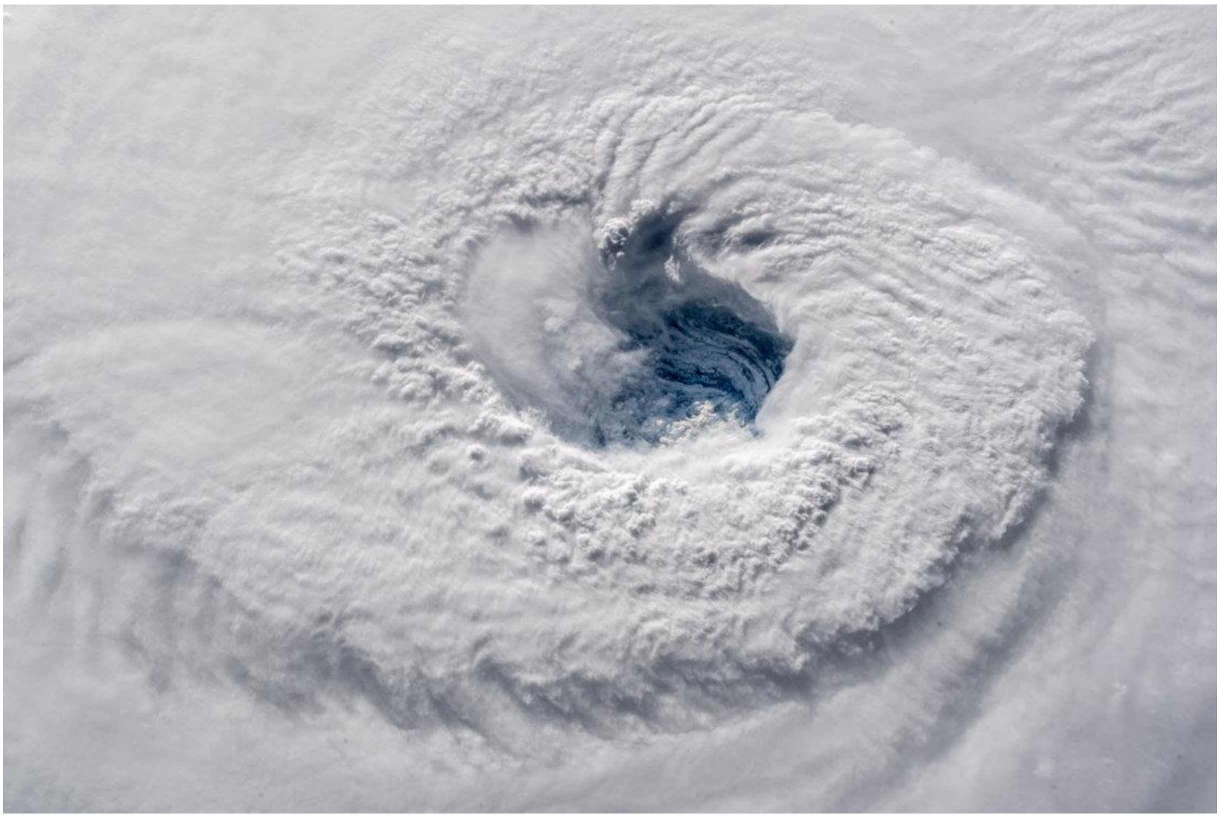
THESIS

The impact of hurricanes on residential property value



‘A case study of the effects of the 2004 hurricane Charley in the Sunshine State’

Enzo van Veelen
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Educational institution: University of Groningen
Landleven 1
9747 AD Groningen
050 363 9111
Faculty: Faculty of Spatial Sciences
Degree: MSc Real Estate Studies
Supervisor: Prof. dr. ir. A.J. van der Vlist
Second assessor: dr. M. van Duijn

Author: T.E.J. van Veelen
Student number: S3549941
E-mail: t.e.j.van.veelen@student.rug.nl
enzovv@live.nl

Cover Photo: ESA/NASA-A. Gerst [ID: 399408]: ESA astronaut Alexander Gerst took this image of Hurricane Florence on 12 September 2018 from the International Space Station (ISS) at an altitude of 400 km. *"Ever stared down the gaping eye of a category 4 hurricane? It's chilling, even from space" – A. Gerst*

ABSTRACT

This thesis considers a quantitative study of the effects of hurricane Charley on residential property values in Orange County Florida in the wake of the hurricane event. This thesis has a specific focus on the differences between the structure type of a residential property. A hedonic model is the basis of the analysis and in order to determine differences between properties and structure types a difference-in-difference model is used. The regression results show a discount in sales price regarding residential properties sold in the target area after the hurricane event, compared to properties sold in the control area. Additionally, results are found that properties with stone exterior walls sell at a discount within the target area in the wake of a hurricane event.

Keywords: *Hurricanes, residential property value, structural characteristics, hedonic model, difference-in-difference model.*

EXPLANATION OF ACRONYMS

DND:	Difference-in-Difference
FBC:	Florida Building Code 2001
JMA:	Japan Meteorological Agency
NCA:	National Climate Assessment
NOAA:	National Oceanic and Atmospheric Administration
PGI:	Punta Gorda Isles
SBC:	Standard Building Code 1993
SFHA:	Special Flood Hazard Area
SII:	Structural Integrity Index
SSZ:	Special Study Zone

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1. INTRODUCTION

1.1 MOTIVATION

Natural hazards and their effects have been studied extensively in recent years. Natural hazards are, to a certain extent, unpredictable events and tend to have a large financial impact when they occur. For instance, according to Munich Re, in 2019 the total cost of natural hazards worldwide amounted USD 150 billion (Ziady, 2020). The climate is the main cause of most natural hazards and is changing in the last few decades due to global warming (Melillo Richmond & Yohe, 2014; Wuebbles et al., 2017). This change in climate has been linked to the increase in intensity of extreme weather events (Emanuel, 2011). Because of global warming and in order to predict the effects of climate change the climate is surveyed more extensively by e.g. National Climate Assessment (NCA). Recent NCAs (2014 and 2017) predict that the frequency and intensity of extreme high temperature events, such as hurricanes, are virtually certain to increase in the future as a result of global warming (Melillo, Richmond & Yohe, 2014; Wuebbles et al., 2017). The United States has approximately 95 natural hazard events on average each year (2008-2018 average), according to Munich Re.

As a result of high exposure to natural hazards the total costs of extreme weather conditions since 1980 have exceeded USD 1.1 trillion in the US (Wuebbles et al., 2017). The natural hazard events that occur in the US are predominantly meteorological events, such as hurricanes (Insurance Information Institute, 2019). Regarding the climate change the five most costly hurricanes took place in the last 15 years in the US (NOAA, n.d.). This correlates with the evidence that 12 of the hottest years occurred in the past 15 years (NOAA, 2013; NOAA, 2017; NOAA, 2020). Hurricanes in particular cause most of the property destruction (44%) compared to all other natural hazards in the United States (Pofleka, 2013). Closer examination of this property destruction reveals that approximately 63% of the real estate that is affected are residential properties (CBO, 2019). Because hurricanes originate in the Pacific and Atlantic Ocean the coastal regions tend to have the largest chance to be affected (NOAA, 2014; Insurance Information Institute, 2019). The coastal regions are, however, attractive regions to households. In the US approximately 40% of the inhabitants live in coastal regions. The coastal regions account for approximately 10% of the total land in the US (NOAA(2), 2013). As of 2018 approximately 60 million US citizens lived in the path of hurricanes (U.S. Census Bureau, 2018). According to Merkens et al. (2016), the population living in ‘low elevated coastal zones’ globally will increase by 58% to 71% until 2050. The increase in population on one hand and the increase in intensity and number of hurricanes in the future on the other means that residential properties at risk and potential damages will most likely rise in the future. Because of the increase of residential properties at risk in coastal regions the aim of this study is to examine the effect of a hurricane of a substantial magnitude, on the value of a residential property.

1.2 REVIEW OF LITERATURE

Earlier studies address the effect of natural hazards such as earthquakes, floods and hurricanes on residential property prices. The studies that examine earthquakes find that residential properties located in areas which are more likely to be affected by earthquakes (Special Study Zones, SSZ) tend to trade at discount (Brookshire et al., 1985; Nakagawa et al., 2007). However, there are contradictory results observed in property devaluation after an earthquake. The results differ between overestimation (Beron et al., 1997) and underestimation (Naoi et al., 2009) of the discount as determined prior to the event.

Literature considering the effect of flood risk on residential property prices find similar results compared to properties in SSZs. Residential properties located in areas which are likely to be affected by flooding (Special Flood Hazard Areas, SFHA) tend to trade at a discount on average as a result of the increased risk. When a flood-event takes place the risk that is determined pre-event, resulting in the discount, tends to be underestimated. Resulting in an additional decrease in property (MacDonald et al., 1987; MacDonald et al., 1990; Harrison et al., 2001; Bin & Polasky, 2004; Bin et al., 2008; Atreya et al., 2013; Bin & Landry, 2013). These results may imply that individuals underestimate risks in hazard-prone areas and adjust their risk perception in the wake of the event. Hallstrom and Smith (2005) identify that residential properties in SFHAs that are in the near-miss area of a major hurricane decrease in value in the aftermath of the event. A similar decrease in values, of residential properties located in SFHAs, is discovered in the work of Morgan (2007) in the wake of hurricane Ivan in 2004.

Literature considering the effect of hurricanes on residential property prices provides comparable evidence. Zhang & Peacock (2009) discover a decrease in residential property value in the years following the 1992 hurricane Andrew. The study finds differences within minority neighborhoods and tenure status with regards to recovery rates of residential property values after a hurricane event.

There are a few studies that consider the differential effects of natural hazards on residential properties *based on their structural characteristics*. Pinelli et al. (2004) describe the five most likely damage modes a hurricane causes to the structure of a residential property. The modes are sometimes dependent on each other, such as breaking of windows increases probability of roof loss, in other cases independent of each other, such as loss of shingles. The research conducted by Meloy et al. (2007) find that residential properties build according to post-Andrew building codes suffer less roof damage from 2004 hurricane Charley compared to the damage of hurricane Andrew in 1992. Corresponding results are found for the Building Standard Law (1981) in Tokyo. The rents of residential properties in SSZs tend to be higher for properties build under the Building Standard Law (1981) than properties build prior (Nakagawa et al., 2007). Furthermore, certain structural characteristics have a positive effect on residential property prices in hazard prone areas such as, mitigation features (Simmons, Kruse and Smith, 2002) and robust materials (Nakagawa et al., 2007).

1.3 RESEARCH PROBLEM

Do effects of hurricanes differ among properties with different structural characteristics? A vast amount of the literature examines natural risks and the effects on residential property prices. To date, however, few studies have examined the effect of hurricanes on residential property prices, with a focus on structural characteristics. Moreover, there is no study that examines the effect of a hurricane on the value of a residential property with a specific focus on wall structure. The aim of the present paper is to examine the effect of hurricanes on residential property prices, with a focus on the wall structure as a structural characteristic of a property, in order to fill the existing gap in the literature. Furthermore, ascertaining the value of investment in structural improvement of residential properties e.g. constructing a residential property with a concrete wall structure can be of societal relevance. Additionally, the study area, Florida, is the third largest populated state in the US, is struck relatively often by hurricanes (Livingston 2015; U.S Census Bureau population division, 2018). However, because it is a coastal state, following the trend as described in chapter 1.1, the population is projected to increase from 21 million in 2018 to 27 million in 2045 (Rayer & Wang, 2019). The increasing number of properties at risk can be of societal relevance. The central research question can be formulated as:

What is the effect of the 2004 hurricane Charley on residential property prices in Orange County Florida?

In order to answer such a comprehensive question, the main research question will be divided into three sub questions, regarding how residential property values are affected by natural hazards in general and hurricanes in particular, and how structural characteristics differentiate this effect. The three sub questions will be answered separately in the remainder of this thesis.

1. How are residential property prices affected by natural hazards?

This sub-question will be answered through the construction of the theoretical framework of this thesis in chapter two. In this chapter the effects of natural hazards, especially hurricanes, on residential properties as described in the literature, are examined. The approach will be to first, explore the prices of residential properties, after which the effect of natural hazards is examined. Findings in these two areas lead to the formulation of the hypotheses of this study.

2. To what extent does a hurricane affect residential property values?

Contrasting with the effect of natural hazards in general, the effect of hurricanes on residential property prices is analyzed in the third chapter. This section contains a statistical analysis of the empirical data on the effect of the 2004 hurricane Charley on the residential property values in Orange County Florida.

3. To what extent do the effects of a hurricane differ between residential properties based on their structural characteristics?

In this section the effect of a hurricane is examined based on the structural characteristics of a property. This in order to analyze differences between structural characteristics of residential properties. Furthermore, the empirical effect of hurricanes is tested for heterogeneity of certain structural characteristics of residential properties. The Chow test (Chow, 1960) will be used in order to examine differences between subgroups of residential properties.
All three sub-questions are integrated in the conceptual model as shown in Figure 1.

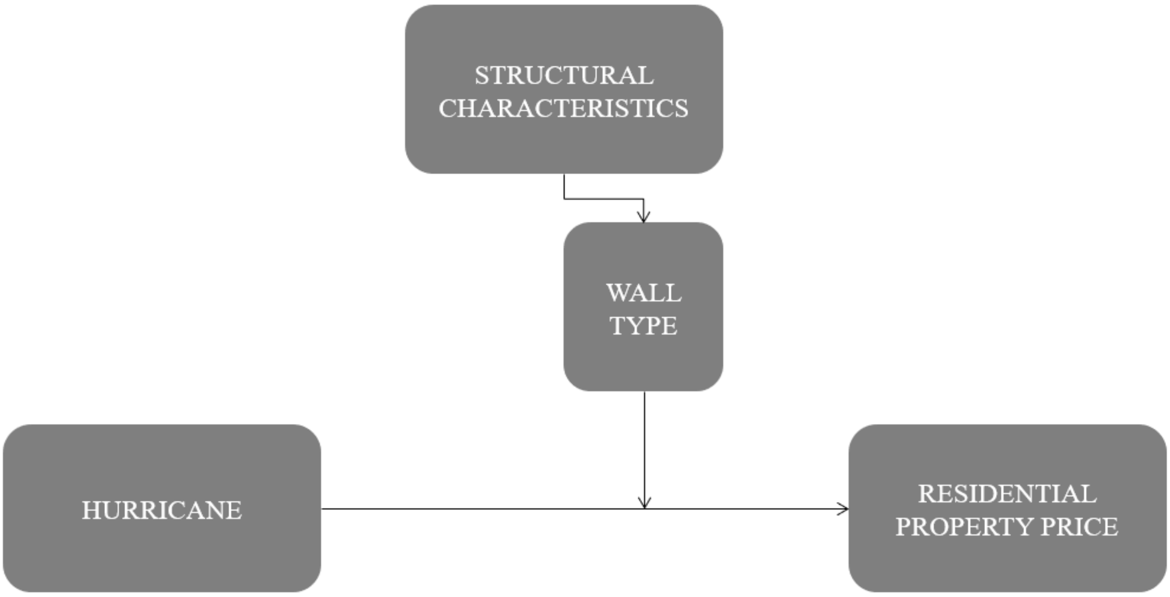

Figure 1: Conceptual Model.

1.4 OUTLINE

The remainder of this thesis is structured as follows. Chapter 2 consists out of the theoretical framework and hypotheses. The third chapter will examine data and methodology. The fourth chapter will include regression results, interpretation and limitations of the study. Chapter 5 discusses limitations of the study. The final chapter will conclude the research.

2. THEORETICAL FRAMEWORK

2.1 RESIDENTIAL PROPERTY PRICES

Real estate in general and residential properties specifically differ from most other products traded in the market due to their immobility and their heterogenous character. The latter because of the fact that there are no properties exactly the same. However, residential properties do, to a certain extent, feature similar characteristics e.g. have a living space, bathroom and are located on a certain piece of land. The sum of these characteristics and features differs from one property to the next. The heterogenous bundle of characteristics and features can be grasped and examined best in a hedonic model according to the literature (Cheshire & Sheppard, 1995; Rosen, 1974). Furthermore, they can be summarized in three extensive categories: neighborhood, location and structural characteristics. These characteristics affect and determine the price of a single residential property (Dubin, 1988; Stamou et al., 2017).

The neighborhood characteristics include neighborhood-effects such as, socio-economic status, physical appearance and quality in property prices (Kiefer, 2011; Can, 1992). Property prices can be affected negatively by neighborhood characteristics such as, high crime rates (Ceccato & Wilhelmson, 2019), abandoned surrounding properties (Han, 2013) and positively by higher education quality (Fack & Grenet, 2010) and redevelopment of industrial heritage sites (van Duijn et al., 2016).

The location characteristics consider geographical aspects of the residential property such as the proximity of and access to certain amenities, e.g. subway stations, schools, greenspace and shopping malls (Dubin, 1988; Can, 1992; Cheshire & Sheppard, 1995; Cheshire & Sheppard, 1998; Daams et al., 2016; Zhang et al., 2019). These amenities positively influence residential property prices. Contrasting, disamenities negatively influence residential property prices such as, industrial sites (de Vor & de Groot, 2011), airports (Jud & Winkler, 2006) and the negative external effects caused by these disamenities such as, pollution and noise (Nourse, 1967; Taylor et al., 1982). In many cases both the neighborhood and location characteristics can be grouped together since the variables included can affect both categories, e.g. proximity to a school can be beneficiary to both the neighborhood and the location (Stamou et al., 2017). Natural hazards are external effects that are, in most cases, geographically tied to a certain location and thus affect the prices of residential property located in these areas. Due to the focus of this study on this subject the natural hazards and their effects will be examined more thoroughly in the upcoming paragraph 2.2.

The structural characteristics include attributes of the residential property. The most important variables of frequent occurrence are, lot size, square feet, number of bathrooms, number of rooms, fireplace, air-conditioning, basement, garage spaces and pool. These characteristics are valued mostly positive in the literature. The age of a property and the time on the market are valued mostly negative in the literature (Sirmans et al., 2005; Dubin, 1988; Stamou et al., 2017).

The residential property prices are determined in the market where the demand meets the supply. In addition, to the fact that residential properties are heterogenous, the supply side of the market is static

(DiPasquale & Wheaton, 1992). This means that prices on the short term are determined by the demand side of the market. The households as economic agents represent the demand side of the market and therefore determine the prices of residential properties. The residential property as a product will be acquired based on the trade-off a household makes between housing and other goods in the first place. However, the combination of trade-offs is finite because a household is constraint by their budget. Households will pursue maximization of utility, within their constraint budget, to a point where exchanging housing for other goods does not result in result in an increase of utility (Harvey & Jowsey, 2003; Sirmans, 2005). In the second place, households derive utility (and therefore value) from the bundle heterogenous characteristics explained previously. However, households possess unique utility functions which complicates the pricing of a residential property even further. This causes difference in the valuation of characteristics across households e.g. a fireplace can be valued higher by one household compared to another. Because of this, as indicated previously, hedonic modelling is used to determine the price of a residential property. However, hedonic pricing models are, to a certain extent, location specific which results in the fact that the results are difficult to generalize across various different locations (Sirmans, 2005).

2.2 EFFECT OF NATURAL HAZARDS

When exogenous risk factors such as natural hazards are analyzed, natural hazards can be perceived as geographical attributes. This means that the risk of occurrence and potential economic loss are capitalized in the values of residential properties in hazard prone areas. Given perfect predictability, one would expect a perfect trade-off between the probability and size of economic loss of natural hazards on one hand, and the discount in residential properties on the other. A trade-off that is discovered in the literature is the difference between prices of residential properties in- and outside hazard prone areas such as, the discount on values within SSZs (Brookshire et al. 1985; Nakagawa et al., 2007). However recent literature also reports contradictory results. The study of Naoi, Seko & Sumita (2009) examines the effect of earthquake risks on housing prices in near miss areas of seismic events larger than JMA 6 (Japan Meteorological Agency) through a Difference-in-Difference (DND) framework based on hedonic pricing with longitudinal data, retrieved from questionnaires. The study reports evidence that consumers alter their assessments of risk just after a massive earthquake. An increase of 0.2% in the probability of an earthquake leads to a decrease of 13% in property value in the wake of an earthquake. Naoi, Seko & Sumita (2009) suggest that consumers are initially unaware or underestimate the risks of earthquakes. When new information is obtained, in this case through an earthquake event, the risk perception of consumers may change, and residential property values adjust accordingly. Bin & Landry (2013) find similar results for residential properties located in SFHAs after major flooding events as a result of hurricanes. The study consists of a hedonic pricing DND-framework on price differentials using cross-sectional combined data of properties. The prices of residential properties located in SFHAs decreased with 5.7% and 8.8% after hurricanes Fran and Floyd respectively. Similar results are found by Hallstrom & Smith (2005) in the wake of hurricane Andrew for near miss areas, resulting in a discount of 19% on repeated sales analysis, using repeat sales in a DND-framework. The discount effect of natural hazards tends to diminish over time and disappears within 5 to 9 years after the event took place (Bin & Landry, 2013; Atreya et al., 2013). Bin & Landry (2013) associate this with the absence of new information about the risks of natural hazards e.g. through recurring flooding. In the consecutive studies of MacDonald et al. (1987; 1990) the trade-off between the present value of insurance premiums in SFHAs and the premium of residential properties located outside hazard prone areas is examined. Both studies use hedonic pricing using cross-sectional data in order to find the willingness to pay of consumers for a marginal reduction of an undesirable state[1]. MacDonald et al. (1990) argue that an unbalanced trade-off can be either assigned to the market as a provider of imperfect information when the risk is not fully priced and, as a result, the premium is less than the insurance payments. On the other hand, it can be attributed to non-insurable costs when the premium is larger than the insurance payments. Both studies by MacDonald et al. (1987; 1990) discover results that demonstrate the latter. On the contrary, Harrison et al. (2001) find opposite results with discounts in property values being less than the insurance premiums, using cross-sectional data in a hedonic pricing model. The literature does not specify any differences for properties in areas that are struck by hurricanes. This could be because it is a lot harder to determine differences, since there are no specific predetermined increased risk areas such as the SFHAs and SSZs. Hurricanes, however, do decrease residential property prices when an area is struck. Zhang & Peacock (2009) find evidence that in the wake of hurricane Andrew of 1992 prices drop with 50.4% in the south of Miami-Dade County on average, using panel models predicting housing recovery with longitudinal tax appraisal data. However, in preliminary analysis compelling differences are observed between the average property prices of properties not struck (+4.4%), minor damage (-6.9%), moderate damage (-29.2%) and extensive damage (-85.2%) in 1993. Zhang & Peacock find that a 1% increase in hurricane damage results in a 4.41% decrease in residential property price in the first year following the hurricane. The study finds diminishing effects in the discount of residential property prices in the years following the hurricane. However, the effects of the hurricane are still visible in 1996 compared to properties that where not struck. The study also finds that the effects of the hurricane disproportionate for properties with extensive damage (effects lasts two years compared to one for properties with less damage), rental properties (-4% 1992, -7,7% 1993 compared to owner-occupied) and properties located in minority neighborhoods[2].

The structural characteristics of a residential property are features that affect the expected devaluation in various ways. Nakagawa et al. (2007) find that the structural characteristics of residential properties; fireproof construction, constructed with robust materials or build under the recent building

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[1] The undesirable state concerns the flood risk in low-elevated areas

[2] 1992: Hispanic -0.40%; Black -0.35% per 1% increase in respective population. 1993: Hispanic -1.2% (threefold increase) Black -0.65% (twofold increase) per 1% increase in respective population

code tend to have a positive effect on the rents of properties located in riskier areas, in a hedonic pricing model using cross-sectional data of rental properties in Tokyo. Results of the positive effect of building codes on rents are also discovered in the research conducted by Meloy et al. (2007). The study consists of damage assessment based on aerial photographs of residential properties in PGI. The research finds that properties build to the recent Standard Building Code (predecessor of the FBC 2001) tend to suffer less damage by hurricanes than properties build prior. One could argue that newer building codes take risk mitigation of natural hazards of frequent occurrence into account. Simmons, Kruse and Smith (2002) investigate whether alterations of the structural characteristics of residential properties, in order to protect them from hurricanes, is capitalized in their prices. This is done in a hedonic study using cross-sectional data. The researchers suggest that self-mitigation, in the form of storm blinds, and a high SII[3] (Structural Integrity index) have a positive effect on the value of a residential property. The results indicate that both a higher SII and storm blinds have a positive effect on residential property value. The latter improving the price with 5% on average. Regarding these results, it is possible that the structural characteristics of a property, for instance the type of construction, have significant effects on the price of that property when exposed to a natural hazard.

2.3 HYPOTHESES

Based on the literature findings two hypotheses can be stated:

H1. Residential properties located in affected areas after the 2004 hurricane Charley sell at a discount just after the hurricane and vary in space and time.

H2. The discount of a residential property, as a result of a hurricane, differs based on the wall type of a property.

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[3] The higher the number the more resilient the structure

3. DATA & METHODOLOGY

3.1 DESCRIPTIVE ANALYSIS

GIS Context

A parcel dataset considering the parcels in Orange County FL. Is used to determine which parcels in Orange County were struck by hurricane Charley in 2004. The parcels dataset consists of 428,827 observations of parcels and their respective geographical locations. In order to examine the track of Charley the NOAA (2005) records of hurricane tracks are consulted. The records include coordinates that pinpoint the path of the hurricane in 2004. According to the data Orange County Florida was struck by hurricane Charley on the 14th of August in 2004. The approximate timeframe when the hurricane passed through the county was between 01:11 AM – 02:19 AM. In order to examine the coordinates (North and West coordinates) of observations of Charley in 2004 within this timeframe the coordinates are converted into Decimal Degrees (DD). The conversion table of the coordinates in DMS (Degrees, Minutes, Seconds) and DD coordinates is included in appendix 3. The location of Orange County within Florida and the track of hurricane Charley through Orange County are presented in figure 2 and 3. Note that hurricane Charley passed through Orange County FL. from south to north.

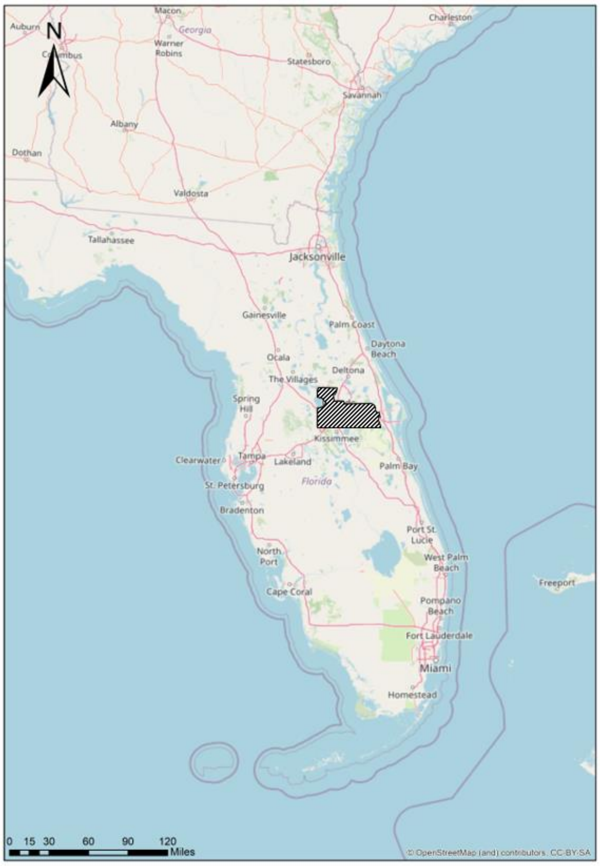

Figure 2: Orange County (OC) in Florida

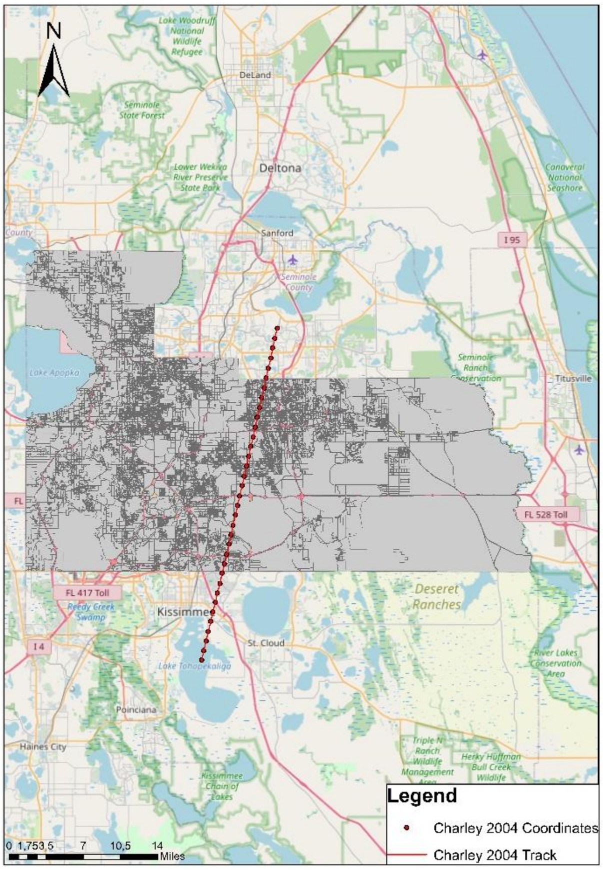

Figure 3: Track of 2004 hurricane Charley through OC

The coordinates of the observations of hurricane Charley (DD format) are inserted into GIS and are plotted as geographical XY coordinates. A line is drawn between these coordinates to determine the path of hurricane Charley through Orange County Florida (figure 3). In order to determine the affected area of properties struck by hurricane Charley a buffer is created with a range of 1,000 meters from the hurricane path. By combining the buffer zone and the parcels of properties included in the Orange County parcel data, the parcels that are assumed to be struck by hurricane Charley in 2004 can be selected through intersection. In Orange County a total of 22,326 parcels intersect with the buffer zone and are assumed to be in the area that was struck by hurricane Charley (= target area), see figure 4[4]. In the parcel data a new binary variable is created for these parcels that meet the condition: *located within 1,000 meters of the hurricane path.* The parcels that meet this condition are given a value of 1 and the remaining parcels are given a value of 0. The separation of the data (in- and outside struck area) is solely based on geographic location. Furthermore, the 2010 census tracts are joined with the parcel data to control for neighborhoods in the regression. The Orange County parcels dataset including hurricane path and census tracts is then exported for the statistical analysis.

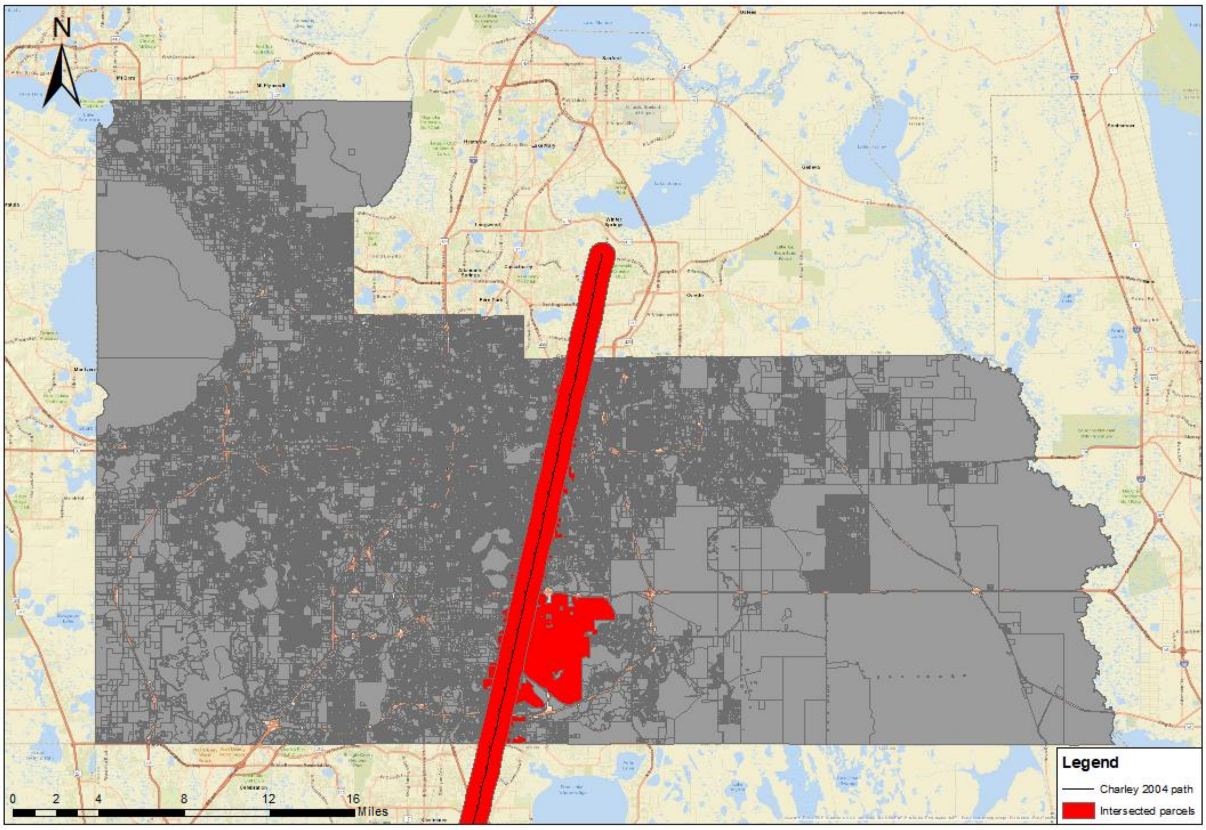

Figure 4: Hurricane path Charley and affected parcels Orange County FL.

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[4] Note that the parcel data includes all parcels of Orange County. The intersection of the buffer zone with the parcel leads to a selection of parcels of which some do not have a residential zoning (e.g. the airport). These observations of parcels are deleted when they are merged with the residential transactions dataset as a result of a 'non-match'.

The missing values for parcel number and duplicate observations are deleted from the parcel dataset. The parcel data is then merged with the transaction data. During this merge the observations of the transaction data are added to the parcel dataset based on parcel ID. The gross number of observations of the dataset transactions including information of parcel, census tracts and hurricane path is 482,760 parcels before statistical analysis (see appendix 2).

Statistical dataset

The empirical analysis in this thesis is based on cross-sectional data that contains a set of 178,206 residential arm's length transactions during the period 2002-2012 in Orange County Florida. The data was gathered by OCPAFL (Orange County Property Appraiser Florida), which is a certified property appraiser in Orange County Florida. The data covers the, transaction date, city codes, and different characteristics of the residential properties, such as, floor area, number of baths, exterior walls and building age. During the merge between the parcel data and transaction data a new dataset was created with 482,760 observations. *Note that the merge included a high number of observations of parcels that did not match any of the transactions which will be removed. This leads to a high number of deleted observations for the first variable.* In order to prepare the dataset for statistical analysis outliers and missing values are removed from the variables. For the variable sales price of residential properties "salesprice" all observations outside the 25.000 - 1,500,000 USD range are dropped. This range of transaction prices is commonly used in literature studying external effects (see e.g. Zhang et al., 2019; Morgan 2007; van Duijn et al., 2016; Bin et al., 2008). This leads to a total of dropped observations of 321,654[5]. Within the structural characteristics the observations are dropped for the variable "totalbedroom" with less than one bedroom (- 84) and one outlier in the variable for baths. When the floor area is considered all observations are deleted outside the range of 150 – 11000 square feet (-15). Furthermore, within the variable for the total heated area the observations with a value less than 20 square feet are deleted (-10). These variables are later transformed to square meters in order to better interpret the results. Note that the final range of both variables as displayed in table 1, floor area (63 – 808 M2) and heated floor area (47 - 520 M2) are consistent with literature studying external effects (see e.g. van Duijn, 2016; MacDonald et al., 1987; Bin & Polasky, 2004; Bin et al., 2008; Atreya et al., 2013). The observations of age of a property (date of sale – year built) with a negative value and an outlier with an unlikely high age are deleted (-23). Note that the range in age (1 – 90 years) as displayed in table 2 is consistent with the literature that studies external effects (see e.g. Bin & Polasky, 2004; Bin et al., 2008; Atreya et al., 2013; Morgan, 2007). For the dummy that indicates if properties are located in the target area (struck by hurricane Charley) the missing values are deleted (-380). The observations for the variable exterior wall type which could not be categorized in either wood, stone or metal are

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[5] Because this is the first variable for which observations are dropped the non-matched observations, as a result of the merge between the parcel dataset and the transaction dataset, will be deleted. This leads to a relative high number of dropped observations for the variable "salesprice".

dropped (-172). The wall types, their specification, and the way they are categorized is included in appendix 4. Finally, the observations with missing values for the variables used are deleted (-332).

Upon closer examination of the mean prices for properties in the target area (within 1,000 m buffer) and outside the target area there is no distinct visible shock in property prices directly after the hurricane (figure 5). Furthermore, the mean property prices seem to in- and decrease at the same rate. Due to this the decision was made to focus the analysis on a smaller sample area that considers all residential properties within 2,000-meter proximity to the hurricane. The sample area is then divided into a target area (the existing 1,000 m proximity to the hurricane path) and control area for properties between 1,000 – 2,000 meters distance to the hurricane path. The use of outer rings as a control area is not unusual in the literature that examines external effect on residential property prices (see e.g. Zhang et al., 2019; van Duijn et al., 2016; Schwartz et al., 2006; Han, 2014). This decision included the removal of observations of transactions at a distance of more than 2,000 meters from the hurricane path (-145,397). The table with dropped values is displayed in appendix 1. The net number of observations for estimation is 14,471 with 6,280 observations for the target area and 8,191 observations for the control area. The descriptive statistics for the total dataset (sample area) are presented in table 1. The definitions of used variables are displayed in table 2.

Table 1: Summary Statistics

Variable	**[1] Mean**	**[2] Std. Dev.**	**[3] Min**	**[4] Max**
Property Price	166,886.2	86,412.93	25,200	1,200,000
Transaction Year	2004.822	3.332059	2000	2012
Total Floor Area	199.8501	63.64127	63.35934	808.3427
Total Heated Floor Area	151.8602	49.75476	47.00855	520.7172
Total number of Bedrooms	3.205445	.687745	1	8
Total number of Baths	1.986241	.5557991	1	5
Age of Property	24.95757	16.82657	1	90
Exterior Wall Wood	.0741483		0	1
Exterior Wall Stone	.9068482		0	1
Exterior Wall Metal	.0190035		0	1
Post Charley Dummy	.5341027		0	1
Target Dummy	.4339714		0	1
Distance to Hurricane Path	1077.607	563.3133	0	1999.666
Year Quarters	180.7662	13.35371	160	211
Census Tracts	15057.88	1650.884	13201	18400

N = 14,471

Table 2: Definition of variables

Variable	Definition
Property Price	The sales price of a residential property denoted in USD
Transaction Year	The year in which the transaction took place
Total Floor Area	The total floor area of a residential property in square meters
Total Heated Floor Area	The total floor area of a residential property in square meters that is heated/air conditioned
Total number of Bedrooms	The total number of bedrooms in a residential property
Total number of Baths	The total number of baths in a residential property
Age of Property	The total age of a property in years at the time of the sale (sale date – construction year = age of property)
Exterior Wall Wood	Dummy for exterior walls made out of wood (wooden exterior wall = 1; no wooden exterior wall = 0)
Exterior Wall Stone	Dummy for exterior walls made out of stone (stone exterior wall = 1; no stone exterior wall = 0)
Exterior Wall Metal	Dummy for exterior walls made out of metal (metal exterior wall = 1; no metal exterior wall = 0)
Post Charley Dummy	Represents a time indicator for properties sold in the period after hurricane Charley occurred. Properties sold after hurricane Charley are given a value of 1 (sold after hurricane Charley = 1; sold before hurricane Charley = 0)
Target Dummy	Represents a geographical indicator for transactions of properties located in the area which was struck by hurricane Charley in 2004 (= 1,000m buffer zone). Properties located in this area and sold between 2000-2012 are given a value of 1 (located in area =1; not located in area = 0)
Distance to Hurricane Path	Indicates the Euclidian distance between the property and the path of the hurricane in meters
Year Quarters	Year-quarter fixed effects are measured in year quarters from Q1 2000 – Q4 2012
Census Tracts	Location fixed effects are measured in small geographical areas known as census tracts. The 2010 census tracts were used

Due to the decision to split the data in two sub samples histograms of the property prices of sample area, target and control area are displayed in figure 6. The histograms of the property prices within the target and control area suggest equal distributions. Because of the positive skewed distributions, the natural logarithm of the property prices is used for statistical analysis. Additionally, the summary statistics of both sub-samples (target and control) is displayed in table 3. The statistical bookkeeping file (Stata), with the transformation of variables and data is included in appendix 2.

Table 3: Summary Statistics Target and Control area

	Target area (0-1,000 m)				Control area (1,000-2,000 m)			
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Property Price	160,804	81,905.92	25,200	960,000	173,316.1	89,340.72	25,200	1,200,000
Transaction Year	2004.825	3.290488	2000	2012	2004.82	3.363782	2000	2012
Floor Area	194.709	62.63493	68.37607	608.1382	203.7918	64.12741	63.35934	808.3427
Heated Floor Area	149.2804	50.52731	50.53883	520.7172	153.8382	49.06554	47.00855	519.5095
# of Bedrooms	3.189172	.6848837	1	7	3.217922	.6897124	1	8
# of Baths	1.954443	.574141	1	4.5	2.010621	.5400844	1	5
Age of Property	25.19172	18.16818	1	87	26.54474	15.69646	1	90
Exterior Wall Wood	.0859873		0	1	.0650714		0	1
Exterior Wall Stone	.8944268		0	1	.9163716		0	1
Exterior Wall Metal	.019586		0	1	.018557		0	1
Post Charley Dummy	.5401274		0	1	.5294836		0	1
Dist. to Hurricane Path	522.3102	297.1524	0	999.7981	1503.351	274.2657	1000.049	1999.666
Year Quarters	180.7497	13.2024	160	211	180.7789	13.46935	160	211
Census Tracts	14947.48	1653.262	13201	18400	15142.53	1644.145	13201	18400
Number of obs.	*6,280*				*8,191*			

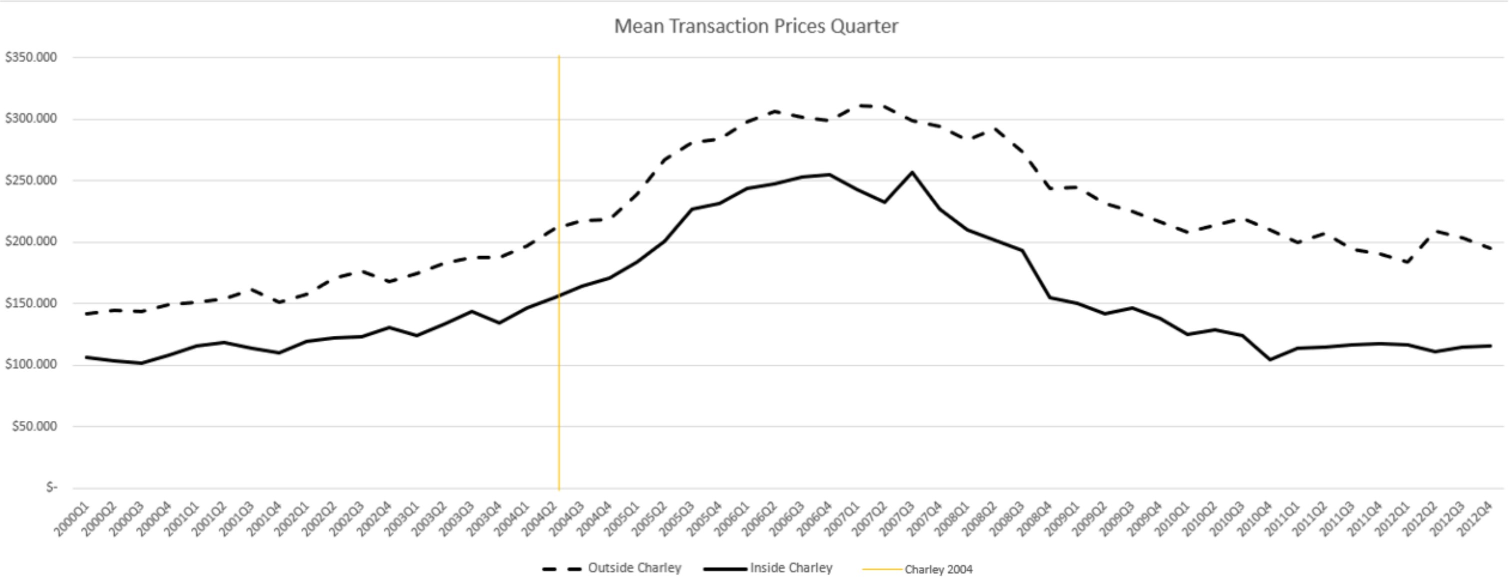

Figure 5: Mean property prices per quarter within the 1,000 m proximity buffer of Charley and outside this buffer (= all other residential properties sold in Orange County)

Figure 6: Histograms property prices sample area, target area and control area

3.2 METHODOLOGY

Hedonic model

Hedonic modelling is used extensively in the literature that examines natural hazards and widely recognized in the field as a relevant approach in order to explain external effects (see e.g. Sirmans, 2005; Naoi et al., 2009; Hallstrom & Smith, 2005; van Duijn et al., 2016; Zhang et al., 2019). The hedonic model is used in those studies to value the monetary risk of certain natural hazards which are otherwise difficult to appraise. The hedonic model presents the price of a property as a bundle of attributes represented by the aspects characteristics, location and neighborhood and can be described as $Z = (z_1, z_2, \ldots, z_n)$. A hedonic model provides a method to estimate residential property values while certain change e.g. exposure to a hurricane in a ceteris paribus scenario (Rosen, 1974; Sirmans, 2005). When the hedonic model is constructed as described the market price of a residential property can be expressed as:

$$P = f(L, N, S) + \varepsilon$$

Where P represents the price of a residential property, L represents a vector of location aspects, N is a vector of neighborhood aspects and S represents a vector of structural characteristics of a residential property. The ε serves as a vector of error terms (Stamou et al., 2017). The hedonic model assumes that the points between residential property prices and a given attribute is established by the equilibrium interactions of consumers and producers. The premises are twofold, a competitive market and all consumers buy at market prices. Based on hedonic methodology the base hedonic price model is established and can be expressed as:

$$\begin{aligned} ln\,(P_{ijt}) = {} & \beta_0 + \beta_1 \cdot ln(Floor\ Area) + \beta_2 \cdot ln(Heated\ Floor\ Area) + \beta_3 \cdot ln(Bedrooms) \\ & + \beta_4 \cdot ln(Baths) + \beta_5 \cdot ln(Property\ Age) + \beta_6 \cdot Wall\ Type + \varepsilon_{it} \end{aligned} \qquad [1]$$

Where $ln(P_{ijt})$ is the natural logarithm of the price of the residential property i within geographical location j in year quarter t. β_0 represents the constant. The *ln(Floor Area)*, *ln(Heated Floor Area)*, *ln(Bedrooms)*, *ln(Baths)* and *ln(Property Age)* represent the natural logarithms of the structural variables and Wall Type is a dummy variable for exterior wall type of properties. The ε_{it} serves as an error term for random errors. Considering the formula, the control variables for characteristics of the properties are limited within the dataset. Variables that are used commonly in the literature, that are not included in the dataset, are the presence of certain characteristics such as a, balcony, terrace, fireplace, pool or carport (Zhang et al., 2019; MacDonald et al., 1987; Hallstrom & Smith, 2005). This could cause omitted variable bias. However, since these structural characteristics are viewed as positive elements in the literature causing an increase in property price when present, the estimation is predicted to have a positive bias.

Difference-In-Difference framework

In order to examine differences between properties in and outside, before and after, the hurricane struck area a difference-in-difference framework is used. Chapter 2 emphasizes that the difference-in-difference framework is used extensively within the literature in the examination of external effects on residential property prices. The DND-method can determine the differences between a target and control group, post intervention, given a certain treatment which is limited to the target area. The effect measured in the DND-framework and thus the difference in difference is the intervention effect. Given the DND-framework the intervention effect in this case is the effect of the 2004 hurricane Charley on property prices within the 1,000-meter area. The hedonic DND-model can be specified as follows:

$$\begin{aligned} ln\ (P_{ijt}) = \beta_0 + \beta_1 \cdot ln(Floor\ Area) + \beta_2 \cdot ln(Heated\ Floor\ Area) + \beta_3 \cdot ln(Bedrooms) \\ + \beta_4 \cdot ln(Baths) + \beta_5 \cdot ln(Property\ Age) + \beta_6 \cdot Wall\ Type + \beta_7 \cdot Target \\ + \beta_8 \cdot Target \times Post + \varepsilon_{it} \end{aligned} \qquad [2]$$

Where *Target* is a dummy variable that indicates if a property was within 1,000-meter proximity of the 2004 Charley hurricane path. In order to estimate the effect of the hurricane on property prices in the target area an interaction term is added between *Target* and *Post*, where post indicates whether a property was sold after hurricane Charley. The coefficient of the interaction estimates the intervention effect of the hurricane on residential property prices and subsequently tests the first hypothesis of this thesis. In order to examine differences in wall structure the DND-model will be modified to:

$$\begin{aligned} ln\ (P_{ijt}) = \beta_0 + \beta_1 \cdot ln(Floor\ Area) + \beta_2 \cdot ln(Heated\ Floor\ Area) + \beta_3 \cdot ln(Bedrooms) \\ + \beta_4 \cdot ln(Baths) + \beta_5 \cdot ln(Property\ Age) + \beta_6 \cdot Wall\ Type + \beta_7 \cdot Target \\ + \beta_8 \cdot Target \times Post + \beta_9 \cdot Target \times Post \times Wall\ Type + \varepsilon_{it} \end{aligned} \qquad [3]$$

Where the interaction between *Target x Post x Wall Type* estimates the intervention effect of a hurricane on the prices for residential properties with specific wall types in the target area sold after the hurricane. The intervention effect that is measured tests the second hypothesis of the paper and determines whether certain wall types do influence the effect a hurricane has on the residential property value. This in order to examine differences between wall structure in the target area.

4. RESULTS

4.1 EMPIRICAL ANALYSIS

Regression results

Table 4 shows the regression results for model 1, 2 and 3. Model 1 uses structural variables, year-quarter fixed effects and location fixed effects to estimate the effect differences between sales prices. The coefficients for total area, total heated area and number of baths show a positive effect at the 1% level, where an increase with 1 percent in one of these structural variables leads to an increase in the sales price. The variable property age shows a negative effect at the 1% level, where an increase in age leads to a decrease in sales price. Which can be explained by the fact that properties on average decrease in value when the building ages which is consistent with the literature (Sirmans et al., 2005). The coefficient of the variable number of bedrooms is positive but does not have a significant effect. This can be attributed to the fact that more bedrooms in most cases equals more floor space area. Considering the exterior wall type both wood (-1.3%) and metal (-1.3%) have a negative effect on the sales price of a property compared to properties with stone walls. However, both coefficients are insignificant.

Model 2 includes the target dummy which specifies if properties are within (1,000 m) or outside the hurricane struck area. Furthermore, it includes a post dummy indicating if a property was sold after the hurricane event. Both the target and post dummy are interacted with each other in order to estimate effects for properties in the target area sold after the hurricane. The adjusted R^2 does slightly increase compared to the previous model. Model 1 and 2 explain respectively 74.65% and 74.70% of the variance. This can be explained by the fact that in both models the census tracts (small geographical areas) and year quarters are used to control for location and time fixed effects. Compared to the literature that examines the effect of natural hazards the explained variance is above average from a low 14% (Naoi et al., 2005) ranging to a high 90% (Nakagawa et al., 2007)[6]. The target dummy is significant at the 1% level. The property that is located within the target area trades at a discount of 1.9% on average. This discount is visualized in the mean prices per quarter as displayed in figure 5 and yields no surprise. Note that the target dummy is limited to indicate solely the location of the property. The interaction term between target and post has a negative significant coefficient at the 5% level. The coefficient estimates a discount in residential property prices of 1.9% when properties are located in the target area and sold after the hurricane compared to properties sold outside the hurricane struck area.

Model 3 includes interaction terms between the target dummy, post dummy and exterior wall types, also including reciprocal interactions between the dummies. The coefficient of the target dummy decreases to a discount of approximately 1.3% for properties sold in the target area. Additionally, the coefficient is only significant at the 10% level. However, the interaction term between target and post

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[6] Approximately five out of nine studies, examining natural hazards, that denote the R-squared have a lower explained variance (Naoi et al., 2009; Nakagawa et al., 2007; Macdonald et al., 1987 & 1990; Harrison et al., 2001; Brookshire et al., 1985; Bin & Polasky, 2004; Hallstrom & Smith, 2005; Zhang & Peacock, 2010).

dummies shows a larger discount, for properties sold after the hurricane in the area that was struck, of -2.4%. The interactions between the target dummy and wall types shows a negative and significant (1% level) coefficient for wooden exterior walls. When compared to properties sold in the target area with stone walls, prices of properties with wooden walls are 6.15% lower. Considering the interactions between target post and wall type dummies only wooden exterior walls are significant at the 10% level. This can be interpreted as properties located in the hurricane struck area sold after hurricane Charley with wooden exterior walls sell at a premium compared to similar properties with stone walls located in the same area that were sold after the event. These results suggest that residential properties with stone or metal exterior walls[7] are valued less in the wake of a hurricane in the area struck compared to properties with wooden exterior walls.

Table 4: regression results

	[1]	**[2]**	**[3]**
Sample	**<2,000 m**	**<2,000 m**	**<2,000 m**
Target area	**0-1,000 m**	**0-1,000 m**	**0-1,000 m**
Control area	**1,000-2,000 m**	**1,000-2,000 m**	**1,000-2,000 m**
Ln Total Area M2	.4435093***	.4414814***	.4399631***
	(.021115)	(.0210997)	(.0211058)
Ln Total Heated Area M2	.2427307***	.2414342***	.2413123***
	(.0209731)	(.0209522)	(.020951)
Ln # of Bedrooms	.0125973	.0145583	.0146888
	(.0129618)	(.0129547)	(.0129606)
Ln # of Baths	.1202724***	.1171417***	.1176707***
	(.0104272)	(.0104299)	(.0104331)
Ln Property Age	-.0900106***	-.0924174***	-.0926771***
	(.0034637)	(.0034892)	(.0034898)
Exterior Wall Wood	-.013293	-.0102173	.0148603
	(.0093465)	(.0093591)	(.0160669)
Exterior Wall Metal	-0.0133204	-.0116561	.0040289
	(.0153762)	(.0153628)	(.0303634)
Target		-.0191945***	-.0128382*
		(.0071631)	(.0075493)
Target x Post		-.0198483**	-.024362***
		(.0083806)	(.0088224)
Target x Exterior Wood[i]			-.0634534***
			(.0221042)
Post x Exterior Wood[i]			-.0190889
			(.0223364)
Target x Post x Exterior Wood[i]			.0597706*
			(.0317262)
Target x Exterior Metal[i]			.0095095
			(.0469021)
Post x Exterior Metal[i]			-.0116495
			(.0408402)
Target x Post x Exterior Metal[i]			-.0494428
			(.0616527)
Constant	7.567393***	7.63131***	7.634023***
	(.0629474)	(.0642387)	(.0642578)
Year-quarter Fixed Effects	Yes	Yes	Yes
Location Fixed Effects	Yes	Yes	Yes
Number of observations	14,471	14,471	14,471
Adjusted R^2	0.7465	0.7470	0.7471

*Note: The dependent variable is the natural logarithm of the sales price ***p<0.01 **p<0.05 *p<0.10*

[i] The reference category is stone exterior walls

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[7] Insignificant coefficient for metal exterior wall equals the same trend as reference category, which is stone exterior wall.

Chow test

In order to test for heterogeneity between subsamples a Chow test is performed between the three subsamples of the wall types, stone, wood and metal. The Chow test determines whether the parameters of the subsamples differ from each other in such a way that they are better estimated in three separate regressions instead of a pooled regression (Chow, 1960). The Chow test can be formulated as:

$$F = \frac{(RSSp - (RSS1 + RSS2 + RSS3))}{(RSS1 + RSS2 + RSS3)} * \frac{(n - 3k)}{(3k - k)}$$

Where *RSSp* is the sum of residuals for the pooled model. *RSS1*, *RSS2* and *RSS3* are the sum of residuals of the individual models of the three subsamples, respectively, stone, wood and metal. *k* indicates the number of parameters and *n* the total number of observations. Because all models estimate the coefficients for the wall types a fourth regression model is constructed. This fourth model is based on the second model but excludes the wall types. The fourth regression model, as well as estimates for the subsamples, are included in appendix 5. A chow-test is performed on based on this fourth regression model[8]. This gives us:

$$F = \frac{(880.971153 - (775.678641 + 64.6065552 + 14.1670553))}{(775.678641 + 64.6065552 + 14.1670553)} * \frac{(14{,}471 - 3*94)}{(3*94 - 94)} = 2.342$$

The critical value for F, given 14,189 and 94 degrees of freedom, is 1.373 at the 1%-level. The F-value obtained from the Chow test is larger with 2.342. This means that H0 can be rejected at the 1%-level[9] and the estimated parameters between properties with the wall types stone, wood and metal are not equal. One could argue that based on this result, given the fact that property values are estimated in different regressions, there is a higher chance that wall-types as a structural characteristic of a residential property have different values. This would result in a partial confirmation of the second hypothesis. However, there is no evidence to substantiate this claim. The separate regressions based on wall type indicate that residential properties with the wall type stone sold after the hurricane trade at a discount. The interaction is insignificant for the wall types wood and metal. This does, to a certain extent, contrast the results of the third regression model. Additionally, the result confirms the second hypothesis where: *The discount of a residential property, as a result of a hurricane, differs based on the wall type of a property.*

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[8] The estimates for the pooled model used in the Chow test differ marginally compared to the second model.

[9] The critical F-value at the 5%-level is 1.253 and 1.192 at the 10%-level.

4.2 DISCUSSION

The literature examines natural hazards as geographical attributes that are tied to certain areas e.g. SSZs and SFHAs. When a household locates outside the increased risk areas they pay a premium for the residential property. In a perfect market the trade-off between expected loss from a natural hazard and the premium for locating outside increased risk areas would be equal. However the literature finds that this is not the case and household either underestimate or overestimate the risk depending on the number of occurrences and the number of years since the last natural hazard (see e.g. Brookshire et al., 1985; Nakagawa et al., 2007; Naoi et al., 2009; Bin & Landry, 2013; Harrison et al., 2001).

This study tried to ascertain whether properties located in an area that was struck by the 2004 hurricane Charley are affected in financial terms, residential property prices. Considering the first hypothesis: "*Residential properties located in affected areas after the 2004 hurricane Charley sell at a discount just after the hurricane and vary in space and time"* seems to be accurate based on the regression results. This can be observed in the significant interaction in model 2 between the target area and post Charley dummy. There is a discount for residential properties sold after the hurricane within 1,000-meter proximity of the hurricane. This suggests that properties in the outer-band (1,000 – 2,000 m) sell at a higher price on average after a hurricane, explaining the variation in space between the target and control area as indicated in the first hypothesis. This follows the trend of literature examining natural hazards. However, the literature finds higher discounts in residential property prices for instance, Bin & Landry (2013) -5.7% and -8.8% in SFHAs and Naoi et al. (2009) -13% in SSZs compared to the result of -1.9% and -2.4% in this study. The higher discount could be because of the fact that properties examined in the literature are located in "high risk" (SSZs and SFHAs) areas and a bias in the risk assessment of households. Compared to the dataset used none of the properties are located in these high risk areas which means that the price will therefore experience a smaller correction. The discount for residential properties is larger in high risk areas because the risk is not fully priced in property prices. This fallacy of improper risk assessment by households is discovered in the studies of Harrison et al. (2001) and Naoi et al. (2009). The variation in time is harder to acknowledge given the interactions used in the model. However, there is an observed difference between the prices for properties post event in the target area versus properties sold in the control area using the same interaction term. In the literature the variation in time is present with diminishing effects over 5 to 9 years in the wake of the natural hazard (Bine & Landry, 2013; Atreya et al., 2013). However, this is mostly attributable to the absence of new information through e.g. recurring flooding in the high risk areas. This leads to the situation as explained previously where households, when time passes by, underestimate risk. A more plausible scenario is explained by Zhang & Peacock (2009), where the effects of a hurricane are predominantly visible in the first year after the hurricane. Regarding the dataset used there are more similarities with this thesis since the natural hazard examined was predominantly a wind event and the effects are not based on perceived risk by households.

The second hypothesis: *The discount of a residential property, as a result of a hurricane, differs based on the wall type of a property* seems to be accurate for properties with wooden walls based on the estimates in the third model. The regression results show a slightly significant premium for residential properties with wooden walls inside the struck area, compared to properties with stone walls. The literature suggests that mitigation features such as storm blinds, a high SII (Simmons et al., 2002), robust materials and build under the most recent building codes (Nakagawa et al., 2007) have a positive influence on residential property prices. Based on the effect of robust materials and a high SII in the literature one would expect a premium for properties with either stone or metal wall types compared to properties with wooden walls. However, the results indicate a contradictory result and places a premium on properties with wooden walls in the target area sold after the hurricane. Furthermore, the Chow test indicates that the estimates for properties based on their wall type are not equal. The regression for the residential properties with a stone wall type indicate a significant discount in the interaction between the target and post dummies. Which means that residential properties located in the struck area that are sold after the hurricane with stone walls trade at a discount. This partially contrasts the finding in the third regression model since properties with the wall type wood no longer trade at a premium. However, it is partially consistent with the results from model three where compared to stone walls, a property with wooden wall traded at a premium. This would mean that, when isolated, either wood walls sell at a premium or stone walls sell at a discount. I find results that suggest the latter.

5. LIMITATIONS OF STUDY

There are a number of limitations to this study one of them being the fact that with every division in the data (e.g. Charley dummy, wall types and sub samples) the sample size gets smaller and the eventual coefficient will be less reliable. Which leads to the problem that the sample might not be representative. Additionally, compared to other natural hazards such as flooding, earthquake events and hurricanes are less likely to be recurring based on geographic location. For instance, flood zones are determined locations with a certain chance to flood every 100 years. Hurricanes on the other hand are less likely to recur on the exact same location and are less predictable on a geographical level. Which makes it hard to determine a discount for this type of event. It might very well be the case that Florida as a coastal state has a discount on property values on average compared to other states that are not likely to be struck as often as Florida. Furthermore, it might be interesting to examine the state that was struck directly when the hurricane made landfall, since the wind speeds of the hurricane will be at their peak level and observed destruction will be larger. The hurricane of this thesis, Charley, made landfall in Charlotte County and traveled approximately 200 kilometers before reaching Orange County. During this travel over land the hurricane lost wind speed and the damage was limited to approximately 881 million USD.

6. CONLUSION

This thesis examined the effects of hurricane Charley on residential property values. In particular the study focused on the differences between structural characteristics regarding the property values in the wake of the event. The literature identified that natural hazards can be viewed as geographical attributes to certain regions. The attributes include a trade-off between chance of occurrence and the potential damage on one hand versus a discount in residential property price on the other. In the literature these trade-offs are observable in SSZ's and SFHA's where properties trade at a discount compared to 'control' areas. However, results seem to vary when distance to and moment of occurrence are considered, with diminishing effects when both indicators increase. Furthermore, the literature finds that structural characteristics matter in terms of property value regarding residential properties in the SSZ's and SFHA's. For instance, properties build under newer building codes or constructed with certain safety features are valued higher than similar properties without these characteristics. Based on these findings two hypotheses were formulated and tested.

The analysis of residential property values was two-fold with the descriptive analysis including the preparation of data through the plotting of the hurricane, target and control areas in GIS in the dataset that considers all parcels in Orange County and merging these parcels that include new information with the transaction dataset. Within Stata the new dataset based on matched values (approx. 160,000) was cleaned of outliers and missing values. Finally, the observations outside the sample area (> 2,000 m) are deleted and the final dataset for statistical analysis considers 14,471 observations of which 6,280 in the target area (< 1,000 m) and 8,191 in the control area (1,000 – 2,000 m). The second phase considers the statistical analysis of the data. Through hedonic difference-in-difference model results are found that indicate that properties located in the struck area sell at a discount after the event of 1.9% - 2.4% on average. Furthermore, results are found that residential properties located in the hurricane struck area with wooden walls trade at a premium compared to properties with either metal or stone walls, after the hurricane took place. The results suggest that both hypotheses are accurate. The Chow test that was performed between the three wall-types indicated inequality between the parameters of the subsamples. The result of the third regression, when isolated, lead to a discount for residential properties with stone walls sold after the hurricane in the hurricane struck area.

Considering the results and method there are a few limitations to this study. One of the most notable limitations is the fact that the dataset gets divided multiple times into smaller sub-samples making the coefficients less reliable. Furthermore, hurricanes in general are not recurring events or geographical attributes as much as floods or earthquakes are, this could mean that the results are less observable. Additionally, when hurricane Charley reached Orange County the hurricane had decreased in wind speed, which also decreased its destructive power. It would be interesting to study the results for a coastal county like Charlotte County where the hurricane made landfall in 2004 and wind speed would be at its peak level.

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APPENDICES

APPENDIX 1 DROPPED VALUES TABLE

Table A: Dropped Values table

Dropped Observations	**Command**	**Number of dropped obs.**
Gross Observations		**482,760**
Dropped observations with property price below $ 25,000 threshold	“Keep if salesprice>25000”	-16,366
Dropped observations with property price above $ 1,500,000 threshold	“Drop if salesprice>1500000”	-305,288
Dropped observations with less than one bedroom	“Drop if totalbedroom<1”	-84
Dropped observations with less than one baths	“Drop if totalbath<10”	0
Dropped outlier in observations with transformed number of baths	“Drop if totalbath_real>20”	-1
Dropped observations with total area less than 150 sqft	“Drop if totalareasqft<150”	-2
Dropped observations with total area more than 11,000 sqft	“Drop if totalareasqft>11000”	-13
Dropped observations with total heated area less than 20 sqft	“Drop if totalcamaareasqft<20”	-20
Dropped missing values for the Charley dummy	“Drop if Charley_DU>1”	-380
Dropped observations with unclassified exterior wall types	“Drop if exteriorwallcode1_n==1”	-37
	“Drop if exteriorwallcode1_n==10”	-22
	“Drop if exteriorwallcode1_n==3”	-6
	“Drop if exteriorwallcode1_n==31”	0
	“Drop if exteriorwallcode1_n==33”	-1
	“Drop if exteriorwallcode1_n==5”	-56
	“Drop if exteriorwallcode1_n==9”	-50
Dropped observations with a negative or unlikely high age	“Drop if propertyage<0”	-22
	Drop if propertyage>400	-1
Dropped missing values	“Drop if missing ln_propertyage”	-14
	“Drop if missing real_tract”	-539
Deleted values outside the sample area of 2,000-meter proximity	“Drop if samplearea<1”	-145,397
Net Observations		**14,471**

APPENDIX 2 DO FILE AND BOOKKEEPING

The Syntax for GIS and Stata are intentionally excluded.

APPENDIX 3 CONVERSION TABLE COORDINATES CHARLEY

Table B: Conversion table coordinates (NOAA, 2005)

CONVERSION TABLE

Source coordinates expressed in North West			Conversion in DMS coordinates		Conversion in DD coordinates	
			Longitude	**Latitude**	**Longitude**	**Latitude**
08/14/2004 01:11:34	28.226 N	81.384 W	81°23'02"	28°13'33"	-81,3838889	28,2258333
08/14/2004 01:13:34	28.239 N	81.381 W	81°22'51"	28°14'20"	-81,3808333	28,2388889
08/14/2004 01:15:34	28.252 N	81.377 W	81°22'37"	28°15'07"	-81,3769444	28,2519444
08/14/2004 01:17:34	28.265 N	81.374 W	81°22'26"	28°15'54"	-81,3738889	28,2650000
08/14/2004 01:19:34	28.279 N	81.370 W	81°22'12"	28°16'44"	-81,3700000	28,2788889
08/14/2004 01:21:35	28.292 N	81.367 W	81°22'01"	28°17'31"	-81,3669444	28,2919444
08/14/2004 01:23:35	28.305 N	81.363 W	81°21'46"	28°18'18"	-81,3627778	28,3050000
08/14/2004 01:25:35	28.318 N	81.360 W	81°21'36"	28°19'04"	-81,3600000	28,3177778
08/14/2004 01:27:35	28.331 N	81.356 W	81°21'21"	28°19'51"	-81,3558333	28,3308333
08/14/2004 01:29:35	28.345 N	81.353 W	81°21'10"	28°20'42"	-81,3527778	28,3450000
08/14/2004 01:31:35	28.358 N	81.349 W	81°20'56"	28°21'28"	-81,3488889	28,3577778
08/14/2004 01:33:35	28.371 N	81.346 W	81°20'45"	28°22'15"	-81,3458333	28,3708333
08/14/2004 01:35:35	28.385 N	81.342 W	81°20'31"	28°23'06"	-81,3419444	28,3850000
08/14/2004 01:37:34	28.398 N	81.339 W	81°20'20"	28°23'52"	-81,3388889	28,3977778
08/14/2004 01:39:34	28.411 N	81.336 W	81°20'09"	28°24'39"	-81,3358333	28,4108333
08/14/2004 01:41:34	28.425 N	81.332 W	81°19'55"	28°25'30"	-81,3319444	28,4250000
08/14/2004 01:43:34	28.438 N	81.329 W	81°19'44"	28°26'16"	-81,3288889	28,4377778
08/14/2004 01:45:34	28.451 N	81.326 W	81°19'33"	28°27'03"	-81,3258333	28,4508333
08/14/2004 01:47:34	28.465 N	81.322 W	81°19'19"	28°27'54"	-81,3219444	28,4650000
08/14/2004 01:49:34	28.478 N	81.319 W	81°19'08"	28°28'40"	-81,3188889	28,4777778
08/14/2004 01:51:35	28.492 N	81.315 W	81°18'54"	28°29'31"	-81,3150000	28,4919444
08/14/2004 01:53:35	28.505 N	81.312 W	81°18'43"	28°30'18"	-81,3119444	28,5050000
08/14/2004 01:55:35	28.519 N	81.309 W	81°18'32"	28°31'08"	-81,3088889	28,5188889
08/14/2004 01:57:35	28.532 N	81.305 W	81°18'18"	28°31'55"	-81,3050000	28,5319444
08/14/2004 01:59:35	28.545 N	81.302 W	81°18'07"	28°32'42"	-81,3019444	28,5450000
08/14/2004 02:01:35	28.559 N	81.299 W	81°17'56"	28°33'32"	-81,2988889	28,5588889
08/14/2004 02:03:35	28.572 N	81.295 W	81°17'42"	28°34'19"	-81,2950000	28,5719444
08/14/2004 02:05:35	28.586 N	81.292 W	81°17'31"	28°35'09"	-81,2919444	28,5858333
08/14/2004 02:07:34	28.599 N	81.288 W	81°17'16"	28°35'56"	-81,2877778	28,5988889
08/14/2004 02:09:34	28.613 N	81.285 W	81°17'06"	28°36'46"	-81,2850000	28,6127778
08/14/2004 02:11:34	28.626 N	81.282 W	81°16'55"	28°37'33"	-81,2819444	28,6258333
08/14/2004 02:13:34	28.640 N	81.278 W	81°16'40"	28°38'24"	-81,2777778	28,6400000
08/14/2004 02:15:34	28.654 N	81.275 W	81°16'30"	28°39'14"	-81,2750000	28,6538889
08/14/2004 02:17:34	28.667 N	81.272 W	81°16'19"	28°40'01"	-81,2719444	28,6669444
08/14/2004 02:19:34	28.681 N	81.268 W	81°16'04"	28°40'51"	-81,2677778	28,6808333

APPENDIX 4 CODES AND DEFINITIONS EXTERIOR WALLS

Table C: Exterior wall code definitions

EXTERIOR WALL CODE DEFINITIONS

Nr.	Definition
Dropped values	
1	Inexpensive, minimal materials
10	Above-average materials
3	Below average materials
31	Exceptional/unique wall
33	Average façade
5	Average wall
9	Corrugated fiber panel
Wood exterior walls	
11	Board & batten above average
12	Cedar/redwood
13	Prefabricated wood panel/Masonite
14	Wood shingle
16	Wood frame stucco
2	Composition wall board
36	Log walls
4	Single siding wood
6	Board & batten average
8	Wood on sheathing
Stone exterior walls	
15	Concrete/cinder block
17	Concrete block stucco
22	Precast concrete panel
23	Reinforced concrete
30	Ornamental cement plaster
37	Hardie board
7	Cement & fiber shingle
18	Cement brick
19	Common brick
20	Face brick
21	Stone veneer
Metal exterior walls	
24	Corrugated metal
25	Modular metal
26	Aluminum or Vinyl siding
27	Prefinished metal

APPENDIX 5 CHOW TEST ESTIMATES POOLED AND SUB SAMPLES

Table D: Chow test estimates pooled and sub samples

	POOLED	**SUBSAMPLES**		
	[4]	**Stone walls**	**Wood walls**	**Metal walls**
Sample	**<2,000 m**	**<2,000**	**<2,000**	**<2,000**
Target area	**0-1,000 m**	**0-1,000 m**	**0-1,000 m**	**0-1,000 m**
Control area	**1,000-2,000 m**	**1,000-2,000 m**	**1,000-2,000 m**	**1,000-2,000 m**
Ln Total Area M2	.4429539***	.4252775***	.3362328***	.5181909***
	(.0210672)	(.0221794)	(.0844199)	(.1663447)
Ln Total Heated Area M2	.2398316***	.2337322***	.4361275***	.0762784
	(.0209137)	(.0217929)	(.0919622)	(.1658453)
Ln # of Bedrooms	.0162927	.013872	-.0194153	-.099721
	(.0128842)	(.0136762)	(.0497822)	(.0970419)
Ln # of Baths	.1162991***	.1205528***	.1183071**	.1190634
	(.0104062)	(.0108146)	(.049082)	(.0912809)
Ln Property Age	-.0925465***	-.0953005***	-.0679787***	-.1681514**
	(.0034863)	(.0035529)	(.0227867)	(.0696789)
Target	-.0196696***	-.0143899*	.0148131	-.0717615
	(.0071497)	(.0075705)	(.0259581)	(.072711)
Target x Post	-.0197992**	-.0243331***	-.0109103	-.1118981
	(.00832793)	(.0087029)	(.0332138)	(.0789457)
Constant	7.634583***	7.736024***	7.158242***	8.258031***
	(.0641769)	(.0672967)	(.2743647)	(.711555)
Year-quarter Fixed Effects	Yes	Yes	Yes	Yes
Location Fixed Effects	Yes	Yes	Yes	Yes
Number of observations	14,471	13,122	1,071	275
Adjusted R^2	0.7470	0.7505	0.7665	0.6867
RSS	880.971153	775.678641	64.6065552	14.1670553

*Note: The dependent variable is the natural logarithm of the sales price ***p<0.01 **p<0.05 *p<0.10*