year flood zone were given value of one, while homes who were outside were assigned a value of zero.

This process was then repeated for the historic 100-year floodplains, the data for which was obtained from the Snohomish County GIS team. Now the housing dataset contains census block group IDs and binary variables that indicate the property's flood status through time.

Euclidean Distance

To analyze how distance from a 100-year flood zone impacts property values, I used the Euclidean Distance tool to measure the distance from every home sale point to the nearest flood zone. The Euclidean Distance tool creates a raster of cells and measures the straight-line distance from each cell to the nearest target feature. In this case the target features are the 100-year flood zone boundaries. The tool was set to create 10-meter raster cells to produce a raster file with a precise enough grid to correspond with the size of property parcels.

Once the distances were calculated I joined them to the home sale points. To join the raster values to the home sale points I utilized the Extract Value to Points tool. This tool extracts the value of the raster cell that each point is located within. The final output contains every home sale observation with its associated census block group ID, binary variables indicating flood zone status, and the distance to the nearest flood zone.

Repeat Transaction Model

Before estimating the hedonic pricing model to reveal the impact of remapping, I perform a repeat transaction model to identify how a property's nominal value changed through time. This method takes the simple difference between a property's first sale price and subsequent sales to create a price index for a group of observations. Essentially, this will allow us to determine the percent change and rate of appreciation or depreciation in a group of properties through time. The advantage of the Repeat Transaction Model comes from the fact that it analyzes the same property though out time. By comparing the same property throughout time, I efficiently hold all other variables constant. Assuming the property has not changed in any way between transactions it allows us to isolate the effects of time on the property's value. This is repeated for each property who sold multiple times to create an index of property values through time. The only drawback to this method is data availability, specifically gathering information about the physical improvements or the changes in neighborhood idiosyncrasies. Without this data bias may be introduced into the index since these changes are not controlled for within the model. In essence, the model is not able to differentiate the effect of time vs uncontrolled for improvements to a property between transactions. Equation 1 is an example of the repeat transaction equation being used.

$$\ln(P_{\mathrm{T}}) - \ln(P_t) = \sum_{t=0}^{\mathrm{T}} \delta^t D^t + \mu_i^t = \ln\left(\frac{P_T}{P_t}\right) \quad (1)$$

Here P_T is the nominal price of the transaction at time T; P_t is the nominal sale price of a subsequent transaction at time *t*; *T* denotes the year of the first transaction; *t* is the time period of the second sale; D takes a value of 1 in the recent sale period, -1 in the previous sale period, or 0 if else; *i* denotes each property; μ_i^t is the error term for observation *i* in time *t*.

I utilize this framework and subset our data into four groups switch in, switch out, always in, and always out properties in order to explore if the switch observations appreciated differently over time from the groups they left (Netusil et al., 2019). This will reveal if the treatment groups, switch in and switch out properties, values change after being remapped out of their respected group. Since I know the updated preliminary FIRM maps were released in 2010, if there is an observable change in the switch in or switch out sale price indexes in this year, then I can infer that this treatment may be the cause.

Hedonic Regression Analysis

Hedonic Model

As described by Rosen (1974), home values are a function of the bundle of attributes they possess. For example, value is dependent on the number of rooms, bathrooms, total square footage, and any other factor that may impact the way an individual perceives the value of the bundle. However, since these attributes are traded as a bundle, not individually, within a market, their marginal values are not explicitly known. Rosen's hedonic model provides a framework, utilizing Ordinary Least Squares (OLS) regression analysis, through which the value of these attributes can be implicitly revealed by comparing differentiated products. The indispensable idiosyncrasy of the hedonic model is derived from its ability to hold all other factors equal while analyzing the relationship between the dependent and each independent variable. This isolates consumer's Willingness to Pay (WTP) for each attribute within the model and allows us to assign these implicit marginal values.

However, OLS regressions are built from the five Gauss-Markov assumptions; if these assumptions are violated, then the results of the analysis lose their integrity. All five of these assumptions must hold true for the model to provide the Best Linear Unbiased Estimator (BLUE) for each attribute. In this study, I am primarily concerned if the model contains any bias or is subject to heteroskedasticity, which if left unaddressed causes inefficient estimates and errors when calculating the statistical significance.

Firstly, I want to ensure that the model will not contain any type of bias. The most significant threat to our model's validity is omitted variable bias: occurring when a correlated attribute is not included within the model. This can cause other independent variables to act as a sort of proxy variable for the omitted effect, which will then render biased estimates for our independent variables. To mitigate our model's exposure to omitted variable bias, I utilize the fixed effects approach at the census block group scale. The fixed effects geographically isolate groups of transactions based on their block group ID to make within group comparisons. Each property within a block group is exposed to relatively the same market conditions, therefore, by identifying the relationships within each group and then averaging the effect allows us to hold the omitted factors in each block group constant. Now that I have addressed the issue of bias, we turn to controlling for the presence of heteroskedasticity.

Heteroskedasticity is the phenomenon that occurs when the variability in one independent variable is in some way predicted by the range of values of another independent variable. The presence of heteroskedasticity can be revealed by evaluating the residual plots for each of the independent variables. If the variance of the residual plots is not consistent across the values of each independent variable, then our standard errors are skewed, and our error term is not normally distributed. For example, if the variance of the residuals increase as *Total Floor SqFt* increases, heteroskedasticity is present within the model. Since our standard errors are skewed by heteroskedasticity, it creates issues when pursuing to demonstrate statistical significance for each independent variable. Therefore, to address these empirical issues and correct for heteroskedasticity I estimate heteroskedastic robust standard errors and utilize a log-linear functional form regression equation. With these empirical issues addressed, I continue with building the hedonic pricing model. Equation 2 provides a representation of a linear regression model.

$$\ln(P_t) = \beta_0 + \mathrm{B}\mathbf{X}_t + \varepsilon_t$$
$$\boldsymbol{X} = \{\boldsymbol{X}_1, \boldsymbol{X}_2, \dots, \boldsymbol{X}_n\} \tag{2}$$

Note. Natural log to fit the observed functional form of price.

Here ln(P) represents the natural log of the price of the home (the dependent variable). **B** is a vector of the coefficients estimating the correlation between the independent variable and ln(P). ε represents the error term and represents a matrix of covariates containing the attributes of the property. For example, x_1 could be the number of bedrooms or total square feet of living space.

Quantifying the Impact of Remapping

Our essential purpose is twofold, I utilize the hedonic model's framework to reveal consumer preference, their WTP, to avoid flood risks and identify how this effect manifests when a property switches flood zone status through time. Primarily, I exploit the old and new flood zone Boolean variables to create a binary variable indicating if a property was located inside a flood zone at the time of its sale, this will show how the presence of flood risk at the time of sale impacts the value of a property.

To accomplish our second task, I construct two more binary variables: *Switch In After* and *Switch Out After. These variables* indicate if a property was remapped *into* or *out of* a flood zone and *sold after* the treatment year. The coefficients for these variables will reveal the impact of switching flood zone status. Then, to control for the unique market conditions in each year I interact these flood status variables with multiple time binary variables, which indicate the year of transaction. The interaction of these terms will establish how the treatment effect of switching into or out of a flood zone changes through time. Furthermore, I utilize the log-linear functional form to account for the diminishing marginal returns between property values and quantity of attributes. Equation 3 represents the fixed effects hedonic pricing model that was estimated.

$$\ln(P_{ibt}) = \beta_0 + \beta_1 Flood_{ibt} * Urabn + Urban * (\beta_2 SwitchInAfter_{ibt} + \beta_3 SwitchOutAfter_{ibt}) * (\beta_4 Y2000_{ibt} + \beta_5 Y2001_{ibt} + \ldots + \beta_{15} Y2020_{ibt}) + \beta_{16} BlockGroupId_b + \beta_{17} Bedroom_{ibt} + \beta_{18} TotalSqFt_{ibt} + \beta_{19}(Bedroom_{ibt} * TotalSqFt_{ibt}) + \beta_{20} YearBuilt_{ibt} + \beta_{21} Acres_{ibt} + \beta_{22} Distance_{ibt} + \beta_{23} Distance_{ibt}^2 + Urban + \varepsilon_{ibt} \quad (3)$$

Note. BlockGroupId represents model fixed effects.

Here ln(P) represents the natural log of the *real sales price* in 2020, the subscript *i* is the observation's index, *b* indicates what block group the sale occurred in, and *t* represents the time of the sale. *Flood* takes a value of 1 if the property is in the current flood zone; *SwitchInAfter* indicates if the observation was remapped into a flood zone; *SwitchOutAfter* indicates if a property was remapped outside a flood zone; *Y2000*, and its accompanying binaries, indicate the year an observation was sold; *BlockGroupId* is the unique block group the sale occurred in, the fixed effects control; the variable *Bedrooms* tallies the number of bedrooms for each home; *TotalSqFt* identifies the homes total living space in square feet; *YearBuilt* controls the for age of the home; *Acres* denotes the parcel's total land area in acres; *Distance* indicates the straight line distance from the parcel's centroid the nearest flood zone boundary; $Distance^2$ accounts for the nonlinear relationship between distance and sale price; finally, *Urban* is a binary variable taking a value of 1 if the property is located within city boundaries.

CHAPTER VI

RESULTS

Repeat Sales Model

For this model, I subset the primary dataset into four categories: properties *always inside* the 100-year floodplain, properties always outside the 100-year floodplain, properties that *switched into* a floodplain, and properties that *switched outside* a floodplain. The properties that have always been inside or outside act as a sort of control group and will be used to compare the price action of homes that were subjected to the treatment of remapping. The summary statistics for each group can be seen in Table 2.

Table 2

Summary statistics for repeat transaction groups

	Sample Size	Min.	Median	Mean	Max.	Standard Deviation
Switch In	447	$ 10,000	$ 255,268	$ 308,207	$ 1,250,000	$ 204,038
Switch Out	405	$ 30,000	$ 254,000	$ 331,561	$ 2,050,000	$ 286,155
Always In	2,520	$ 1,000	$ 224,368	$ 331,863	$ 5,171,000	$ 208,125
Always Out	51,457	$ 960	$ 289,990	$ 261,975	$ 4,750,000	$ 201,965

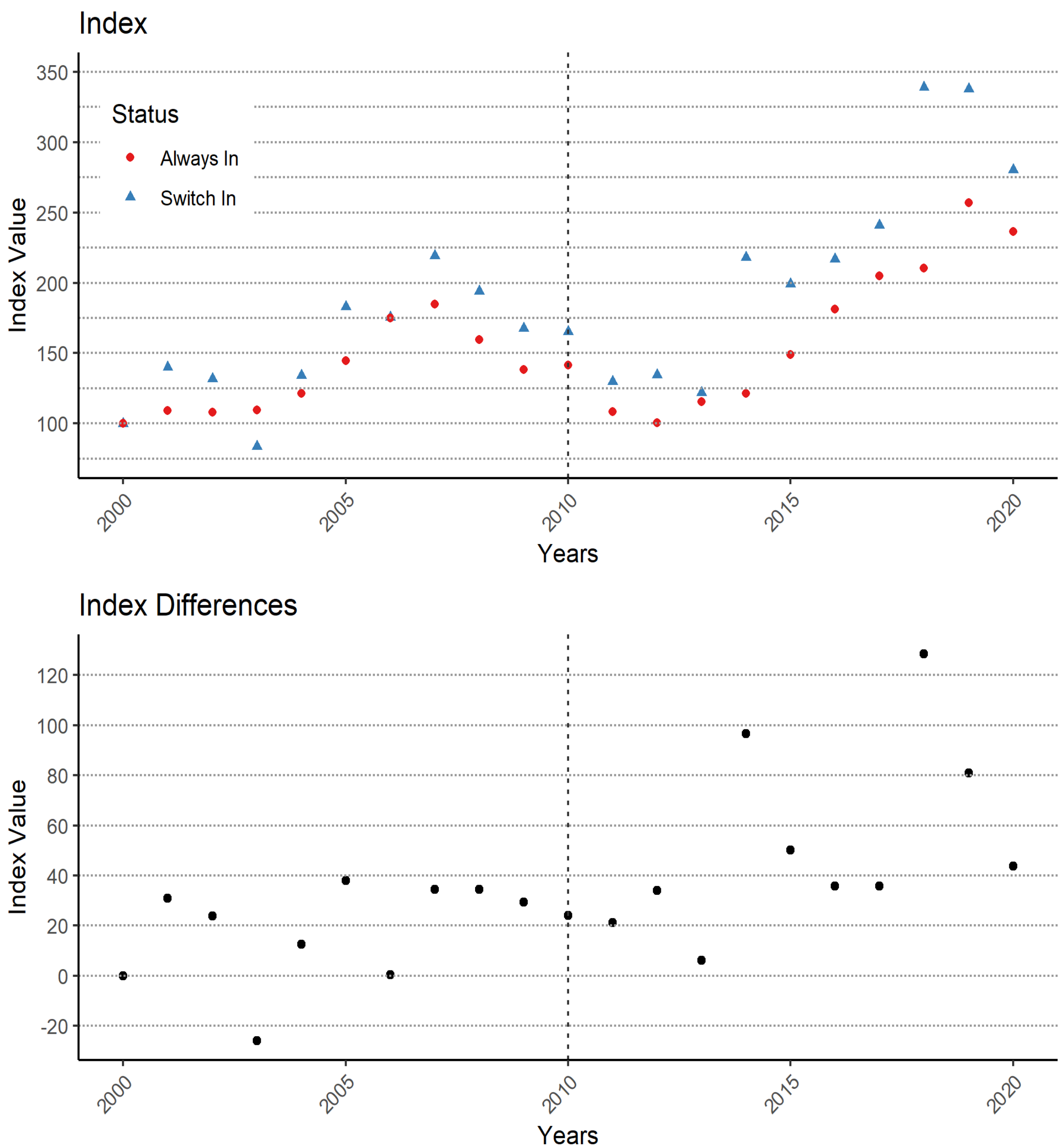
Note. Measured in nominal dollars.

Repeat Sales: Switch In

The resulting index scatterplots and yearly differences between the Switch In and Always In groups are presented in Figure 7. This is to investigate whether consumers begin to value Switch in properties differently after the remapping date. The combined plotting of these groups will reveal if the value for Switch In properties converge with the value demanded by properties who have always been within a flood zone, thereby indicating a relative discount for properties newly mapped into a flood zone.

Figure 7

Switch in and control indexes



Note. Difference is equal to Switch In minus Always In

Since this is an index of prices, all groups take a value of 100 at the base year. The Control group, Always In properties, displays a cyclical pattern of appreciation over time. There are no sharp increases or decreases in their index value and they maintain a relatively predictable trend through time. The Switch In properties follow the same cyclical trend as the Control group or properties that have always been inside a 100-year flood zone, but they tend to demand higher nominal sales prices. However, the Switch In group are more variable and less predictable each year, especially after the treatment year.

In 2004, 2006, and 2013 the Switch In group breaks the set trend by having their index value converge with or fall below the Control group (properties always inside a flood zone). These decreases may be explained by flooding events that occurred in these years. Even though these homes were not officially in the flood zone at the time, they could have been physically impacted since they are near a flood zone or the event could have cautioned consumers about the presence of flood risks. Essentially a large event, in some way, could have discouraged buyers. Specifically, the Switch In group's behavior between 2010 to 2013 is interesting because it seems to decrease at a greater rate and allows the Control group to nearly overtake them in terms of price indexes. The differences between the groups are plotted in Figure 7. Furthermore, the Switch In group upsets the trend by remaining stagnant or even decreasing while the Control group increases. After 2013 the Switch In properties become more variable but remain at a greater index value that the properties who have always been within a flood zone. This indicates that after the release of flood maps the values demanded for Switch In properties converge with the properties who have always been within a flood zone, then after 2013 they are valued with a comparative premium.

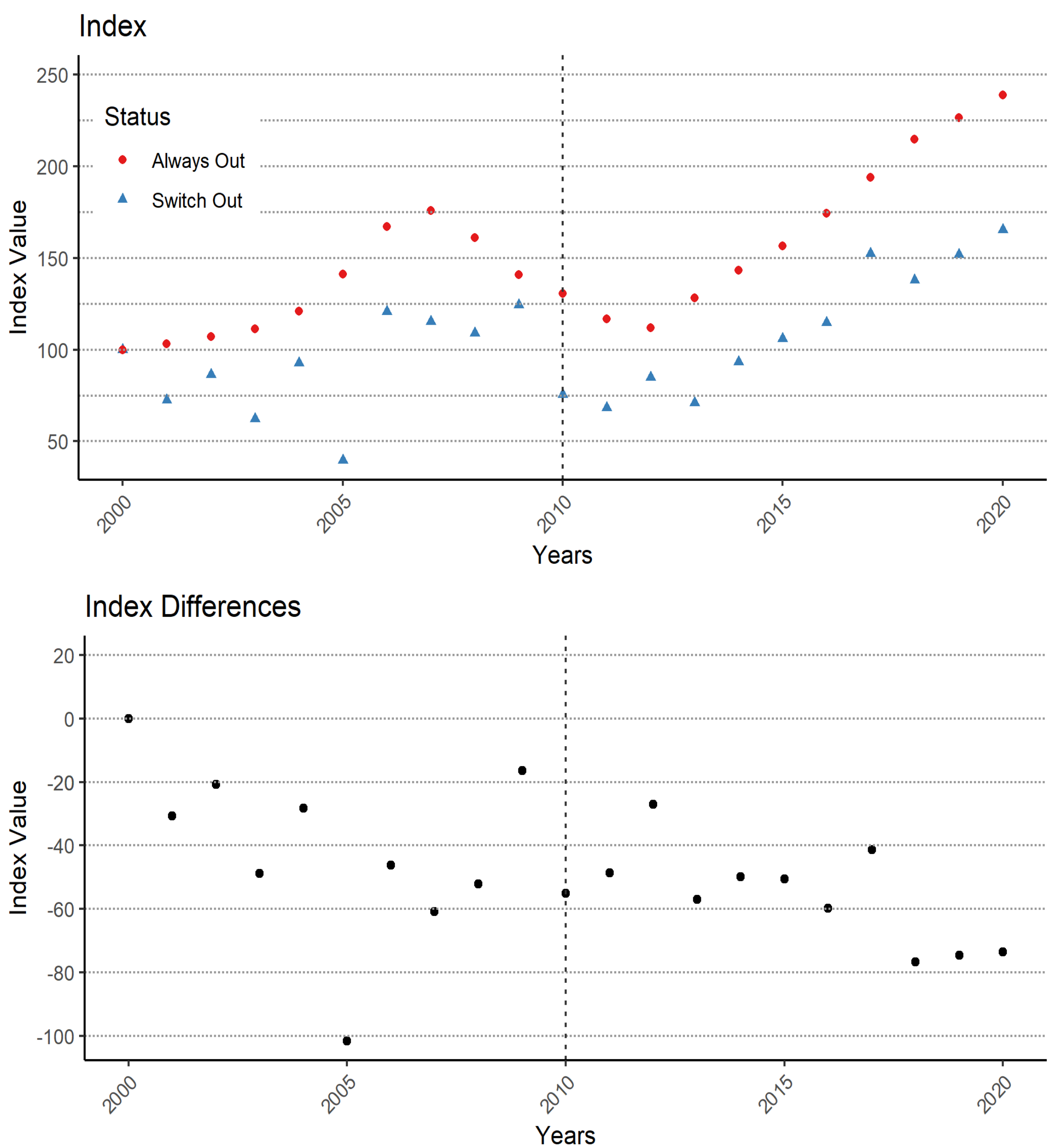
Repeat Sales: Switch Out

The Switch Out group attempts to follow the same cyclical pattern as displayed by properties who have always been outside a flood zone. However, it is even more sporadic than the Switch In properties: see Figure 8. The first three years we see that Switch Out class significantly varies, increasing and decreasing each year. Then, in 2004 this group sees an increase to a value just below 100 but dramatically decreases again in 2005 to a value under 50. This is interesting to observe because there were select portions of Snohomish County, high population density areas, which were remapped in 2005 and again in 2010. The properties within the Switch Out group would have been present within the old flood zones, therefore, some of these observations may have been officially remapped into a flood zone in 2005, perhaps explaining this price action. Unfortunately, the 2005 flood zone boundaries were not readily available, therefore, its influence is speculative and not controlled for within the model.

After the treatment year, 2010, we see this group behave similarly to the Switch In properties, as they remain stagnant for the next three years and linger around a value of 75. After this, they continually increase, except for the year 2018, until 2020 but never advance enough to even approach the Control group. The index shows that these properties are consistently undervalued compared to properties that have remained outside the flood zone. After the treatment of switching out of the flood zone these properties are still undervalued and never converge with the Control group or properties who have always been outside a flood zone.

Figure 8

Switch out and control indexes



Note. Difference is equal to Switch Out minus Always Out.

These plots show that the Switch In and Switch Out groups follow the same general trend as groups they joined, but are impacted by other factors causing the observed variability in their index values. This is a simple difference so we cannot state with certainty what these factors are, however, we do observe that these properties are subjected to being valued differently through time compared to the rest of the market. Therefore, we now turn to the hedonic model to better isolate the remapping treatment effects.

Hedonic Model Results

The coefficients and heteroskedastic robust standard errors for the variables of immediate concern are reported in Table 3. Since the model is estimated using the log-linear functional form, these coefficients represent the relationship as a semi-elasticity, indicating percent change in *Real Sale Price* per one-unit change in the independent variable. For ease of interpretation, the percent impact of variables with coefficients less than .1 or greater than -.1 on *Real Sale Price* can be estimated by multiplying the coefficients by 100, though this is not an exact metric. However, this method does not hold true when interpreting coefficients larger than .1 or less than -.1. To estimate the effect of these coefficients more accurately we must transform them from the natural logarithmic by raising Euler's number, *e* or approximately 2.718, by the targeted coefficient, then subtract the result by 1 and multiplying by 100 for a percent change interpretation.

Table 3

Hedonic model flood related coefficients

Variable	ln Sale Price (2020)
Flood	0.002 (0.014)
Urban	-0.043** (0.020)
Switch In After	0.059 (0.068)
Switch Out After	0.012 (0.104)
Flood:Urban	-0.025 (0.019)
Urban:Switch In After	0.162** (0.071)
Urban:Switch Out After	0.044 (0.119)
Switch In After:Y2010	0.183 (0.133)
Switch In After:Y2011	0.081 (0.141)
Switch In After:Y2012	-0.175 (0.151)
Switch In After:Y2013	-0.225 (0.140)
Switch In After:Y2014	-0.047 (0.114)
Switch In After:Y2015	0.053 (0.119)
Switch In After:Y2016	0.063 (0.110)
Switch In After:Y2017	0.066 (0.100)
Switch In After:Y2018	0.036 (0.169)
Switch In After:Y2019	0.067 (0.093)
Switch Out After:Y2010	-0.126 (0.332)
Switch Out After:Y2011	-0.074 (0.227)
Switch Out After:Y2012	-0.057 (0.188)
Switch Out After:Y2013	-0.067 (0.184)
Switch Out After:Y2014	0.019 (0.138)
Switch Out After:Y2015	0.123 (0.173)
Switch Out After:Y2016	0.042 (0.133)
Switch Out After:Y2017	0.126 (0.151)
Switch Out After:Y2018	0.251 (0.153)
Switch Out After:Y2019	-0.099 (0.171)
Urban:Switch In After:Y2010	-0.527*** (0.156)
Urban:Switch In After:Y2011	-0.543** (0.234)
Urban:Switch In After:Y2012	-0.197 (0.228)
Urban:Switch In After:Y2013	-0.111 (0.189)
Urban:Switch In After:Y2014	0.054 (0.395)
Urban:Switch In After:Y2015	-0.168 (0.122)
Urban:Switch In After:Y2016	-0.122 (0.195)
Urban:Switch In After:Y2017	-0.133 (0.113)
Urban:Switch In After:Y2018	-0.241 (0.196)
Urban:Switch In After:Y2019	-0.076 (0.097)
Urban:Switch Out After:Y2010	0.097 (0.342)
Urban:Switch Out After:Y2011	0.069 (0.244)
Urban:Switch Out After:Y2012	0.037 (0.221)
Urban:Switch Out After:Y2013	-0.203 (0.235)
Urban:Switch Out After:Y2014	-0.185 (0.167)
Urban:Switch Out After:Y2015	-0.228 (0.188)
Urban:Switch Out After:Y2016	-0.345*(0.201)
Urban:Switch Out After:Y2017	-0.159 (0.167)
Urban:Switch Out After:Y2018	-0.339** (0.172)
Urban:Switch Out After:Y2019	-0.220 (0.286)
Adjusted R^2	.582
Note:	*p<0.1 **p<0.05 ***p<0.01

The *Flood* variable is statistically insignificant and suggests that homes within Snohomish County who are located in a flood zone, on average, sell for .2% more than the expected sale price of an equivalent home not within a flood zone. For an average home this is equivalent to a premium of approximately $760 in 2020 dollars. The impact of switching into a flood zone after the treatment year is estimated to be positive and again statistically insignificant at the 95% confidence level. The model revealed that, on average, properties who switched into a flood zone sold for approximately 6.08% more than an equivalent home that is in a flood zone, *ceteris paribus*. For an average home in Snohomish County this equals a premium of about $23,120 in 2020 dollars. Switching out of a flood zone has been shown to positively impact the sale price of the property, but this variable has a large standard error and is not statistically significant.

The remaining variables are the interactions between the switching flood status variables, the binary time variables, and the binary urban variable controlling for a property's presence within current urban growth boundaries. These interactions reveal how the impact of switching into or out of a flood zone changes with time and space. Furthermore, to explore if the impact of being with a flood zone differs between rural and urban locations, I interact the flood and urban binary variables. Interaction terms are used when the impact of one variable is dependent on the value of another independent variable. These coefficients represent the discrete effect in each year and are not cumulative impacts. Meaning that the effect in each year is found simply by totally the coefficients from the base switching variable and the interaction of the desired year, for example, in 2013, three years after the remapping, homes who switched in, on average, sold for 14.07% less than a comparable home in a flood zone or a discount equivalent to

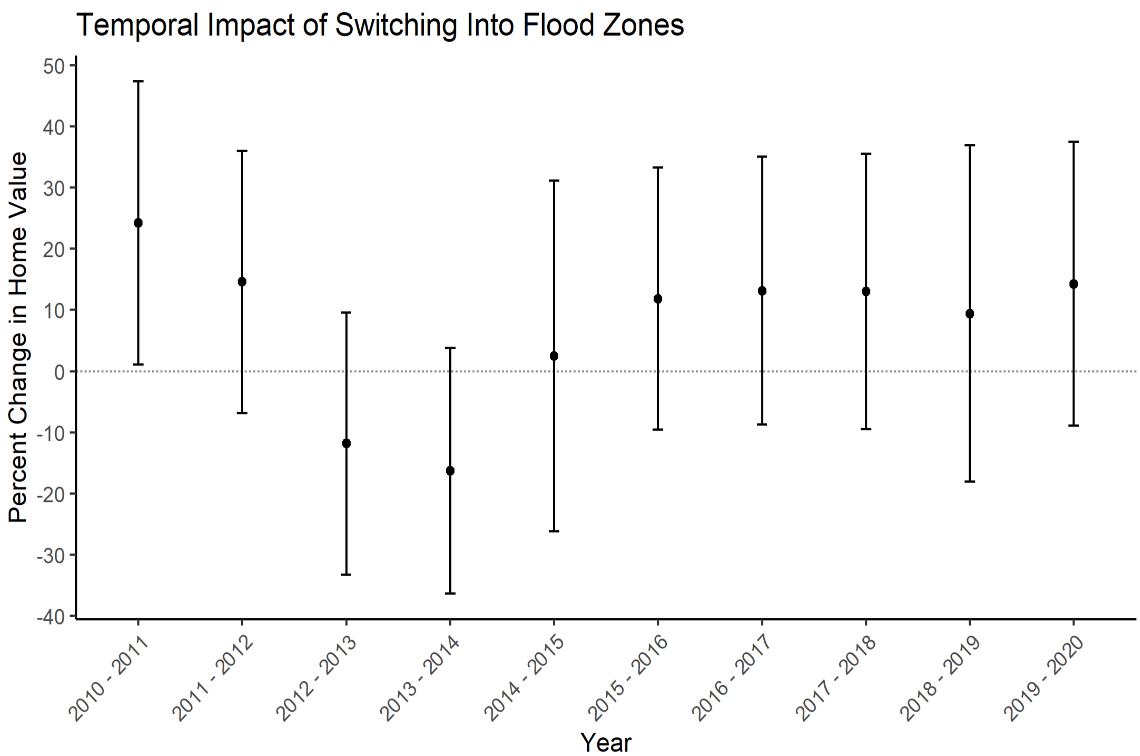
$53,500 in 2020 dollars, holding all other factors equal. Only one of the time and flood variable interactions are statistically significant at the 90% confidence levels: *Switch In After 2013*.

The interactions between the flood, time, and urban variables suggests that homes who are sold within urban growth areas and are remapped are valued statistically differently than home who are outside urban areas and are remapped. Based on the interaction terms we can infer that not only does is the overall impact of remapping differ by location, but location also affects the impact of remapping through time as well. Overall, the model suggests that homes within flood zones, on average, have a negative Average Marginal Effect (AME) of 1% which is significant at the 95% confidence interval. This implies that homes who are located within flood zones are associated with a statistically significant discount of 1% anywhere within Snohomish County.

Additionally, to evaluate whether the cumulative effect of switching flood zone status is statistically different from zero through time, I utilize an F test to determine if the Switch In and time interaction terms are jointly significant. I revealed a p-value of 0.0001253 indicating that the interaction terms for Switching In and the year control variables are jointly significant and different than zero. To provide further detail about the impact and significance of switching flood zone status through time, I perform multiple linear hypothesis tests for the switch variables and their associated time interaction terms. Then, I plot their 95% confidence intervals to reveal if or how long the impact of switching flood zone status is significant. If the impact is statistically significant its confidence interval will not include 0, suggesting that the impact in that year is statistically different than 0. Figure 9 shows the plotted confidence intervals for switching into a flood zone.

Figure 9

Confidence intervals for switch in properties: temporal impact and significance



Note. To be statistically significant the confidence intervals must not include zero.

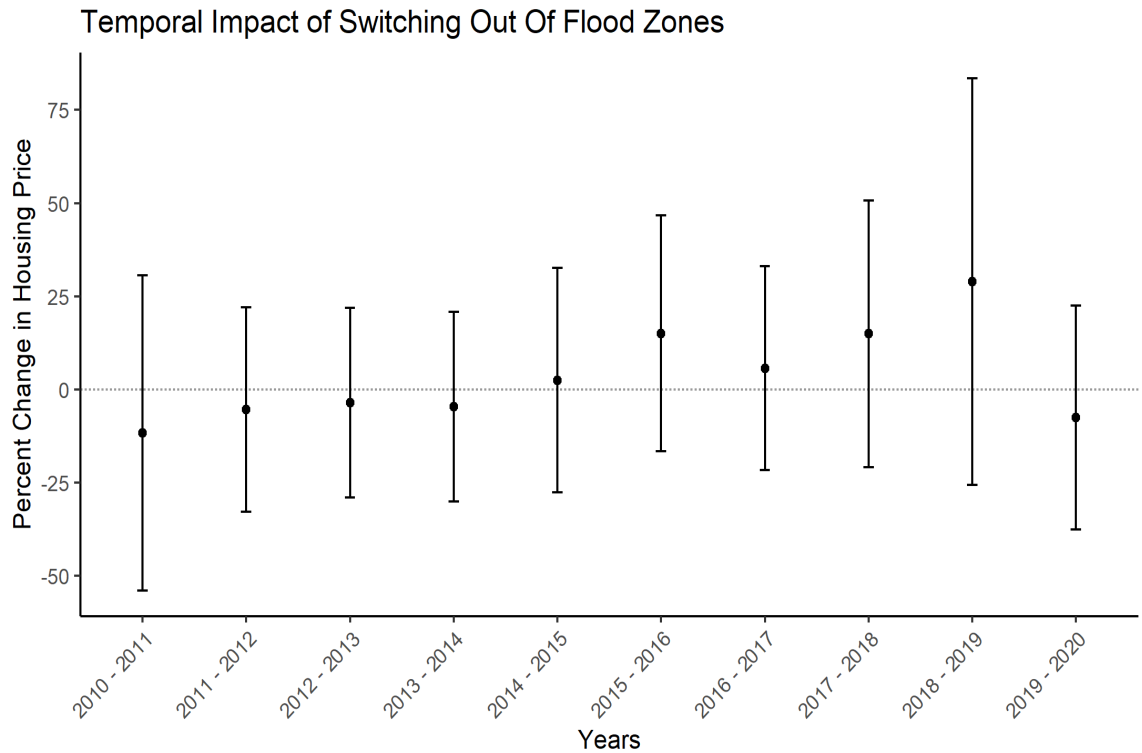
Within the first year of remapping, homes that switched into flood zones were statistically valued more than homes that have always been within a flood zone at the 95% confidence level. This is expected because consumers have not yet adjusted to the release of the preliminary maps leading to these homes being relatively overvalued. These homes, on average, sold for 24% or approximately $91,000, in 2020 dollars, more when compared to an equivalent home that is in a flood zone, ceteris paribus. Between 2012 and 2014 this point estimate turned and remained negative however this impact is statistically insignificant at the 95% confidence level. The model suggests that between

1-4 years after the release of preliminary maps, homes that switched into a flood zone are, on average, undervalued between 11-16% compared to an equivalent home within a flood zone, holding all other factors equal. For an average home in Snohomish County this equates to be a discount between approximately $42,000-$61,000, however, once again this impact is not statistically significant at the 95% confidence level. After 2015, the point estimate of being remapped into a floodplain turned and remained positive until 2020, however, their confidence intervals include zero and are therefore is not statistically valued differently than homes within flood zones. Therefore, this plot suggests that before remapping Switch In properties were statistically valued more, then after the remapping their prices converge with properties who have always been within a flood zone and are no longer valued statistically different. The Average Marginal Effect (AME) for Switching Into a 100-year flood zone was suggested to be a 10% premium compared to homes in flood zones, but this effect is statistically insignificant at the 95% confidence level.

Similar to the repeat sales model, there is extreme variability in sale prices for homes that Switched Out of a flood zone, as revealed by the large confidence intervals (see Figure 10). The first three years after remapping this group may see a positive impact, however, this impact is not statistically significant. The model indicates that there is no statistically significant effect from being remapped out of a flood zone. The AME for switching out is suggested to be a relative premium of .7% but this is not statistically significant.

Figure 10

Confidence intervals for switch out properties: temporal impact and significance



Note. To be statistically significant confidence intervals must not include zero.

CHAPTER VII

DISCUSSION

As discussed earlier, Snohomish County's remapping history is convoluted with many small treatments impacting isolated groups between 1999-2020. This makes it rather difficult when attempting to efficiently parse out the effects of switching flood zone status through time. The limited remapping done in 2005, preliminary release of maps in 2010, and the 10 years of amendments and asymmetric information caused the results to not be statistically significant. Although the results may not be as conclusive, due to the lack of a concrete and official remapping treatments, they still provide valuable insight into a less known topic by evaluating how the release of preliminary flood information impacts the value of properties predicted to switch status in the future.

The model implies that the AME of being remapped into a flood zone increases the expected value of a property by approximately 7% when compared to an equivalent home in a flood zone. However, this impact is not constant through time as revealed by our *Year* interaction terms and is not statistically significant at the 95% confidence interval. The market's reaction to the release of preliminary flood maps was delayed by a year as shown by the plotted confidence intervals.

The model suggests that within the first year of the preliminary maps being released homes who were remapped into a flood zone were overvalued by 24% compared to an equivalent home within the flood zone, holding all other factors equal. This was expected because consumers simply may not be aware of the preliminary FIRMs, do not understand the risk associated, do not think the home will be officially remapped, or neglect the risk all together. Most likely consumers have not been updated about the potential risks associated with the property yet and therefore purchase at a premium.

One to four years after the remapping there is a 11-16% discount associated with these properties, suggesting that consumers may have been informed or at least aware of the remapping efforts and potential for these homes to be officially remapped into a flood zone. We observe this point estimate discount though as shown by the confidence intervals it is insignificant at the 95% confidence level. This insignificance could be derived from the fact that these are preliminary maps and are subject to LOAs. If presented with ample evidence suggesting their property is not at risk, such as proving their home is above the BFE, FEMA will amend the property out of the flood zone. This uncertainty may have signaled to consumers that even though the property was Switched In, as indicated by the preliminary maps, but there is a chance that this could be reversed in the future.

This phase of LOAs was long and drawn out, lasting for approximately 10 years until June 2020, when the updated FIRMs were accepted by the County and made official. The absence of an absolute treatment may have caused confusion and uncertainty within the market therefore impacting the statistical significance of the effect for switching into a flood zone. However, both models illustrate that these properties are being influenced by variables that are not impacting the rest of the market, indicating that this change in value may be caused by flood related factors.

The hedonic model shows that properties who switched into a flood zone were statistically valued more than a home exposed to flood risks before the release of preliminary flood information. Then, after the release that positive effect is lost, and they are no longer statistically valued differently from homes within flood zones. This converging of prices indicates that consumers now view these Switch In homes in the same way they view homes that have always been in a flood zone. This demonstrates, at the very least, that the release of preliminary flood maps did negatively impact properties who Switched Into a flood zone.

In conclusion, my research expresses that the preliminary release of updated flood risk information negatively impacts the value of properties who have been remapped into a flood zone. This research offers insight into how consumers react to a preliminary change in flood risk rather than an official change. Most studies have utilized official remapping events therefore, our model is unique in this way. Due to data constraints I was not able to continue this research to evaluate the impact from the official release of the updated FIRMs and compare how consumers react to each event.

Conversely, properties who Switched Out of a flood zone did not see any statistically significant effect. This suggests that consumers do not recognize the potential for the reduction in risk. This is interesting because it seems that consumers reacted to the potential for an increase in risk but are not willing to make any adjustments in their behavior for a preliminary decrease in risk. These results are consistent with the Shr and Zipp (2019) revealing that these Switch Out properties do not see a rebound in value after being remapped out of a flood zone. Essentially, our results are consistent with the current literature suggesting that switching into a flood zone negatively impacts property values and switching out has no determinable effect (Shr & Zipp, 2019).

In terms of Snohomish County, this research reveals that consumers are delayed by a year in their awareness of a property being switched into a flood zone. The effect observed in properties who Switched Into a flood zone indicates that consumers are relatively aware flood risks within the county and stay up to date on current risks.

Additionally, the repeat transaction model results suggest that the release of preliminary FIRMs may cause more confusion and variability to be introduced into the market because consumers do not know what to expect in the future. The hedonic model suggests that consumers in Snohomish County do mitigate their exposure of risk by accounting for any possible increase of risk as communicated with the preliminary maps by valuing the Switch In properties the same as properties who have always been in a flood zone. With the converging of prices for properties who Switched In, Snohomish County can assume that their homeowners are relatively aware of contemporary flood risks. However, in the context of preliminary remapping events their understanding needs to be enhanced about the reduction of risk associated with being remapped out of a flood zone. Although this effect is not uncommon and has been observed in other communities.

Problems and Future Research

One major limiting factor in this research is the absence of an isolated and absolute remapping date. As discussed earlier the lack of a single release event that indicates the precise day when the entirety of new flood risk information was released does not allow us to efficiently isolate the effect, therefore, creating difficulties when estimating coefficients and their statistical significance. Instead of a specific event date, FEMA releases preliminary information while they finalize and adjust their results. They allow for an implementation period where homeowners can contest this preliminary remap results through the submission of LOAs. During this period homeowners are subjected to a type of asymmetric information where neither buyer nor seller is truly informed about the flood risks associated with a property. This can result in inefficient transactions causing losses or gains within the market. In the case of Snohomish County this transition period lasted for 10 years further diluting the impact of remapping through time. Therefore, each study that analyzes the effect of switching flood zone status will have to address this issue, even if using the official remapping date.

Another issue present within this research is the potential for omitted variable bias, though our exposure was mitigated through fixed effects and clustered errors. Our fixed effects were at the Census block group level the second finest scale of neighborhood groups. However, there is still potential for omitted variables present within these block groups to impact our coefficient estimates. This can be further limited by utilizing smaller fixed effect scales, but we must be aware of the number of observations within each group. Since there are a finite number of properties that switch flood status, I was forced to settle with block group polygons as our fixed effect scale. Alternatively, and perhaps more efficiently, this can also be addressed through specifying a spatio-hedonic model utilizing spatial weight matrixes in the independent and error terms.

Given these considerations, future work should focus on a state-level approach and explore the price action of homes who have been impacted by past inundation events. Due to the prolonged preliminary period associated with the release of flood maps, perhaps future work should avoid this altogether and perhaps utilize another metric for presence of flood risk or status. Furthermore, this research could be continued to investigate the how the release of official flood maps differs from preliminary maps. Overall, future work should attempt to avoid situations of prolonged exposure to preliminary information, though this is largely out of the researcher’s control, and further mitigate omitted variable bias by utilizing a spatio-temporal hedonic model.

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APPENDIXES

Appendix A

HEDONIC MODEL COEFFICIENTS

Variables	ln Sale Price (2020)
Flood	0.002 (0.014)
Urban	-0.043** (0.020)
Switch_In_After	0.059 (0.068)
Switch_Out_After	0.012 (0.104)
Y2010	-0.493*** (0.019)
Y2011	-0.801*** (0.019)
Y2012	-0.808*** (0.020)
Y2013	-0.685*** (0.020)
Y2014	-0.587*** (0.020)
Y2015	-0.473*** (0.018)
Y2016	-0.374*** (0.018)
Y2017	-0.223*** (0.017)
Y2018	-0.110*** (0.017)
Y2019	-0.046*** (0.017)
Y2000	-0.691*** (0.020)
Y2001	-0.636*** (0.018)
Y2002	-0.660*** (0.019)
Y2003	-0.620*** (0.018)
Y2004	-0.670*** (0.018)
Y2005	-0.497*** (0.018)
Y2006	-0.294*** (0.018)
Y2007	-0.230*** (0.019)
Y2008	-0.305*** (0.021)
Y2009	-0.434*** (0.019)
Bedroom	-0.002 (0.008)
Tot_Sq_Ft	0.0003*** (0.00001)
I(Tot_Sq_Ft2)	-0.00000*** (0.000)
Year_Built	-0.001*** (0.0001)
Acres	0.021*** (0.001)
Distance	-0.00003*** (0.00001)
I(Distance2)	0.00000*** (0.000)
Grade_Num25	0.083 (0.092)
Grade_Num35	0.203** (0.091)
Grade_Num41	0.273*** (0.092)
Grade_Num45	0.344*** (0.092)
Grade_Num49	0.463*** (0.092)
Grade_Num55	0.545*** (0.092)
Grade_Num65	0.695*** (0.093)
Grade_Num75	0.348** (0.141)
Flood:Urban	-0.025 (0.019)
Urban:Switch_In_After	0.162** (0.071)
Urban:Switch_Out_After	0.044 (0.119)
Urban:Y2010	-0.007 (0.024)
Urban:Y2011	-0.017 (0.025)

Urban:Y2012	0.006 (0.025)
Urban:Y2013	0.017 (0.025)
Urban:Y2014	0.044* (0.024)
Urban:Y2015	0.038* (0.023)
Urban:Y2016	0.063*** (0.023)
Urban:Y2017	0.026 (0.022)
Urban:Y2018	0.033 (0.022)
Urban:Y2019	0.006 (0.021)
Switch_In_After:Y2010	0.183 (0.133)
Switch_In_After:Y2011	0.081 (0.141)
Switch_In_After:Y2012	-0.175 (0.151)
Switch_In_After:Y2013	-0.225 (0.140)
Switch_In_After:Y2014	-0.047 (0.114)
Switch_In_After:Y2015	0.053 (0.119)
Switch_In_After:Y2016	0.063 (0.110)
Switch_In_After:Y2017	0.066 (0.100)
Switch_In_After:Y2018	0.036 (0.169)
Switch_In_After:Y2019	0.067 (0.093)
Switch_Out_After:Y2010	-0.126 (0.332)
Switch_Out_After:Y2011	-0.074 (0.227)
Switch_Out_After:Y2012	-0.057 (0.188)
Switch_Out_After:Y2013	-0.067 (0.184)
Switch_Out_After:Y2014	0.019 (0.138)
Switch_Out_After:Y2015	0.123 (0.173)
Switch_Out_After:Y2016	0.042 (0.133)
Switch_Out_After:Y2017	0.126 (0.151)
Switch_Out_After:Y2018	0.251 (0.153)
Switch_Out_After:Y2019	-0.099 (0.171)
Urban:Y2000	0.153*** (0.024)
Urban:Y2001	0.101*** (0.023)
Urban:Y2002	0.110*** (0.023)
Urban:Y2003	0.121*** (0.023)
Urban:Y2004	0.109*** (0.023)
Urban:Y2005	0.104*** (0.023)
Urban:Y2006	0.084*** (0.023)
Urban:Y2007	0.077*** (0.024)
Urban:Y2008	0.065*** (0.025)
Urban:Y2009	0.024 (0.024)
Bedroom:Tot_Sq_Ft	0.00000 (0.00000)
Urban:Switch_In_After:Y2010	-0.527*** (0.156)
Urban:Switch_In_After:Y2011	-0.543** (0.234)
Urban:Switch_In_After:Y2012	-0.197 (0.228)
Urban:Switch_In_After:Y2013	-0.111 (0.189)
Urban:Switch_In_After:Y2014	0.054 (0.395)
Urban:Switch_In_After:Y2015	-0.168 (0.122)
Urban:Switch_In_After:Y2016	-0.122 (0.195)
Urban:Switch_In_After:Y2017	-0.133 (0.113)
Urban:Switch_In_After:Y2018	-0.241 (0.196)
Urban:Switch_In_After:Y2019	-0.076 (0.097)
Urban:Switch_Out_After:Y2010	0.097 (0.342)
Urban:Switch_Out_After:Y2011	0.069 (0.244)
Urban:Switch_Out_After:Y2012	0.037 (0.221)
Urban:Switch_Out_After:Y2013	-0.203 (0.235)
Urban:Switch_Out_After:Y2014	-0.185 (0.167)

Urban:Switch_Out_After:Y2015	-0.228 (0.188)
Urban:Switch_Out_After:Y2016	-0.345* (0.201)
Urban:Switch_Out_After:Y2017	-0.159 (0.167)
Urban:Switch_Out_After:Y2018	-0.339** (0.172)
Urban:Switch_Out_After:Y2019	-0.220 (0.286)
Constant	14.046*** (0.236)

Note: Robust standard errors; $^{*}p^{**}p^{***}p<0.01$