A Slippery Slope: A Hedonic Property Value Study of Landslide Risk and Economic Costs in Watauga County

By

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Abstract

As the threat of climate change becomes more apparent, it is important to consider the local impacts on the environment, communities, and the economy. A significant impact of climate change for Watauga County is an increase in precipitation, and a subsequent increased prevalence of landslides. In order to quantify part of the costs of climate change to Watauga County, this thesis aims to measure the reduction in the value of residential properties from increased landslide risks through three distinct landslide risk measures: slope of a parcel, an instability index, and distance from the nearest landslide. This is achieved through the use of geographic information systems (GIS) and statistical analyses of data provided by the North Carolina Geological Survey (NCGS), the Watauga County tax office, and the US Census Bureau's American Community Survey. Using hedonic pricing methods, this thesis estimates the loss in residential property values due to increased landslide risks. The analysis shows mixed evidence with regards to slope and the instability index, but the distance from a landslide measure shows significant promise. The analysis suggests that landslides occurring within 0.50 miles of a home can reduce the selling price by between 5.0-5.7%. As landslides occur closer to these properties, this effect is even more prevalent.

Introduction

Within our current culture, climate change remains a looming threat that increasingly affects numerous facets of our lives. Though climate change is natural over the span of centuries, the magnitude of change that has occurred since the 1950s is believed to be primarily due to anthropogenic causes (Pan 2017), with a 1.5° F rise in global temperatures since the industrial revolution (Auffhammer 2018). With the exacerbation of climate change comes dangerous consequences such as erratic weather, more intense seasonal patterns, increased precipitation fluctuation, more frequent hurricanes and tropical storms, rising sea-levels, increased soil erosion, and a list of other secondary effects on our environment. To add to this, increases in temperatures are positively correlated with higher energy demand during warmer periods, coupled with the subsequent increase in greenhouse gas emissions, which then exacerbates the climate change crisis (Eekhout et al. 2018). In economics, a market failure is described as an event where the free market structure fails to take into account negative externalities caused by firms within a market (e.g., pollution, corruption, deforestation); thus, the climate change crisis can be considered "the greatest and widest-ranging market failure ever seen", as coined by the famed economist Sir Nicholas Stern (Stern 2007).

As previously mentioned, climate change can have dangerous repercussions in different regions. One of the many vulnerable communities to such a change would be mountain communities. These communities are projected to experience further increases in precipitation in smaller periods of time, which would further the threat of flash flooding and slope instability (Andersen & Sugg 2019). Rainfall is the most widespread trigger of landslide events in the world and an increase in frequency and intensity of precipitation could rip through mountain communities in a devastating way (Kirschbaum & Stanley 2018). The purpose of this thesis is to determine the economic cost of climate change to Watauga County residents. The method to achieve this is to look at how landslide risk is capitalized in residential property values. The market value of residential properties can capitalize many different aspects of the region around a property: recreation benefits, viewshed, nearby amenities, and even negative effects like crime and risk of natural disasters. The purpose of this thesis is to see whether landslide risk is capitalized into the values of Watauga properties and by how much, which provides meaningful insight as to how Watauga County and mountain communities may be impacted by a changing climate.

My primary findings are that a number of the variables of interest played small roles in the value of a parcel. Alternative measures of landslide risk, such as slope and an instability index provided mixed evidence. However, the most impactful variable of interest is the distance of a parcel from recorded landslides, specifically those within .50 miles of a landslide. As suggested by my most comprehensive models, such parcels experienced a depreciation in sale price between 5.0-5.7%.

The next section will include a literature review which motivates the research conducted in this paper. Section 3 presents the data sources, processing, and final descriptive statistics, while section 4 explains the methodology behind the hedonic pricing model. Sections 5 and 6 then present the results from the analysis and offer concluding remarks as to how this thesis impacts Watauga County residents and adds to the present literature in economics and climate change research.

Literature Review

Climate change can affect communities around the world very differently, whether it be socially, politically, economically, or environmentally. Understanding how local communities will be impacted by global shifts in temperature, storm frequency, and disasters like famine or blight will give policy makers and the public better tools to combat and mitigate the effects of these events. Within the literature, there is a breadth of knowledge that focuses on climate change, its effects on landslide risk, and individuals' adaptation techniques to mitigate these risks.

Projections of Climate Change

Numerous governmental bodies have aimed to study climate change's effects on our planet. As the Earth's global mean temperature rises, we are estimated to see numerous impacts on our economy and environment. The most recently pressing publication was produced by the Intergovernmental Panel on Climate Change (IPCC). The IPCC was put to task to issue a report on the potential risks of global mean temperatures (GMT) rising by 1.5°C. Within the report, the IPCC (2018) listed varying outcomes that could occur in a future where GMTs rose by 1.5°C. We have already seen a 1.0°C increase since the pre-industrial era and we are set to hit an additional 1.5°C increase between 2030 and 2052 if current trends continue. While that is a global average, certain areas such as the Arctic will see a two to three time increase in temperature. In places that have already experienced a 0.5°C increase in temperature, there have been observed increases in the frequency and intensity of extreme weather events.

The risks associated with a rise in GMT of 1.5°C would be widespread over both the health of the environment and that of humanity. These risks include detriment to human health, food systems, water supply, security, and even economic growth. We would also see an increase of hundreds of millions being plunged into poverty in the event of GMT rising between 1.5°C to 2°C (IPCC 2018) due to drastically changing environments that governments and economies may not be able to quickly adapt to. The IPCC report sheds an enormous amount of light onto the state of our planet and the potential threats we may face in the future at a broader scale.

The Localized Impacts of Climate Change

While climate change is a global threat, its impacts are localized, manifesting themselves differently through different regions. Mountainous regions will experience different hardships than those by the coast, and vice versa. For instance, regions with higher latitudes have experienced a quicker rise in precipitation while subtropical lands have actually experienced less than usual, and this is worsened by an increase in heat waves and heavy precipitation events worldwide (Pan 2019). These local impacts emphasize the importance of conducting spatial analysis and other research of smaller regions to uncover effects that will hit that region the hardest.

Being as these impacts are localized, the perceptions and attitudes of the community of the region play a role in how mitigation responses are handled. If residents do not perceive a threat to their community, they are less likely to adopt protective measures against these effects. On the other hand, if they do perceive risk, these risks can be mitigated against, or at least, possibly accounted for in the market by being capitalized into the value of assets, such as homes and property values. This capitalization effect can be observed throughout many studies like with research by Hallstrom and Smith (2005) in reference to risk from Hurricane Andrew, one of the strongest hurricanes to hit the U.S. at the time. The study observed a 19% decline in property values in Lee County, Florida, which is a county that experienced no damage from the storm, but experienced capitalization effects from an increase in perceived risk, nonetheless. Just being exposed to the risk of this hurricane conveyed important risk information to the market, and home prices adjusted to include this risk after the hurricane's near-miss. This capitalization effect is incredibly powerful and can reveal much about the surrounding environment of a home or property than initially seen.

Using the hedonic property price model, one is able to isolate the impacts of hazards and risk on property values by holding all else equal through the utilization of multivariate regression models. Numerous studies utilize the hedonic property price model for natural risk and how property values respond to said risk in the housing market. For instance, Bin, Kruse, and Landry (2008) studied this in relation to flood designated zones in Carteret County, North Carolina. The authors found that these flood zones lowered property values by an average of 7.3 percent in the region, which was reflected in the price of the properties and even insurance premiums. Also dealing with flooding, Bin and Landry (2013) used the hedonic valuation model to show that sales prices can capitalize property risk factors in Pitt County, North Carolina. They found that homes with lower flood risk sell at a premium compared to homes that had slightly higher flood risk, all else held equal. Also, using a difference-in-difference framework, the authors find that after Hurricanes Fran and Floyd, though there were no detected market risk premiums prior to 1996, homes exhibited significant price differentials after flood events caused by these storms, with a 5.7% and 8.8% percent decrease respective to each hurricane. These properties were capitalizing the risk of such flood and storm events into the market, conveying key risk signals to potential buyers. Lastly, a meta-analysis of numerous studies on flood risk and home prices by Daniel, Florax, and Reitveld (2009) revealed a 0.3 to 0.8% reduction in price for homes in a 100-

year floodplain. The researchers also observed that the marginal willingness-to-pay for reduced risk exposure increases over time, and that these willingness-to-pay measures were heterogeneous in respect to low- and high-income areas.

Sea-level rise is another natural hazard that is exacerbated by climate change, and that has strong implications on housing markets, especially coastal ones. This can be observed in numerous papers, like how researchers studying the risk of sea-level rise in the Chesapeake Bay found a significant disamenity effect in homes near the water, specifically those in the 0-2 foot sea-level rise zone, which threatens $3 billion worth of homes in the event of a 2-foot sea-level rise. This risk can also be observed in the opposite direction, with mitigation structures at these "at-risk" homes completely alleviating the aforementioned disamenity effect (Walsh et al. 2019). This rise in sea-level could also implicate local governments in massive economic costs, such as the estimated $300 to $900 million cost to the real estate market alone in Hillsborough and Pinellas County, Florida from a 3-foot rise in sea-level (Fu et al. 2016). Again, these economic costs are applicable to other regions being threatened by different natural hazards. Similar disamenity effects could be observable among residential properties in Watauga County, where the leading risk to Appalachia from climate change is an increase in precipitation and landslides.

This hedonic framework also applies to non-hazardous events, such as a reduction in snowfall in ski resort-dependent communities. In 2011, researchers used a hedonic framework to estimate the impacts of climate change, specifically global warming, on home values close to ski resorts in the US and Canada. Their findings showed that homes saw significant positive impacts on their prices from snowfall in the area, as well as heterogeneity in home price impacts related to ski resorts that already struggled with lower snowfall amounts. These hedonic models took into account numerous characteristics of homes and controlled for other factors affecting home values like the population of the census tract, the number of rooms in a home, and even the lift capacity of the nearby ski resorts (Butsic et al. 2011).

This can also be observed with hazards that are not as visibly dangerous, such as coastal erosion. Landry and Hindsley (2011) set out to explore the influence of coastal quality on coastal property values using a hedonic price model and soil erosion as a measure of coastal quality. They find that measures of coastal quality like dune and beach width have positive impacts on property values, and that home prices could be negatively impacted by soil erosion and degradation of these amenities.

The current thesis is a study on the local impacts of climate change in Watauga County, and so it is important to look at how natural disasters are perceived and mitigated against by local residents. Bonevac (2019) observed residents' perceptions in relation to flash flooding in Western North Carolina, finding that individuals' perceptions of climate change risk and natural disasters were heterogeneous across many planes. For instance, those who experienced the impacts of climate change held fewer reservations over climate change's risk to their livelihood. Also, individuals in areas of heightened vulnerability to flash floods had a higher sense of risk. On top of this, public perception of risk directly impacts the passing of proactive policies to mitigate these threats. Leiserowitz (2005) found that Americans perceive climate change as a moderate risk that will predominantly impact distant places far into the future, when the impacts may be much closer than they may be perceived, as well as extremist communities such as nay-sayers and alarmists. From these studies, we can see that the perception of these impacts are heterogenous and this could result in a lack of mitigation to prevent harm in the face of potential natural disaster risk, as well as a lack in potential impacts on residential property values.

Contribution to the Literature

While this is a paper that explores a topic not yet examined in the Appalachian Region, it is a framework that has been replicated and applied to a few similar cases. As discussed above, while there have been numerous empirical applications of hedonic property value methods to flooding, hurricanes, and even snowfall, few have looked into how landslide risks can negatively impact housing markets. The hedonic framework can be easily applied to my research and the context of Watauga County homes. When it comes to hedonic studies on landslide risk's impact on property values specifically, there is a limited literature on the subject. For instance, a study from South Korea using a difference-in-difference framework observed the 2011 Woomeyeon landslide's effect on the housing market there, and showed that apartment and condo values fell by 11.3% since the event due to the revelation of landslide risk in the market (Kim et al 2017). Another study from Canada used the hedonic price model and estimated that homes in La Baie, Quebec saw a 6% reduction in home value due to flood events that increased the risk of landslides. Also, mitigation premiums such as retaining walls and other security measures were seen to have positive impacts on home value in this region (Rosiers & Tossou 2018). Lastly, Gibson and Disberry (2017) studied the impacts of large, slow moving landslides on English and Welsh urban house prices, and found that, at least in these housing markets, while there were negative impacts on home values, the impacts were small in comparison to other common and more impactful nearby disamenities (i.e.- a nearby abandoned property or electricity pylon). While these are valuable studies to look at general trends in the impacts of landslides on home values, I am not aware of any studies on the property value impacts of landslides in North Carolina, especially in Watauga County. This paper would not only add to the literature significantly, but also add to the collective knowledge of the risks to Watauga County residents in the face of climate change and other nearby mountain communities.

Methodology

Hedonic pricing is a statistical analysis tool that was first linked to welfare theory by Sherwin Rosen (1974). According to Rosen, differentiated products all boil down to vectors of objectively measurable characteristics. Hedonic prices are defined as the implicit prices of a product's characteristics that are then revealed to agents as the observed price. These implicit prices translate in this study to the characteristics of the home and neighborhood that a parcel resides in, such as the tract median income and tract population density, as well as characteristics of the parcel itself, such as home quality. Therefore, I am using the hedonic hypothesis throughout this thesis by attempting to isolate the impact of landslide risk by taking into account the contributions of other implicit factors that then impact the observed price of each parcel.

Taking the above into account, the empirical model to be estimated below is

$$p_{ijt} = x_{ijt}\beta + M_t\alpha + R_{ij}\theta + v_j + \varepsilon_{ijt}$$

where p_{ijt} is the real sale price of home i (adjusted for inflation using the Consumer Price Index[1]), in neighborhood j, sold in period t. The vector x_{ijt} is the characteristics of the house structure and the parcel. This application includes acreage of the parcel and the assessed value of the home on the property. If it were available, variables such as number of bathrooms, bedrooms, and home size would be included here, but these were variables that I could not obtain. Instead, I

1 Bureau of Labor Statistics U.S. City Averages: https://www.bls.gov/regions/mid-atlantic/data/consumerpriceindexhistorical_us_table.htm

take into account structure quality using an approach first proposed by Legget and Bockstael (2000) and also exercised by Landry and Hindsley (2011). This approach uses the assessed value of the home structure by itself to proxy overall size, quality, and other characteristics of the home in lieu of these other variables. In some regression models, x_{ijt} also includes characteristics of the surrounding neighborhood, measured at the census tract level. In this thesis, these characteristics include median income of the tract, tract population density, and the percentage of people below the poverty line. I also calculated parcel specific location variables that fall under x_{ijt} in reference to the nearest town (either Boone or Blowing Rock), the nearest major road, the nearest secondary road or route, and elevation, which was used as a proxy measure of viewshed for properties with attractive views.

To control for seasonal and broader housing market effects over time, M_t includes dummy variables denoting the year and month of when the sale took place. Being as there are natural dips in sales during certain time periods, it is imperative to take this seasonality into account and control for it in the regressions.

Of most interest, R_{ij} reflects landslide risks and includes an instability index score (ranging from stable to unstable), slope, and dummy variables that denote if a parcel has experienced a landslide within different distance bins, namely within 0.25 miles and 0.26-0.50 miles. These risk characteristics are key measurements of how susceptible a property is to landslides, taking into account topography, geological conditions, and just the general propensity for a landslide, as proxied by nearby landslides that did or will occur, as of the time of the sale.

Some regression models include neighborhood fixed effects v_j, which are measured at the census tract level. Neighborhood fixed effects control for all observed and unobserved time invariant factors associated with a particular neighborhood that may affect the sales price. And

ε_{ijt} is an assumed normally distributed error term. The key coefficients to be estimated are β, the estimated effect of the quality of the home on the parcel, α, the estimated effect of time and seasonality of sales, and of particular interest, θ, which reflects the marginal effect of a change in landslide risk on the value of a home.

Data

Data Sources

The data analyzed in this paper was obtained from numerous agencies. There are three main datasets that played important roles in this research: parcel and sales data, geological and landslide data, and community demographics data.

Firstly, the parcel and sales data came from the Watauga County Tax Office in Boone, NC. I was provided property characteristics of all properties and property transactions in Watauga County, including fields of the sale price and date of the *last* transaction as of that tax year, parcel IDs, appraised building and land values, parcel classifications, acreage, and other fields for each tax year from 2014-2019. It should be known that these data included sales outside of 2014-2019, sometimes going all the way back to 1973. This data was processed using ESRI's ArcMap software, a Geographic Information System (GIS), and Stata (a statistical analysis program). In GIS, the parcel polygons were converted to point centroids, which represent the central point within each parcel. This allowed for easy computation and analysis of a parcel throughout the analyses.

Using these data, I was able to control for home quality using the appraised value of the home, which is assessed separately from the land and its location. The data does not include information on key structural variables, such as number of bedrooms, bathrooms, interior square footage, etc. Thus, the assessed value of the house itself is used as a proxy to control for heterogeneity in home quality and its impact on overall property transaction prices. This approach has been used by other hedonic studies in the peer-reviewed literature (Leggett & Bockstael 2000; Landry and Hindsley, 2011). Using assessed building value captures much of the positive effects of a home's characteristics even if the specific characteristics are not known to the researcher.

Elevation is a valuable measurement that is meant to account for amenity effects related to viewshed, or the view that residents of a home may enjoy from a high altitude. The elevation data was retrieved from the NCOne Map service[2], and measures feet above sea-level at a resolution of 20 x 20-foot grid cells across North Carolina. Using GIS clipping tools, I was able to clip this elevation raster to the shape of Watauga County and then assign every parcel an elevation value using the "Identity" tool based on where they laid on the raster grid. This measurement plays an important role in controlling for any housing premiums associated with an attractive view from one's property. Also, using this elevation raster grid, I was able to use the "Slope" tool in GIS to calculate the degree difference in elevation from one parcel to surrounding spaces, allowing me to have a reliable and consistent average slope value for every parcel.

Another important variable to keep in mind that has a large impact on property value is distance from a major road or a large town. Being near a town and public roads can impact property values positively due to increased access to nearby amenities, as well as negatively due to excessive noise or traffic, for example. Road distances were calculated based on data obtained

2 NCOne Map online service: https://services.nconemap.gov/secure/rest/services/Elevation/DEM20ft_DEM/ImageServer. Accessed on December 7, 2019.

from the North Carolina Department of Transportation.[3] These data consisted of major roads and secondary roads that stretched the entirety of North Carolina and were then also clipped in GIS to just Watauga County. Major roads were roads that were recognized on national datasets and consisted of roads that mainly went through town centers like Boone and Blowing Rock, while secondary roads referred to other non-major public roads. The nearest town variable was derived by determining the coordinates of downtown Boone and Blowing Rock. Using GIS, I calculated the distance from every parcel to the nearest major road, secondary road, and major town. Distance from roads are often cited as being loosely correlated with landslides (Andersen et al. 2019) and can also have positive or negative influence on property values. Inclusion of the road distance variables attempts to address concerns over omitted variable bias, which can occur if a significant variable is not taken into account in a model.

The North Carolina Geological Survey's (NCGS) work on the tracking and reporting of landslides in Watauga County, as well as a formulation of a stability index map, are both utilized in this thesis[4]. The data was imported into GIS and analyzed in reference to the parcel data to create parcel-specific variables that measured the distance of a parcel centroid to the nearest landslide and other potential predictors of landslide vulnerability. One such predictor is the aforementioned the stability index map. The index entails six categories ranging from stable to unstable. In order to make the index more intuitively align with increases in landslide risk, the values 1-6 were reversed to reflect an *instability* index, with one denoting a stable land area and 6 reflecting very unstable land. This provides a direct measure of the relative risk of each parcel

3 Major and minor road GIS layers were retrieved from NC Department of Transportation: https://connect.ncdot.gov/resources/gis/Pages/GIS-Data-Layers.aspx. Accessed on December 15, 2019.

4 The geological data was retrieved from the North Carolina Geological Survey (NCGS): https://deq.nc.gov/about/divisions/energy-mineral-land-resources/north-carolina-geological-survey. Accessed November 1, 2019.

regardless of whether there have been landslides near it in the past or not. The distribution of the instability index across all 6,465 sales in the sample can be seen below in Table 1:

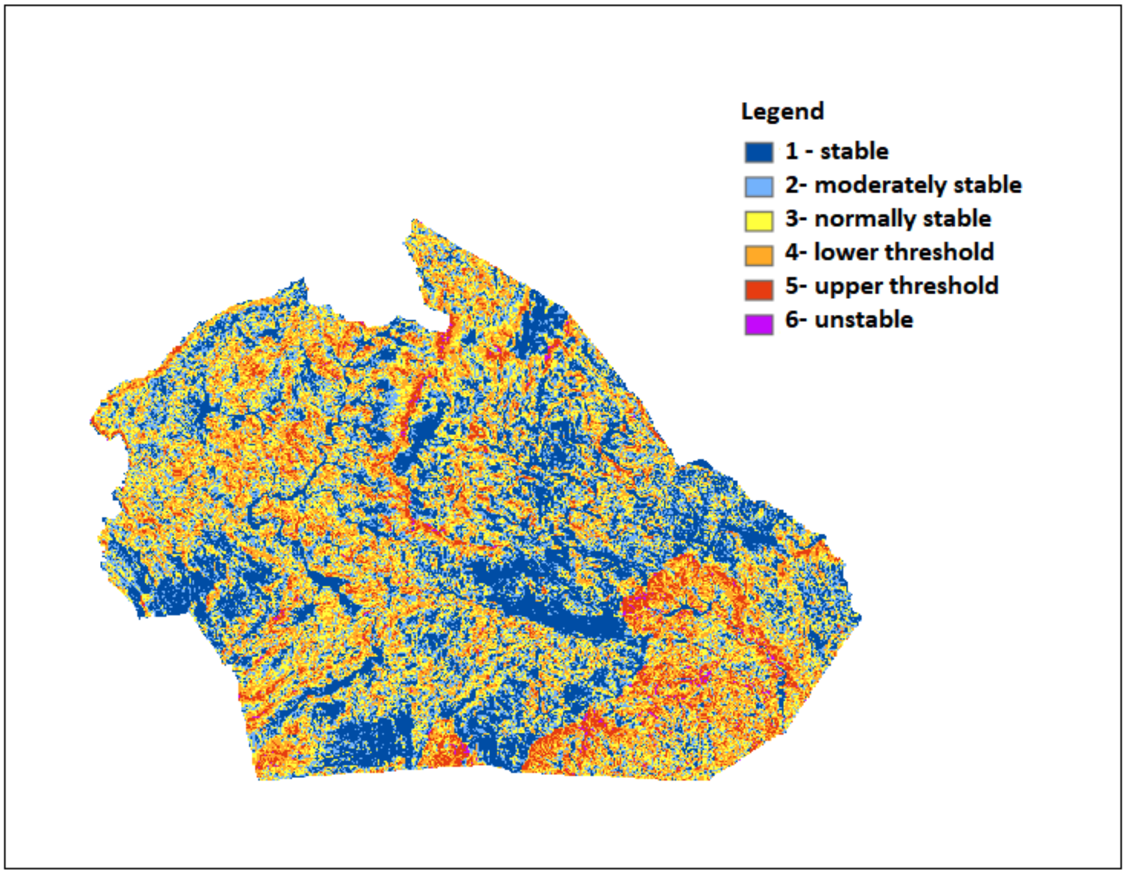
Table 1: Instability Index Distribution of All Sales in Final Sample

Instability Index Score	Stability Description	Freq.	Percent
1	Stable	2,930	45.32
2	Moderately Stable	827	12.79
3	Normally Stable	1,096	16.95
4	Lower Threshold of Instability	1,078	16.67
5	Upper Threshold of Instability	479	7.41
6	Unstable	55	0.85

This table represents the derived instability index after cleaning data and the stability descriptions are derived from the NCGS's descriptions of stability in their original stability index.

As can be seen in Table 1, the majority of the sales in Watauga County that are included in this thesis are either stable, normally stable, or of the lower threshold of instability. Less than 1% of parcels lie in the unstable category, and 7.41% lie in the upper threshold of instability. There is noticeable spatial variation in the instability index and the location of residential parcels across all of Watauga County, as can be seen in the below maps in a raster grid of 20 x 20-ft cells across the entire county:

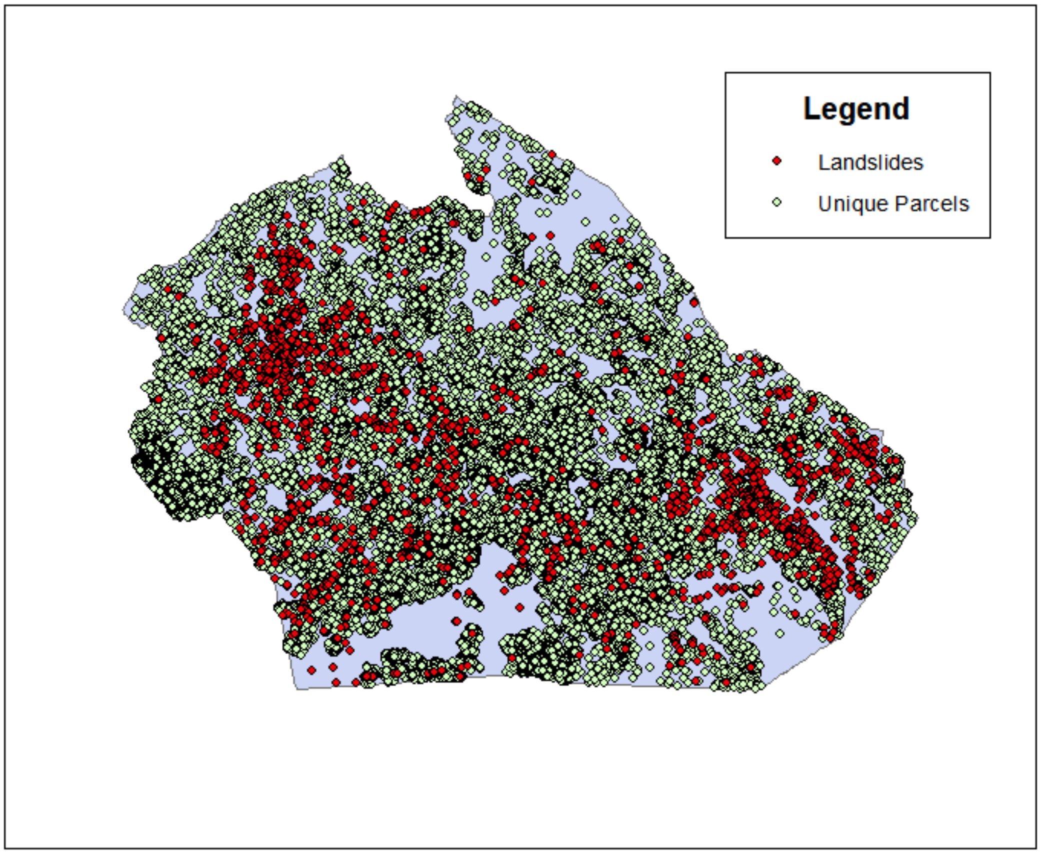
Figure 1: Instability Index Scores over Watauga County



This map was produced using data from the stability index created by the NCGS.

The above map provides a visual representation of the most stable and unstable regions of Watauga County, with key regions such as the limits of the town of Boone and other small towns being in the most stable regions. Unstable regions are peppered throughout the map, mostly on the ridges of mountains. When cross-referenced with Figure 2, one can see how the residential parcels and actual landslides examined in this thesis are distributed throughout the county.

Figure 2: Parcels and Landslides over Watauga County



This map was produced using data from the NCGS and the Watauga County Tax Office.

As can be seen above, while there is a considerable number of parcels in the most stable of regions, parcels are still located near and within some of the most unstable zones. On top of this, the geographic coordinates of past landslides have been recorded, and it can be seen in Figure 2 that these landslides have occurred extremely close to some residential parcels. Few of these recorded landslides occurred far from a residential parcel, meaning that there is a high likelihood that neighboring residents may be aware of these landslides. However, it is still an open question as to whether or not landslides can serve as visual cues that then lead to revisions in buyers' and sellers' perceptions of landslide risk, and in turn, are capitalized into housing values.

The community demographics data retrieved from the 2010 American Community Survey (ACS)[5] played an important role in accounting for neighborhood quality. Using census tract variables of median income, median housing value and percentage of the tract population under the poverty line, I was able to account for overall neighborhood quality. Additionally, subsequent models incorporate tract-level fixed effects to account for any time-invariant fluctuations in property values across census tracts. This accounts for observed factors, such as those mentioned above, as well as unobserved factors like school quality, crime, economic development, etc. The census tract level data was the smallest geographic unit available. I acknowledge that there is variation within these tracts of all of these measurements that may be important to account for, but due to data constraints I must assume homogeneity within the tract, conditional on the other parcel-specific spatial characteristics included in the models (e.g., distance to town centers, major roads, and elevation).

Data Cleaning

The analysis of this thesis uses both statistical and GIS software to clean and analyze data pulled from many sources. Using ArcMap 10.3 and Stata/IC 16.1, I was able to plot and process parcel, census, elevation, and landslide data, derive summary variables at the house transaction-level, and subsequently run multiple regression models. The ultimate objective is to isolate the capitalization effects of landslides on residential property values, and thus infer effects on the well-being of Watauga County residents. Using GIS, I was able to derive many important spatial variables, such as the distance of each parcel to the nearest landslide, slope measurements,

5 Census tract demographic data retrieved from the American FactFinder using the American Community Survey of 2010: https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=CF . Retrieved on 12/27/2019.

instability risk values in numeric terms, area measurements, and assign elevation values to parcels. Combining this with census tract and demographic data, I was able to create a fully encompassing map of Watauga County with data built into it. Then, once all of this data was joined together, I exported it as two tables to then import into Stata for further processing and to conduct multivariate regression analysis.

Using Stata, I was able to more easily manipulate the data and its variables. For example, I was able to identify and drop duplicate parcel transaction observations, rename and drop variables, and compute statistical analyses of the newly cleaned data. The raw, uncleaned data from the Watauga County Tax Office consisted of 327,102 initial sales and 48,281 unique parcels. The multiple years of sales data were appended together to form a master dataset of every "most recent sale" as of the end of the corresponding tax year, from 2014 to 2019. There were multiple reasons to drop much of the master dataset, including dropping duplicates of sales within a tax year, dropping observations with incomplete data, and removing outliers according to either arbitrary boundaries or dropping the top and bottom one percent of observations, as is later discussed.

Beginning with the parcel data, I firstly focus on the 38,860 residential parcels defined as R1, R2, and R3. Other classifications, such as apartment complexes and townhomes, can behave in different ways and can be considered a different "market" than single-family homes, so they are therefore excluded to provide a consistent set of homes for analysis, as is common in the literature (e.g. Case & Shiller 1988; Stull 1975; Bailey 1966). Therefore, the dataset was reduced from 327,102 transactions and 48,281 unique properties to 260,405 transactions and 38,860 unique properties.

It was next important to drop observations missing key variables such as sale price, parcel ID, date records, and assessed building value. After dropping these observations, I began to further narrow the scope of the data for analysis. A large portion of the dataset consisted of parcels that saw no sales throughout the study period and were subsequently dropped from the analysis. Also, while the annual parcel datasets covered tax years 2014-2019, there were sales that dated back as far as 1973. I focus on transactions from 2010-2019 because the ACS data was taken in 2010, and it allowed me to circumvent some of the confounding housing market effects of the 2010 housing market bubble and the 2008 subprime mortgage crisis. After limiting transactions to only those between 2010 and 2019, I am left with 45,314 transactions and 10,355 unique properties. Then I started renaming and dropping unnecessary variables and merging the multiple datasets by their unique parcel IDs, adding elevation, slope, and parcel land area to all transaction observations. In the final stretch, it was imperative to adjust all transaction price values for inflation, putting them into 2019 dollars using the Consumer Price Index[6].

To minimize the possible influence of outliers on the statistical analysis, observations pertaining to the top and bottom percentiles of the real sales price of the homes and the assessed building values were dropped. A similar trimming was also done with respect to the acreage variable, where I excluded residential parcels above six acres[7] and those below the first percentile of 0.037 acres. I then created dummy variables denoting the month and year of the sale, to account for seasonal effects and yearly fluctuations in the housing market. Lastly, I converted the distance variables from the nearest road and town to inverse distances to take into consideration that the price gradient with respect to distance from a major road may be non-

6 Bureau of Labor Statistics U.S. City Averages: https://www.bls.gov/regions/mid-atlantic/data/consumerpriceindexhistorical_us_table.htm

7 Six acres was a bound that was chosen arbitrarily and was meant to limit the dataset to a reasonable size.

linear. This was also where I created a population density variable that took into account how dense a census tract's population was with respect to its area in households per square mile. After performing all of this cleaning of the data, I was left with my finalized dataset.

Descriptive Statistics of the Finalized Dataset

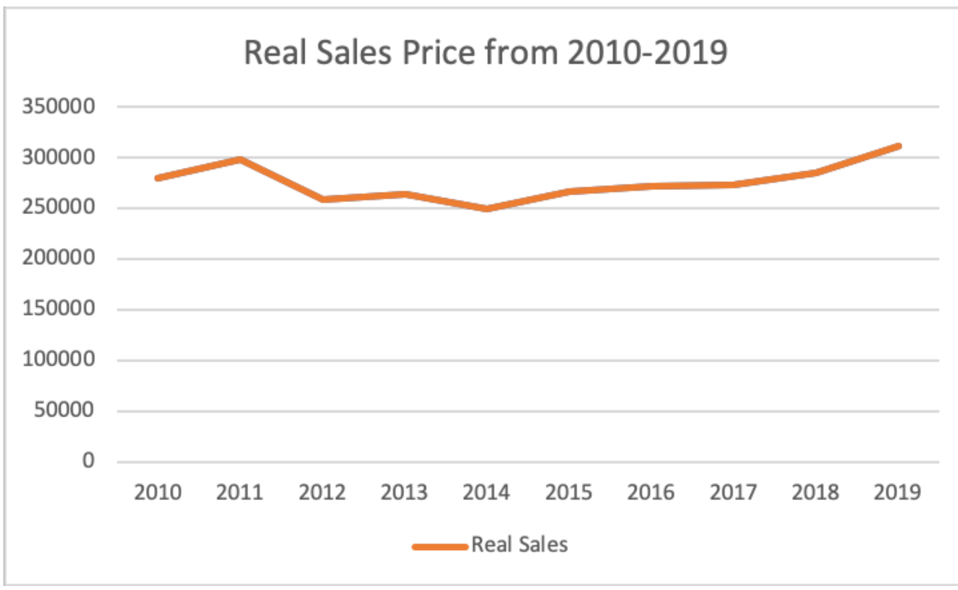
This finalized dataset left me with the aforementioned 6,465 transactions (of 5,490 unique residential properties) for the subsequent regression analysis. Table 2 presents descriptive statistics for the key variables:

Table 2: Descriptive Statistics of Key Variables.

Variable	Obs	Mean	Std. Dev	Min	Max
Sales Price ($)	6,465	276,417	185545.6	555.5707	1,618,899
Home Appraisal ($)	6,383	216,661	130895.8	800	786,100
Home Appraisal Missing Dummy	6,465	.01315	.1139	0	1
Instability index	6,465	2.3061	1.4139	1	6
Acreage	6,465	0.9558	0.9824	0.037	6
Elevation (ft)	6,465	3474	536.2861	1459	5170
Slope (degrees)	6,465	14.4958	7.5069	0	42.967
Dist. To Minor Rd. (miles)	6,465	0.0219	0.0149	0.0003	0.2257
Dist. To Major Rd. (miles)	6,465	0.7813	0.8381	0.0108	5.546
Dist. To Nearest Town (miles)	6,465	5.3790	3.7044	0.0573	15.0951
Landslide Dist. Dummy: <0.25 miles	6,465	0.3751	0.4841	0	1
Landslide Dist. Dummy: 0.26-0.50 miles	6,465	0.3131	0.4637	0	1

As can be seen, the average sales price for a property in the sample is $276,417. This, like previously mentioned, was adjusted for inflation. As can be seen below in Figure 3, real prices from 2010-2019 were relatively stable, on average, and seemed unencumbered by impacts from the aforementioned 2010 housing bubble and the 2008 subprime mortgage crisis. By including dummy variables denoting year and month of transaction, I am able to then control for broader effects in the later regression analysis.

Figure 3: Real Prices Over Time



The above graph shows the average price of homes in the sample from 2010-2019.

The mean appraisal value for just the home structure (excluding the land value and its location) on a parcel is $216,661. It is important to know that there is a lower observation count for home appraisal due to missing values, therefore, the reported summary is for non-missing values of home appraisal. The missing home appraisal dummy is simply a signal of whether or not a value is missing, and shows that 1.31% of the home appraisal values were missing. These missing values are accounted for in the regression results by including this dummy variable within each model. The average residential parcel has a mean instability score of 2.30 in the instability index, which is considered to be between moderately stable and normally stable. The distribution of the instability index across sales is shown in Figure 4 below:

Figure 4: Distribution of Sales and their Corresponding Instability Index Scores

This graph indicates a visual distribution of sales and their corresponding instability scores with 1=stable and 6=unstable.

Like previously discussed, these instability scores were formulated by reversing the default order of the stability index developed by NCGS. The higher the score, the less stable the land where a house is located. As one can see, the majority of Watauga County parcels are very stable, however, there are a considerable amount that are in more hazardous zones. These parcels are of most interest for this thesis as they are the most at risk of feeling the effects of landslide risk on their property values.

Other important variables of interest include slope, which shows the average parcel with a 14.49-degree slope, but these slope values range from 0 degrees, a completely flat parcel, to almost a perfect 45-degree sloped property, which would be considered a very steep parcel. It is important to also recognize that slope within a parcel can vary, so these mean values are simply averages of a parcel's slope based on the 20 x 20 ft grid data that was derived from the corresponding elevation data grid.

Other metrics such as distance to the nearest landslides, roads, and towns are also reported above. While metrics of distance from the nearest road and town are important explanatory variables that must be controlled for, the distance variable of most interest is the distance to the nearest landslide. From the landslide distances, I derived two dummy variables denoting two different distance bins - one that denotes that a landslide is within a distance of 0.25 miles, and another that denotes distance of a landslide between 0.26-0.50 miles. Because of the binary nature of a dummy variable being equal to either 0 or 1, the means of the variables actually indicate a percentage of the sample that holds that designation. This is true for parcels with landslides within 0.25 miles, which comprises 37.5% of all sales in the sample. As for sales within the 0.26-0.50-mile distance bin, this accounts for 31.3% of the sample. With a total of 68.8% of the sample within 0.50 miles of a landslide that occurred at some point in time, it is clear that the risk of landslides is widespread and reflects how its impacts can be felt throughout the entire region.

Results

Two types of models were formulated in Stata for this thesis: a standard ordinary least squares (OLS) regression model and a fixed-effects model, where the fixed effects are designated by neighborhoods according to the 13 census tracts. In table 3, the results from the multiple OLS regressions show the percentage change in the sale price of homes in the study with respect to key landslide risk variables. Only the coefficients of interest are shown, but the full results are in Table A1 of the Appendix. Although not of primary interest, the results for other control variables are generally as expected. For instance, home appraisal and parcel acreage have a highly significant positive effect on home value.

Table 3: OLS Regression Results – Key Variables of Interest

VARIABLES	(1) ln(Sale Price)	(2) ln(Sale Price)	(3) ln(Sale Price)	(4) ln(Sale Price)
Slope	0.00174			-0.00225
	(0.00131)			(0.00224)
Instability Index		0.0158**		0.0230**
		(0.00630)		(0.0101)
Landslide Dummy: <0.25 miles			0.0647	0.0561
			(0.0388)	(0.0381)
Landslide Dummy: 0.26-0.50 miles			0.0362	0.0329
			(0.0432)	(0.0425)
Year Dummies	yes	yes	yes	yes
Monthly Dummies	yes	yes	yes	yes
Census Tract Characteristics	yes	yes	yes	yes
Home Quality Characteristics	yes	yes	yes	yes
Observations	6,465	6,465	6,465	6,465
R-squared	0.387	0.387	0.387	0.388

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results of interest in the above regressions point towards a few significant findings. In OLS model 1, slope by itself seems to not reveal any significant effects on home value. It must be noted that slope simply takes into account topography and no other factors that may surround slope, such as geological conditions. Meanwhile, the other models do take into account location specific factors. The above table shows that in OLS model 2, with a unit change in the instability index of one category closer to instability, a home's price will increase by 1.58% (at a 95% confidence level). A similar effect can be observed in model 4 where the instability index was regressed alongside other key landslide risk variables - slope and proximity to landslides – with increases in price of 2.3% (at a 95% confidence level). This effect is counterintuitive to what one would expect from landslides being as landslides and its risks do not provide amenities. Therefore, it is hypothesized that this effect comes from an omitted variable bias. By not including some other variable or factor in the model, it seems that the instability index is falsely estimating a net positive effect on home value. This issue could potentially be addressed with the addition of other variables or using alternative models, as I do further on in the analysis.

When it comes to the other variables of interest, the findings in this set of models were less conclusive. The distance bin dummies denoting proximity to landslides show that properties that experience landslides within 0.25 miles and within 0.26 to 0.50 miles experience a statistically insignificant effect.

I next estimated a series of neighborhood fixed-effect (FE) regression models to better account for spatially correlated effects. The fixed-effects account for many of the tract-level variables like median income, tract population density, and others that are constant for all homes within a census tract. Such observed census tract variables are thus omitted in the FE models. Therefore, using this model I was able to estimate the same key variables of interests while controlling for both observed and unobserved time-invariant factors that affect home values within a census tract. Only the coefficients of interest are shown, but the full results are in Table A2 of the Appendix. The results for the key landslide risk variables of interest can be seen below in Table 4:

Table 4: Fixed Effect Model – Key Variables of Interest

	(1)	(2)	(3)	(4)
VARIABLES	ln(Sale Price)	ln(Sale Price)	ln(Sale Price)	ln(Sale Price)

Slope	0.00150			-0.000446
	(0.00125)			(0.00201)
Instability Index		0.0109*		0.0143
		(0.00591)		(0.00991)
Landslide Dummy: <0.25 miles			-0.0503*	-0.0570*
			(0.0275)	(0.0286)
Landslide Dummy: 0.26-.50 miles			-0.0499*	-0.0515*
			(0.0250)	(0.0255)
Year Dummies	yes	yes	yes	yes
Monthly Dummies	yes	yes	yes	yes
Census Tract Characteristics [8]	no	no	no	no
Home Quality Characteristics	yes	yes	yes	yes
Observations	6,465	6,465	6,465	6,465
R-squared	0.352	0.352	0.352	0.353
Number of FIP	13	13	13	13

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

When confronting the previous issue with the instability index, using the FE model here seems to have reduced the severity and significance of the omission bias in the OLS model. In model 2, this is seen by the slightly smaller instability coefficient estimate and reduced confidence level to 90%. In model 4, the instability coefficient estimate loses all statistical significance. While there is still a possible omission bias apparent here, the fact that it was at least partially alleviated points to the fact that accounting for spatially correlated fixed effects can help minimize the issue of omission bias in this thesis.

Better controlling for spatially correlated variables using the neighborhood FE models also affected the price effects associated with the landslide distance bins. When included in FE model 3, where these bins were the sole landslide risk variable, the estimated coefficients suggest that a home will see a drop in price of 5.03% if within 0.25 miles of a landslide and a 4.99% drop

[8] Census tract characteristics accounted for by FE model.

if within a 0.26-0.50 mile distance from a landslide (both estimated at the 90% confidence level). This is also reflected when included with other landslide variables of interest, such as in model 4, which actually estimates an even steeper drop in price than before, with homes within 0.25 miles of a landslide experiencing a reduction in sale price of 5.70%, and a drop of 5.15% in sales price for homes within 0.26-0.50 miles of a landslide (again, both at a 90% confidence level). By better controlling for spatially correlated omitted variables using the FE model, the previously estimated positive and insignificant landslide distance bin variables become both negative and statistically significant. This suggests that the FE model improves the landslide risk estimates' accuracy by taking into account omitted variables that were unaccounted for in the previous OLS model.

From these results, one can conclude that there are significant omitted variables that are still at play in the price of a home in the county, however, using a FE model such as model 4, the most comprehensive of models, is most representative of the actual market and its relationship to landslide risk. Landslides are more likely to occur in areas that have already seen landslides in the past (Samia et al. 2017) and this metric of distance to a landslide can be used to reflect landslide risks in many areas. While the index may be useful from a research perspective, it is likely that many homebuyers and sellers are not aware of this index to begin with, therefore the market does not necessarily capitalize its effects into the selling price of a home. In contrast, local homebuyers and sellers are more likely to be aware of landslides that have occurred in the area.

Being as the instability index was delivering results below expectations, as a robustness check, I examine whether the effects of the instability on home values are non-linear, rather than linear. For instance, an increase in the instability score from 1 to 2 could have a much different effect on sale price than an increase from 5 to 6. Therefore, by squaring the instability index term, one can account for such differences. Using the same set of models as seen above, these models were rerun again with a squared term included to capture the potential non-linear effects. The results are presented below in Table 5:

Table 5: OLS Regression Results - Key Variables of Interest with Instability Index Squared

VARIABLES	(5) ln(Sale Price)	(6) ln(Sale Price)
Slope		-0.00230
		(0.00227)
Instability Index	0.1000**	0.107***
	(0.0351)	(0.0341)
Instability Index ^2	-0.0154**	-0.0152**
	(0.00600)	(0.00565)
Landslide Dummy: <0.25 miles		0.0550
		(0.0382)
Landslide Dummy: 0.26-0.50 miles		0.0307
		(0.0421)
Year Dummies	yes	yes
Monthly Dummies	yes	yes
Census Tract Characteristics	yes	yes
Home Quality Characteristics	yes	yes
Observations	6,465	6,465
R-squared	0.388	0.389

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As can be seen in Table 5 above, the OLS model results appear similar with the addition of the instability index squared term. In OLS model 5, one can see that the counterintuitive positive effect of the instability index remains, however, the negative and significant squared instability index term suggests that this positive effect diminishes as landslide risk increases. This is also reflected in OLS model 6, where the original instability index has an even larger influence and even larger confidence level while the squared term shrinks but remains at the same confidence level. This means that while it is valuable to look at the instability index in this form, the counterintuitive sign suggests that it may not communicate to markets very well the risk of landslides, possibly due to a lack of awareness and information dissemination in the region. While this index is publicly available, I hypothesize that it is rarely used in price-setting or buying decisions.

When turning to the landslide bins again in Table 5, just like in the Table 3, the OLS models show no statistically significant impacts associated with distance to a landslide. This is again, at least partially, due to the lack of controls for neighborhood fixed effects. I next re-estimate the FE models with the included instability index squared term to account for nonlinearities. The results of which can be seen in Table 6:

Table 6: Fixed Effects Model - Key Variables of Interest with Instability Index Squared

VARIABLES	(5) ln(Sale Price)	(6) ln(Sale Price)
Slope		-0.000510
		(0.00204)
Instability Index	0.0944**	0.0996**
	(0.0321)	(0.0339)
Instability Index ^2	-0.0152**	-0.0155**
	(0.00553)	(0.00556)
Landslide Dummy: <0.25 miles		-0.0580*
		(0.0287)
Landslide Dummy: 0.26-0.50 miles		-0.0536*
		(0.0254)
Year Dummies	yes	yes
Monthly Dummies	yes	yes
Census Tract Characteristics[9]	no	no
Home Quality Characteristics	yes	yes
Observations	6,465	6,465
R-squared	0.353	0.354
Number of FIP	13	13

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[9] Census tract characteristics accounted for by FE model.

The same pattern in regards to the instability index terms observed in the OLS models in Table 5 are also seen in the FE version of these models in Table 6. As can be seen in FE models 5 and 6, the counterintuitive positive and nonlinear relationship between the instability index and house prices is now significant, even after the inclusion of neighborhood fixed effects. Again, this is suggesting that omitted variables may be confounding this result. Nonetheless, the estimated decrease in sale price of 5.03% (with a 90% confidence level) for homes within 0.25 miles of a landslide, and 4.99% (also at a 90% confidence level) for homes between 0.26-0.50 miles of a landslide from Table 4 remain robust.

Finally, it should be recognized from the R_2 values of each of the previous regressions, that the models all perform reasonably well in terms of overall statistical fit. The highest R_2 among all models is 0.389, which indicates that the model accounts for 38.9% of the variation in home price. This is impressive considering all of the factors included in these regressions. It is not expected in this thesis to take into account every single factor that goes into the price of a property, but it is to estimate, to a reasonable degree, how much landslide risk impacts the price of these properties, which requires one to take into account other factors of price variability.

Looking at these results overall, one can draw a few conclusions about the key variables of interest. For one, slope seems to play an insignificant role in the price of a home. None of the models above indicate that the coefficient estimate corresponding to the variable *Slope* is statistically significant at conventional levels. This may be due to a mixture of preferences regarding slope being as properties with steep slopes may have both a valuable viewshed and high landslide risk.

The instability index tended to act in a counterintuitive manner, with many of the estimates being statistically significant but positive, suggesting that the higher a parcel is in terms of land instability, and hence landslide risk, the higher the price. This is most likely due to an omitted variable bias where other variables that contribute to the selling price of a parcel have not been controlled for in the regressions, and therefore are being represented in the coefficient estimate for the instability index. In addition, local residents and potential homebuyers may have little direct knowledge of the stability zones used to develop the instability index. Together, this potential lack of knowledge and possible omitted variable bias likely contribute to the net positive price effect associated with the instability index. Future research may be able to better control for such omitted variables by, for example, deriving a more exact measurement of scenic viewsheds.

The most telling variable of interest, the landslide distance bins, informed this thesis the most in how landslide risks impact home values. In the initial OLS models, neither of the landslide distance bins were statistically significant. However, when introduced to the fixed effects models, these distance bins told a much different story, with all estimates being significant at a 90% confidence level. When controlling for tract level fixed effects such as in model 4 of Table 4, one can see a 5.7% decrease in home values when a landslide lies within 0.25 miles of the home and 5.15% decrease for homes with a landslide within 0.26-0.50 miles. While this is one result among many mixed results, it can be concluded that, when controlling for fixed effects within a census tract, the proximity to a landslide can have significant impacts on home values in a negative way. Using these most comprehensive models, we can estimate that properties within 0.50 miles of a landslide could see a 5.0-5.7% decrease in value.

<u>Conclusion</u>

This analysis adds to the existing literature by not only using a hedonic model to estimate the effects of landslide risk on property values specific to Watauga County, but also by adding to the shallow pool of literature on a key local disamenity that is projected to increase due to climate change – landslide risks. Property values capitalize the benefits of amenities like public parks, school quality, etc., but can also reflect negative effects of hazards, like crime and natural hazards. Therefore, research such as this can provide local policymakers with crucial insights into how to best mitigate the effects of climate change in the future. The ability for local policymakers to have relevant data and studies curtailed to their region specifically allows for more accurate and appropriate policies to be implemented. With these findings, I hope that policymakers and those with conditions similar to Watauga County can then implement better mitigation efforts to curtail the negative impacts of climate change and also shed light onto how climate change can specifically impact mountain communities.

The overall findings of this thesis are that a property's distance from landslides can impact home values negatively when taking into account neighborhood quality via tract-level fixed effects. The impacts could result in a 5.03-5.7% reduction in property sale price if landslides have occurred within 0.25 miles of the property, and a 5.0-5.15% reduction if a landslide was within 0.26-0.50 miles. It should be recognized that the measure used in this thesis is the distance in miles from the *nearest* landslide. Properties could have had multiple landslides within 0.5 miles, but this analysis only accounts for the closest, and thus disregards possible variation in the severity and frequency of landslides in close proximity. Additionally, although the neighborhood FE models 4 and 6 are the most comprehensive, there is still a possible omission bias present, at least to some degree. This is most apparent in the FE model 6, where the counterintuitive positive and statistically significant effects associated with the instability index remain even after controlling for neighborhood fixed effects. This potential bias could be further mitigated in the future through the inclusion of more spatial characteristics that affect property values, such as a more accurate measure of scenic views.

While this thesis can stand on its own, there is more than enough room for further research into this field of study. In future work, I intend to pursue a quasi-experimental difference-in-differences methodology and account for the frequency of past landslides. Doing so will better control for spatially correlated variables that may confound the current study results, and better exploit both spatial and temporal variation in landslides.

In spite of the aforementioned constraints, this thesis is the first impactful analysis on the effects of increased risk of landslides on Watauga County residents. Climate change is a threat that is projected to only worsen in the coming years, and it is important for local governments to prepare and implement policies with these threats in mind. While there are gaps to fill to provide a more comprehensive and insightful look into these impacts, the hope is that this thesis will provide a steppingstone for future researchers to look further into how Watauga County and similar mountain regions will be impacted by climate change in the future.

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Appendix

A1: Full OLS Regressions Results

VARIABLES	(1) lnrprice	(2) lnrprice	(3) lnrprice	(4) lnrprice	(5) lnrprice	(6) lnrprice
Slope	0.00174			-0.00225		-0.00230
	(0.00131)			(0.00224)		(0.00227)
Instability Index		0.0158**		0.0230**	0.1000**	0.107***
		(0.00630)		(0.0101)	(0.0351)	(0.0341)
Instability Index^2					-0.0154**	-0.0152**
					(0.00600)	(0.00565)
Landslide Dist. Dummies: <0.25 miles			0.0647	0.0561		0.0550
			(0.0388)	(0.0381)		(0.0382)
Landslide Dist. Dummies: 0.26-0.50 miles			0.0362	0.0329		0.0307
			(0.0432)	(0.0425)		(0.0421)
ln(Home Appraisal)	0.569***	0.569***	0.569***	0.568***	0.568***	0.567***
	(0.0224)	(0.0223)	(0.0220)	(0.0225)	(0.0224)	(0.0225)
Missing Home Appraisal	-0.684***	-0.684***	-0.683***	-0.684***	-0.685***	-0.684***
	(0.172)	(0.172)	(0.172)	(0.171)	(0.170)	(0.170)
Acreage	0.0437***	0.0423***	0.0459***	0.0434***	0.0434***	0.0445***
	(0.00833)	(0.00813)	(0.00821)	(0.00758)	(0.00826)	(0.00776)
Elevation	3.67e-05	3.99e-05	5.64e-05	5.84e-05	3.85e-05	5.67e-05
	(6.84e-05)	(6.67e-05)	(5.90e-05)	(5.93e-05)	(6.57e-05)	(5.83e-05)
Inv. Major Rd. Dist.	-0.000347	-0.000262	-0.000395	-0.000260	-0.000163	-0.000164
	(0.00145)	(0.00143)	(0.00140)	(0.00140)	(0.00139)	(0.00136)
Inv. Minor Rd. Dist.	6.93e-05	7.32e-05	5.96e-05	6.66e-05	7.31e-05	6.67e-05
	(0.00026)	(0.00026)	(0.00026)	(0.00026)	(0.00026)	(0.00026)
Inv. Nearest Town Dist.	0.138***	0.139***	0.144***	0.145***	0.141***	0.147***
	(0.0209)	(0.0204)	(0.0225)	(0.0227)	(0.0206)	(0.0229)
Tract Med. Income	4.08e-06	4.16e-06	4.29e-06	4.38e-06	4.03e-06	4.24e-06
	(3.21e-06)	(3.15e-06)	(2.94e-06)	(2.91e-06)	(3.15e-06)	(2.90e-06)
Tract Population Density	0.00113	0.00117	0.000911	0.00101	0.00113	0.000963
	(0.00083)	(0.00080)	(0.00070)	(0.00066)	(0.00080)	(0.00066)
% below Poverty Line	0.00381	0.00381	0.00369	0.00370	0.00388	0.00377
	(0.00312)	(0.00311)	(0.00296)	(0.00300)	(0.00309)	(0.00299)
d2011	-0.134	-0.136*	-0.135*	-0.137*	-0.138*	-0.139*
	(0.0757)	(0.0755)	(0.0757)	(0.0748)	(0.0751)	(0.0745)
d2012	-0.225***	-0.225***	-0.226***	-0.226***	-0.226***	-0.227***
	(0.0620)	(0.0627)	(0.0619)	(0.0625)	(0.0632)	(0.0629)
d2013	-0.0784*	-0.0798*	-0.0796*	-0.0815*	-0.0817*	-0.0834*
	(0.0430)	(0.0426)	(0.0431)	(0.0439)	(0.0430)	(0.0443)
d2014	-0.123**	-0.124**	-0.122**	-0.123**	-0.125**	-0.125**
	(0.0557)	(0.0558)	(0.0548)	(0.0551)	(0.0553)	(0.0546)
d2015	-0.0559	-0.0563	-0.0569	-0.0575	-0.0573	-0.0584

	(0.0362)	(0.0365)	(0.0358)	(0.0359)	(0.0367)	(0.0362)
d2016	-0.0423*	-0.0431*	-0.0410	-0.0424	-0.0444*	-0.0437*
	(0.0235)	(0.0239)	(0.0236)	(0.0239)	(0.0244)	(0.0244)
d2017	0.0122	0.0119	0.0122	0.0117	0.00998	0.00988
	(0.0267)	(0.0270)	(0.0270)	(0.0271)	(0.0277)	(0.0278)
d2018	0.0532	0.0524	0.0532	0.0521	0.0501	0.0498
	(0.0387)	(0.0390)	(0.0378)	(0.0378)	(0.0386)	(0.0375)
d2019	0.106**	0.107**	0.107**	0.108**	0.105**	0.106**
	(0.0440)	(0.0436)	(0.0446)	(0.0442)	(0.0448)	(0.0453)
dfeb	0.0178	0.0164	0.0187	0.0165	0.0142	0.0143
	(0.0717)	(0.0710)	(0.0724)	(0.0717)	(0.0712)	(0.0719)
dmar	-0.0218	-0.0229	-0.0187	-0.0208	-0.0267	-0.0246
	(0.0617)	(0.0616)	(0.0613)	(0.0616)	(0.0606)	(0.0605)
dapr	0.0507	0.0501	0.0535	0.0523	0.0470	0.0491
	(0.0558)	(0.0554)	(0.0573)	(0.0565)	(0.0553)	(0.0564)
dmay	0.0623	0.0625	0.0642	0.0643	0.0602	0.0620
	(0.0559)	(0.0558)	(0.0575)	(0.0565)	(0.0563)	(0.0569)
djun	0.0436	0.0433	0.0452	0.0445	0.0411	0.0423
	(0.0522)	(0.0516)	(0.0526)	(0.0512)	(0.0513)	(0.0509)
djul	0.0892	0.0886	0.0913	0.0902	0.0875	0.0891
	(0.0660)	(0.0653)	(0.0662)	(0.0658)	(0.0652)	(0.0656)
daug	0.0338	0.0323	0.0358	0.0333	0.0307	0.0317
	(0.0619)	(0.0616)	(0.0633)	(0.0619)	(0.0611)	(0.0614)
dsep	0.0578	0.0560	0.0585	0.0558	0.0544	0.0541
	(0.0761)	(0.0756)	(0.0766)	(0.0756)	(0.0755)	(0.0756)
doct	0.100*	0.0991*	0.102*	0.101*	0.0970*	0.0984*
	(0.0523)	(0.0514)	(0.0529)	(0.0521)	(0.0518)	(0.0525)
dnov	0.0931**	0.0912**	0.0946**	0.0917**	0.0885*	0.0890*
	(0.0419)	(0.0413)	(0.0416)	(0.0413)	(0.0414)	(0.0414)
ddec	0.0793	0.0780	0.0810	0.0789	0.0758	0.0767
	(0.0532)	(0.0530)	(0.0535)	(0.0532)	(0.0528)	(0.0530)
Constant	5.017***	5.003***	4.935***	4.924***	4.938***	4.863***
	(0.379)	(0.377)	(0.377)	(0.379)	(0.364)	(0.369)
Observations	6,465	6,465	6,465	6,465	6,465	6,465
R-squared	0.387	0.387	0.387	0.388	0.388	0.389

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Variables denoted as "d2011, d2012, …" and "dfeb, dmar, …" represent dummy variables for year and month, which was included in every regression set.

A2: Full Fixed Effects Regression Results.

VARIABLES	(1) lnrprice	(2) lnrprice	(3) lnrprice	(4) lnrprice	(5) lnrprice	(6) lnrprice
Slope	0.00150			-0.000446		-0.000510
	(0.00125)			(0.00201)		(0.00204)
Instability Index		0.0109*		0.0143	0.0944**	0.0996**
		(0.00591)		(0.00991)	(0.0321)	(0.0339)
Instability Index^2					-0.0152**	-0.0155**
					(0.00553)	(0.00556)
Landslide Dist. Dummies: <0.25 miles			-0.0503*	-0.0570*		-0.0580*
			(0.0275)	(0.0286)		(0.0287)
Landslide Dist. Dummies: 0.26-0.50 miles			-0.0499*	-0.0515*		-0.0536*
			(0.0250)	(0.0255)		(0.0254)
ln(Home Appraisal)	0.548***	0.548***	0.548***	0.547***	0.547***	0.546***
	(0.0202)	(0.0202)	(0.0199)	(0.0202)	(0.0204)	(0.0204)
Missing Home Appraisal	-0.704***	-0.705***	-0.708***	-0.707***	-0.705***	-0.708***
	(0.177)	(0.177)	(0.180)	(0.179)	(0.176)	(0.178)
Acreage	0.0457***	0.0453***	0.0472***	0.0448***	0.0465***	0.0460***
	(0.00854)	(0.00887)	(0.00898)	(0.00873)	(0.00902)	(0.00883)
Elevation	0.000113	0.000114	0.000115	0.000114	0.000111	0.000111
	(7.39e-05)	(7.38e-05)	(7.23e-05)	(7.38e-05)	(7.31e-05)	(7.31e-05)
Inv. Major Rd. Dist.	-0.000236	-0.000219	-0.000289	-0.000149	-0.000122	-4.94e-05
	(0.00159)	(0.00157)	(0.00160)	(0.00160)	(0.00154)	(0.00157)
Inv. Minor. Rd. Dist.	2.65e-05	2.86e-05	2.61e-05	3.26e-05	2.85e-05	3.27e-05
	(0.00025)	(0.00025)	(0.00025)	(0.00026)	(0.00026)	(0.00026)
Inv. Nearest Town Dist.	0.0760***	0.0768***	0.0649***	0.0660***	0.0775***	0.0664***
	(0.0144)	(0.0143)	(0.0124)	(0.0127)	(0.0148)	(0.0131)
Tract Med. Income	-	-	-	-	-	-
Tract Population Density	-	-	-	-	-	-
% below Poverty Line	-	-	-	-	-	-
d2011	-0.147*	-0.148*	-0.147*	-0.148*	-0.150*	-0.150*
	(0.0747)	(0.0747)	(0.0759)	(0.0750)	(0.0744)	(0.0746)

d2012	-0.235***	-0.235***	-0.236***	-0.236***	-0.236***	-0.237***
	(0.0604)	(0.0609)	(0.0601)	(0.0605)	(0.0614)	(0.0610)
d2013	-0.0879*	-0.0892*	-0.0892*	-0.0895*	-0.0912*	-0.0916*
	(0.0450)	(0.0447)	(0.0447)	(0.0452)	(0.0452)	(0.0457)
d2014	-0.136**	-0.136**	-0.138**	-0.138**	-0.137**	-0.139**
	(0.0546)	(0.0546)	(0.0551)	(0.0554)	(0.0541)	(0.0549)
d2015	-0.0671*	-0.0675*	-0.0674*	-0.0673*	-0.0685*	-0.0682*
	(0.0369)	(0.0370)	(0.0371)	(0.0373)	(0.0372)	(0.0375)
d2016	-0.0502*	-0.0507*	-0.0512*	-0.0520*	-0.0521*	-0.0533*
	(0.0250)	(0.0251)	(0.0244)	(0.0248)	(0.0257)	(0.0254)
d2017	0.00590	0.00558	0.00518	0.00528	0.00363	0.00330
	(0.0276)	(0.0278)	(0.0277)	(0.0278)	(0.0285)	(0.0285)
d2018	0.0483	0.0476	0.0477	0.0472	0.0453	0.0448
	(0.0360)	(0.0361)	(0.0362)	(0.0363)	(0.0358)	(0.0359)
d2019	0.104**	0.104**	0.102**	0.103**	0.103**	0.101*
	(0.0456)	(0.0453)	(0.0459)	(0.0454)	(0.0465)	(0.0466)
dfeb	0.0133	0.0127	0.0141	0.0123	0.0106	0.0101
	(0.0727)	(0.0722)	(0.0719)	(0.0714)	(0.0724)	(0.0715)
dmar	-0.0151	-0.0156	-0.0129	-0.0151	-0.0195	-0.0190
	(0.0620)	(0.0616)	(0.0607)	(0.0613)	(0.0604)	(0.0600)
dapr	0.0578	0.0575	0.0575	0.0565	0.0543	0.0533
	(0.0579)	(0.0576)	(0.0575)	(0.0567)	(0.0575)	(0.0565)
dmay	0.0709	0.0709	0.0697	0.0702	0.0685	0.0677
	(0.0577)	(0.0578)	(0.0582)	(0.0572)	(0.0582)	(0.0577)
djun	0.0525	0.0523	0.0529	0.0526	0.0501	0.0504
	(0.0541)	(0.0537)	(0.0549)	(0.0537)	(0.0534)	(0.0533)
djul	0.0962	0.0959	0.0968	0.0955	0.0948	0.0944
	(0.0680)	(0.0674)	(0.0678)	(0.0674)	(0.0672)	(0.0672)
daug	0.0380	0.0369	0.0377	0.0362	0.0353	0.0344
	(0.0626)	(0.0625)	(0.0625)	(0.0610)	(0.0619)	(0.0605)
dsep	0.0606	0.0596	0.0617	0.0598	0.0578	0.0580
	(0.0772)	(0.0769)	(0.0774)	(0.0766)	(0.0768)	(0.0765)
doct	0.108*	0.107*	0.110*	0.108*	0.105*	0.106*
	(0.0532)	(0.0526)	(0.0532)	(0.0523)	(0.0529)	(0.0527)
dnov	0.0824*	0.0816*	0.0833*	0.0807*	0.0790*	0.0780*
	(0.0419)	(0.0412)	(0.0417)	(0.0414)	(0.0412)	(0.0414)
ddec	0.0837	0.0831	0.0843	0.0827	0.0809	0.0805
	(0.0545)	(0.0543)	(0.0540)	(0.0538)	(0.0540)	(0.0535)
Constant	5.174***	5.172***	5.227***	5.222***	5.110***	5.161***
	(0.417)	(0.419)	(0.412)	(0.414)	(0.408)	(0.404)

Observations	6,465	6,465	6,465	6,465	6,465	6,465
R-squared	0.352	0.352	0.352	0.353	0.353	0.354
Number of FIP	13	13	13	13	13	13

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Variables denoted as “d2011, d2012, …” and “dfeb, dmar, …” represent dummy variables for year and month, which was included in every regression set.