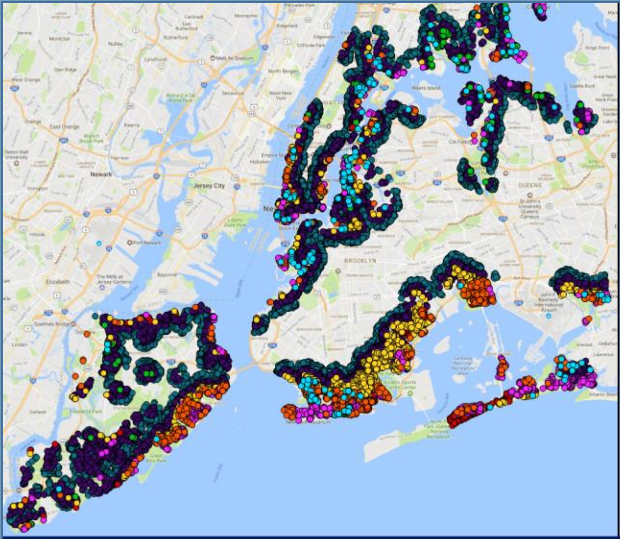

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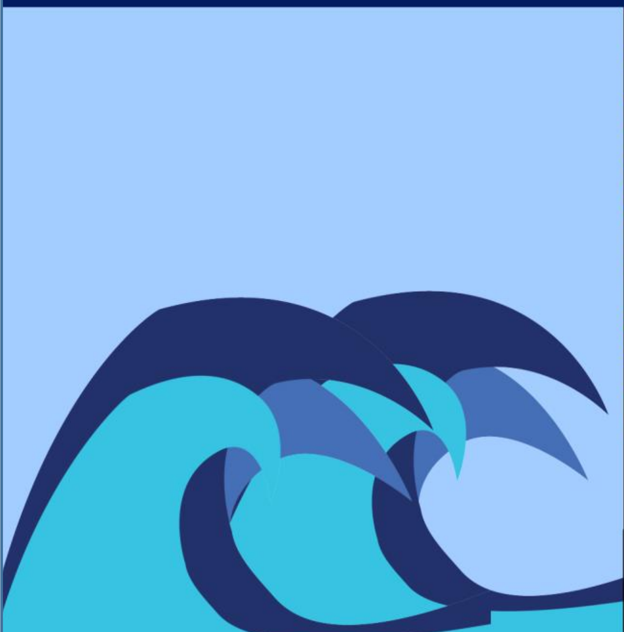
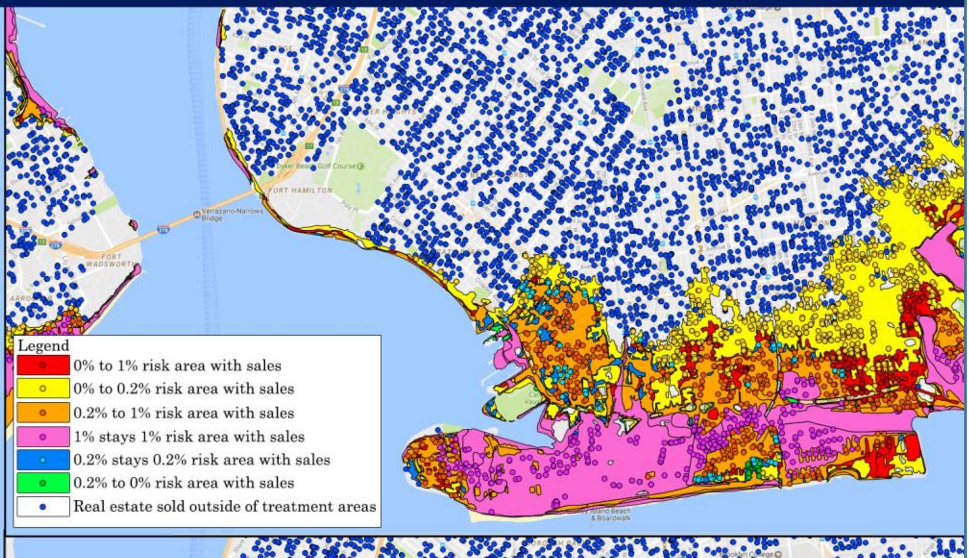
Date: 08-06-2017
Word count: 19825 (excluding appendix)

A spatial difference-in-difference analysis of the impact of Hurricane Sandy and the update of a flood risk map on New York City housing prices





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Abstract

This thesis uses a difference-in-difference analysis to find out what the impact of two treatments was on New York City housing prices. The first treatment is hurricane Sandy that hit the city in October 2012. This treatment measures the effect of direct flood experience on housing prices. The second treatment is the introduction of an official new flood risk map by the Federal Emergency Management Agency (FEMA). This second treatment measures the effect of indirectly experiencing higher flood risk. Both these treatments where hypothesized to have a negative effect on housing prices. Sandy through direct damage in the short run and increased risk perception in the long run. The new flood risk map only through increased risk perception.

This thesis uses changes housing prices as an operationalization of damage done and increased risk perception. For this thesis an entirely new geospatial dataset was constructed by merging three existing datasets, the old flood risk map, the new flood risk map and 600 thousands coordinates that represent different real estate sales in New York City between 2003 and 2015. The treatment groups of this thesis are based on whether or not a sold property was situated in an area that changed in flood risk with the new flood risk map of 2015. The treatment areas are the areas where the old and the new flood risk map overlap. These are the areas in which flood risk officially changed in 2015. To determine which houses where sold in these areas (treatment groups) and which were not (control group), a Point-in-Polygon (PIP) analyses was conducted using Geographical Information System (GIS) software. This analysis determines if a point (sold property) was in a polygon (changing flood risk zone). 117 such PIP analyses were conducted to determine the treatment or control group for each observation.

After analysing this newly constructed dataset I find significant negative effects of hurricane Sandy on New York City housing prices. This effect is found to be robust. In some boroughs and treatment groups this effect only showed in the short run, while in others also in the long run. The short term effect is most likely caused by direct damage, while the long term effect is most likely caused by increased risk perception. The second treatment, the flood risk map update, does not show a significant negative effect on housing prices.

Table of contents

1. Introduction

Although climate change is still a vague concept to some, it is becoming a real problem for the citizens of coastal cities all around the world. For example, the amount of flood days has more than doubled since 1980 in the United States (Climate Central, 2016). Furthermore, it is projected that by 2100 the homes of between 4.2 and 13.1 million Americans will be at risk of flooding because of the rising sea levels (Hauer, Evans and Mishra, 2016). This risk is very hard or even impossible to insure, as floods can be seen as a 'common shock' that hits everyone at the same time, while the idea of insurance is based on the idea that risk is randomly distributed and independent of someone else's risk (Barr, 2012: 88). Furthermore, these common shocks will occur more often as sea levels are rising with 3.4 mm per year according to NASA (2016). As a result, by 2050 between $66 billion and $160 billion worth of American real estate will be under sea level (Bloomberg et al, 2014: 4). By 2100 this amount will be between $238 billion and $507 billion. To put this in perspective, the 2007-2008 subprime mortgage crisis happened when a $600 billion real estate bubble burst (Bernanke, 2008).

Although rising sea levels have been studied extensively in the past, this was mostly done because of the interest in the natural phenomenon itself. Since rising sea levels start to have a more socio-economic impact, science should look into these socio-economic effects of rising sea levels. It is known that, due to rising sea levels, coastal floods are going to occur more frequently. It is however still quite unclear if and how how rising flood risk impacts risk perception, housing markets and the way governments can best circumvent the negative effects of increased flood risk. Therefore it is of big economic and societal importance that science gets insight into the causal mechanisms at play in the interaction between flood risk, risk perception, housing markets and the role that government communication plays in this interaction.

In this thesis we use an experimental design to determine the effects of directly and indirectly experiencing flood risk on housing prices. New York City (NYC) experienced two events that are used to measure these direct and indirect experiences. First, on October 29th 2012 the city was hit by Hurricane Sandy, causing 48 deaths and between $30 billion and $50 billion in damages (CNN, 2012). Sandy also caused major flooding (Ortega and Taspinar, 2016: 28). This event is therefore used to measure the effect of direct flood experience. I argue that Sandy negatively impacts housing prices through direct damages and increased risk perception. The second event is more indirect in nature. In 1983 the Federal Emergency

Management Agency (FEMA) introduced its first flood risk map for New York City. This map showed exactly in which flood risk zone a property was. Rising sea levels, erosion, physical flood defence structures and better information on flooding mechanisms influenced the actual flood risk over time. Therefore, on January 31st 2015 FEMA introduced an update of the flood risk map, called the Preliminary Flood Insurance Rate Map (FIRM). On this new map big parts of New York City had their flood risk changed (typically the flood risk increased). On March 27th 2015 every NYC property owner that was in or close to a new flood risk zone received a letter, informing them about this new flood risk map[1]. The new flood risk map is preliminary, meaning that it does communicate the updated flood risk, but it is not yet used for calculating flood risk insurance premiums. This map update thus captures the information of increased flood risk, while filtering out the direct effect of increased premiums. Of course there might still be an anticipation effect. It is hypothesized that this new information will increase flood risk perception and thus reduce housing prices of the properties situated in the new flood risk zones. Both Sandy and the flood risk map update are thus treatments that are hypothesized to impact flood risk perception.

Research question

By exploiting Hurricane Sandy and a FEMA flood risk map update in a experimental design, this study will provide insight into the effects of natural flood hazards and publicly provided flood risk information on housing prices. The research question of this thesis therefore is:

“To what extent did Hurricane Sandy and the introduction of FEMA’s Preliminary Flood Insurance Rate Map (FIRM) impact New York City’s housing prices?”

The logic here is that both Hurricane Sandy and the flood risk map update provide the NYC housing market with new information on flood risk. This new information is then hypothesized to increase the risk perception of buyers and sellers in this market. Increased risk perception will eventually cause housing prices to decrease. As mentioned before, a second option is that Sandy influenced housing prices through direct damages. These two mechanisms thus happen at the same time. I argue however, that the damage only affects housing prices in the short run, while increased risk perception would also influence housing prices in the long run.

Methodology and data

[1] The Property Owner Notification Letter of FEMA can be found in Appendix 1.

Increased risk perception reduces housing prices (Oates, 1969). In this thesis I use NYC housing prices to operationalize and measure flood risk perception. This "hedonic" approach is based on the notion that the value of a house is defined by a bundle of its characteristics (Rosen, 1974). These separate characteristics, such as flood risk, can thus be seen as having implicit costs and benefits where people are (not) willing to pay for. If one of the characteristics changes, its effect can thus be measured as a change in housing prices. In this thesis the dependent variable are the housing prices of sold real estate, while the explanatory variables will be events that are hypothesized to increase risk perception, Hurricane Sandy and FEMA's flood risk map update, along with a number of control variables like the type of housing and area fixed effects.

For this study I created an entirely new dataset by merging the old flood risk map, the new flood risk map and geospatial real estate transaction data of New York City. This data includes all real estate sold in New York City between January 2003 and December 2015. Merging these three datasets resulted in a new dataset that consists of more than 600 thousand observations. A natural experiment needs treatment groups and control groups. By doing Point-in-Polygon analyses in the Geographic Information System (GIS) software QGIS I was able to determine whether a sold property was in a changing flood risk zone or not. This was a very time consuming exercise which took multiple weeks to complete. This data constructing process is discussed at large in the data section. The first treatment group consists of houses sold in an area where the risk of flooding increased from 0% yearly flood risk to 1% yearly flood risk. The second treatment group consists of houses sold in an area where the risk of flooding was 1% before the map update and also 1% after the map update. The control group is defined as houses sold in an area where the flood risk was 0% before the map update and remained 0% after the map update and at the same time is within 500 meter of a treatment area. We study the effect on the transaction prices of the houses sold in the treatment groups using differences-in-differences (Angrist and Pischke, 2009: 221-246). We consider two different treatments: i) Hurricane Sandy and ii) the FIRM update. We first test whether hurricane Sandy negatively affected the housing prices of the treatment groups. Next, we test whether the map update significantly affected housing prices in the treatment groups. Here we expect a different effect for the two treatment groups, with a bigger effect for the area in which the risk increased from 0$ to 1%. The effect is expected to be bigger for this treatment group, because according to the flood risk map of that moment they were in a 0% flood risk zone. From, risk perception theory (Wachinger et al., 2012) it follows that direct experience has a bigger impact on risk perception than indirect experience . Hence, we expect that Sandy has a bigger impact on both treatment groups than the flood risk map update. Finally, it is hypothesized that the impact of the flood risk map is bigger for the city districts (boroughs) that were hit harder by Hurricane Sandy. We also consider a number of robustness checks.

Results

I find that Hurricane Sandy did significantly impact housing prices in New York City. For some boroughs this effect was temporary and thus most likely caused by direct damages. For Brooklyn and Queens the effects of Sandy were still found for the year 2015 by using quarterly interaction effects. Since direct damages did not take that long to repair, I argue that this effect is due to increased risk perception. The quarterly interaction effects also provided evidence for the effect being causal. The quarterly interactions were not statistically significant before Sandy and highly significant (and negative) after Sandy. Contrary to the hypotheses I do not find a negative effect of the introduction of the new flood risk map on housing prices. In a few specifications I do find a statistically significant effect, which however is not robust to changes in the specification. This might be due to the fact that the risk perception of homeowners was already corrected by hurricane Sandy and thus was not be furtherly adjusted with the flood risk map. I discuss this interpretation and some other possibilities in the conclusion section.

Societal relevance

This thesis is of societal relevance, because it gives insight into how and when governments should provide flood risk information and what the impact of this information is on risk perception and housing prices. A flood risk map update is a policy tool that provides citizens with better flood risk information. It is important to evaluate whether such a policy indeed increases flood risk perception, like it is supposed to do. Secondly, as stated above, to prevent another housing bubble it is necessary to understand the causal mechanisms behind risk perception, flood risk and its interactions with the housing market. Thirdly, due to climate change coastal floods are something governments will increasingly have to deal with both in terms of prevention and crisis management. From theory we learn that where natural hazards in the past were mostly seen as uncontrollable, people now increasingly perceive natural hazards such as floods as induced by humans and thus controllable (Wachinger et al, 2012: 1062). If flood risk is perceived as controllable, an actual flood might make people think that government did not do enough to prevent the flood. This places government in an increasingly awkward position in which citizens start blaming government for not preventing floods, while

(Western) governments at the same time are “rolling back” in size and thus are less capable of dealing with these kinds of natural hazard risks (Wachinger et al, 2012: 1059). A better understanding of how risk perception works in relation to publicly provided flood risk information and natural hazards could help solving this potential problem.

Relation to the literature

Previous studies have found that providing new flood risk information to the market significantly increases risk perception and decreases real estate prices (Pope, 2008; Votsis and Perrel, 2016) and that floods caused by hurricanes have an even bigger impact (Ortega and Taspinar, 2016; Bin and Laundry, 2013). In this thesis I will look at both hurricane Sandy and the flood risk map update at once while controlling for each effect. To my knowledge, this design has not been used before in researching flood risk perception. If after a big storm a new flood risk map does no longer impact housing prices, where it normally did, there is probably a different mechanism at play. It could be that the storm already updated the risk perception and therefore the map update no longer shows an effect. Of course it is of scientific relevance to uncover this causal mechanism. Finally, this thesis is innovative as it merges three geospatial datasets to produce the dataset the analysis of this thesis is based upon.

Outline of the thesis

The outline of the thesis is as follows. Section 2 starts off with a literature review. This section starts off with the theory of risk perception in relation to natural hazard risk, and continues with the empirical findings of related studies. Next, Section 3 discusses the construction of the data set for the empirical analysis. Section 4 discusses the empirical methodology. Section 5 then provides graphical evidence along with regression results, and a number of robustness checks. In Section 6 we consider some limitations of the analysis and conclude.

2. Literature review

This section consists of two parts. First, I discuss the theory of risk perception , with a focus on the relation of risk perception in the context of natural hazards. Second, I discuss the main empirical findings from related studies on flood risk.

Theoretical Framework

Almost all of the studies we discuss are based on the theoretical notion of “hedonic pricing” and it’s methodological equivalent “hedonic regressions”. In his classic article, Rosen (1974) proposes the idea of hedonic prices and implicit markets. Rosen states that goods can be seen as a package of multiple characteristics. Prices reflect these different characteristics. In practice this means there is an implicit market for flood risk. For instance, when the flood risk increases by 1% this will be seen as an implicit cost to homeowners. This implicit cost will then reduce the price of the house. The idea is that a decrease in value is then the price of living in an area in which the risk increased by 1%. The prices of flood risk can thus be calculated using a hedonic regression model in which the dependent variable is housing prices and (changing) flood risk is one of the explanatory variables. The hedonic regression empirically measures the willingness to pay for a certain characteristic of a house. As mentioned earlier, it is important to realize that risk perception is not the only way in which the housing prices get influenced. Damage by hurricane Sandy probably also negatively impacted housing prices in the short run (Ortega and Taspinar, 2016). A hedonic regression just tells us whether or not the housing prices decreased, not per se what exactly caused it. I argue that the effects of direct damage and increased risk perception can be partly disentangled though. Damage most likely only impacts property in the short run, while risk perception also impacts housing prices in the long run (Ortega and Taspinar, 2016; Bin and Polasky, 2004). What is also important to understand is that the framework of hedonic pricing is based on the idea of rational decision makers that have full information. Since this is an implausible assumption, the interpretation of hedonic regression outcomes can be ambiguous. A significant effect of new flood risk information can only be interpreted as the marginal value of extra flood risk if the rationality assumption holds (Pope, 2008: 570). As already said, the hedonic regression measures an effect, not necessarily what exactly caused this effect. Therefore, theory on risk perception and information processing will now be explained, before discussing actual empirical findings on increased flood risk.

The availability heuristic

Theory on judgement under uncertainty, biased perceived risk, heuristics and bounded rationality find their origin in cognitive psychology (Tversky and Kahneman, 1973;1974;1981; Kahneman, 2003). Most of the studies mentioned below use the theory of `the availability heuristic' of Tversky and Kahneman (1973) as their theoretical framework. They argue that individuals are not completely rational when making decisions. They can be in theory, but in practice humans are guided by heuristics or cognitive rules-of-thumb when facing difficult decisions under uncertainty. The availability heuristic is such a short cut that the brain uses when making difficult decisions. Kahneman and Tversky (1973; 1981; 1982) did research on individuals that had to make complex decisions under uncertainty and found that a significant amount of these individuals based their decision on the ease with which the brain could produce an answer to a question. For example, people decided that there are more words in the English language that start with a "K" than of which the third letter is a "K" (Tversky and Kahneman, 1973: 211). In fact however, there are more words with a "K" as a third letter than as a first letter. It is however easier to think of words that start with a "K", these words are more "available" to the brain. This in short is the availability heuristic. As can be seen in the example above this heuristic can easily lead to irrational decision making, called *biases* in cognitive psychology. For research on risk perception in combination with natural hazards the availability heuristic is used (not always explicitly mentioned) to explain why sometimes risk perception is high and sometimes low. If a flood is still "fresh in memory" and thus more available to the human brain, the risk perception is higher and thus effects choices. If time goes by and the flood is slowly forgotten, this memory is less available to the brain and thus the impact of risk and thus housing prices decreases. This is relevant for this thesis, as hurricane Sandy hit New York City in 2012, while the introduction of the updated flood risk map was in 2015. During this time the flood risk might have become less "available" to the brain, which might to a reduction in Sandy's effect over time.

The availability heuristic is one of the reasons that the market is not constantly fully informed on flood risk. The perception of flood risk is higher after a flood, but this information "leaks away" over time because of the availability heuristics. Just "forgetting" about the flood does not seem to be enough to explain the complex mechanisms that underlie risk perception in relation to natural hazards. That is why, on top of using the availability heuristic in the theoretical framework of this thesis, it will be supplemented with theory on risk perception in combination with natural hazards, especially in relation with government and government communication.

Risk perception in relation to natural hazard risk

Wachiger et al. (2012) review 35 empirical studies on natural hazard risk perception and try to come up with a more general framework. They find four categories to be present in almost all reviewed empirical studies, namely: “risk factors”, “informational factors”, “personal factors” and “contextual factors”. Also they provide a useful definition of risk perception: “*the process of collecting, selecting, and interpreting signals about uncertain impacts of events, activities or technologies*”. The four categories will now be discussed.

Risk factors can be seen as the “scientific” definition of risk, such as calculatable probability and frequency, thus not “Knightian” unknowable uncertainty (Knight, 1921). According to Wachiger et al (2012: 1051) perceived likelihood, perceived frequency and perceived magnitude do not impact risk perception significantly in the case of natural hazards such as flooding. This has interesting implications for evaluating the impact of the treatments, as homeowners receive a letter at home that their flood risk increased or decreased by 0.2%, 0.8% or 1%. With a risk of 0.2% a flood happens once in 500 years. Based on Wachiger et al (2012: 1051) it can be argued that this kind of small probabilities of hazardous events are not tangible for individuals and might therefore not have an effect. This case is even further strengthened by the fact that FEMA’s 0.2% flood risk zone has not mandatory flood insurance. These notions will be used later on in the thesis to create “condensed” treatment groups were the 0.2% flood risk is seen as 0% flood risk to create two treatment groups instead of six.

Informational factors can be seen as information sources and the perceived quality of information. According to Wachiger et al (2012: 1051) these factors are only important for risk perception if the particular individual did not directly experience such a risky event in the past. Trust also plays an important role when receiving information. If the organization or individual providing the information is considered trustworthy, the impact on the risk perception is higher. In a growingly more complex world, trusting experts on their information can be seen as a “shortcut” to a decision, preferred to making a rational decision (Wachinger et al, 2012: 1053).

Personal factors that influence risk perception are characteristics, “*such as age,* *gender, educational level, profession, personal knowledge, personal disaster experience, trust in authorities, trust in experts, confidence in different risk reduction measures, involvement in cleaning up after a disaster, feelings associated with previously experienced floods, world views, degree of control, and religiousness*" (Wachiger et al, 2012: 1051-1052). Most of these personal factors are deemed to have an ambiguous impact on risk perception. Direct experience of disasters, trust in authorities and confidence in protective measures however were found to significantly impact risk perception in multiple studies (Wachiger et al, 2012: 1051-1052). It is important to realize that this thesis uses transactional data from the NYC housing market to assess risk perception. The dataset used for this thesis does not include information on the buyer or seller of NYC property. Therefore, it is impossible to control for individual characteristics that might have an influence on risk perception. Although this thesis cannot control for personal characteristics, it does control for time-invariant effects of different neighbourhood levels. Since neighbourhoods can reflect certain personal factors at an aggregate level, such as income and unemployment rates, it can be argued that this thesis takes some of the personal factors into account (at an aggregate level) by using neighbourhood fixed effects.

Contextual factors are influences from the environment that an individual is in, such as "*economic factors, vulnerability indices, home ownership, family status, country, area of living, closeness to the waterfront, size of community and age of the youngest child*" (Wachinger et al, 2012: 1052). Contextual factors mainly impact risk perception in combination with other personal factors. Ruin et al (2007) found that experience with flooding in the past tends to lead to overestimating danger, while for not having experienced floods makes people underestimate flood risk. Other studies find that this causal effect only exists if property was damaged (Wachinger et al, 2012: 1052). Again, it should be noted that these contextual factors mainly influence personal perception of risk. And as this thesis looks at differences in housing transactions only, these factors cannot be controlled for. What is possible however, is to look at the different boroughs separately, as they have their own socio-economic and cultural factors at play. This will be done in the analysis of this thesis. Important for this thesis is also the fact that proximity to a disaster was found to have a stronger effect on risk perception than the probability of a similar disaster (Wachinger et al, 2012: 1052-1053). This is one of the reasons why the control group for this thesis is defined as the real estate transactions that happened in a 500 meter buffer around the treatment groups.

Other than direct experience, indirect experience has an impact on risk perception as well (Wachinger et al, 2012: 1052-1053). Indirect experience are ways in which an individual can gain information on the risk at hand, such as via education, the media, hazard witnesses and government communication. The flood risk map update, can thus be seen as indirect experience, while Sandy's "treatment" is direct experience. From the literature on risk perception we know that indirect experience has an ambiguous effect on risk perception, depending on contextual and personal factors. It is however clear that indirect experience has a smaller effect (if any) than direct experience. It is therefore hypothesized that the map update has a smaller impact than the direct experience of hurricane Sandy.

Wachinger et al (2012) state that indirect experience such as government communication, if any, has a relatively weak effect on risk perception and thus housing prices. Therefore in their discussion they recommend governments to make people envision "the negative emotional consequences of natural disasters" and to use "communication methods close to personal experience" (Wachinger et al, 2012: 1059-1060). This recommendation can be used to assess the effectiveness of the FEMA letter, of which a part has been quoted below:

"*Flooding is the most frequent and costly disaster in the United States. The risk for flooding changes over time due to erosion, land use, weather events and other factors. The likelihood of inland, riverine and coastal flooding has changed along with these factors. The risk for flooding can vary within the same neighbourhood and even property to property, but exists throughout New York City. Knowing your flood risk is the first step to flood protection. The Federal Emergency Management Agency (FEMA) is in the process of developing updated flood maps for New York City. The new maps -- also known as Preliminary Flood Insurance Rate Maps (FIRMs) -- reflect current flood risks, replacing maps that are up to 30 years old.* ***This letter is to inform you that your property is mapped in or near a Special Flood Hazard Area.*"** (FEMA, 2016).

Although Hurricane Sandy is not mentioned in the FEMA letter, by using words such as "flooding" and "costly disaster", individuals might have been reminded about Sandy. This in combination with the sentence stating that their property is mapped in or near a "Special Flood Hazard Area", might increase risk perception. Therefore it is interesting to estimate whether or not people that do receive the letter, but already live in the 1% flood risk zone, get impacted by the map update. This will be checked with the "1% stays 1% risk" treatment group (treatment group 2).

Empirical findings of related studies

There are two ways of implementing a hedonic regression. First there is cross-sectional research, which looks at if there is a significant price difference between living in a FEMA flood risk zone and living in a none risk zone. Zhang (2016) uses a spatial quantile regression model on real estate transaction data in Fargo-Moorhead (North Dakota) and finds that buildings that are situated in a river flood risk zone have a significantly lower value. This difference between being inside or outside a flood risk zone ranges between 4% and 12% depending on the value of the property (Zhang, 2016: 12). Such a cross-sectional research design has its limitations however, as the difference in price can also be explained by heterogeneity between the two groups instead of by a causal effect of flood risk. For instance, property that is not in a flood zone might have more value because it is situated on a hill with a nice view or because it is close to a good school. A more credible research design for retrieving the causal effect is that of natural experiments. These studies rely on exogenous variation in treatment. The studies discussed below exploit such situations by measuring whether or not there is a difference between the housing prices before and after a treatment for the treatment group relative to a control group. The control group is the group of observations that did not receive a treatment. Studies looking at natural experiments typically use differences-in-differences (DID). Three types of these natural experiments and their outcomes will now be discussed: the effect of floods on housing prices, the effect of providing flood risk information on housing prices and specifically the effect of updating flood risk maps.

Bin and Landy (2013) find that Hurricane Floyd "reminds" the market that certain properties are in a FEMA flood risk zone, resulting in significant effects ranging between -6% and -20.2%. Even when a hurricane misses a flood risk zone, it has this "reminding" effect. Allstrom and Smith (2005) find that even though Hurricane Andrew did not hit Lee County (Florida), it did significantly affect real estate prices in high flood risk zones by -19%. The devastation in neighbouring towns served as a reminder that their properties were in the flood risk zone. It can thus be concluded that even though a property does not have its flood risk changed, flood risk information can serve as a reminder or signal to the housing market that the particular property is in risk of flooding. This insight is important for this thesis as the first treatment group learns that its flood risk officially increased, while the second treatment group is only reminded by the flood risk map update that it already was in a flood risk zone. A second insight that this study and other studies provide is that the effect of a flood is discounted over time (Bin and Landry, 2013; Atreya, Ferreira and Kriesel, 2013). Bin and Landry (2013) for instance find that effects induced by storm-related floods disappeared after six year.

Pope (2008) studies the effect of a flood risk information disclosure law in North Carolina. North Carolina is an American state on the East Coast that has seen an increase in coastal flooding, both in magnitude and in frequency. In 1995 it introduced the Residential Property Disclosure Act (Pope, 2008: 559). This law stated that homeowners are obliged to fill in a form with 20 questions in which they disclose information of interest about the building and its surroundings to potential buyers. The last question was formulated as following: "*Do you know of any FLOOD HAZARD or that the property is in a FEDERALLY-DESIGNATED FLOOD PLAIN?*". The 1% flood risk zone did not significantly differ in price with the control group before the mandatory disclosure, significant cross section differences where thus not found before the treatment. After the treatment however, the housing prices in the flood zone decreased by between 3.8% and 4.5%, which is between $5400 and $6400 in real value (Pope, 2008: 569). The information about the flood risk zones are always publicly available. The most striking finding in Pope's (2008: 570) study is therefore that simply providing the same information through mandatory disclosure has a statistically and economically significant effect on housing prices. It is therefore important to understand to which extent buyers and sellers on the real estate market have full information on flood risk before the regression results can be interpreted.

Based on a survey of buyers' knowledge on flood risk and insurance premiums Chivers and Flores (2002) found that 60% of the individuals found out about the flood risk after the bidding on the house already closed, 4% after moving into the new house and 6% even later when their property actually flooded. 70% of the buyers on the researched housing market were thus not fully informed about the flood risk their potential property was in. This information asymmetry can be used to explain significant negative effects of risk information on housing prices. To explain why there is no hypothesized significant negative effect by using information theory requires the assumption of full information and full rationality to hold. Unfortunately for the interpretation of the DID-regression results of this thesis there is no empirical study on on the knowledge of flood risk of (potential) property buyers in New York City.

In a meta-analysis of 19 US studies Daniel et al (2009) find that an increase in flood risk probability by 1% a year is associated with a decrease of 0.6% in transaction prices. In these different studies different events were studied that provided the housing market with new information, namely floods, change in flood risk insurance premiums, new flood risk disclosure rules or increased media coverage (Daniel et al, 2009: 359). It is important to realize that all these studies check whether some form of flood risk information provision changes the prices of property that is already in a risk zone. These new batches of information thus can be seen as a "reminder" of this risk, rather than a provision of completely new knowledge.

Votsis and Perrels (2016) study whether the introduction of completely new flood risk maps in Finland impacts housing prices for property that was close to the coast of river beddings. Based on geospatial real estate transaction data and the new flood risk map they found a significant negative effect on housing prices for property that was designated as "flood risk area" by the new flood risk map. These effects ranged from -0.105% and -1.067% differing from 0.20 yearly flood probability and 0.001 yearly flood probability. These effects are somewhat smaller than that of the American studies as discussed above. It is important to note that this could be because of two reasons. Firstly, because of differing housing market mechanisms. Secondly, because the "reminding" effects on houses that are already in designated zones are inherently different from the "completely new information" effect of introducing maps where there first were none. The 0% to 1% flood risk treatment group in this thesis do not see the "reminder effect" and thus it would be interesting to see if they experience the "completely new information" effect.

Ortega and Taspinar (2016) use an experimental design to study whether New York City adjusted its real estate prices to the risk of living close to the waterfront after hurricane Sandy hit on October 29th 2012. They find a relatively large negative and statistically significant effect of Sandy on housing prices. Interesting here is that they find this effect to be significant for both damaged and undamaged houses.. This study is interesting for two reasons. Firstly, because it looks at the same city as this thesis, which creates a great deal of new insights[2]. Secondly it is interesting, because it uses other treatment and control groups than the research mentioned above. It compares prices of damaged houses with non-damaged houses and that of flooded houses with non-flooded houses (Ortega and Taspinar, 2016: 2). To define whether property was damaged or flooded or not, geospatial damage assessment data of FEMA was used. It is important to realize that areas that were flooded by Sandy (the treatment group) are not per se the same areas that FEMA designated as flood risk areas. Therefore the treatment areas of this thesis and Ortega's and Taspinar's research do not

[2] I only found this article when I was done constructing the dataset. Otherwise, I could have used their way of also controlling for Sandy's direct damage done.

necessarily overlap. If they did exactly overlap, the treatment effect of Sandy in this thesis should be of the same magnitude as the effect as found by Ortega and Taspinar (2016) which found a long term effect ranging from -0.06 and -0.26 logistic points, depending on the specification. To check whether these effects are causal, they check whether quarterly interaction effects are significant before and after Sandy (Ortega and Taspinar, 2016: 23). They deem that Sandy’s effect is causal, because the treatment-year interaction term is positive but not significant before Sandy and negative and highly significant after Sandy. Sandy’s effect will arguably not be exactly the same in this thesis, as this thesis controls for FEMA’s flood risk map update in 2015, while Ortega and Taspinar (2016) do not. It might therefore be possible that they overestimated the effect of Sandy.

Ortega and Taspinar (2016) use the same transaction data of real estate for their DID-regression as this thesis does. Next to doing a DID fixed effects regression on repeated cross-sections, also a smaller dataset was devised of buildings that were sold both before and after Sandy. This also allowed them to also estimate property fixed effects of Sandy in a panel data analysis, which gave approximately the same results (Ortega and Taspinar, 2016: 14;30). It is important to realize that the strategy of using individual property fixed effects is not used in this thesis, which only uses a repeated cross-sections design to estimate the treatment effects by running different DID-regression models. The downside of the repeated cross-sections approach is however, that it introduces a new assumption that has to hold before a found significant effect can be deemed “causal”, namely that there is homogeneity between the cross sectional observations before and after the treatments. After the map update or after Sandy the characteristics of sold houses may thus not differ from the sold houses before these treatments.

Hypotheses

From the literature we deduce three hypotheses that we test in the empirical analysis. Firstly, rational choice theory states that by providing the housing market with more and better information on flood risk the prices will be adjusted accordingly. According to the empirical findings of other studies there seems to be a difference between that property is in a flood risk zone and increasing the actual flood risk level. The effects for the two different treatment groups thus seem to be based on different causal mechanisms. Although the magnitude may thus differ between the two treatment groups, the direction is hypothesized to be the same for both the “Hurricane Sandy treatment” and the “flood risk map update treatment”. This leads to the first two hypotheses:

Hypothesis 1: *Hurricane Sandy negatively affected the housing prices of both the treatment groups in New York City.*

Hypothesis 2: *The introduction of the new Preliminary Flood Insurance Rate Map (FIRM) in New York City in 2015 negatively affected the housing prices of both treatment groups.*

Irrational behaviour such as heuristics and emotional memories of directly experiencing floods influence housing prices through higher risk perception (Wachinger et al, 2012). The notion that direct experience is a significant factor in risk perception is of theoretical value for this thesis. In the price movement per borough we namely see that certain areas were hit harder than others in the past by Hurricane Sandy. Therefore it is hypothesized that these areas should see a higher increase in housing prices once the flood risk map is updated. For individuals that did not experience any floods, the mechanism works the other way around. Ortega and Pensinar (2016: 28) find that 0.68% of New York City was experienced major flooding during Hurricane Sandy. The Bronx saw 0.01% of its borough flooded, Manhattan 0.23%, Queens 0.45%, Brooklyn 0.65% and Staten Island 3%. It is therefore hypothesized that because direct experience of past flooding has a significant effect on risk perception, the boroughs that got the highest percentage of flooding will see a higher impact on housing prices after the map update. Also, since direct experience seems to have a bigger effect than indirect experience it is hypothesized that Hurricane Sandy has a bigger treatment effect than the flood risk map update.

Hypothesis 3: *The NYC boroughs that had more major flooding because of Hurricane Sandy will have a higher impact of the new FIRM on housing prices*

To test these hypotheses a difference-in-difference regression with the two different treatments will be run simultaneously. This will be explained in the methodology section. However we first discuss the construction of the data set.

3. Data

New York City experienced two events that this thesis exploits in a natural experiment setup: Hurricane Sandy than came ashore on October 26th 2012 and the introduction of a new flood risk map on January 31st 2015. This section discusses how information on these two events were distracted from multiple sources and then combined so that the hypotheses of this thesis could be tested.

The first source of data for this thesis is the National Flood Hazard Layer (NFHL), the map that FEMA uses to calculate flood insurance premiums. This is the old flood risk map. This map was updated in 2015 significantly for the first time since 1983. This updating produced the second source, the new flood risk map (the Preliminary FIRM of 2015). These two maps were used in the QGIS open source software for Geographical Information Systems (GIS) to determine different treatment and control areas. In these areas the risk of flooding increased, decreased or stayed the same. The actual observations that will be used in a differences-in-differences regression are real-estate sales from January 2003 up to and including December 2015. These sales are made public by the NYC Financial Department and have been converted to geospatial data by New York University. These geospatial data can be thought of as coordinate points on a map that contain rows of usable information, namely: year, borough, neighbourhood, zip code, lot, block, building category, total square feet, year in which the building was built, the sale date, price of the transaction, longitude, latitude and Borough-Block-Lot unit (BBL). This BBL number is the unique identifier for property in the dataset.

By doing a “Point-in-Polygon” (PIP) Analysis in QGIS® of each transaction it can be determined whether it’s in the area in which the flood risk was officially updated in January

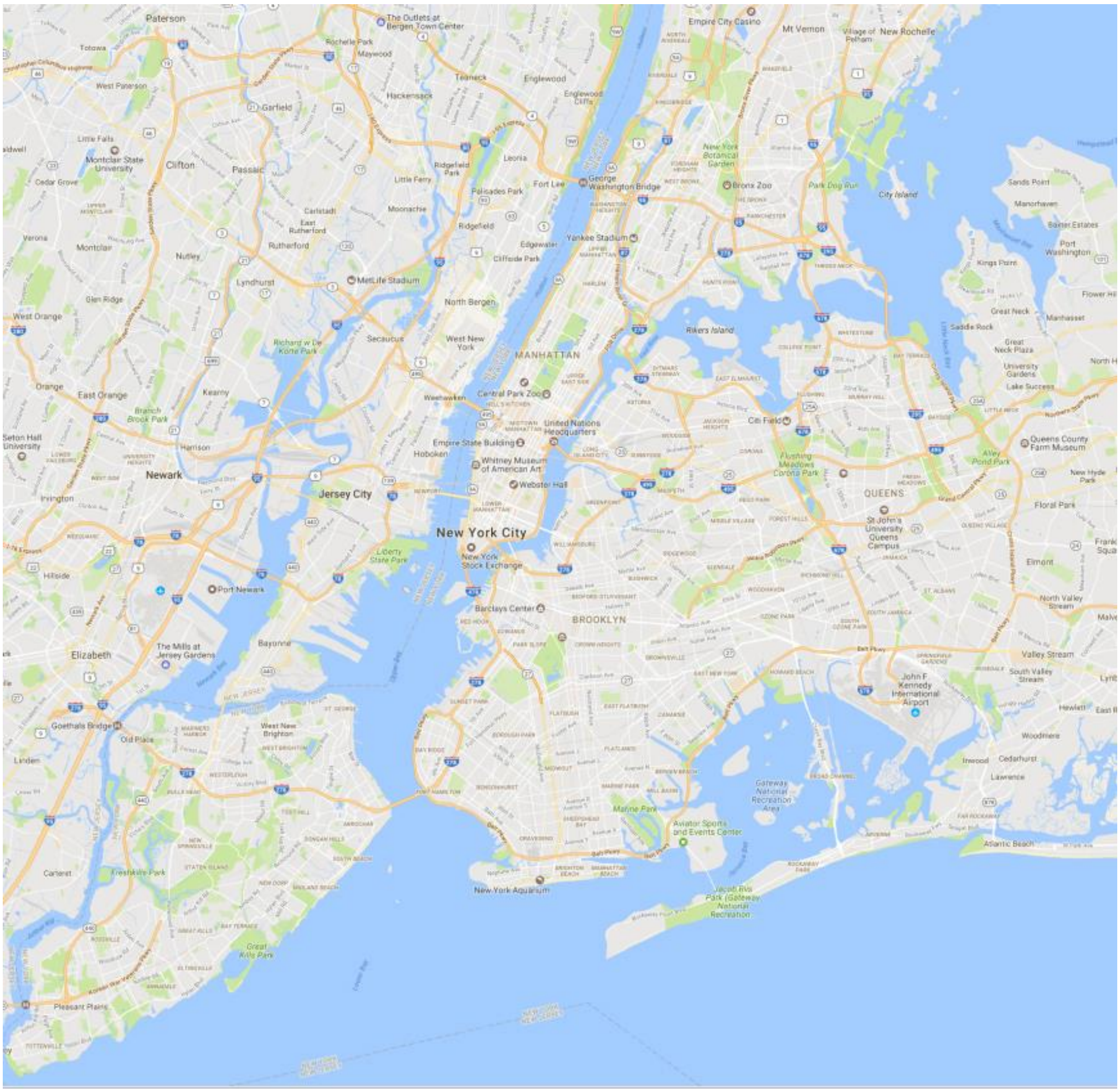

Figure 2. Google Base Map of New York City

2015. This PIP analysis is thus used to determine in which group the property is. There are six possible “treatments” for the transactions: the risk went up from 0% to 1%, from 0% to 0.2%, from 0.2% to 1%, the risk stayed 1%, the risk stayed 0.2% and the risk went down from 0.2% to 0%. Also the control groups were made using this PIP method. The statistical programming language R was then used to turn the geospatial shape files into analysable data frames. Below the methods of finding out which area and thus which treatment group a real estate transaction was in is explained.

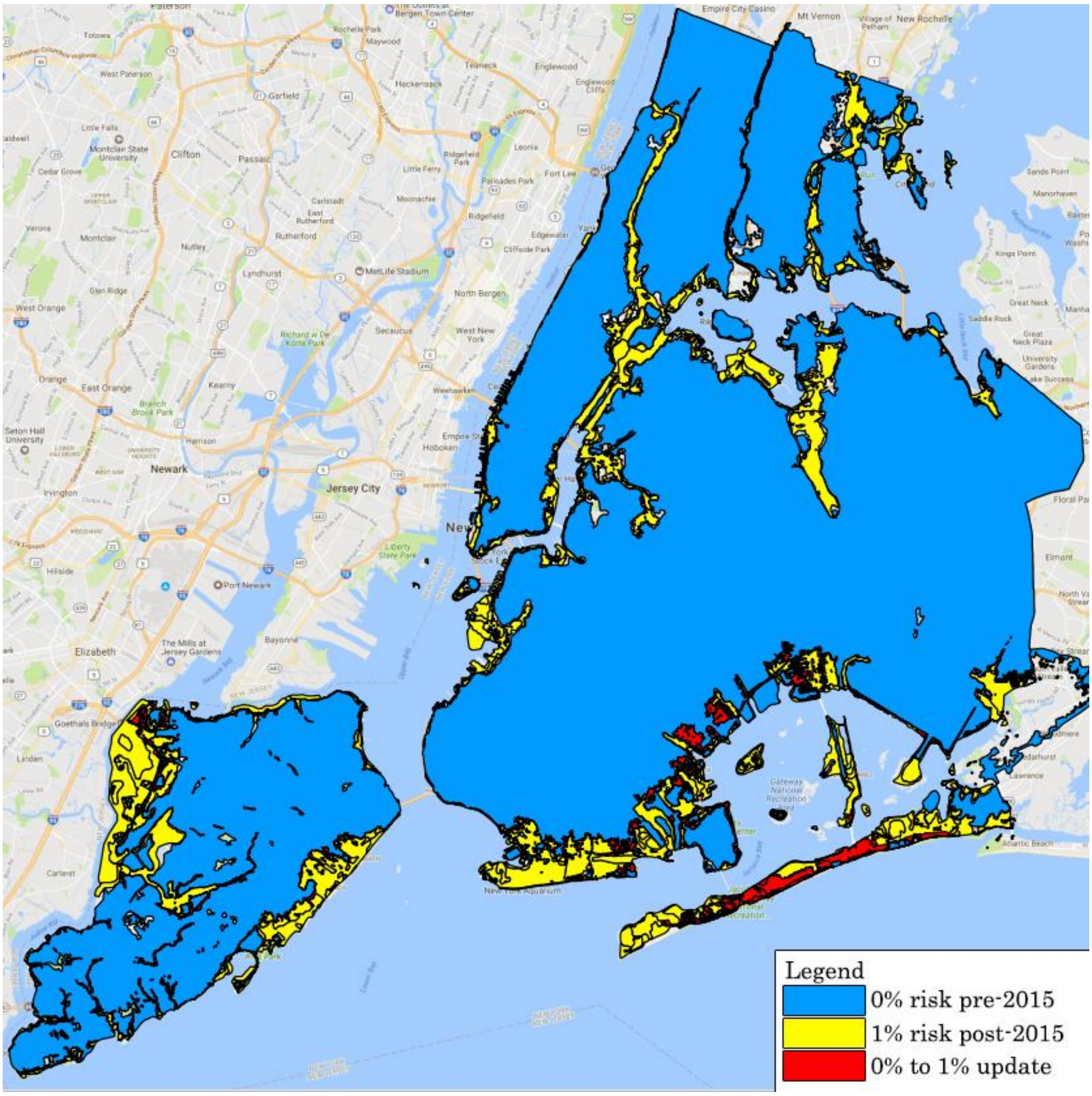

Figure 3. New York City with pre- and post-2015 flood risk layers. Produced in QGIS®

Figure 2 and 3 both show Google base maps of the New York City area. On top of figure 3 there are coloured layers. These layers were extracted from the old flood risk map (pre-2015 NFHL) and the new flood risk map (Preliminary FIRM of 2015). Both are publicly available FEMA flood risk maps. These layers were used to determine all treatment areas. Figure 3 shows only one of the possible risk changes. The blue layer is the 0% per year chance of flood layer of the pre-2015 NFHL. The yellow layer is the 1% per year chance of flood layer of the 2015 Preliminary FIRM. This whole thesis is based on the idea that where these areas overlap, the risk changed. The two layers overlap in the areas that had a 0% chance of floods in the pre-2015 map and a 1% chance of floods in the 2015 map. The overlapping area is thus one of the treatment areas is it depicts the area where the official flood risk level changed in 2015.

By using QGIS to determine the intersection between the two layers the red layer was created. The red layer is thus the area in which all property got the “treatment” of getting their flood risk officially updated from 0% to 1%. This red area (0% to 1% flood risk) is only one of 7 possibilities. The table below shows all the nine possible risk changes. It also shows however that not all of these changes were found in the dataset. Only a few small areas go down in risk and only from 0.2% to 0%. This is mostly likely due to physical coastal flood protection such as dams. Big flood risk decreases (1% to 0% or 1% to 0.2%) do not exist in New York City. Since these risk decreases are not available in the dataset, unfortunately it cannot be tested whether flood risk decrease has the opposite effect and magnitude as flood risk increase. The intersect method used to determine the 1% flood risk increase treatment area was then used to determine the other five treatment areas. The result can be seen below in Figure 4.

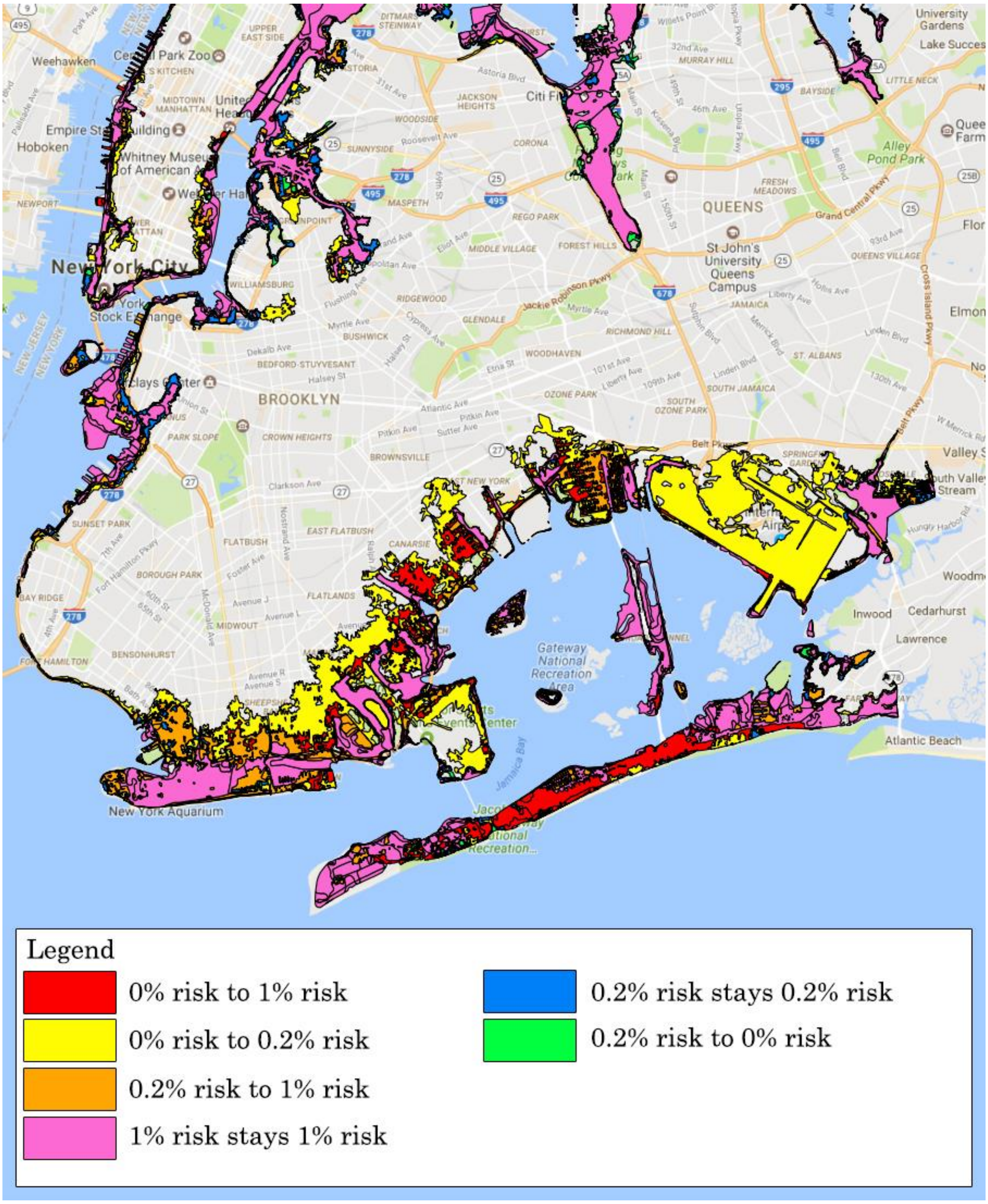

Figure 4. NYC, Parts of Manhattan, Brooklyn and Queens with all treatment areas. Produced in QGIS®

The red, yellow and orange areas are the areas that increased in flood risk in the FEMA update of January 2015 by 1%, 0.2% and 0.8% respectively. The pink and blue areas did not have their flood risk changed, they stayed at 1% and 0.2% flood risk respectively. The light-green areas are the areas in which the flood risk went down from 0.2% to 0%. From figure 4 we can conclude that the area in which the flood risk went up (red, yellow and orange) is relatively large as it covers big parts of southern Brooklyn and half of the Rockaway peninsula. Also the area in which the risk of floods that year remained 1% (pink) is relatively large. The blue and light-green areas are rather small however. These six areas were used to construct two treatment groups. To go down from six to two treatment groups, all the 0.2% areas were labelled as 0% risk zones. This is discussed in more detail later one.

The method to determine treatment areas has been discussed above. But how do we go from treatment areas to different treatment groups? This will be done by combining NYU's geospatial real estate transaction data and the treatment areas in a Point-in-Polygon (PIP) Analysis. In a Point-in-Polygon Analysis an algorithm is asked to determine whether or not a transaction (point) falls within a certain area (polygon). These areas are the different treatment areas. The points used are the spatial points of the NYC Geocoded Real Estate Sales Geodatabase[3]. These points are thus not just points on a geographical map, but represent the sale of actual real estate within the years 2009-2015.

For understanding the point-in-polygon analysis it is important to understand the concept of polygons. Polygons are objects that are made up from ordered coordinates that are connected with lines. The polygons as used in thesis are two dimensional, as they represent flat flood risk maps, but polygons can be 3D objects or 1D objects (one point of coordinates) as well. The FEMA flood risk maps are made up from hundreds of different polygons and

[3] NYU Spatial Data Repository (2016),' 2016 NYC Geocoded Real Estate Sales Geodatabase, Open Source Version', on: https://geo.nyu.edu/catalog/nyu_2451_34679 (visited on 11-01-2017)

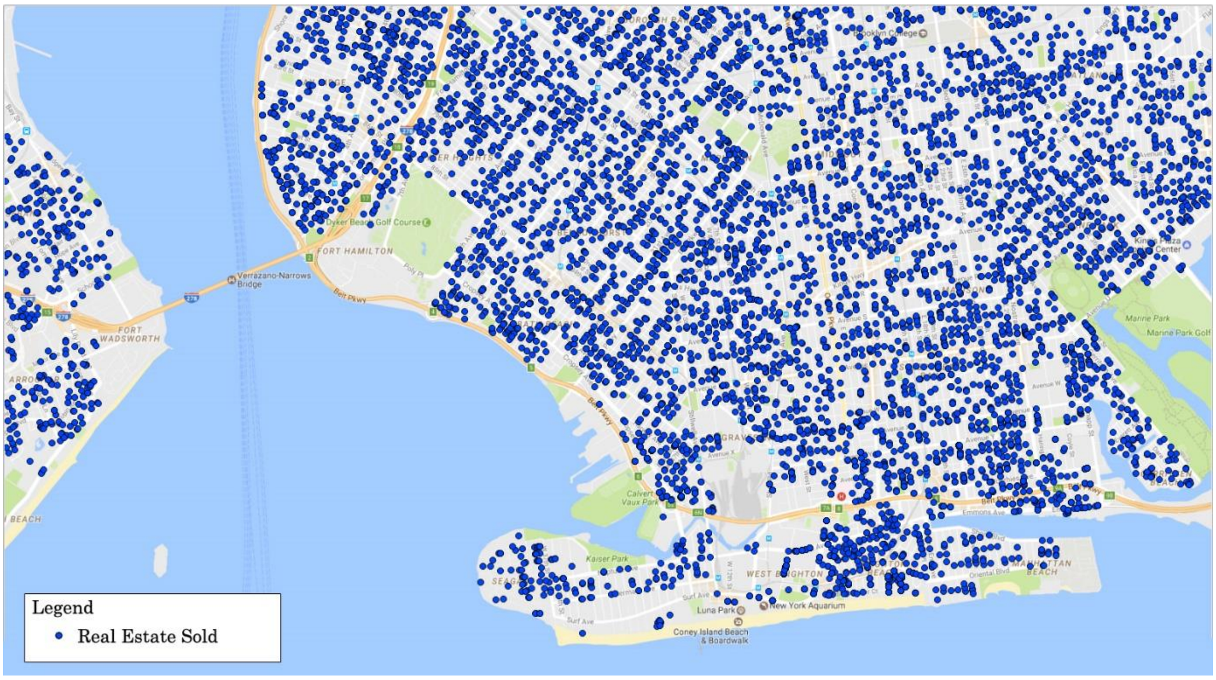

Figure 5. NYC South Brooklyn Area with the real estate sales of 2015

each polygon has information attached to it, such as which flood zone it represents. As already discussed in the data segment, treatment zones (changing flood risk) are created by calculating the overlap betweenthe old and the new flood risk maps.

The GIS Lab of the Newman Library (2016) of the New York University used the address of every real estate sale as provided yearly by the NYC Financial Department and used an algorithm to turn these addresses into a geospatial point (a coordinate). By then asking the QGIS software program to calculate whether a this spatial point was in a changing flood zone polygon (point-in-polygon analysis) the treatment group was established.

By using a Point-in-Polygon algorithm in QGIS it can be determined in which treatment area a certain real estate sale was. And thus it can be determined in which treatment group a real estate sale is. Once this has been determined, its shapefile is labelled with the treatment and a dummy is then added as the shapefile is loaded into R. Figure 5 shows the data points of real estate sales in 2015.

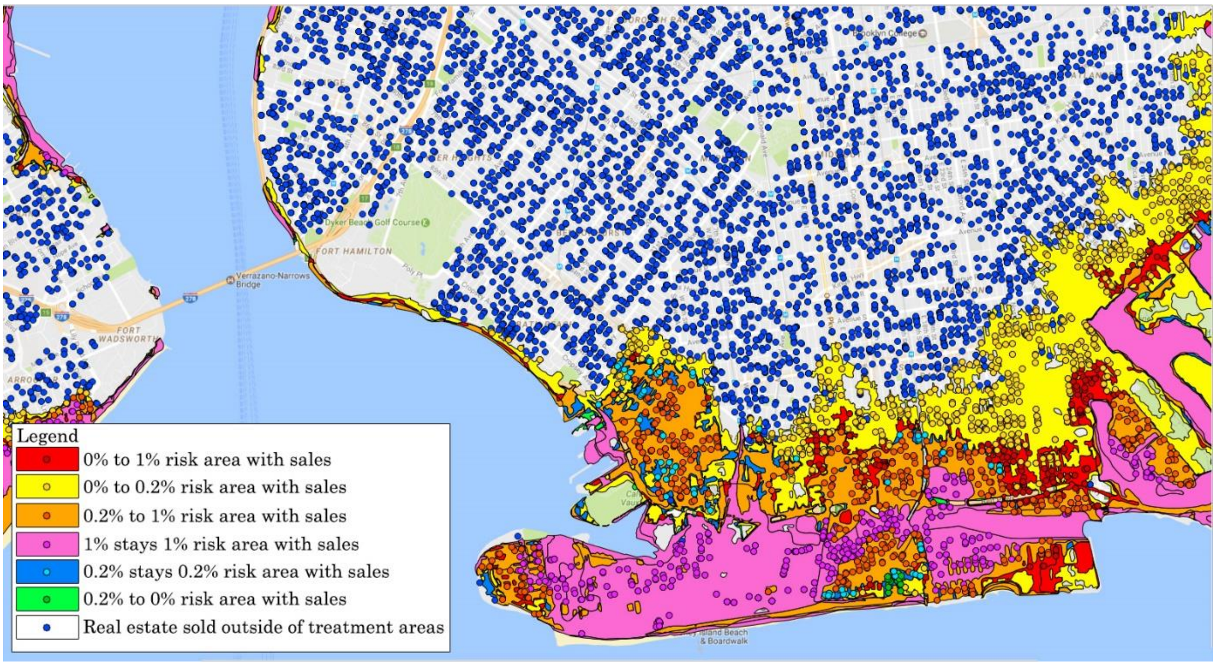

Figure 6. NYC South Brooklyn Area with the different treatment areas and their sales

There are six treatment zones and three control zones (as will be discussed later). The real estate transaction data consists of thirteen years and 600.000+ observations. For each year nine PIP analyses had to be conducted to determine the treatment and control groups. Therefore in total at least 117 PIP analyses were conducted to create the dataset for this thesis. Each PIP analysis took between 40 minutes and six hours to complete. It can thus be stated that creating the data used was relatively labour intensive and time consuming.

In figure 5 all the real estate sales in 2015 can be seen before the Point-in-Polygon analysis. In figure 6 the very same spatial data points can be seen after the Point-in-Polygon analysis. They are no longer all blue. The other colours depict the different changes in flood risk. This is thus the way to create treatment groups from combining information of the real estate transaction data spatial points and the newly defined treatment areas as based on the pre-2015 and post-2015 FEMA flood risk maps. Below the six different treatment area and groups can be seen as defined by their different colours.

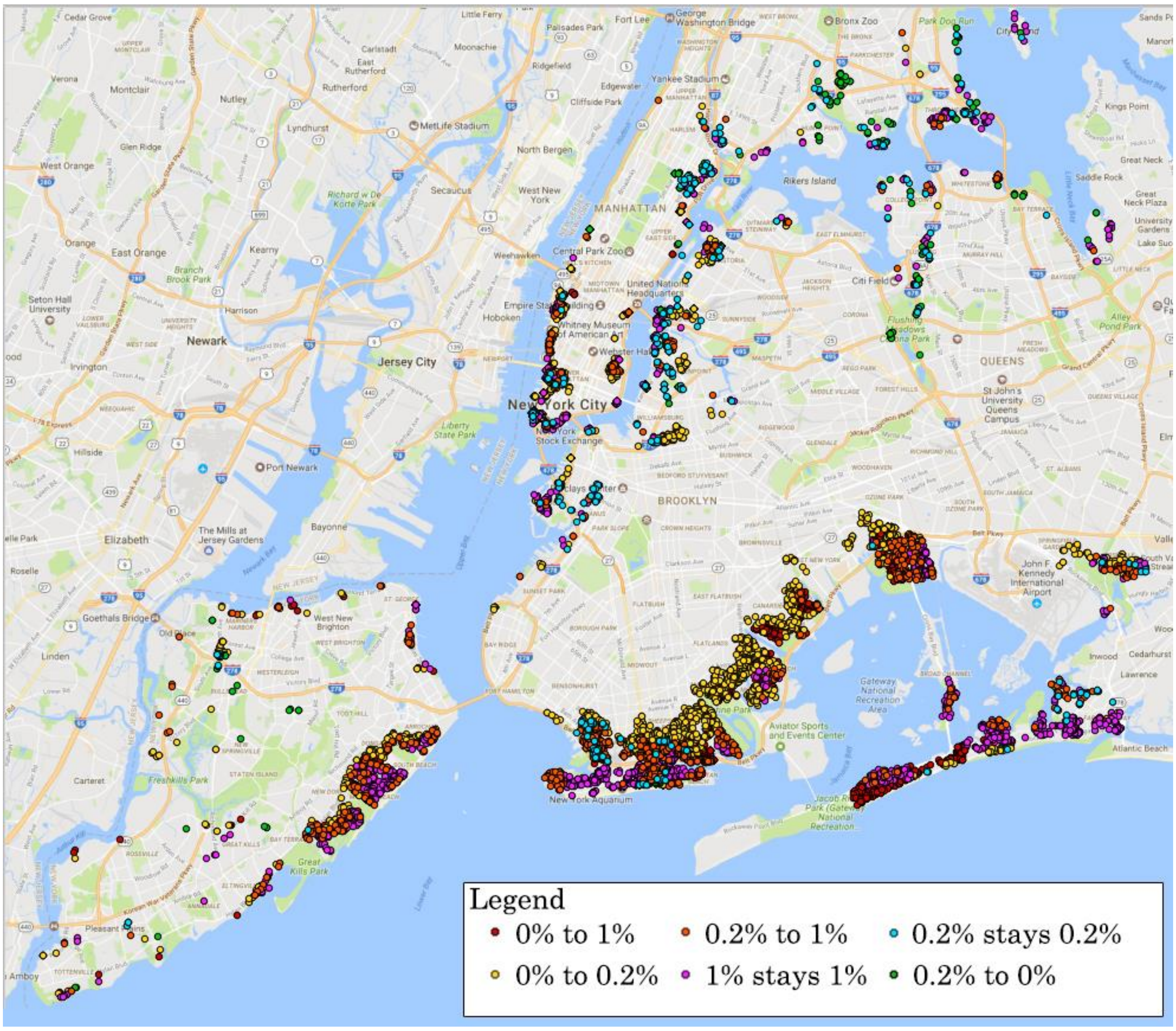

Figure 7. New York City with all different flood risk change transactions

The dark blue points in figure 6 are outside the treatment areas. These observations will later be used to create the control groups. Finally, in figure 7 the six different treatment groups can be seen covering all parts of the New York City coastline. It is important to notice that the treatment groups exists in all five boroughs; Manhattan, The Bronx, Queens, Brooklyn and Staten Island. Manhattan as can be seen on the map as the borough in the north. In the east, Manhattan is connected to The Bronx. South of The Bronx and across the East River the borough Queens is situated. In the west Queens is connected to Brooklyn. Finally, Staten Island is the island in the southwest only connected to Brooklyn by the Verrazano-Narrows Bridge. Brooklyn, Queens and Staten Island on first sight seem to have the most treatment observations. This could be a deception however, as Manhattan has a lot of high buildings, which "stacks" observations on top of each other.

The main reason of doing the Point-in-Polygon analysis is determining in which treatment group a certain real estate sale observation is. Once this became clear, then this sale will get the TREAT dummy variable for this particular treatment group. Since the transaction data also gives a date of sale, also the post treatment dummies could be constructed.

Since the DID-regression compares treatment groups with control groups, it is important to define the control groups carefully (Angrist and Pischke, 2009: 241). Some studies on flood risk that used GIS data defined the control group just as the accumulation of all the observations that are not in the treatment group (Ortega and Taspinar, 2016). Votsis and Perris (2016) and Pope (2008) have a more precise approach that in which control groups are (geographically) more similar to the treatment groups. They argue that the control group should be geographically close to the treatment group to make it more credible that the observations actually only differ in receiving the treatment while all the other determinants of housing prices are approximately the same. They do so by defining the control group as the group of real estate transactions that did not receive the treatment of a flood risk map update, but are within a 300 meter distance from the treatment area. I argue that while this approach might seem favourable above just including all non-treated observations, there are some caveats to this approach. Firstly, while these control observations did not get their flood risk map updated, they did receive new information on their flood risk, namely that they are just outside of the new flood risk zone. This 'relieve' effect could have a positive effect on the housing prices of the control group because of two reasons. The relieve will be positively capitalized by the relieved homeowners. Also homes that are just outside of the updated zone will increase in demand, as they have the same positive attributes as their treated counterparts apart from the fact that they have a lower flood risk.

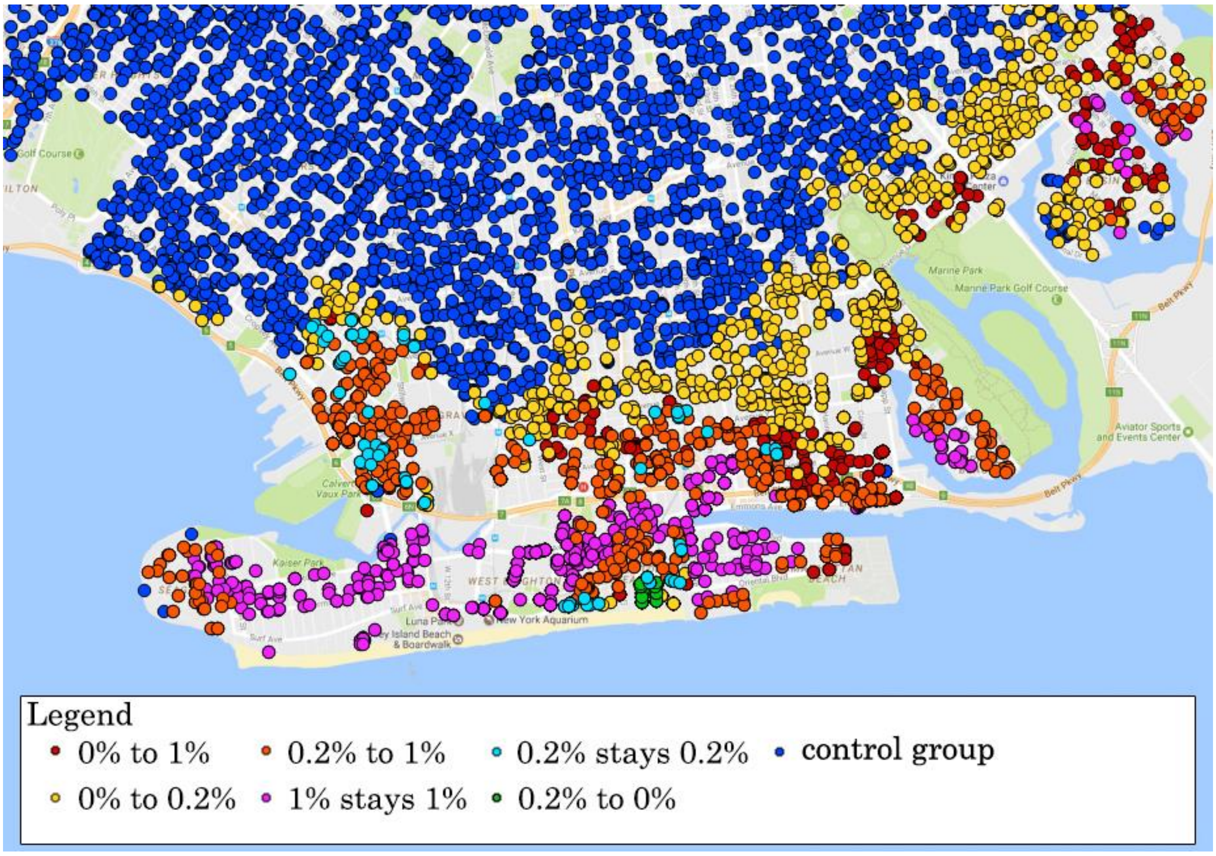

Figure 8. Different treatment groups in southern Brooklyn and the broadly defined control group.

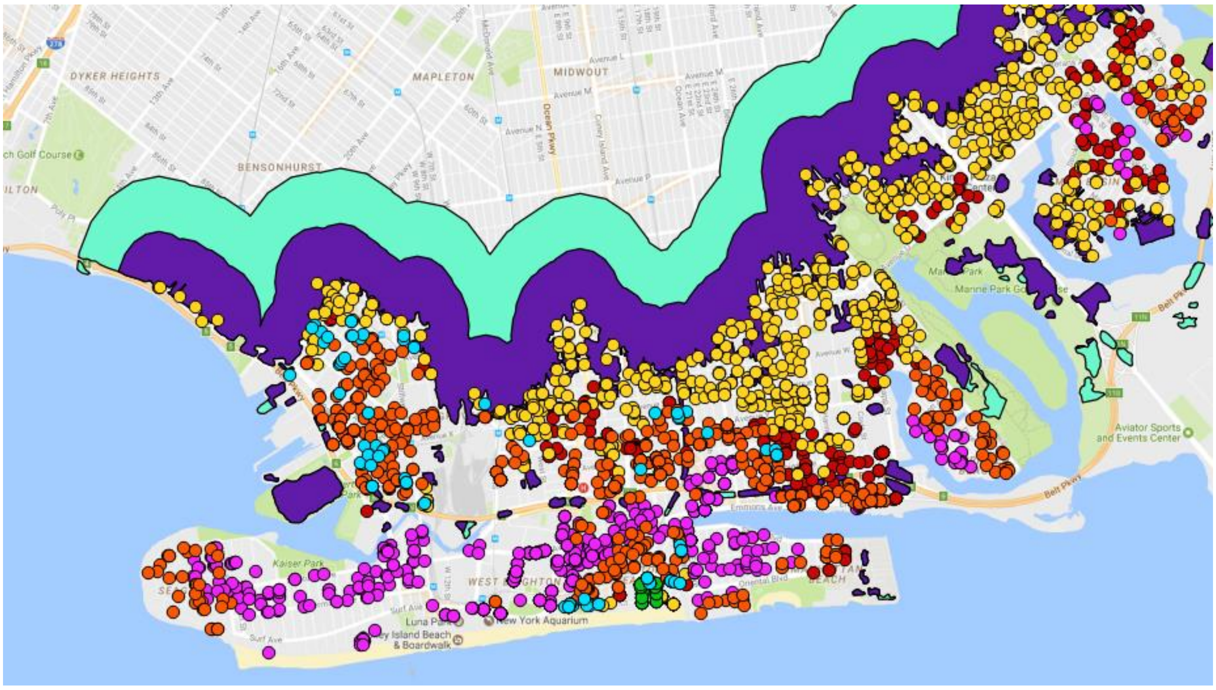

Figure 1. Southern Brooklyn. The different risk changes and the idea of a buffer zone to define the control group.

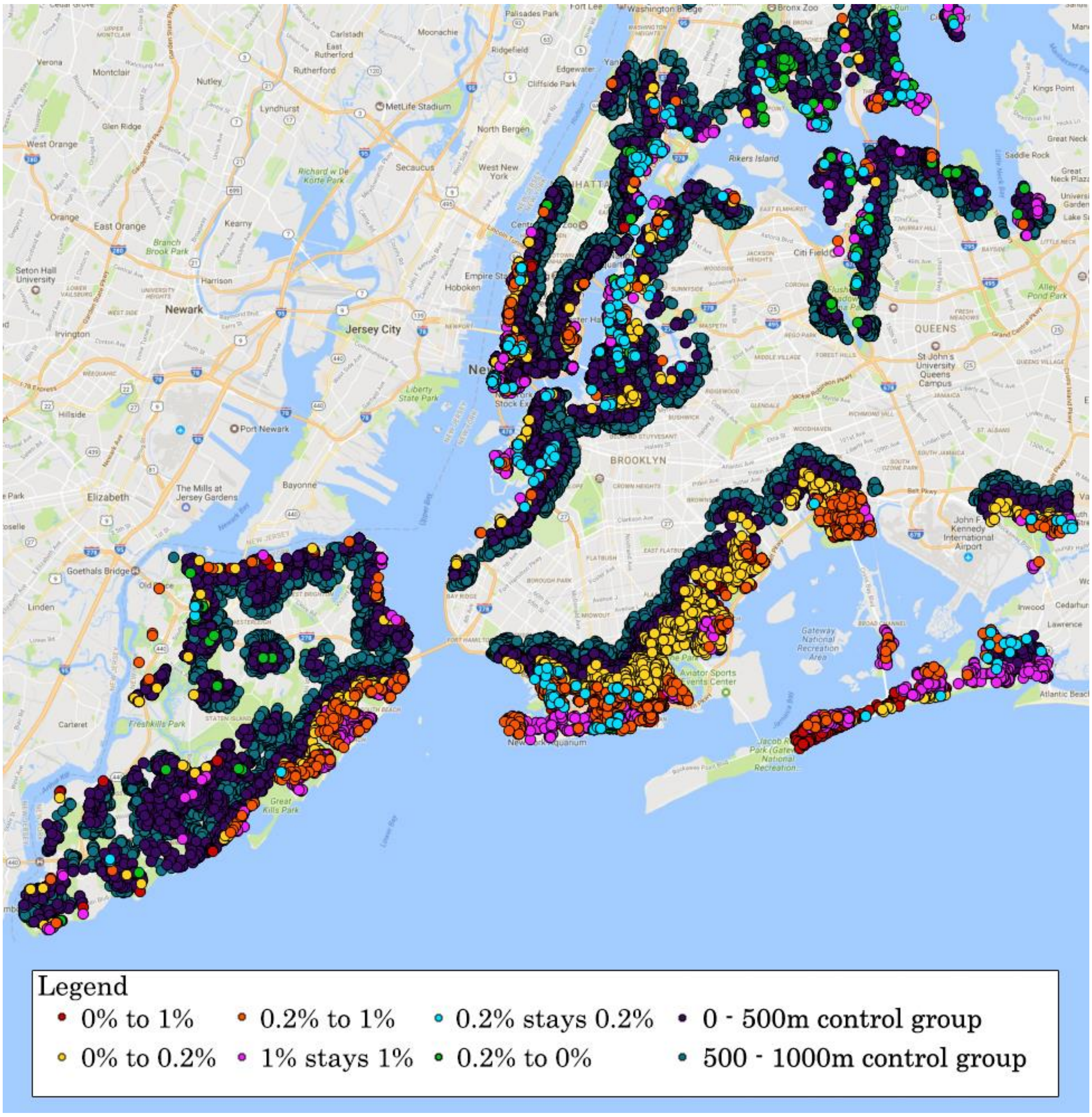

Figure 10. The different flood risk changes and the control groups defined by two different buffer sizes.

As said earlier, in this thesis a different approach is followed to make it more credible that the homogeneity assumption holds. Namely, the control group still has 0% flood risk before and after the map update, but now they fall in a 0 to 500 meter buffer from the treatment group transactions. These buffers were created in QGIS. All treatment observations were merged into one group that thus contained all different treatment groups of all different years. Then the two different buffers were drawn around all these treatment group observations. Since this buffer overlapped with several treatment areas, QGIS was asked to generate the overlap of these two buffers with the 0% stays 0% risk area. This created the final buffers, which are thus defined as being at least 0 meters from a treatment observation and being in the 0% stays 0% control area. The final 500m buffer can be seen in figure 9. After the buffers is defined as a separate polygon, the 500m control group was created through the same Point-in-Polygon analysis that was used to define the treatment groups. All different treatment groups and the buffer control group can be seen in figure 10.

By using this approach of using buffer zone to define control groups, a lot of observations that are too far away from the shore lines are left out from the dataset used in the first regression. If the control groups were "broadly defined" as Ortega and Taspinar (2016) even observations up to 3 km from the shoreline would be taken into account. For this thesis this approach makes less sense, because when studying flood risk the buffer control groups can be assumed to be more relevant as they lie closer to the coast and also have roughly the same characteristics as the treatment group. This makes the homogeneity assumption between the control and treatment group more plausible.

It is important to note that in the first DID-analysis that follows there are only two treatment groups considered. Since the DID-regressions are run per borough there were not enough observations per borough for each of the six flood risk changes. Therefore all observations that had 0.2% yearly flood risk before or after 2015 were considered to belong to the 0% group. This made it possible to create two "condensed" treatments and one condensed control group. The condensed treatment of 0% to 1% flood risk is thus created from of the original 0% to 1% flood risk group and the 0.2% to 1% flood risk group. The 1% stays 1% flood risk group remains the same. The 500 meter control group is the original 500 meter buffer control group plus the 0% to 0.2% flood risk group, the 0.2% stays 0.2% flood risk group and the 0.2% to 0% flood risk group.

4. Empirical Methodology

We use differences-in-differences to estimate the treatment effect of hurricane Sandy and the map update. The DID analysis is based on the philosophy of the counterfactual definition of causality (Angrist and Pischke, 2009: 221-246). This counterfactual way of thinking is depicted in Figure 12. The transparent red line is the assumed counterfactual. The assumption is that that this transparent line would have been the outcome for the treatment group if they would not have received the treatment in the shape of hurricane Sandy and the updated flood risk map. In this case, that would be the group that goes down in risk, as the price goes up. The difference between the counterfactual point and the observed point is the Average Treatment Effect (ATE). This method is called a Differences-in-Differences analysis, because it takes the differences between the two groups after the treatment and subtracts the difference between the two groups before the treatment to get the Average Treatment Effect.

The example in figure 12 only uses two different groups over two different moments in time. Also in a simple DD with only four points it is impossible to check whether the ATE is significant or just an effect caused by chance. To be able to say something the about statistical significance of the treatment effect, the method of DD-regression is most commonly used (Angrist and Pischke, 2009: 233). In its simplest form a DD-regression model looks like this:

$$Y_{dt} = \alpha + \beta TREAT_d + \gamma POST_t + \delta_{rDD}(TREAT_d * POST_t) + e_{dt}$$

Where Y_{dt} is the dependent variable, α is the intercept, $TREAT_d$ is a dummy variable which has a value of 1 if a specific observation is inside the treatment area, $POST_t$ is a dummy variable which has a value of 1 if the specific observation happened after the treatment, $(TREAT_d * POST_t)$ is an interaction variable which coefficient measures the Average Treatment Effect, finally e_{dt} is the error term. The $(TREAT_d * POST_t)$ interaction variable is the most important variable in this regression model. As both $TREAT_d$ and $POST_t$ are dummy variables the interaction is quite intuitive. If they both have a value of 1, the interaction dummy is also 1 as 1 * 1 = 1. If one of the dummies is 0 the interaction dummy is also 0. This means that an observation is in the treatment area and was observed after the treatment. The coefficient of this interaction δ_{rDD} thus measures the average treatment effect.

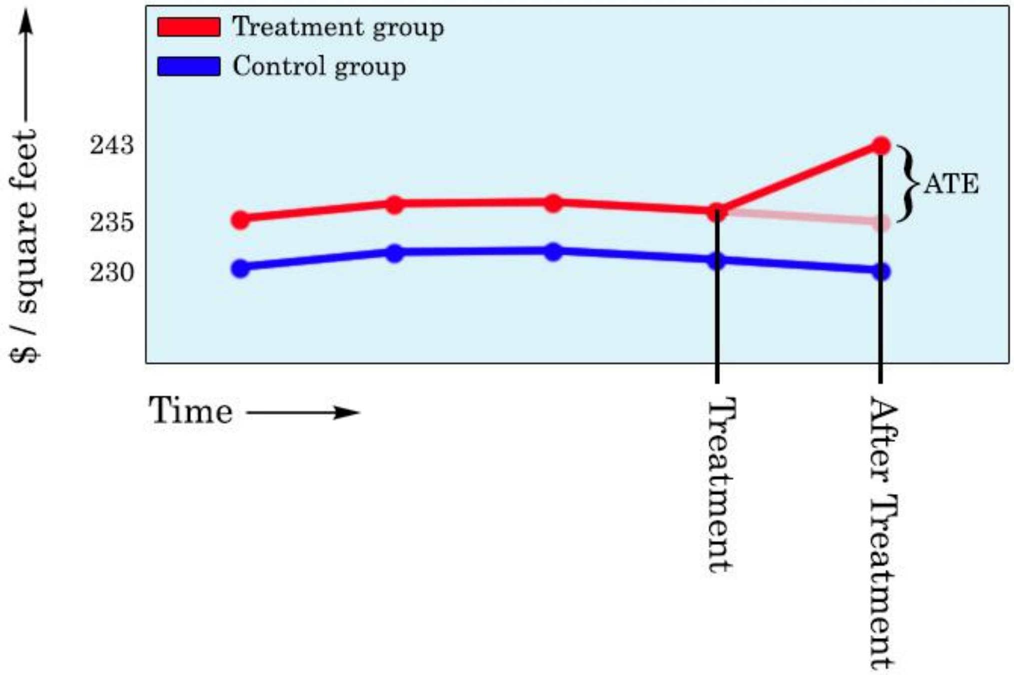

Figure 12. Visualization of the differences-in-differences example

The most important assumption that has to hold in order to infer a causal effect is that the time effects of the treatment and control group are the same in absence of the treatment (Angrist and Pischke, 2009: 221-246). The logic then is that when this is the case, a divergence from this trend must be caused by the treatment. When this assumption holds it is thus possible to talk of a causal effect rather than just a correlation. Although that is the most important assumption that has to hold, there are three others (Toskhov, 2016: 233-234). Firstly, the assumption that must hold is that there is no factor that affected the outcome of the treatment group and the control group differently. Secondly, the assumption is that the control group and the treatment group would both react in the same way if they both got the treatment. This is called the assumption of homogeneity. To make the homogeneity assumption more likely to hold, the control group is not simply defined as "all the real estate transactions that are not in the treatment group". Rather, for the first DID-analysis the control group is defined as transactions that fall within a 500 meter buffer from the treatment group, to make it more likely that the groups are comparable. The final assumption is that of non-interference. This assumption holds when the treatment on the treatment group does not influence the control group. This assumption might be harder to hold, because it might be possible that there is a "relieve effect" in the 500 meter buffer control group. These homeowners might have expected to see their risk go up and are relieved to see that this is not the case. This might in turn increase their housing prices.

Since the DD-regression model is relatively easy to expand, in this study we also control for area fixed effects. Central in the idea of fixed effects models is that every individual or group inherently has certain unobserved and fixed characteristics that do influence the dependent variable (Angrist and Pischke, 2009: 222). This effect is called fixed as it does not vary over time. Since it does not vary over time this fixed effect can be thought of as a different intercept and slope for every single group or cluster in the model. The coefficients of these dummies will therefore represent the unobserved individual or group effects and the time effects, quarters in this thesis.

A difference-in-differences approach in a way already captures unobserved fixed group-level variables, because it already captures the unobserved fixed effects of the treatment and control group (Angrist and Pischke, 2009: 227). However, since both the control and treatment groups are present in most parts of New York City, the model used will control for fixed effects by including dummy variables for all different neighbourhood levels included in the dataset. Furthermore, we will also control for neighbourhood-specific trends (Angrist and Pischke, 2009: 238). Ortega and Taspinar (2016: 13) in their research on the price effects on Hurricane Sandy use different group-levels fixed effects in their DID-regression: borough, neighbourhood, zip code and building block. They prefer to control for fixed effects on city block level and cluster the standard error at the same level. Since their analysis also uses the transactions data set from the Finance Department, this research will follow their example and control for the same fixed effects levels.

In the DID-regression standard errors need to be clustered, because observations in the same cluster are not independent from each other (Angrist and Pischke, 2009: 293-325). By clustering the standard error on the city block level the estimated effects are adjusted for the fact that observations within a city block are not independent from each other, as they are influenced by the same characteristics of the geographical area[4]. For this approach it is important that there are enough different clusters. With too few clusters, the serial correlation or intraclass correlation is underestimated (Angrist and Pischke, 2009: 319). Angrist and Pischke (2009: 319) as a rule of thumb state that standard errors can only be effectively adjusted for clustering if there are at least 42 clusters in the analysis. Therefore in the DID-regression only controls for fixed effects for the level that has at least 42 clusters.

The data used in this thesis is "repeated cross sections" data. This means that a house sold in 2003 is typically not sold again in 2004, 2005, etc. Most of the real estate sold in

[4] This was done automatically by using the "cluster" command in STATA.

between 2003 and 2015 only appears once in the dataset. This characteristic of the transaction data makes that it is not fit for panel data analysis, such as Panel OLS with a “within” fixed effects or random effects estimators (Field, 2012: 855-909). Since controlling for time-invariant fixed effects of different geographical areas in which the transactions took place, the Least Squares Dummy Variables (LSDV) method is used. This means that the cluster above the transaction, the neighbourhood for example, is added as a dummy variable in a normal OLS regression to control for its time-invariant fixed effects. The same goes for the time fixed effects as for each of the fifty-two different quarters a dummy variable is added. The number of groups in a level determines the amount of dummy variables. While adding more observations (rows) to a regression causes no problems, adding too many dummy variables (columns) does. For this reason not all fixed effects could be taken into consideration. However, since the data was split up per borough it was possible to control for fixed effects on the city block level. Fixed effects for zip codes were excluded from the regression, as the number of zip code areas within each borough is lower than 42. In the analysis therefore the regression is run four times for every borough. Once with neighbourhood fixed effects, once with lot fixed effects, once with block fixed effects and finally once with block fixed effects while also controlling for the year in which the building was built and the building category. Some boroughs have more zip code areas than neighbourhoods. In this case the zip codes are used as a clusters, as this will increase the amount of clusters to above 42.

Ortega and Taspinar (2016) find that Hurricane Sandy had a significant negative effect on real estate prices in New York city. This hurricane happened in 2012, but still had a time-varying coefficient that was significant for 2015. We also know that the effect of Hurricane Floyd on housing prices diminished over 5 or 6 years (Bin and Landry, 2013). Since there are only just over 2 years between Hurricane Sandy hit New York City and the flood risk map update, the effect of Hurricane Sandy needs to be controlled for in the DID-analysis. This is done by not only including the interaction effect of (POST * TREAT) for the treatment groups and the time after the map update, but also for the treatment group and the time after Hurricane Sandy. This will hopefully disentangle the effects of Sandy and the flood risk map update. If the effect of the flood risk map update is significant when controlled for Sandy, the effect can be seen as causal. This brings us to the following base specification of the difference-in-differences model as used in the first analysis:

$$\begin{aligned} Log(price) = \; & \alpha + \beta 1(Treatment\_0\_to\_1) + \beta 2(Treatment\_1\_stays\_1) + \beta 3(Post\ Sandy) + \\ & \beta 4(Post\ Map\ Update) + \beta 5(Treatment\_0\_to\_1 * Post\ Sandy) + \\ & \beta 6(Treatment\_1\_stays\_1 * Post\ Sandy) + \beta 7(Treatment\_0\_to\_1 * Post\ Map \\ & Update) + \beta 8(Treatment\_1\_stays\_1 * Post\ Map\ Update) + \beta 9(Quarter\ Time \\ & Dummies) + \quad \beta 10(geographical\ fixed\ effects) \end{aligned}$$

The dependent variable in this DID-analysis is the natural log of the inflation corrected transaction price. Treatment_0_1 is a dummy variable that is “1” for the observations which flood risk goes up from 0% to 1% in 2015. Treatment_1_stays_1 is a dummy variable that is “1” for the observations which flood risk remains 1% after 2015. “Post Map Update” is a dummy variable that is “1” after the introduction of the preliminary FIRM on January 31st 2015. “Post Sandy” is a dummy variable that is “1” for all the transactions after Hurricane Sandy hit New York City on October 29th 2012. β5 and β6 are coefficients of the interaction effect between being in a treatment group and being a transaction after the flood risk map update. These dummy variables are thus “1” if a transaction is in the specific treatment group and after the flood risk map update. These two coefficients are the treatment effects of the flood risk map update. β7 and β8 are the coefficients of the interaction effects between being in a specific treatment group and being a transaction after Hurricane Sandy. These two coefficients are the treatment effects of being in a treatment zone after Sandy. These dummy variables are thus “1”if a transaction in the specific treatment group was made after Hurricane Sandy. These two coefficients are in the model to control for Sandy’s effect on housing prices. Finally β9 and β10 are the coefficients of the variables that are included to control for quarterly time effects and fixed geographical effects.

5. Results

In this section we discuss the results separately per borough. The order of discussed borough results is based on the extent to which Hurricane Sandy flooded each borough[5]. This is done, because it is hypothesized that the borough that got hit hardest by Sandy will also show the biggest effects. The borough that got the biggest part of its area flooded (Staten Island) is discussed first, while the borough that go hit the least (Manhattan), will be discussed last[6]. The amount of flooding caused by Sandy is not the only reason to analyse the NYC boroughs separately. Each of these boroughs namely also differs in culture, socio-economic composition, city planning, demand on the housing market and in type of buildings. First the descriptive statistics of each borough will be discussed. This is important, as the DID-analysis requires that both treatment groups are comparable with the control group (Angrist and Pischke, 2009: 241-243). Secondly, the price movements per treatment group are analysed graphically per borough. This is important because the causal inference of the difference-in-difference analysis is based on the common trend assumption (Angrist and Pischke, 2009: 227-233). This assumption is thus tested graphically. Thirdly, this section will discuss the DID-regression results per borough. Finally, to check whether these findings are robust, in the last part of this section several robustness checks are implemented and their results discussed.

In table 1 the descriptive statistics of the real estate sold on Staten Island is shown. It covers three periods in time, before Hurricane Sandy, between Sandy and the flood risk map update and after this map update. For each of these periods it shows the descriptive statistics for the control group and both the treatment groups. The first thing that can be seen in this table is that the mean of transaction prices is very similar for the three groups in all three periods. In the middle period the standard deviation of the first and second treatment group are large compared to that of the control group. This could be due to price shocks after Hurricane Sandy. For all three groups the years in which the sold property was built is very similar over the years. Finally, if we look at the composition of building types, we can conclude that the composition is relatively similar, although treatment group 2 has less condos and more coops than the other two groups[7].

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[5] The Bronx saw 0.01% of its borough flooded, Manhattan 0.23%, Queens 0.45%, Brooklyn 0.65% and Staten Island 3% (Ortega and Taspinar, 2016: 28)

[6] The borough of The Bronx was not analysed in thesis due to multiple long periods of missing data for the treatment groups. On top of that it saw only 0.01% of its area flooded by Hurricane Sandy.

[7] A condo or "condominium" is a type of building that consists of multiple units that can be owned separately, while a part of the property is shared with other owners. Condos are mostly seen in high-rise

Descriptive statistics Staten Island

Staten Island	Pre Sandy (Jan 2013 - Oct 2012)			Post Sandy & pre map (Nov 2012 - Jan 2015)			Post map (Feb 2015 - Dec 2015)		
	Control (n = 21604)	Treatment 1 (n = 1759)	Treatment 2 (n = 2660)	Control (n = 3721)	Treatment 1 (n = 259)	Treatment 2 (n = 627)	Control (n = 1703)	Treatment 1 (n = 152)	Treatment 2 (n = 372)
Mean Price	$465,891	$454,588	$431,410	$420,495	$447,865	$395,004	$426,300	$395,884	$418,035
SD Price	$446,372	$424,449	$243,165	$237,311	$1,083,680	$1,405,254	$201,821	$137,531	$181,051
Mean Log(Price)	12.92	12.88	12.85	12.83	12.76	12.61	12.85	12.81	12.85
SD Log(Price)	0.53	0.54	0.54	0.52	0.56	0.62	0.50	0.45	0.46
Mean Year built	1973.99	1976.34	1974.82	1974.48	1969.08	1967.69	1973.29	1971.55	1951.95
SD Year Built	30.73	27.21	30.68	30.66	30.50	32.83	30.15	28.00	40.36
% 1-family	64.81%	71.18%	74.96%	63.05%	71.81%	79.74%	64.83%	78.29%	64.25%
% 2-family	24.57%	19.73%	13.42%	25.45%	19.31%	10.21%	24.72%	15.13%	6.99%
% 3-family	0.78%	0.51%	0.94%	0.54%	1.54%	1.12%	0.88%	0%	0.27%
% Condos	8.45%	2.05%	7.48%	9.30%	1.54%	5.26%	7.40%	1.97%	27.69%
% Coops	1.39%	6.54%	3.20%	1.67%	5.79%	3.67%	2.17%	4.61%	0.81%

Table 1. Descriptive statistics Staten Island

Average price movements per treatment and control group for Staten Island

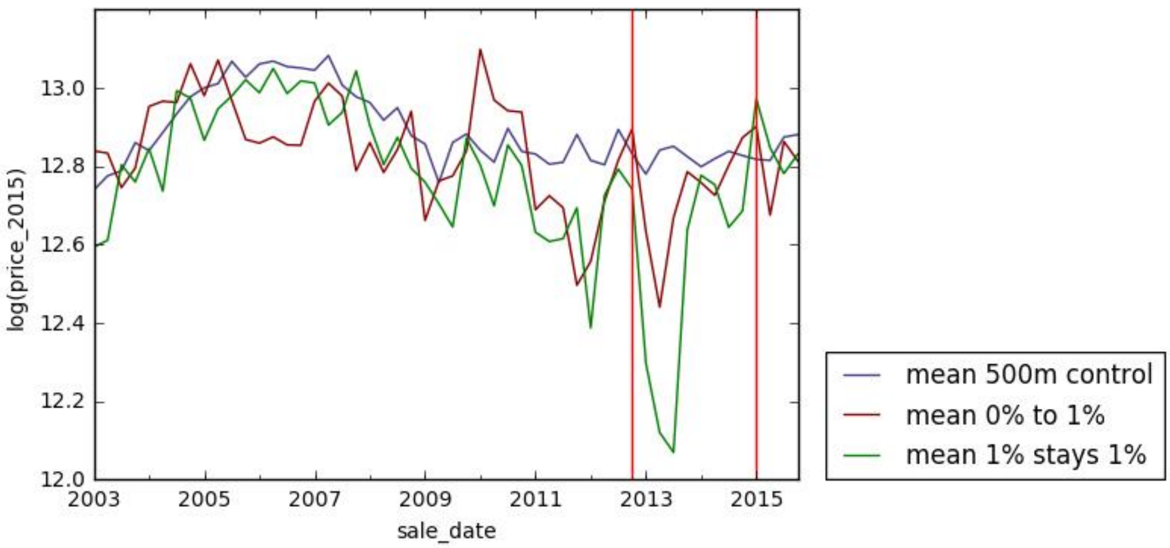

Figure 13. Price movements Staten Island, 2003-2015

buildings. Coops is not a distinct building type per se. Its name originates from the fact that multiple people are member of a co-operative association that is the owner of the property that the members live in. Although coops are not a distinct building type, it is seen more often in high-rise buildings as well.

Figure 13 shows the average price movements per quarter for the control group and the two treatment groups on Staten Island. There are two vertical red lines shown in the graph. The first one depicts the date that Hurricane Sandy hit New York City (26-10-2012). The second vertical line depicts the introduction of FEMA's new preliminary FIRM (31-01-2015). According to Ortega and Taspinar (2016: 28) Staten Island saw the highest percentage of floods due to Hurricane Sandy as compared to the other boroughs. The graph seems in line with this statement as it shows a large drop in housing prices for both treatment groups after Sandy. This price drop is deeper and wider when compared to the price drop in other boroughs. Apart from an upward spike for treatment group 1 in 2010 and the effects of Sandy, the price movements of the three groups are relatively similar. This is important in the light of the common trend assumption on which the DID-regression is based. Before the map update both treatment groups see their housing prices rise, while the control group stays stable. After the map update however, the prices drop for both the treatment groups. This partly recovers after two or three quarters. The price of the control group goes up after the flood risk map update

Table 2 shows the DID-regression results for Staten Island. Before looking at the table it is important to understand how a significant effect should be interpreted. The first set of regressions include five types of variables, three of which are included in the regression tables. The first is the treatment group dummy variable. This variable shows whether or not there is a significant time-invariant difference between the treatment group and the control group. Then the post Sandy and post map update variables show whether or not there is a significant difference between all observations before the treatment and all observations after the treatment. The third type of variable is the interaction effect variable, which measures the effect of being both in a treatment group and in the time period after the treatment. This effect is thus as compared to the control group. If the control group remains stable, but the treatment group decreases in price, the interaction effect is most likely negative. The two variables that are included in the DID-model, but not in the regression table are the quarter time dummies and the geographical fixed effect levels. This is due to the fact that it does not fit on one page and also these variables are mainly included to control for (time) fixed effects rather than having an intrinsic value of their own for this thesis.

Difference-in-differences regression results Staten Island

Staten Island	(1)	(2)	(3)	(4)	(5)
Treat 0% to 1%	-0.032	-0.059	-0.007	-0.001	-0.006
	[0.050]	[0.053]	[0.018]	[0.013]	[0.014]
Treat 1% stays 1%	-0.064	-0.081***	-0.027	0.008	0.001
	[0.056]	[0.016]	[0.027]	[0.020]	[0.023]
Post Sandy	0.064	0.135***	0.018	0.023	0.010
	[0.040]	[0.026]	[0.051]	[0.049]	[0.050]
Post map	-0.035	-0.043	-0.080	-0.107**	-0.152***
	[0.068]	[0.063]	[0.054]	[0.044]	[0.044]
(Treat 0% to 1%	-0.015	-0.032	-0.013	-0.014	-0.028
* Post Sandy)	[0.049]	[0.038]	[0.034]	[0.034]	[0.035]
(Treat 1% stays 1%	-0.168**	-0.157***	-0.112***	-0.118***	-0.129***
* Post Sandy)	[0.077]	[0.026]	[0.041]	[0.041]	[0.045]
(Treat 0% to 1%	0.035	0.029	0.003	0.000	0.002
* Post map)	[0.040]	[0.044]	[0.044]	[0.044]	[0.047]
(Treat 1% stays 1%	0.286**	0.201***	0.209**	0.174***	0.129***
* Post map)	[0.132]	[0.037]	[0.090]	[0.065]	[0.050]
Observations	32857	32857	32857	32857	29534
R-squared	0.204	0.141	0.452	0.488	0.428
FE level	Neighbourhood	Lot	Block	Block	Block
Clustered S.E. level	Neighbourhood	Lot	Block	Block	Block
Number of clusters	52	960	1935	1935	1914
Controlled for building type and year built	No	No	No	Yes	Yes
Type of buildings	All	All	All	All	Family Houses

Table 2. Difference-in-differences regression results for Staten Island. Each model (column) runs the same base specification, but differs in the fixed effect level and the level at which the standard error is clustered. One asterisk (*) depicts a p-value of < 0.1, two asterisks (**) a p-value of < 0.05 and three asterisks (***) a p-value of < 0.01. In the last column (model 5) the same base specification is run, but on a subset of only family houses.

Table 2 shows the DID-regression results for Staten Island. Each of the five columns depicts a different model that was run. These models differ on the level of fixed effects and the level at which the standard error is clustered. The first model has highest level of fixed effects and clustering at a neighbourhood level, while the models after that have smaller clusters, namely the lot and block levels. The table will be discussed per model.

In the model (1) we see that both the treatment group fixed effects are not significant, meaning that the time-invariant effects of the treatment groups in comparison with the control group are not significant. The same goes for the “Post Sandy” and the “Post Map” variables. In general there is thus no significant difference between the time before Sandy and the time after Sandy and between the time before the map update and after the map update. Being in the first treatment group (0% to 1% flood risk) and in the post Sandy period has no significant effect as compared to being in the control group. For the first treatment group Hurricane Sandy thus does not induce a significant treatment effect. The interaction effect between treatment group 2 (1% stays 1%) and the Post Sandy variable is negative and significant however. The treatment effect is -16.8 logistic points, which is roughly an effect of -16.8%. This significant effect says nothing without interpretation. The housing prices could be affected because of directed damage caused by hurricane Sandy. Another possibility is the “reminding” effect. Hurricane Sandy as a bringer of information might have reminded the market that those houses were in a flood risk zone, leading to lower housing prices. If we look at the effect of the introduction of the updated flood risk map on the treatment groups we see two things. First, the map has no significant effect on treatment group 1, even though this was hypothesized. The interaction effect between the flood risk map and treatment group 2 is statistically significant and positive. This is strange, as I hypothesized that increased flood risk information would decrease the housing prices. This significant effect might therefore be due to other reasons. For instance, the control group might have dropped in value more than the treatment group after the map update. The price movements in figure 1 do not show this however. Another possibility is that property with waterfront view increased highly in demand in 2015. This is also implausible however, because treatment group 1 does not show such an effect. Another interpretation could therefore be that the effect of Sandy faded out in the year 2015. Other studies found that the effects of storms only fade out after five or six years, so this interpretation is rather speculative (Bin and Polasky, 2004).

The other models show very similar results when being controlled for more precise geographical fixed effects. Sandy’s treatment effect on treatment group 2 remains negative and significant for all models. Its magnitude does decrease however when controlling for lot fixed effects and building block fixed effects. Also the effect of the post map period on treatment group 2 remains positive and significant for the other models. This effect also decreases when more precise fixed effects are controlled for. Interesting to notice is that when the same specification is run on a subset of family houses (model 5) while controlling for age and building type, these effects still do not change.

Results Brooklyn

In table 3 the descriptive statistics of the real estate sold in Brooklyn is shown. The first interesting thing it shows is that for the first and second period the average prices of sold real estate is relatively similar. For the period after the flood risk map update however, the control group sees a sharp increase in the mean price. Also the standard deviation of the price sees a relatively large increase. The composition of housing types is relatively balanced, with the remark that treatment group 2 has less 2-family houses and treatment group 1 has less condos. Overall it can be concluded that the treatment and control groups for Brooklyn are quite similar in their characteristics.

Figure 14 shows the average price movements per quarter for the control group and the two treatment groups for Brooklyn between 2003 and 2015. Brooklyn shows different price movements than Staten Island. First, the price averages are more apart from each other. The average price movements of treatment group 1 (0% to 1% flood risk) are relatively similar to that of the control group, even though the control group overall shows a higher average price. The similar trend assumption thus seems to hold for these two groups. The second treatment group (1% stays 1%) shows a price movement that is not so similar to the other two groups however. Whether the similar trend assumption holds for this treatment group is therefore more obscure. What can furthermore be seen in figure 14 is that treatment group 2 shows a large price drop after Hurricane Sandy. For treatment group 1 only a minor price drop is shown. Both the treatment groups show a drop in housing prices after the flood risk map update, while the average price of the control group keeps increasing. The drop that the treatment groups show only seems to be for one quarter. From the graph it can therefore not be concluded that whether this price drop is significant and causal. These topics will be discussed below.

Descriptive statistics Brooklyn

Brooklyn	Pre Sandy (Jan 2013 - Oct 2012)			Post Sandy & pre map (Nov 2012 - Jan 2015)			Post map (Feb 2015 - Dec 2015)		
	Control (n = 38590)	Treatment 1 (n = 8046)	Treatment 2 (n = 3761)	Control (n = 7051)	Treatment 1 (n = 1522)	Treatment 2 (n = 787)	Control (n = 2950)	Treatment 1 (n = 665)	Treatment 2 (n = 355)
Mean Price	$618,843	$489,454	$608,708	$767,310	$477,557	$605,363	$929,199	$492,120	$627,141
SD Price	$544,742	$346,986	$660,511	$808,878	$665,048	$642,790	$1,196,089	$309,995	$586,318
Mean Log(Price)	13.12	12.91	13.03	13.23	12.86	12.96	13.40	12.92	13.04
SD Log(Price)	0.69	0.66	0.76	0.82	0.66	0.82	0.82	0.63	0.75
Mean Year built	1951.08	1954.59	1956.04	1948.85	1956.34	1956.50	1953.29	1955.85	1960.73
SD Year Built	36.34	23.86	31.51	38.40	27.06	30.93	39.01	25.78	31.05
% 1-family	16.87%	24.00%	20.90%	15.67%	25.95%	23.63%	17.56%	26.47%	21.13%
% 2-family	23.57%	29.27%	11.70%	21.67%	28.97%	10.16%	22.64%	28.27%	12.39%
% 3-family	7.18%	6.43%	4.12%	7.96%	5.65%	3.94%	6.85%	4.81%	3.38%
% Condos	34.97%	19.44%	37.70%	35.88%	17.67%	29.61%	35.93%	17.14%	29.86%
% Coops	17.41%	20.87%	25.58%	18.82%	21.75%	32.66%	17.02%	23.31%	33.24%

Tabel 3. Descriptive statistics Brooklyn

Average price movements per treatment and control group for Brooklyn

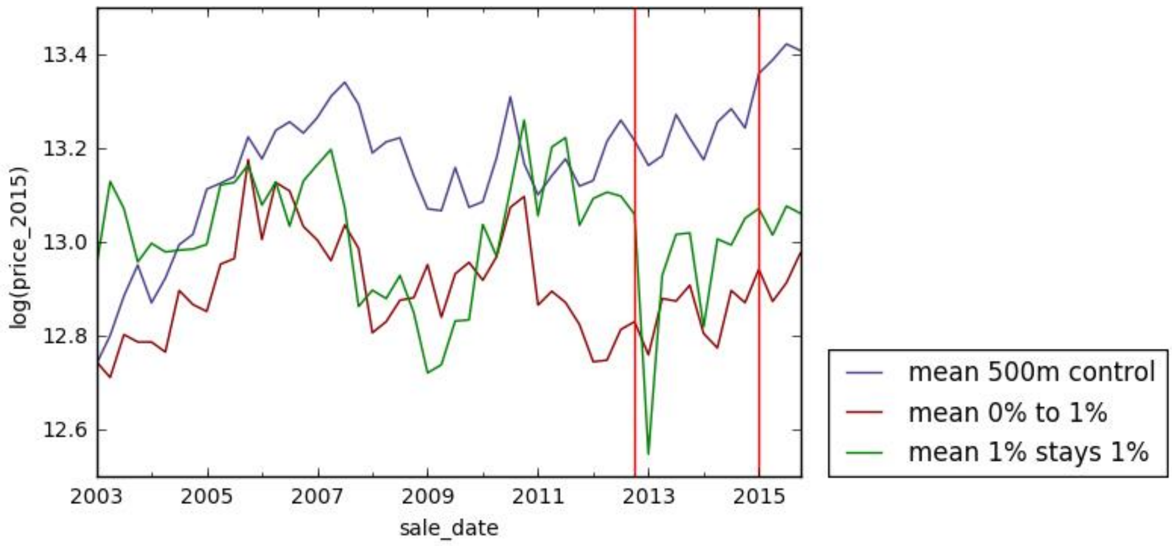

Figure 14. Price movements Brooklyn, 2003-2015

Difference-in-differences regression results Brooklyn

Brooklyn	(1)	(2)	(3)	(4)	(5)
Treat 0% to 1%	-0.061	0.007	-0.130***	0.014	0.0135
	[0.048]	[0.018]	[0.024]	[0.011]	[0.011]
Treat 1% stays 1%	-0.032	-0.070	-0.060	0.0133	-0.021
	[0.101]	[0.079]	[0.046]	[0.058]	[0.025]
Post Sandy	0.094***	0.030	0.072	0.024	0.094
	[0.030]	[0.040]	[0.047]	[0.035]	[0.061]
Post map	-0.113*	-0.123**	-0.068	-0.080*	-0.042
	[0.058]	[0.048]	[0.056]	[0.041]	[0.040]
(Treat 0% to 1%	-0.153***	-0.164***	-0.161***	-0.145***	-0.116***
* Post Sandy)	[0.050]	[0.023]	[0.026]	[0.020]	[0.025]
(Treat 1% stays 1%	-0.130***	-0.097**	-0.138***	-0.121***	-0.126**
* Post Sandy)	[0.055]	[0.041]	[0.038]	[0.038]	[0.059]
(Treat 0% to 1%	-0.093***	-0.046	-0.097***	-0.056*	-0.039
* Post map)	[0.031]	[0.032]	[0.034]	[0.031]	[0.037]
(Treat 1% stays 1%	-0.067	-0.030	-0.094*	-0.039	0.048
* Post map)	[0.054]	[0.048]	[0.049]	[0.037]	[0.074]
Observations	63755	63755	63755	63755	30888
R-squared	0.230	0.512	0.1775	0.5945	0.450
FE level	Neighbourhood	Block	Lot	Block	Block
Clustered S.E. level	Neighbourhood	Block	Lot	Block	Block
Number of clusters	52	2146	2383	2146	1997
Controlled for building type and year built	No	No	No	Yes	Yes
Type of buildings	All	All	All	All	Family houses

Table 4. Difference-in-differences regression results for Brooklyn. Each model (column) runs the same base specification, but differs in the fixed effect level and the level at which the standard error is clustered. One asterisk (*) depicts a p-value of < 0.1, two asterisks (**) a p-value of < 0.05 and three asterisks (***) a p-value of < 0.01. In the last column (model 5) the same base specification is run, but on a subset of only family houses.

After Staten Island the borough of Brooklyn was had the highest percentage of floods due to Hurricane Sandy in 2012. The DID-regression results of this borough are shown in table 4. Again the models represent the same DID base specification, while each model controls for fixed effects at another level. Model 1 shows highly significant effects for three of the four treatment effects. First, hurricane Sandy's effect is -15.3 logistic points on treatment group 1 and -13.0 logistic point on treatment group 2. Both these effects are in the hypothesized direction. What is also interesting about the first model is that the introduction of the new flood risk map seems to have a negative effect of -9.3 logistic points on treatment group 1. This effect was also hypothesized. This map update effect does not show for treatment group 2 however. When we look at model 2, it can be seen that the effect of the flood risk map update disappears when controlling for the fixed effects of more clusters, namely blocks. The effect of Sandy on both treatment groups remains highly significant and negative however. Also the post map period becomes significant and negative in this model. The post Sandy dummy and the treatment fixed effects do not show significant correlations. In model 3, controlling for fixed effects at the lot level, a significant effect of treatment group 1 can be seen. Compared to the control group this treatment group thus has lower housing prices independent of time in this model. Also the treatment effect of Hurricane Sandy is significant and negative again for both treatment groups. The flood risk map update is significant for treatment group 1 and almost significant ($p < 0.1$) for treatment group 2. When model 4 also controls for building type and age the effect of the map update becomes insignificant again for both treatment groups. The effect of Hurricane Sandy remains negative and highly significant however. This remains unchanged when running the same model on a subset of family houses in model 5.

Results Queens

In table 3 the descriptive statistics of the real estate sold in Queens is shown. The means of the prices are very similar. The standard error of the control group in the first period is, with almost six times the mean, is relatively large though compared with the treatment groups. Both the age and building types of Queens seems to be relatively balanced, with the footnote that the control groups has more coops and treatment group 1 has more 1-family houses. Overall can be concluded that the Queens data is relatively balanced.

Descriptive statistics Queens

Queens	Pre Sandy (Jan 2013 - Oct 2012)			Post Sandy & pre map (Nov 2012 - Jan 2015)			Post map (Feb 2015 - Dec 2015)		
	Control (n = 21290)	Treatment 1 (n = 4464)	Treatment 2 (n = 5882)	Control (n = 4516)	Treatment 1 (n = 768)	Treatment 2 (n = 878)	Control (n = 1670)	Treatment 1 (n = 375)	Treatment 2 (n = 439)
Mean Price	$540,860	$528,664	$472,876	$501,649	$470,667	$460,979	$543,007	$497,887	$468,844
SD Price	$3,233,918	$399,924	$286,058	$448,017	$319,250	$314,836	$396,826	$354,049	$322,661
Mean Log(Price)	12.96	12.96	12.90	12.89	12.82	12.80	12.98	12.88	12.80
SD Log(Price)	0.68	0.74	0.63	0.72	0.79	0.76	0.70	0.76	0.79
Mean Year built	1961.74	1961.60	1962.27	1965.45	1957.41	1960.22	1964.44	1961.54	1957.96
SD Year Built	29.39	29.18	37.34	30.60	28.32	37.73	30.99	27.70	35.49
% 1-family	23.47%	40.30%	32.40%	16.52%	42.32%	30.07%	20.72%	41.33%	33.71%
% 2-family	24.75%	27.82%	35.53%	16.98%	29.04%	25.51%	20.30%	26.40%	32.12%
% 3-family	4.45%	5.31%	6.72%	3.48%	4.04%	5.92%	4.25%	2.93%	5.24%
% Condos	22.95%	16.42%	14.97%	35.21%	13.15%	22.21%	28.02%	16.80%	13.21%
% Coops	25.37%	10.15%	10.56%	27.81%	11.46%	16.29%	26.71%	12.53%	15.72%

Table 5. Descriptive statistics Queens

Average price movements per treatment and control group for Staten Island

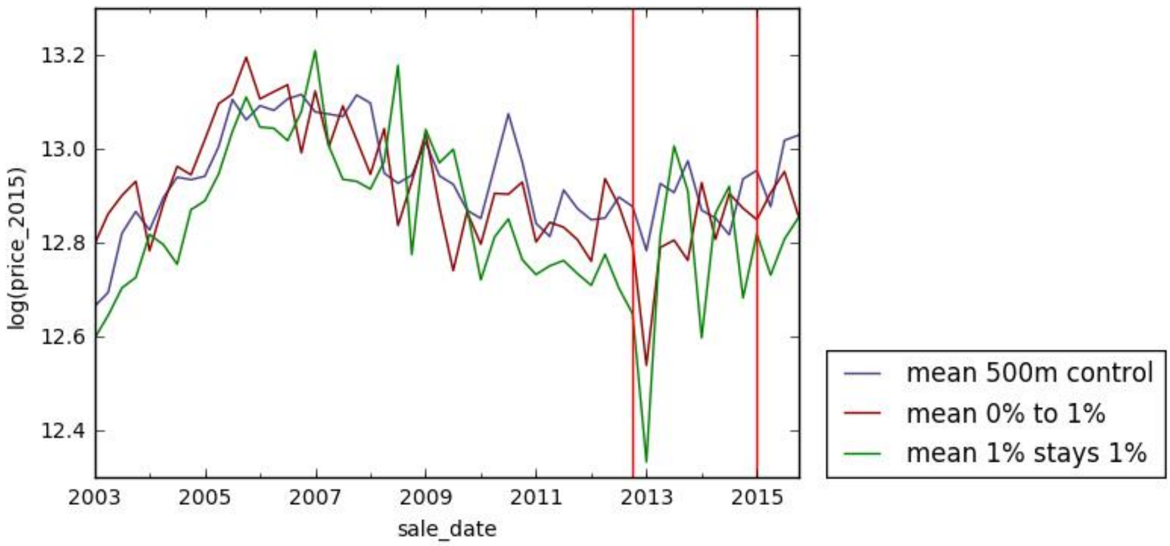

Figure 15. Price movements Queens, 2003-2015

Figure 15 shows the average price movements per quarter for the control group and the two treatment groups for Queens between 2003 and 2015. Of all the boroughs analysed Queens shows the most similar price movements between the three groups. The similar trend assumption thus seems to hold for this borough. After Hurricane Sandy all three groups see their average housing prices fall. Treatment group 2 sees the biggest price drop, followed by treatment group 1 and then by the control group. Since the control group also drops in price after Sandy, this could mean that the effect of Sandy on the treatment groups is underestimated in the DID-regressions. This is the case because the DID-regression results are the results as compared to the control group. If this same control group is also affected by a treatment, the estimated treatment effect is thus underestimated. After the flood risk map update treatment group 2 and the control group initially drop in price, to recover after in the next quarters. For treatment group 1 this is the other way around, its average price first rises before it drops in the following quarters. These graphical effects might be due to chance or quarterly trends. Therefore now the DID-regressions will be discussed.

Table 6 shows the DID-regression results for Queens. The first model, with zip code fixed effects, shows no significance for any of the eight variables. In the second model, that controls for lot fixed effects, two significant correlations show. First, there seems to be a significant negative effect for being in treatment group 2 as compared to the control group. Also there is a significant effect of -7.6 logistic points of Hurricane Sandy on treatment group 1. The flood risk map is almost significant for treatment group 2. In model 3, that controls for building block fixed effects, Hurricane Sandy has a significant negative effect on the housing prices of both treatment groups of -13.9 and -13.8 logistic points. Also the post map and post sandy dummies are negative and significant for this model. There is no sign of a treatment effect of the flood risk map update however. When also controlling for age and housing type in model 4 there is still no visible effect of the flood risk map update. The effect of Sandy remains negative and significant however. Also the period after the introduction of the flood risk map has a negative and significant effect on housing prices in general. In the last model, that uses the same specification on a subset of family houses, this effect of the post map disappears. The effect of Hurricane Sandy on both treatment groups remain negative and significant. This effect even seems to increase in magnitude. The map update still does not show a significant effect on the housing prices of either treatment group.

Difference-in-differences regression results Queens

Queens	(1)	(2)	(3)	(4)	(5)
Treat 0% to 1%	0.143	-0.049	-0.016	-0.032	-0.001
	[0.095]	[0.036]	[0.027]	[0.025]	[0.018]
Treat 1% stays 1%	-0.064	-0.114**	-0.012	-0.007	0.062**
	[0.078]	[0.045]	[-0.027]	[0.027]	[0.027]
Post Sandy	-0.022	-0.061	-0.139***	0.008	-0.023
	[0.074]	[0.055]	[0.034]	[0.042]	[-0.083]
Post map	-0.062	-0.076	-0.095**	-0.092**	-0.109
	[0.051]	[0.060]	[0.045]	[0.042]	[0.072]
(Treat 0% to 1%	-0.085	-0.076**	-0.139***	-0.129***	-0.163***
* Post Sandy)	[0.078]	[0.032]	[0.034]	[0.032]	[0.035]
(Treat 1% stays 1%	-0.107	0.006	-0.138**	-0.115**	-0.260***
* Post Sandy)	[0.091]	[0.059]	[0.054]	[0.050]	[-0.035]
(Treat 0% to 1%	0.010	-0.028	0.037	0.005	0.023
* Post map)	[0.070]	[0.048]	[0.052]	[0.044]	[0.056]
(Treat 1% stays 1%	-0.001	-0.089*	-0.006	-0.025	0.005
* Post map)	[0.075]	[0.052]	[0.037]	[0.036]	[0.050]
Observations	40294	40294	40294	40294	23006
R-squared	0.186	0.187	0.540	0.588	0.451
FE level	Zip code	Lot	Block	Block	Block
Clustered S.E. level	Zip code	Lot	Block	Block	Block
Number of clusters	53	1391	1938	1938	1855
Controlled for building type and year built	No	No	No	Yes	Yes
Type of buildings	All	All	All	All	Family houses

Table 6. Difference-in-differences regression results for Queens. Each model (column) runs the same base specification, but differs in the fixed effect level and the level at which the standard error is clustered. One asterisk (*) depicts a p-value of < 0.1, two asterisks (**) a p-value of < 0.05 and three asterisks (***) a p-value of < 0.01. In the last column (model 5) the same base specification is run, but on a subset of only family houses.

Results Manhattan

In table 4 the descriptive statistics of the real estate sold in Manhattan are shown. This table shows that Manhattan is very different from the other boroughs for multiple reasons. Firstly, it has very few family houses. Most of Manhattan consists of condos and coops. This big amount of high-rise buildings is also the reason that the control group is very large in comparison to the treatment groups. The treatment groups do have a higher price mean, which could be due to the proximity to the waterfront and the view that comes with it. Furthermore, the standard deviation of these prices is relatively large as well. This shows that within Manhattan there is a big difference in housing prices. Finally the buildings in the control group are older relative to the treatment groups in the first two periods. Overall it can be concluded that Manhattan with big differences within its borough has less balanced data. Overall it can be concluded that Manhattan has big differences within its borough and between treatment groups. This makes it a rather problematic case for a DID analysis.

Figure 16 shows the average price movements per quarter for the control group and the two treatment groups for Manhattan between 2003 and 2015. The first thing that stands out is that the housing market of Manhattan is more volatile compared to the other boroughs, as can be seen at the extreme ups and downs of especially the second treatment group. What is also interesting, is that while in the other boroughs the control group seems to have a higher average price than the treatment groups, this is not the case for Manhattan. The two treatment groups, that are closer to the water, have a higher average price for almost every quarter between 2003 and 2015. Since Manhattan has mostly high-rise buildings, that probably has to do with the fact that buildings close to the waterfront have a view that is in high demand. If we look at the period following Hurricane Sandy we see that only treatment group 1 experiences a drop in average housing prices. Treatment group 2, contrary to the hypotheses, shows an average price increase after Sandy. The average price of the control group seems to remain relatively stable after Sandy. After the flood risk map update all three groups see their average prices decrease. Over the following quarters, however, the average prices move back up for all three groups as well.

Descriptive statistics Manhattan

Manhattan	Pre Sandy (Jan 2013 - Oct 2012)			Post Sandy & pre map (Nov 2012 - Jan 2015)			Post map (Feb 2015 - Dec 2015)		
	Control (n = 50774)	Treatment 1 (n = 1525)	Treatment 2 (n = 3466)	Control (n = 10217)	Treatment 1 (n = 347)	Treatment 2 (n = 843)	Control (n = 4083)	Treatment 1 (n = 133)	Treatment 2 (n = 282)
Mean Price	$1,185,832	$1,787,841	$1,728,393	$1,443,659	$1,686,669	$2,200,082	$1,805,975	$2,302,292	$2,375,038
SD Price	$2,336,759	$5,679,821	$2,453,483	$3,027,529	$1,844,317	$2,104,937	$4,639,272	$2,301,131	$2976130
Mean Log(Price)	13.60	13.82	13.95	13.71	13.98	14.25	13.91	14.27	14.23
SD Log(Price)	0.84	0.94	0.86	0.92	0.89	0.84	0.95	0.91	0.90
Mean Year built	1955.42	1967.39	1977.41	1953.74	1973.06	1966.52	1960.68	1971.08	1970.50
SD Year Built	34.03	35.63	36.70	34.11	34.29	44.12	36.39	41.53	40.38
% 1-family	0.41%	0.33%	0.20%	0.60%	0%	0.36%	0.47%	0.75%	0.71%
% 2-family	0.46%	0.26%	0.17%	0.65%	0.29%	0.47%	0.51%	0%	0.35%
% 3-family	0.28%	0.26%	0.20%	0.31%	0.86%	0.12%	0.22%	1.50%	0%
% Condos	61.92%	69.64%	77.47%	52.27%	74.64%	79.60%	56.04%	71.43%	74.47%
% Coops	36.92%	29.51%	21.96%	46.17%%	24.21%	19.45%	42.76%	26.32%	24.47%

Table 7. Descriptive statistics Manhattan

Average price movements per treatment and control group for Staten Island

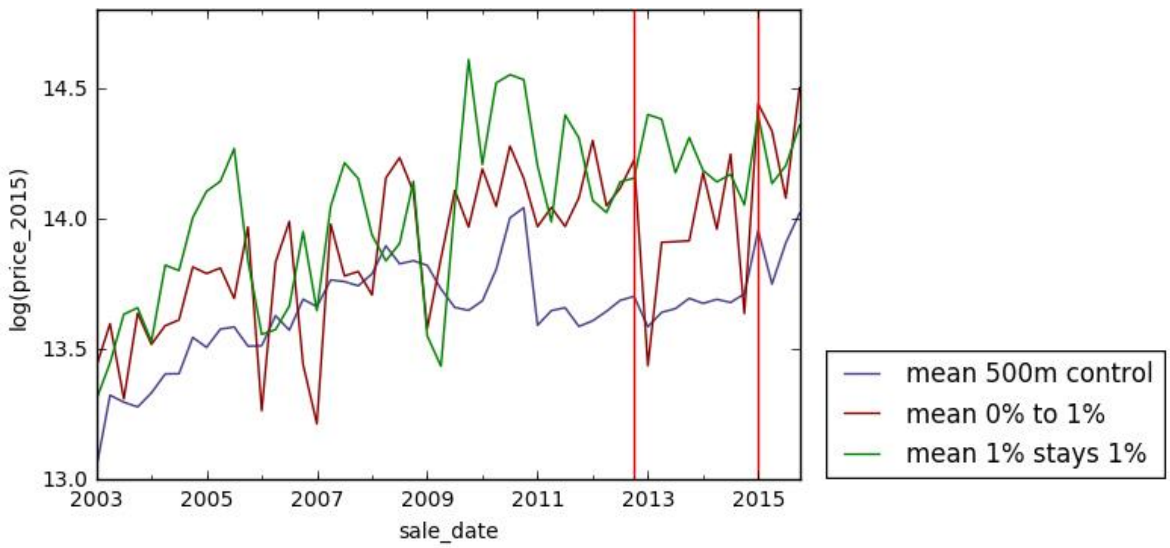

Figure 16. Price movements Manhattan, 2003-2015

Difference-in-differences regression results Manhattan

Manhattan	(1)	(2)	(3)	(4)	(5)	(6)
Treat 0% to 1%	0.121*	0.144	0.110**	0.127***	-.138	0.119
	[0.062]	[0.112]	[0.047]	[0.034]	[0.094]	[0.123]
Treat 1% stays 1%	0.137*	0.192	0.182***	0.181***	0.163	-0.048
	[0.078]	[0.188]	[0.034]	[0.031]	[0.181]	[0.199]
Post Sandy	0.066	0.056	0.044	0.025	0.029	-0.078
	[0.065]	[0.043]	[0.052]	[0.048]	[0.038]	[0.292]
Post map	-0.164**	-0.101*	-0.102	-0.134	-0.110*	-0.080
	[0.082]	[0.0608]	[0.080]	[0.08]	[0.056]	[0.319]
(Treat 0% to 1%	0.102	0.023	-0.008	-0.005	0.023	-0.839***
* Post Sandy)	[0.078]	[0.065]	[0.065]	[0.061]	[0.061]	[0.263]
(Treat 1% stays 1%	0.193**	0.113**	0.204***	0.210***	0.092	-0.381
* Post Sandy)	[0.084]	[0.055]	[0.044]	[0.043]	[0.058]	[0.279]
(Treat 0% to 1%	0.130	0.006	0.189**	0.136	-0.024	0.577
* Post map)	[0.155]	[0.089]	[0.085]	[0.085]	[0.085]	[0.574]
(Treat 1% stays 1%	-0.080	-0.072	-0.175***	-0.182***	-0.040	1.008***
* Post map)	[0.058]	[0.056]	[0.067]	[0.062]	[-.048]	[0.358]
Observations	72964	72964	72964	72964	72964	847
R-squared	0.250	0.439	0.241	0.301	0.5084	0.733
FE level	Zip Code	Block	Lot	Lot	Block	Block
Clustered S.E. level	Zip Code	Block	Lot	Lot	Block	Block
Number of clusters	56	598	3557	3557	598	198
Controlled for building type and year built	No	No	No	Yes	Yes	Yes
Type of buildings	All	All	All	All	All	Family houses

Table 8. Difference-in-differences regression results for Staten Island. Each model (column) runs the same base specification, but differs in the fixed effect level and the level at which the standard error is clustered. One asterisk (*) depicts a p-value of < 0.1, two asterisks (**) a p-value of < 0.05 and three asterisks (***) a p-value of < 0.01.

In the descriptive statistics table and the price movement graph we saw that Manhattan's housing market as a case in a DID analysis is rather problematic. Table 8 shows the DID-regression results with different fixed effect level models for this borough. Since the case of Manhattan is deemed problematic and shows no consistent outcomes, this table will only be discussed briefly. The main thing that should be understood from reading this table is that both the Sandy treatment and the flood risk map update treatment show no consistent negative significant effects. Also the treatment group dummies and the post dummies show inconsistent outcomes. To strengthen the impression that Manhattan's housing market is too volatile and therefore a problematic case for DID analysis, see model 6. When running the base specification on a subset of Manhattan family houses the post map interaction with treatment group 2 becomes extremely large and positive with 100.8 logistic points. Also Sandy has an incredibly large negative effect on treatment group 1, which did not show an effect in the previous models. Of course this extreme outcome is also due to the fact that it only uses 847 observations over thirteen years while including 198 fixed effects clusters and 52 time fixed effects, depriving the degrees of freedom for this model.

Robustness checks

Above the results of the first DID-regression results were discussed. To check whether these results are robust, now different robustness checks will be implemented and their outcomes discussed. The tables of these robustness checks are included in the appendix. In all these tables the preferred model without robustness checks is shown first as a point of reference. In the first DID analysis we already found that Manhattan showed no consistent treatment or dummy effects. This does not change in the robustness check models. Therefore these outcomes will not be discussed.

The transaction data used for this thesis spans from 2003 up to and including 2015. Hurricane Sandy did not hit only far into the year 2012. Between the beginning of the dataset in 2003 and the moment Sandy hits there are multiple other events that heavily influenced the New York City housing market. The most relevant of these events are the subprime mortgage crisis and financial crisis of 2007-2008. In most of the price movement graphs there is an upward trend visible before these crises and a downward trend afterwards, approximately until 2009. The first robustness check consists of using the same kind of DID-regression, but for the years 2009-2015 instead of the full thirteen years. This does not really influence the outcomes for Staten Island, Brooklyn and Queens. On average the treatment effects that were significant, remain significant when adding this test. The most apparent effect is that it decreases the magnitude of Sandy's effect. Also for Brooklyn the effect of Sandy on treatment group 2 seems to disappear.

FEMA's flood risk map update was introduced on January 31st 2015. Homeowners received their letter however on March 27th 2015. In the basic regressions above the post-dummy was based on the date of the map update. The second robustness check will check whether using the moment of receiving the letter for defining the post-dummy will change the outcomes. Changing this post-dummy does not affect the treatment effects for Brooklyn and Queens. Also for Staten Island the effects stay significant, but do decrease in magnitude.

As could be seen in the price movement graphs, the NYC housing market is rather volatile. Although some price outliers have already been deleted from the dataset, it would be interesting to see whether the treatment effects of Sandy still persist if only looking at core values. To create such a core group the extreme price observations at the higher and lower end of the distribution have been deleted. I choose to cut out 30% of the observations for this robustness check. To do this the first five percentiles of the dataset were deleted, as well were the upper 25 percentiles. This robustness check seems to have more effect than the ones testes before. For Staten Island all significant treatment effects disappear. It could be that the effect was stronger or only existing for more expensive houses. Or it was caused because the more extreme values introduced more noise into the data. This interpretation is strengthened by the fact that for Brooklyn the effect of Sandy on treatment group 2 completely disappears, while the effect on treatment group 1 decreases in magnitude. Also the effects in Queens see their treatment effects greatly decreasing in magnitude, although still remaining significant.

The fourth robustness check looks whether using the broadly defined control group instead of the 500 meter buffer control group changes the outcomes. This bigger control group uses all observations that remain in the 0% flood risk zone, instead of only using the observations in the 500 meter buffer. This model needs a remark though. It uses neighbourhood fixed effects, because the city block fixed effect could not be included in this model, because of its high demand on working memory. Since a lot of variance can be explained by the city block fixed effects, using this model is a robustness check is therefore not ideal. It does not change the outcomes for Staten Island. For Brooklyn all treatment effects become significant, where first they were not. Finally, the effect of Sandy on treatment group 2 loses its significance.

Although DID-regressions are widely used in scientific research, its outcomes cannot always be interpreted as causal effects straight away. There may be unobservable events that cause an effect other than the treatment effect. A placebo effect can be added to the model in the year before the treatment to check if there was already a significant trend then. Since the flood risk map update was found to be significant, the placebo interaction is done for the entire year before Hurricane Sandy. If this interaction with the treatment groups is not significant and the interaction between Sandy and the treatment groups still is, Sandy's effect can be interpreted as causal. The second robustness check thus involves such a placebo interaction. The placebo effect is not significant for Staten Island. Brooklyn does show a significant placebo effect, but this effect disappears when also controlling for group specific trends in model 8. Unfortunately Queens does show a significant placebo effect the year before Sandy. This effect disappears only in one of the two models when controlling for group specific trends.

The treatment groups and the control group follow trends disregarding a possible treatment. Therefore it is important to control for such trends, because maybe the treatment effect is caused, weakened or enhanced by such a trend (Angrist and Pischke, 2009: 238-241). The sixth robustness check thus controls for the trends of the control group and the two treatment groups. The general trend is 1 for the first quarter of 2003 and 53 for the last quarter of 2015. By multiplying this trend with the dummy variables of the control and treatment groups, group specific trends are created. For example, the group specific trend dummy for the control group in December 2004 is "8" while for the treatment groups in this same month the value of the control specific trend is "0". A group specific trend can thus be thought of as the effect of going up one quarter for a specific group. After adding these group specific trends for Staten Island and Brooklyn their treatment effects remain significant. For Queens the treatment effects seem to disappear.

Overall for Staten Island it can be concluded that the effects found earlier are robust. For Brooklyn the effect of Sandy on treatment group 1 is robust and in the hypothesized direction. Its effect on treatment group 2 is more ambiguous as it is not significant in four of the nine models. For Queens the effects are relatively robust, while controlling for group specific trends does seem to render some treatment effects insignificant. For all the boroughs no significant treatment effect is found for the flood risk map update.

Quarterly interaction effects

Since from theory it is known that risk perception discounts over time, it is important to look at the treatment effects per quarter (Bin and Polasky, 2004). This is done by estimating the interaction effects of the two treatment groups with every quarter time dummy, while still controlling for city block fixed effects and time fixed effects. These estimations have two purposes. Firstly, if these quarterly effects are not significant before Sandy, but they are afterwards, it makes it more likely that Sandy did indeed have a causal effect on housing prices. Secondly, quarterly interaction effects create insight on whether the effect is temporary and whether the magnitude of the effect changes over time. The coefficients of these quarterly interaction effects and its confidence intervals are depicted in the graphs below. The red line shows the quarterly interaction effect on treatment group 1, the blue line on treatment group 2. The first vertical dotted line is the moment Hurricane Sandy hit New York city, the second one the moment the new flood risk map was introduced. If the coefficient is significant (at a $p < 0.05$ level) an asterisk (*) is included for that coefficient.

Coefficients interaction effects per quarter for Staten Island, 2011-Q1: 2015-Q4

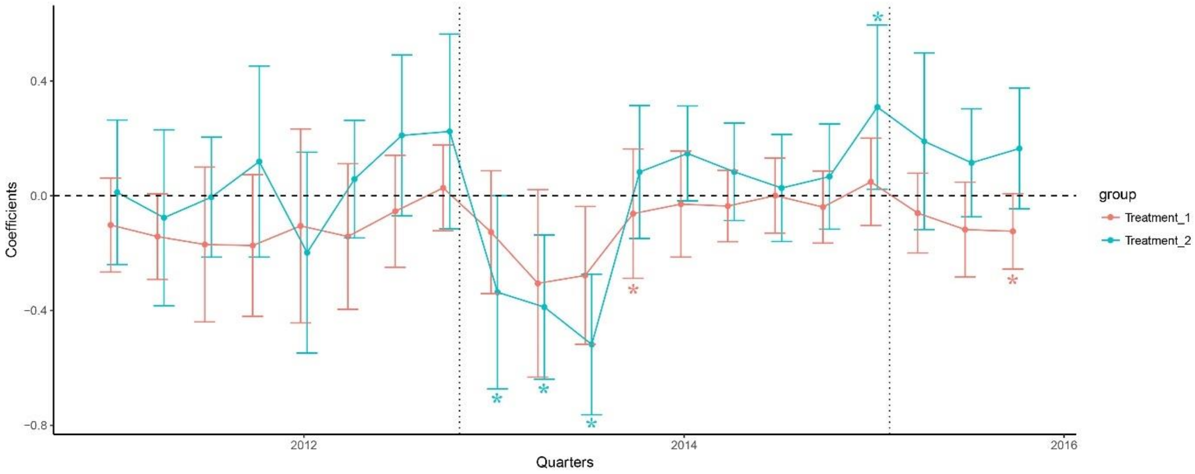

Figure 17. Quarterly interaction effects for both treatment groups on Staten Island, 2011-2015. The coefficients that are marked with an asterisk (*) are significant at a $p < 0.05$ level.

Coefficients interaction effects per quarter for Brooklyn, 2011-Q1: 2015-Q4

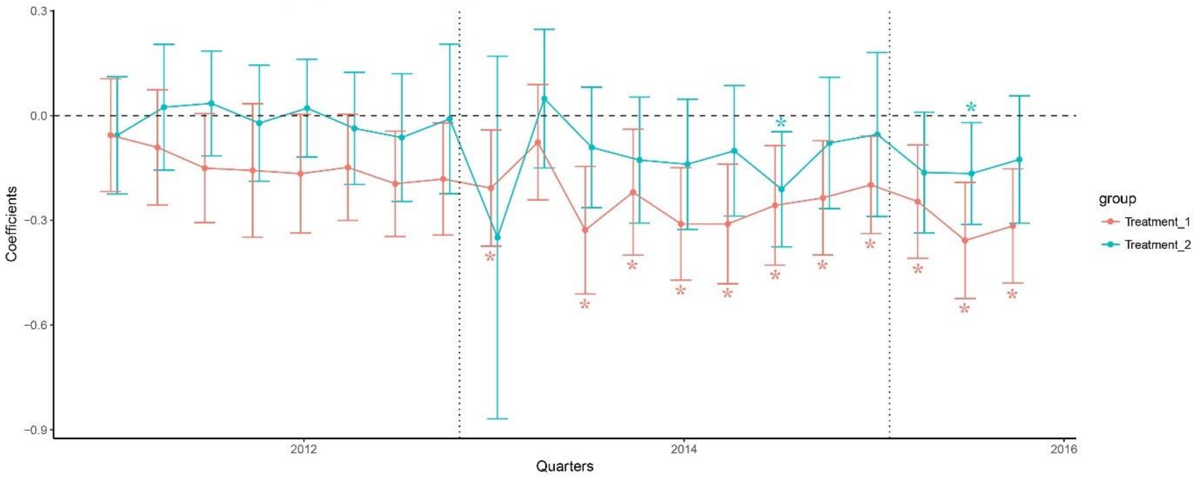

Figure 18. Quarterly interaction effects for both treatment groups in Brooklyn, 2011-2015. The coefficients that are marked with an asterisk (*) are significant at a $p < 0.05$ level.

Coefficients interaction effects per quarter for Queens, 2011-Q1: 2015-Q4

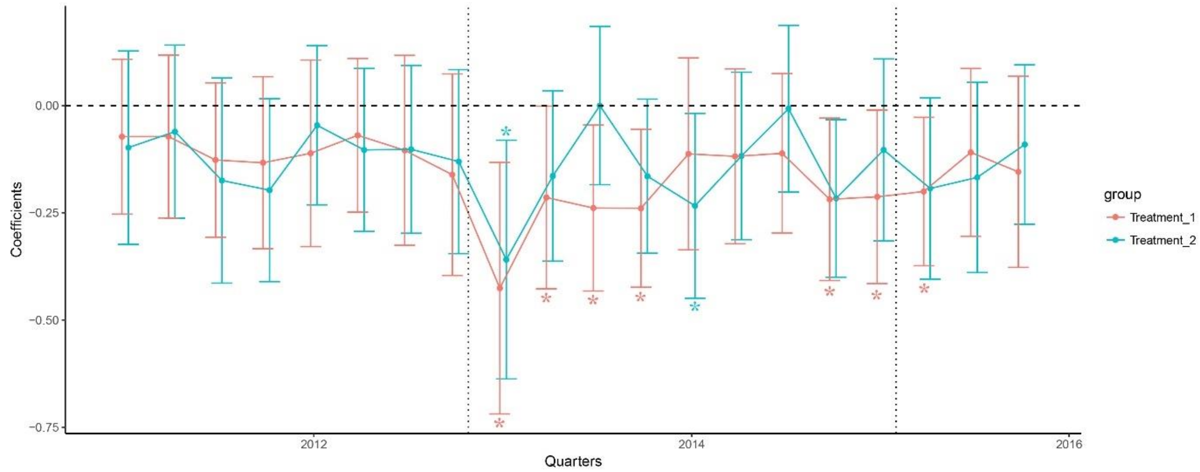

Figure 19. Quarterly interaction effects for both treatment groups in Queens, 2011-2015. The coefficients that are marked with an asterisk (*) are significant at a p < 0.05 level.

Coefficients interaction effects per quarter for Manhattan, 2011-Q1: 2015-Q4

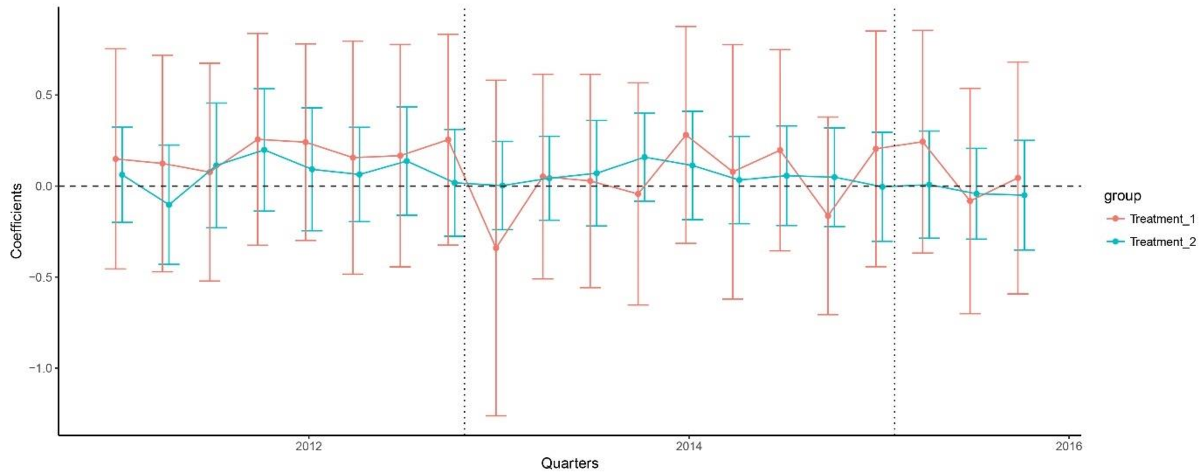

Figure 20. Quarterly interaction effects for both treatment groups in Manhattan, 2011-2015. None of the coefficients were found to be significant, therefore none are marked with an asterisk (*).

Figure 17 shows the quarterly interaction effects for Staten Island. First, we see that none of the quarterly interaction effects is negative and significant before Sandy for any of the treatment groups. After Sandy however, the coefficients go down from positive to negative for treatment group 2 for three quarters. These effects are significant. After this the coefficients become positive and insignificant again. This might show that Sandy only had a temporary effect on housing prices. I argue that temporary effects are more likely to be caused by direct damage than by increased risk perception. Treatment group 1 shows two quarters to have a significant negative effect after Sandy, but not directly after Sandy.

Brooklyn shows the most clear cut effect of Sandy in figure 18. Before the hurricane there are no significant effects, while afterwards for treatment group 1 eleven out of twelve coefficients show significant negative effects. This graph thus shows that the effect of Sandy on treatment group 1 in Brooklyn is very likely to be causal. Treatment group 2 does show a dip after Sandy, but this effect is not significant. Also over the following quarters only two out of twelve coefficients show significant negative effects.

Figure 19 shows the quarterly interaction effects for Queens. Again it shows no significant effects before Sandy. After Sandy however, the interaction effects with treatment group 1 are negative and significant seven out of twelve times. Also here it does not just show a short term effect. This makes it more likely to next to an effect of direct damage, there also is an effect of increased risk perception which does not fade out. Treatment group 2 shows only a short term effect.

Figure 20 depicts the quarterly interaction effects for Manhattan. Almost every quarter shows a positive coefficient for both treatment groups. This is most likely because of the high demand for Manhattan real estate. Treatment group 1 however shows a negative coefficient for the quarter after Hurricane Sandy however. This negative effect disappears in the quarter after that however. Also there is no apparent coefficient change after the flood risk map update. Manhattan shows not significant quarterly interaction effects for any quarter for any of the treatment groups.

Sale frequencies

The DID-regression results for both the initial models as well for the robustness check models found a significant effect of Sandy on housing prices, but not for the flood risk map update. It could be argued that although there were no price effects, there were effects in composition of sales after the map update. To check for such an effect, graphs of the used control variables over time will be analysed.

Average age of sold real estate per quarter

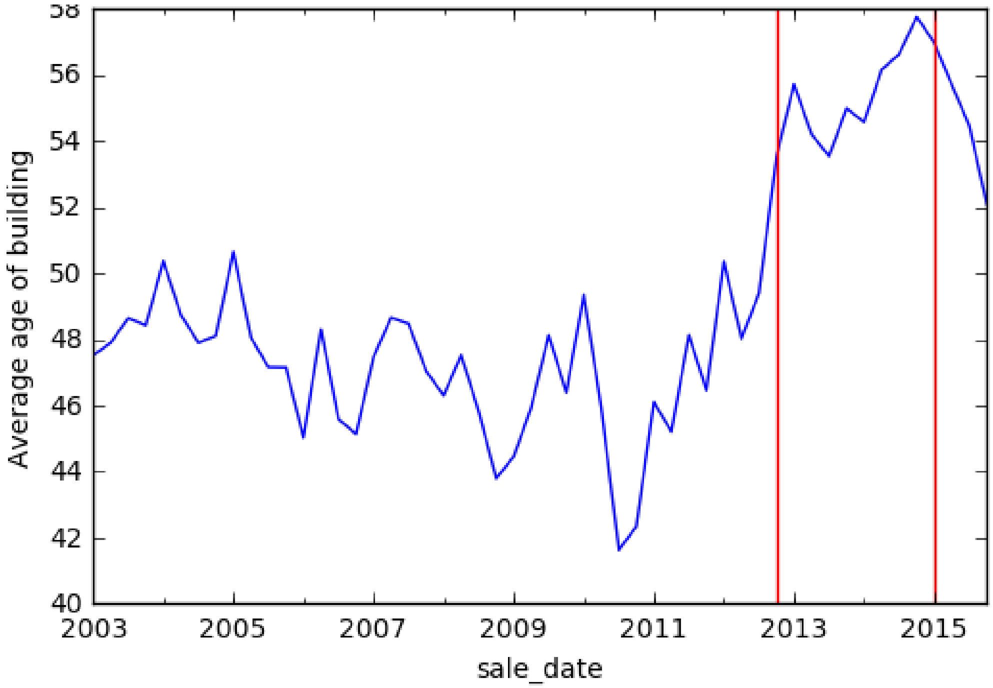

Figure 21. Average age of sold real estate per quarter.

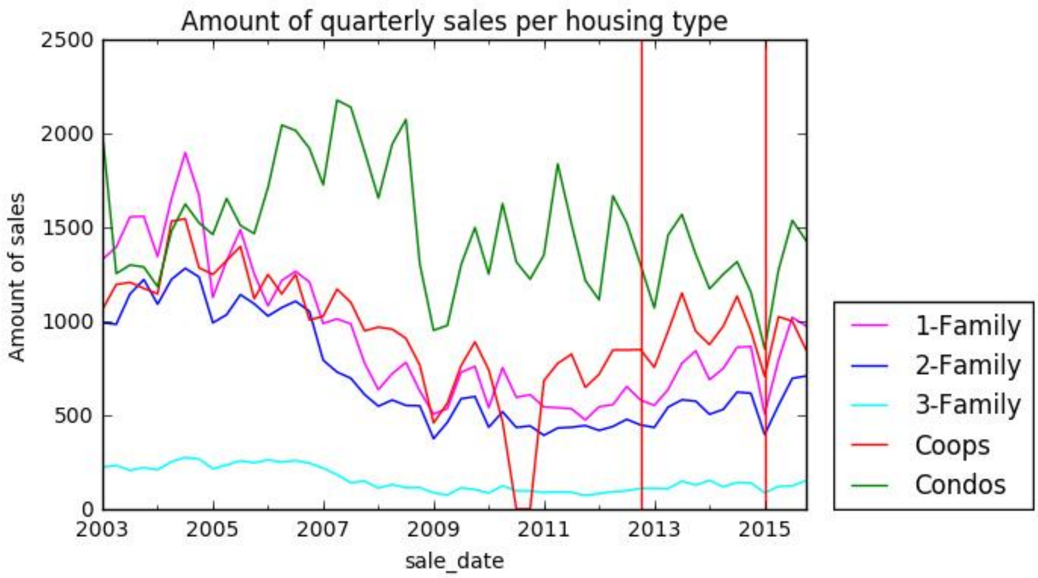

Figure 22. Amount of sales per housing type per quarter

Sales per quarter per group

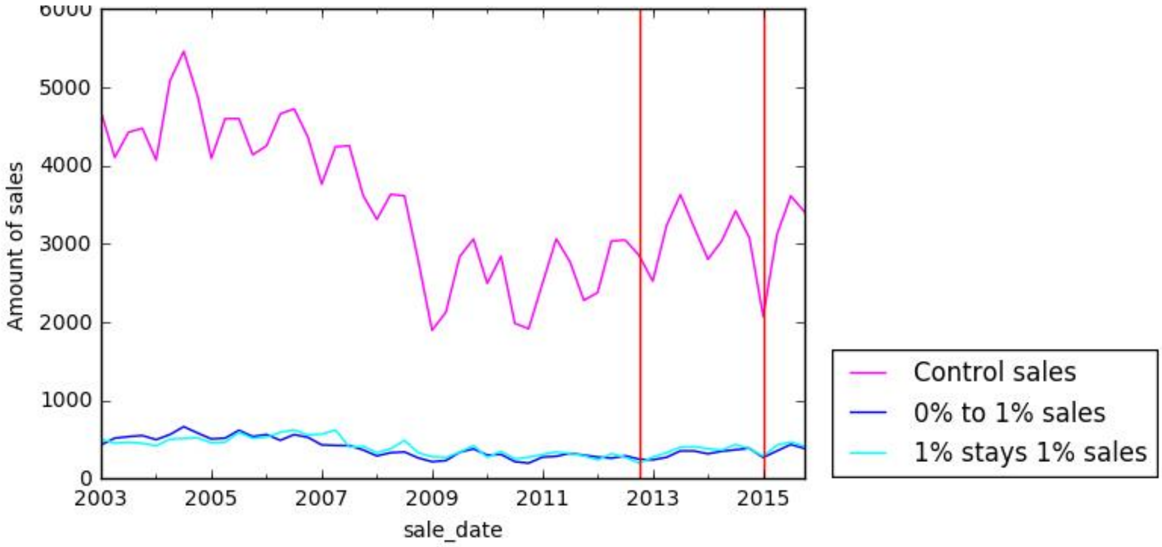

Figure 23. Amount of sales per quarter

Figure 21 shows the average age of the building on the moment of transaction. Hurricane Sandy and the flood risk map update both do not seem to have an effect on this control variable. In figure 22 the amount of sales per housing type is depicted. They seem to move in similar trends, especially after 2009. What is striking is the fact that there seems to be an effect on the moment of the map update (second red vertical line). All housing types fall in the amount of sales, except for the 3-family houses. Below this downward spike will be further analysed, this time to check if the amount of sales per control and treatment group changes at the same point.

In figure 23 it can be seen that Sandy does not affect the amount of sales in any of the groups. There does seem to be a decrease in the amount of real estate sold in the quarter of the introduction of the flood risk map. Uncertainty on the housing market because of the new flood risk map might have caused this effect.

6. Discussion and conclusion

The research question of this thesis was the following:

"To what extent did Hurricane Sandy and the introduction of FEMA's Preliminary Flood Insurance Rate Map (FIRM) impact New York City's housing prices?"

Based on studies on flood risk and literature on risk perception it was hypothesized that providing more information on flood risk to the market (by means of Sandy and the FIRM) would increase its risk perception, which would in turn decrease the average housing prices (Daniel et al. 2008; Pope, 2008; Votsis and Perrel, 2016; Ortega and Taspinar, 2016). Also, from risk perception theory we learned that past experience of flood hazard increases risk perception in the future (Wachinger et al. 2012). Since the different boroughs were hit to a different extent by Sandy, it was therefore hypothesized that boroughs that were hit harder by Sandy would also see a higher price decrease after the release of the updated risk map. The results of this thesis were used to test these hypotheses and answer the research question.

Effects hurricane Sandy

By doing a difference-in-differences analysis we were able to estimate the effect of Sandy on the two different treatment groups. The dependent variable in this analysis was the natural log of housing prices. The first group was defined as all the real estate transactions of property that was in a 0% flood risk zone before the map update of 2015 and in a 1% risk zone afterwards. The second treatment group had 1% before this map update and 1% after this map update. Through defining the treatment groups in this way, the effects of Sandy and the effects of the flood risk map update could be controlled for each other. This thesis finds that treatment group 1 was significantly affected by hurricane Sandy in two of the four analysed boroughs. This effect was found for Brooklyn and Queens and ranged between -6.5 and -17.2 logistic points. In these two boroughs Sandy's effect was also found to be robust.

For treatment group 2 the effect of hurricane Sandy was found to be significant and robust for Staten Island and Queens, with effects ranging from -8.7 and -16.8 logistic points. Brooklyn also showed significant effects between -9.7 and -13.8 logistic points, but these effects only continued to be significant in four of the eight robustness check models.

Interesting to note is that there is almost no difference in Sandy's average effects between the two treatment groups[8]. We would have suspected a difference between the two groups if the total price decrease was caused by increased risk perception alone. Treatment group 2 already knew it was officially in a flood risk zone before Hurricane Sandy hit New York City. Treatment group 1 was still officially in a 0% flood risk zone when Sandy hit. I claim that it would therefore be logical that the risk perception in treatment group 1 increased to a bigger extent than that of treatment group 2 due to a surprise effect. Since there does not seem to be a difference between the effect of hurricane Sandy on treatment group 1 and 2, this strengthens the idea that the price decrease was largely due to the damage done not through an increase in risk perception. If we look at the quarterly interaction effects of Staten Island this idea seems to be confirmed, as the significant effect only lasts a few quarters after Sandy. However, if we look at Brooklyn and Queens Sandy also affects housing prices in the treatment zones in the long run. Therefore the effect of Sandy is most likely a mix of direct damage (short term) and increased risk perception (long term).

Effects new flood risk map

It was hypothesized that the introduction of a new flood risk map would provide the housing market with more information, which would then lead to lower housing prices for property that was not officially in a flood risk zone before (treatment group 1). Secondly, the map update might have had a reminding effect on treatment group 2. No significant treatment effects were found for the flood risk map update in any of the boroughs however. The DID-regression results at first showed a significant effect for the map update on treatment group 1 in Brooklyn. This effect disappeared however when city block fixed effects were controlled for. Also the robustness checks showed no significant effect for the flood risk map update.

Both Hurricane Sandy and the flood risk map update are argued to affect housing prices via the same mechanism, namely by providing the housing market with better flood risk information. Why is it then that the flood risk map does not show this hypothesized effect? This could be due to multiple reasons. The most plausible reason is that Hurricane Sandy already "updated" everyone's risk perception in 2012. Therefore, when the flood risk map was updated in 2015, nobody was surprised by it and it thus did not provide the market with new flood risk information or influence housing prices. A second possibility is that the flood risk map had no effect, because it did not increase flood risk insurance premiums yet.

[8] Sandy's average effect on treatment group 1 is -12.87 logistic points (-308.8 / 24). And Sandy's average effect on treatment group 2 is -12.53 logistic points (-363.3 / 29).

We could expect an anticipation effect for these higher premiums, but the results from the DID analysis do not support this expectation as no negative significant effect is found. A third possibility is based on the notion of information asymmetry, the situation in which the seller of the property has more information on flood risk than the buyer. Since the letter about the flood risk map update was only sent to the homeowners and these same owners are not obliged to inform potential buyers about this new information, it can be argued that the homeowners had more and better information on the flood risk of their property. The housing prices thus did not go down after the flood risk map update, because its information was not provided well enough to potential buyers on the housing market. Such an interpretation would be in line with the findings of Chiver and Flores (2002), who found that only 8% of potential homeowners were aware of the flood risk in the area before buying property.

The question of causality

This thesis found a significant statistical effect of hurricane Sandy on both the treatment groups. Statistical significance is however based on rather arbitrary significance levels. The question of causality is more a question of research design than of statistics. This thesis implemented two methods to check for causality, on top of the DID analysis. First, we checked whether the effect might have been caused by something else that started before hurricane Sandy hit New York City. We did so by testing whether the year before Sandy already had a significant negative effect. If this was the case, than the effect on housing prices was most likely not (only) caused by the hurricane. For Staten Island this placebo effect was not significant. For Brooklyn the placebo effect was significant, but disappeared when controlling for group specific trends. Also for Queens the placebo effect was significant, but disappeared in one of the two models when controlling for group specific trends. This evidence seems to support that Sandy's treatment effect did not start before Sandy. The remaining question is then, whether or not the effect started after Sandy. To check this we ran a DID-regression with variables that measured the interaction between the treatment groups and the quarter dummies. We found that before hurricane Sandy none of these interaction effects were significant for any of the boroughs. After Sandy however, the interaction effects became significant for Queens, Staten Island and Brooklyn. For treatment group 1 this quarterly interaction effect is significant and negative eleven out of twelve quarters for Brooklyn, seven out of twelve quarters for Queens and two out of twelve for Staten Island. For treatment group 2 we found two out of twelve interactions to be significant for Brooklyn and Queens and three out of twelve for Staten Island. Although the evidence for the treatment group 2 is not very convincing, that of treatment group 1 definitely is.

Earlier we saw that the price movements in the New York City housing market are rather volatile. Because of this the common trend assumption did not seem to hold for all groups of all boroughs. Since we controlled for thousands of city block fixed effects and other control variables, this assumption can be partly relaxed. This combined with the fact that no significant placebo effects were found and the fact that quarterly interaction effects were only negative and significant after Sandy make it very plausible that Sandy's effect is indeed causal.

Policy recommendations

Based on the findings of this thesis I have two policy recommendations. They both are related to the food risk map update as a policy tool. One of the reasons why the map update shows no significant effect, is information asymmetry. When governments publish such a new flood risk map, I would therefore recommend to actively communicate it towards buyers as well. For instance, it could be made mandatory to inform buyers on the new flood risk zone, because this was found to be an effective strategy in earlier studies (Pope, 2008). The second recommendation regards the timing of releasing a new map. The map does not seem to have an impact, because it was released just after a hurricane. If possible, governments should therefore try to publish such maps before or long after a flood event. Of course this is not possible most of the times, therefore the words used in the government communication should remind people of the just passed flood. Other studies found that this increased the risk perception (Wachinger et al., 2012).

Limitations and future research

This thesis looked at the effect of a flood risk map update in January 2015. The real-estate transaction data was only available until December of that same year. Since the NYC housing market is very volatile and the effect might take some time to show, future research should include the years after 2015 in their analysis[9].

The outcomes of this thesis might be biased because of omitted variables. Although a lot of time-invariant effects have been controlled for by adding city block fixed effects, this approach is not waterproof. One of the factors that most likely influences flood risk perception is the proximity to water. Also, being close to the water comes with the benefit of a

[9] Unfortunately, the real estate sales data of 2016 has not been turned into geospatial data yet. Therefore I could not use it for this thesis.

better view, which also influences housing prices. It could be argued that proximity to water is a time-invariant effect. This would of course be true for a perfect panel data set, since water and houses stay in the same place. In this thesis we use repeated cross-sections however. For this reason the average proximity to water fluctuates a bit over the years. Also, by design the control group for this thesis is further away from the water than the treatment group. I argue that the outcomes of this thesis would have been more precise if the proximity to the waterfront would have been controlled for. Therefore future research should include proximity to big water bodies in meters as a control variable.

Next to proximity to water, there are other variables that should ideally be controlled for in hedonic regressions, such as number of rooms in a sold building, total space in square meters and the proximity to schools, malls and parks. Including these control variables would have made the estimated treatment effects in this thesis more precise. Future research should therefore also take these control variables into consideration.

From theory we learned that the mechanisms behind risk perception are highly subjective (Wachinger et al. 2012). This thesis could not control for individual characteristics however, because it did not have information on the buyers and sellers of property. To be able to further uncover the causal mechanisms behind risk perception, future research should therefore control for individual characteristics of buyers and sellers of property situated in or close to flood risk zones.

In the robustness checks of this thesis, using a subset of core observations greatly influenced the treatment. This could be a sign that the causal mechanisms at play work differently for the different layers in the housing market. For future research it would therefore be beneficial to also include quantile regressions. Quantile regressions are regressions that check whether effects differ for different parts of the distribution (Angrist and Pischke, 2009: 281).

The most important limitation of this thesis however is the fact that it does not control for damage done by Sandy. Ortega and Taspinar (2016) found that Sandy also decreased prices for undamaged property. This thesis did not control for damage done by Sandy however. Therefore is it unable to give a clear cut answer on what part of the price decrease by Sandy was caused by increased risk perception and what was caused by direct damage. Future research should therefore include the extent to which a sold building was damaged by Sandy[10].

[10] FEMA made GIS data on damage assessments available on:

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Appendix

U.S. Department of Homeland Security
Region II
Jacob K. Javits Federal Office Building
26 Federal Plaza, Room 1311
New York, New York 10278

FEMA

March 27, 2015

<<Name>>
<<Second Name>>
<<Street Address>>
<<City, State Zip>>

Dear <<Name>>:
Flooding is the most frequent and costly disaster in the United States. The risk for flooding changes over time due to erosion, land use, weather events and other factors. The likelihood of inland, riverine and coastal flooding has changed along with these factors. The risk for flooding can vary within the same neighborhood and even property to property, but exists throughout New York City. Knowing your flood risk is the first step to flood protection.

The Federal Emergency Management Agency (FEMA) is in the process of developing updated flood maps for New York City. The new maps -- also known as Preliminary Flood Insurance Rate Maps (FIRMs) -- reflect current flood risks, replacing maps that are up to 30 years old.

<u>This letter is to inform you that your property is mapped in or near a Special Flood Hazard Area. FEMA suggests that you take the following actions:</u>

1. **Understand your flood risk and flood insurance purchase requirements:**
   FEMA's Preliminary Flood Insurance Rate Maps can be viewed at
   http://floodhelpny.org

   For additional information, call FEMA's Map Information Exchange at:
   1-877-FEMA MAP (1-877-336-2627) or visit **http://floodhelpny.org**

   You can also view the maps in person at the following locations:
   <u>Bronx</u>: 1932 Arthur Avenue, 5th Floor, Bronx, NY 10457
   <u>Brooklyn</u>: 210 Joralemon Street, 8th Floor, Brooklyn, NY 11201
   <u>Manhattan</u>: 280 Broadway, 3rd Floor, New York, NY 10007
   <u>Queens</u>: 120-55 Queens Blvd, Queens, NY 11424
   <u>Staten Island</u>: 10 Richmond Terrace, 2nd Floor Staten Island, NY 10301

2. **Purchase Flood Insurance**
   Homeowners insurance does not typically cover damage or losses from floods. Direct financial assistance to property owners from the Federal Government is not guaranteed in the event of a flood. When purchasing flood insurance, be a good consumer and talk to several agents. For more information on flood insurance, visit the National Flood Insurance Program (NFIP) website at: **www.FloodSmart.gov**

   If you have a mortgage from a federally-regulated lender <u>or</u> received Federal disaster assistance <u>and</u> the building(s) at this address is mapped within the Special Flood Hazard Area as shown on the Preliminary Flood Insurance Rate Map, federal law states that you **<u>must carry flood insurance</u>** when the Flood Insurance Rate Maps become effective. Flood insurance is available through the NFIP. Contact your insurance agent to learn about options offered by the NFIP for properties being mapped into the Special Flood

Hazard Area for the first time and for properties being mapped into a higher risk area. If you do not have a mortgage, it is still recommended that you purchase flood insurance.

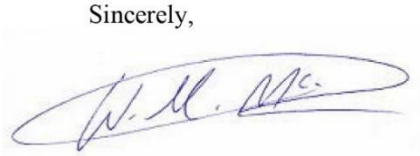
The new maps help promote public safety.
These Flood Insurance Rate Maps are important tools used in the effort to protect lives and properties in New York City. By showing the extent to which areas of the City and individual properties are at risk for flooding, the Flood Insurance Rate Maps help property owners and residents make more informed decisions about personal safety and financially protecting their property. These maps also allow community planners, local officials, engineers, builders and others to make determinations about where and how new structures and developments should be built.

If there is an error in the Flood Insurance Rate Map, you can file a comment or appeal.
The FEMA Flood Insurance Rate Maps are still preliminary. Starting **March 31, 2015** and running through **June 28, 2015**, there will be a regulatory Public Comment and Appeal Period. This is a time when New York City and property owners will have the opportunity to submit technical and/or scientific data to file a comment regarding their individual property, or an appeal regarding the accuracy of the mapping process in general. To learn more about comments and appeals, visit **www.nyc.gov/floodmaps**

When do the maps become effective?
Once all appeals and comments are reviewed and once any appropriate map changes are incorporated, FEMA will issue a Letter of Final Determination. Six months later, the new Flood Insurance Rate Map for New York City will become effective, and flood insurance purchase requirements will go into effect.

Meetings in your community
Meetings will be held with residents and community leaders across all five NYC Boroughs in the coming months to answer questions about the updated Flood Insurance Rate Maps and flood insurance. Please visit **www.nyc.gov/floodmaps** to learn about upcoming meetings and other flood risk information.

Sincerely,



William McDonnell
Deputy Mitigation Director &
Floodplain Management & Flood Insurance Branch Chief
DHS/FEMA Region II
26 Federal Plaza
New York, New York

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This letter is available in English online at: www.region2coastal.com/notification/english
Esta carta está disponible en Español por Internet en: www.region2coastal.com/notification/spanish
это письмо можно прочитать на русском языке здесь: www.region2coastal.com/notification/russian
这封信的中文版本在网站地址: www.region2coastal.com/notification/chinese

Data cleaning process

As discussed earlier, for this research different kinds of geospatial datasets are merged with two different digital flood risk maps. In this section the data cleaning process will be elaborated. Firstly the two different maps and the NYC real estate geospatial data points had to be converted to the same Coordinate Reference Systems (CRS). This was done in R-studio, the Integrated Development Environment (IDE) of the statistical programming language R[11]. As the different data points did not use the same CRS they did not overlap, which made it impossible to do the required data preparation, since the Point-in-Polygon analysis to determine treatment groups is based on the concept of overlap. To solve this problem, all datasets were converted in R-studio to the NAD83 Coordinate Reference System. Transforming the CRS of the different datasets to NAD83 was done with the “rgeos”, “rgdal” and “sp[12]” packages. These packages are widely used for importing, exporting, cleaning, transforming, analysing and plotting geospatial data in R. After this procedure the data did overlap and could thus be analysed in QGIS, an open source software package for geospatial data. When the University of New York created the geospatial dataset from the “normal” real estate transaction dataset of the NYC Department of Finance, they labelled each usable observation with the letter “Y” and unusable observations with the letter “N”. Most of the unusable observations were deemed unusable because their selling price was 0 or extremely close to zero. For this research all the observations labelled as unusable were deleted from the dataset. For dealing with (price) outliers Ortega and Pensinar (2016) used the rather arbitrary cut-off points of $10.000 at the lower end and $15.000.000 and the higher end. For deleting outliers in this dataset the $10.000 lower cut-off point is also used, but the higher end cut-off point is replaced by the more commonly used “Z-score > 3” approach. The Z-score is a value that measures the deviation of an observed value from its expected value. It is measured as the observed value minus the expected value (the mean) divided by the standard deviation of that variable:

$$Z = \frac{X - \mu}{\sigma}$$

[11] RStudio Team (2015),’RStudio: Integrated Development for R’, Boston, MA: RStudio, on: http://www.rstudio.com/

[12] Pebesma, E.J. and R.S. Bivand (2005),’Classes and methods for spatial data in R’, R News 5 (2), on: https://cran.r-project.org/web/packages/sp/index.html (visited on 21-04-2017)

The z-score is a standardised measure, which means that a z-score always has the same meaning, disregarding the type of data. A Z-score of ±3 means that that observation lies at least three standard deviations from the mean. Depending on the distribution of the data, such an observation is rare. If the distribution is normal, the chance of finding such an observation is 0.135% (Field, Miles and Field, 2012: 934). Knowing this, the z-score can be used to find rare observations or "outliers". Therefore for every observation's selling price the z-score was calculated. Then all the observations which price had a z-score of 3 or above where deleted. This approach is more sensible, because it uses the idea of a standard distribution to get rid of outliers, rather than relying on an arbitrary cut-off point. With this approach the higher cut-off point was established at approximately at a real estate price higher than $6 million instead of the $15 million as used by Ortega and Pensinar (2016). When using their approach just over 1100 observations would have been deleted. While when the z-score approach was used it deleted almost 5900 outliers. Using no observations with a price lower than $10.000 drops another 4732 observations.

When the data was visually assessed a mistake in the real estate transaction dataset was found. Sales in the first couple of weeks of 2015 had the label "2015", but their sale date labelled as if the transaction had happened in 2016. Since the data of 2016 is not published until June or July, it was assumed that the creators of the dataset made a typing mistaking when constructing this dataset. Therefore 365 days where subtracted from those corrupted sale dates to make them fall back in line. The visualization of the displaced 2015 sales can be

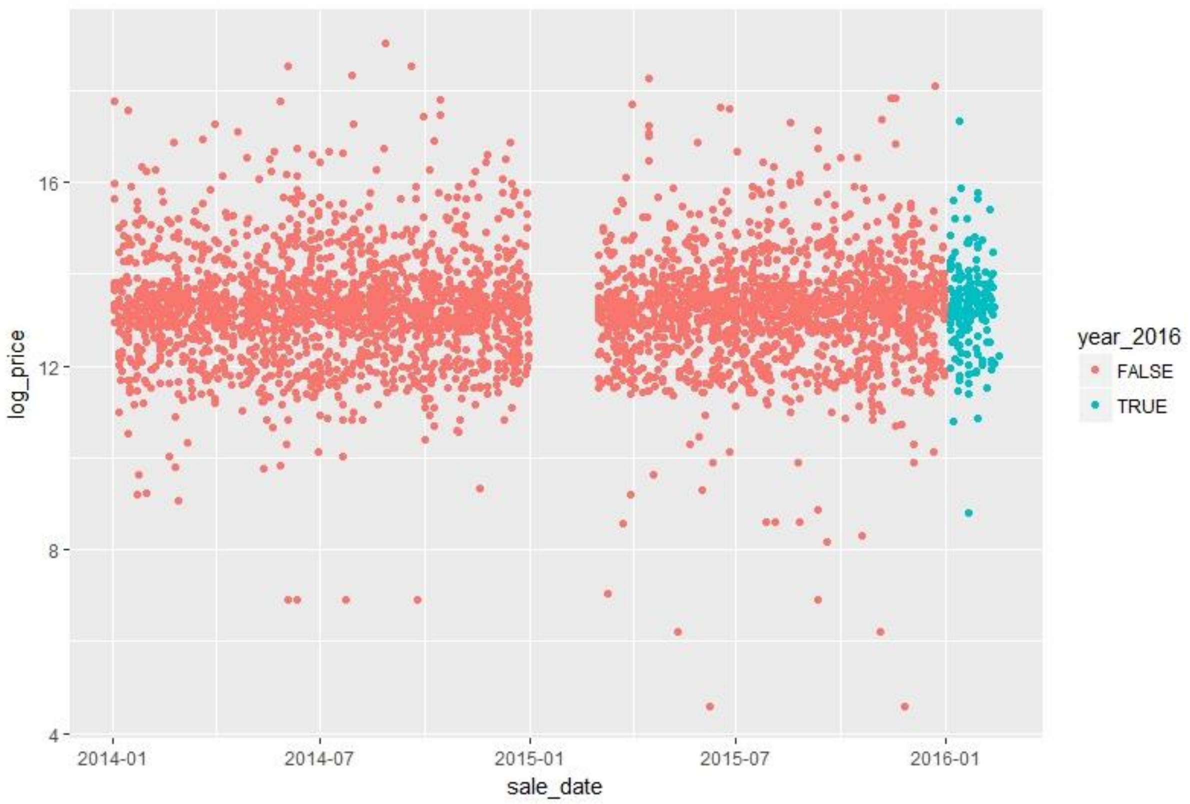

Figure 11. Displaced transaction data

seen in the scatterplot below. After adjusting for this error in the data the observations coloured blue in the scatterplot fell exactly in the gap showing at the beginning of 2015.

In line with hedonic flood risk studies in the past (Ortega and Taspinar, 2016: 5; Votsis and Perris, 2016) all commercial buildings have been deleted from the dataset. Mainly, because of the enormous price differences and the fact that commercial buildings have different price trends and different flood insurance regulation. This research thus only uses family dwellings (one, two, or three-family) and apartments (coops or condos). Since all these observations are assumed to have roughly the same trends and fall under the same mandatory flood insurance rules, using only these observations in the analysis will make them more comparable. Before deleting the commercial units the dataset consisted of 865,368 unique observations. After dropping the commercial real estate from the dataset 740,022 observations remained.

Since the dependent variable in the DID regression is the (natural log of the) price for which real estate is sold, it is important to take price inflation into consideration. The real estate data ranges from 2003 to 2015. A 2015 dollar theoretically was worth $1.29 in 2003. This is a big difference and to be able to compare sale prices the prices of different years were corrected for inflation, so that the price would be in 2015 dollars. The multiplier used for this inflation correct was provided in the code book of the NYC real estate transaction dataset from the New York University.

Since the data handling for this thesis was relatively labour intensive and humans make mistakes, the data and code were checked again manually to look for any errors. Firstly, after all the point-in-polygon analyses it was checked visually whether all the data was located in the right zone, whether it had the correct time label and finally if treatment areas did not overlap.

Year	Year 2015 Multiplier
2003	1.2881
2004	1.2547
2005	1.2136
2006	1.1757
2007	1.1431
2008	1.1009
2009	1.1048
2010	1.0870
2011	1.0537
2012	1.0323
2013	1.0174
2014	1.0012
2015	1.0000

Table 1. Multipliers used for inflation corrections

Tables robustness checks all boroughs

Staten Island	(1)	(2)	(3)	(4)	(5)
Treat 0% to 1%	-0.007 [0.018]	0.036 [0.023]	-0.007 [0.015]	-0.010 [0.011]	-0.029 [0.057]
Treat 1% stays 1%	-0.027 [0.027]	-0.014 [0.052]	-0.026 [0.026]	-0.055** [0.023]	-0.054 [0.053]
Post map	-0.080 [0.054]	-0.108* [0.057]	-0.122** [0.055]	-0.095** [0.042]	-0.134*** [0.048]
Post Sandy	0.018 [0.051]	0.023 [0.052]	0.017 [0.051]	0.021 [0.028]	0.065* [0.035]
(Treat 0% to 1% * Post Sandy)	-0.013 [0.034]	-0.024 [0.041]	-0.005 [0.033]	-0.026 [0.020]	-0.005 [0.050]
(Treat 1% stays 1% * Post Sandy)	-0.112*** [0.041]	-0.152*** [0.046]	-0.087** [0.041]	-0.022 [0.022]	-0.157* [0.079]
(Treat 0% to 1% * Post map)	0.003 [0.044]	0.004 [0.048]	-0.022 [0.045]	0.031 [0.032]	0.020 [0.039]
(Treat 1% stays 1% * Post map)	0.209** [0.090]	0.212*** [0.077]	0.159** [0.071]	0.040 [0.041]	0.269** [0.130]
Observations	32857	12942	32857	23017	62708
R-squared	0.452	0.512	0.452	0.465	0.204
FE level	Block	Block	Block	Block	Neighbourhood
Clustered S.E. level	Block	Block	Block	Block	Neighbourhood
Number of clusters	1935	1796	1935	1716	59
Control for building type and year built	No	No	No	No	No
Type of buildings	All	All	All	All	All

Table 9. Robustness checks Staten Island, first models. Model 1, 2, 3, 4, 5. More robustness check models follow in table 10. Model 1 is the preferred model, without robustness check. Model 2 is a subset for the years 2009-2015. Model 3 uses the date of the letter for the post dummy instead of the introduction of the new preliminary FIRM. Model 4 uses only the 70% core observations of the dataset. Model 5 uses a larger control group than just the 500 meter buffer. All observations of this bigger control group are in a 0% flood risk zone on the old flood risk map as well as on the new flood risk map.

Staten Island	(6)	(7)	(8)	(9)
Treat 0% to 1%	-0.005	0.001	-0.003	0.002
	[0.015]	[0.025]	[0.026]	[0.025]
Treat 1% stays 1%	-0.029	-0.046	-0.046	-0.005
	[0.026]	[0.033]	[0.034]	[0.025]
Post map	-0.080	-0.079	-0.079	-0.090**
	[0.054]	[0.054]	[0.054]	[0.041]
Post Sandy	0.050	0.019	0.053	0.020
	[0.079]	[0.051]	[0.079]	[0.076]
Placebo year before	0.033		0.036	0.017
Sandy	[0.061]		[0.061]	[0.061]
(Treat 0% to 1%	-0.034		-0.030	-0.028
* Placebo)	[0.061]		[0.071]	[0.071]
(Treat 1% stays 1%	0.030		0.003	-0.021
* Placebo)	[0.064]		[0.069]	[0.067]
(Treat 0% to 1%	-0.015	0.001	-0.010	0.011
* Post Sandy)	[0.034]	[0.049]	[0.057]	[0.054]
(Treat 1% stays 1%	-0.110***	-0.147***	-0.147***	-0.144***
* Post Sandy)	[0.041]	[0.050]	[0.051]	[0.048]
(Treat 0% to 1%	0.003	0.005	0.004	-0.001
* Post map)	[0.044]	[0.043]	[0.043]	[0.042]
(Treat 1% stays 1%	0.209**	0.202**	0.202**	0.207**
* Post map)	[0.090]	[0.090]	[0.090]	[0.091]
Trend Control		0.0034**	0.003	0.004**
		[0.0015]	[0.002]	[0.002]
Trend Treat 0% to 1%		0.0029	0.003	0.0037*
		[0.0018]	[0.002]	[0.0022]
Trend 1% stays 1%		0.0047***	0.004*	0.0054**
		[0.0018]	[0.002]	[0.0021]
Age				-0.0033***
				[0.0002]
Observations	32857	32857	40294	32671
R-squared	0.452	0.409	0.540	0.503
FE level	Block	Block	Block	Block
Clustered S.E. level	Block	Block	Block	Block
Number of clusters	1935	1935	1938	1928
Controlled for building type	No	No	No	Yes
Type of buildings	All	All	All	All

Table 10. Robustness checks Staten Island. Models 6, 7, 8 and 9. Model 6 includes a placebo effect for the year before Sandy. Model 7 includes group specific trends. Model 8 includes both the placebo effect and group specific trends. Model 9 includes both the placebo effect and group specific trends, while also controlling for age and building type.

Brooklyn	(1)	(2)	(3)	(4)	(5)
Treat 0% to 1%	0.007	0.055	0.007	-0.006	-0.072
	[0.018]	[0.045]	[0.018]	[0.013]	[0.057]
Treat 1% stays 1%	-0.070	-0.030	-0.071	-0.151**	-0.012
	[0.079]	[0.066]	[0.079]	[0.060]	[0.085]
Post map	-0.123**	-0.127***	-0.069	0.007	-0.101***
	[0.048]	[0.049]	[0.070]	[0.032]	[0.032]
Post Sandy	0.030	0.029	0.030	0.007	0.083***
	[0.040]	[0.042]	[0.040]	[0.036]	[0.023]
(Treat 0% to 1% * Post Sandy)	-0.164***	-0.120***	-0.162***	-0.065***	-0.146***
	[0.023]	[0.026]	[0.023]	[0.017]	[0.040]
(Treat 1% stays 1% * Post Sandy)	-0.097**	-0.062	-0.096**	-0.036	-0.122**
	[0.041]	[0.045]	[0.040]	[0.025]	[0.052]
(Treat 0% to 1% * Post map)	-0.046	-0.045	-0.059*	-0.012	-0.142***
	[0.032]	[0.033]	[0.032]	[0.022]	[0.033]
(Treat 1% stays 1% * Post map)	-0.030	-0.030	-0.037	0.037	-0.113**
	[0.048]	[0.047]	[0.047]	[0.030]	[0.056]
Observations	63755	27930	63755	44629	165584
R-squared	0.512	0.551	0.512	0.515	0.171
FE level	Block	Block	Block	Block	Neighbourhood
Clustered S.E. level	Block	Block	Block	Block	Neighbourhood
Number of clusters	2146	2017	2146	2008	62
Control for building type and year built	No	No	No	No	No
Type of buildings	All	All	All	All	All

Table 11. Robustness checks Brooklyn, first models. Model 1, 2, 3, 4, 5. More robustness check models follow in table 11. Model 1 is the preferred model, without robustness check. Model 2 is a subset for the years 2009-2015. Model 3 uses the date of the letter for the post dummy instead of the introduction of the new preliminary FIRM. Model 4 uses only the 70% core observations of the dataset. Model 5 uses a larger control group than just the 500 meter buffer. All observations of this bigger control group are in a 0% flood risk zone on the old flood risk map as well as on the new flood risk map.

Brooklyn	(6)	(7)	(8)	(9)
Treat 0% to 1%	0.014	0.050***	0.043**	0.034**
	[0.018]	[0.019]	[0.019]	[0.015]
Treat 1% stays 1%	-0.072	-0.061	-0.058	0.028
	[0.079]	[0.090]	[0.093]	[0.089]
Post map	-0.123***	-0.127***	-0.126***	-0.087**
	[0.048]	[0.048]	[0.048]	[0.043]
Post Sandy	0.053	0.018	0.043	0.036
	[0.051]	[0.040]	[0.051]	[0.052]
Placebo year before	0.037		0.029	0.022
Sandy	[0.037]		[0.038]	[0.038]
(Treat 0% to 1%	-0.099***		-0.054	-0.083**
* Placebo)	[0.037]		[0.038]	[0.036]
(Treat 1% stays 1%	0.002		0.019	0.001
* Placebo)	[0.040]		[0.050]	[0.036]
(Treat 0% to 1%	-0.172***	-0.090***	-0.113***	-0.117***
* Post Sandy)	[0.024]	[0.031]	[0.038]	[0.037]
(Treat 1% stays 1%	-0.097**	-0.026	-0.074	-0.148***
* Post Sandy)	[0.043]	[0.050]	[0.058]	[0.048]
(Treat 0% to 1%	-0.045	-0.029	-0.033	-0.037
* Post map)	[0.032]	[0.034]	[0.035]	[0.040]
(Treat 1% stays 1%	-0.030	-0.026	-0.025	-0.037
* Post map)	[0.048]	[0.050]	[0.051]	[0.040]
Trend Control		0.012***	0.012***	0.012***
		[0.001]	[0.001]	[0.001]
Trend Treat 0% to 1%		0.010***	0.010***	0.012***
		[0.002]	[0.002]	[0.002]
Trend 1% stays 1%		0.012***	0.011***	0.013***
		[0.002]	[0.002]	[0.002]
Age				-0.0016***
				[0.0003]
Observations	63755	63755	63755	55124
R-squared	0.513	0.513	0.513	0.604
FE level	Block	Block	Block	Block
Clustered S.E. level	Block	Block	Block	Block
Number of clusters	2146	2146	2146	2122
Controlled for building type	No	No	No	Yes
Type of buildings	All	All	All	All

Table 12. Robustness checks Brooklyn. Models 6, 7, 8 and 9. Model 6 includes a placebo effect for the year before Sandy. Model 7 includes group specific trends. Model 8 includes both the placebo effect and group specific trends. Model 9 includes both the placebo effect and group specific trends, while also controlling for age and building type.

Queens	(1)	(2)	(3)	(4)	(5)
Treat 0% to 1%	-0.016	0.029	-0.016	-0.008	0.047
	[0.027]	[0.051]	[0.027]	[0.021]	[0.036]
Treat 1% stays 1%	-0.012	0.075	-0.012	0.003	-0.072
	[-0.027]	[0.058]	[0.058]	[0.021]	[0.071]
Post map	-0.095**	-0.084*	-0.175	-0.094**	-0.111***
	[0.045]	[0.046]	[0.117]	[0.041]	[0.025]
Post Sandy	-0.139***	-0.028	-0.015	0.029	0.041
	[0.034]	[0.032]	[0.044]	[0.031]	[0.026]
(Treat 0% to 1% * Post Sandy)	-0.139***	-0.090**	-0.144***	-0.073***	-0.107**
	[0.034]	[0.039]	[0.033]	[0.026]	[0.041]
(Treat 1% stays 1% * Post Sandy)	-0.138**	-0.119**	-0.135**	-0.093**	-0.102
	[0.054]	[0.050]	[0.053]	[0.043]	[0.087]
(Treat 0% to 1% * Post map)	0.037	0.004	0.061	0.041	-0.029
	[0.052]	[0.049]	[0.055]	[0.057]	[0.041]
(Treat 1% stays 1% * Post map)	-0.006	0.013	-0.015	0.022	-0.036
	[0.037]	[0.036]	[0.039]	[0.029]	[0.046]
Observations	40294	17831	40294	28212	233152
R-squared	0.540	0.615	0.540	0.603	0.130
FE level	Block	Block	Block	Block	Neighbourhood
Clustered S.E. level	Block	Block	Block	Block	Neighbourhood
Number of clusters	1938	1788	1938	1713	61
Control for building type and year built	No	No	No	No	No
Type of buildings	All	All	All	All	All

Table 13. Robustness checks Queens, first models. Model 1, 2, 3, 4, 5. More robustness check models follow in table 14. Model 1 is the preferred model, without robustness check. Model 2 is a subset for the years 2009-2015. Model 3 uses the date of the letter for the post dummy instead of the introduction of the new preliminary FIRM. Model 4 uses only the 70% core observations of the dataset. Model 5 uses a larger control group than just the 500 meter buffer. All observations of this bigger control group are in a 0% flood risk zone on the old flood risk map as well as on the new flood risk map.

Queens	(6)	(7)	(8)	(9)
Treat 0% to 1%	-0.014	0.026	0.033	0.038
	[0.027]	[0.031]	[0.030]	[0.027]
Treat 1% stays 1%	-0.005	0.038	0.030	0.100**
	[0.059]	[0.077]	[0.078]	[0.047]
Post map	-0.095**	-0.100**	-0.100**	-0.101**
	[0.045]	[0.045]	[0.044]	[0.042]
Post Sandy	-0.028	-0.032	-0.050	-0.015
	[0.069]	[0.045]	[0.068]	[0.068]
Placebo year before	0.002		-0.016	0.011
Sandy	[0.052]		[0.050]	[0.051]
(Treat 0% to 1%	-0.017		0.047	0.025
* Placebo)	[0.042]		[0.046]	[0.045]
(Treat 1% stays 1%	-0.117**		-0.069	-0.096**
* Placebo)	[0.052]		[0.044]	[0.046]
(Treat 0% to 1%	-0.140***	-0.071*	-0.052	-0.033
* Post Sandy)	[0.035]	[0.043]	[0.050]	[0.051]
(Treat 1% stays 1%	-0.146***	-0.057	-0.082	-0.047
* Post Sandy)	[0.055]	[0.050]	[0.055]	[0.050]
(Treat 0% to 1%	0.037	0.054	0.058	0.022
* Post map)	[0.052]	[0.052]	[0.052]	[0.044]
(Treat 1% stays 1%	-0.006	0.015	0.010	0.029
* Post map)	[0.037]	[0.038]	[0.038]	[0.036]
Trend Control		0.009***	0.009***	0.011***
		[0.001]	[0.002]	[0.002]
Trend Treat 0% to 1%		-0.006***	0.006***	0.007***
		[0.002]	[0.002]	[0.002]
Trend 1% stays 1%		0.006**	0.007***	0.007***
		[0.002]	[0.003]	[0.003]
Age				-0.0032***
				[0.0004]
Observations	58288	55124	40294	38043
R-squared	0.521	0.604	0.540	0.604
FE level	Block	Block	Block	Block
Clustered S.E. level	Block	Block	Block	Block
Number of clusters	576	2122	1938	1928
Controlled for building type	Yes	Yes	No	Yes
Type of buildings	All	All	All	All

Table 14. Robustness checks Queens. Models 6, 7, 8 and 9. Model 6 includes a placebo effect for the year before Sandy. Model 7 includes group specific trends. Model 8 includes both the placebo effect and group specific trends. Model 9 includes both the placebo effect and group specific trends, while also controlling for age and building type.

Manhattan	(1)	(2)	(3)	(4)	(5)
Treat 0% to 1%	0.144 [0.112]	0.192 [0.176]	0.114 [0.113]	0.084 [0.054]	0.129*** [0.040]
Treat 1% stays 1%	0.192 [0.188]	0.198 [0.191]	0.192 [0.187]	0.083 [0.085]	0.063 [0.074]
Post map	-0.101* [0.0608]	-0.065 [0.054]	0.146 [0.174]	-0.053* [0.028]	-0.049 [0.064]
Post Sandy	0.056 [0.043]	0.059 [0.045]	0.056 [0.043]	-0.003 [0.026]	0.040 [0.041]
(Treat 0% to 1% * Post Sandy)	0.006 [0.089]	-0.009 [0.093]	-0.001 [0.089]	-0.031 [0.032]	0.221 [0.144]
(Treat 1% stays 1% * Post Sandy)	-0.072 [0.056]	-0.037 [0.055]	0.088 [0.060]	-0.016 [0.035]	-0.110** [0.048]
(Treat 0% to 1% * Post map)	0.023 [0.065]	-0.061 [0.069]	0.025 [0.065]	0.034 [0.038]	0.058 [0.064]
(Treat 1% stays 1% * Post map)	0.113** [0.055]	0.001 [0.0672]	0.115** [0.055]	0.070** [0.035]	0.199*** [0.070]
Observations	72964	33226	72964	51083	187280
R-squared	0.439	0.479	0.439	0.368	0.146
FE level	Block	Block	Block	Block	Neighbourhood
Clustered S.E. level	Block	Block	Block	Block	Neighbourhood
Number of clusters	598	550	589	541	39
Control for building type and year built	No	No	No	No	No
Type of buildings	All	All	All	All	All

Table 15. Robustness checks Manhattan, first models. Model 1, 2, 3, 4, 5. More robustness check models follow in table 16. Model 1 is the preferred model, without robustness check. Model 2 is a subset for the years 2009-2015. Model 3 uses the date of the letter for the post dummy instead of the introduction of the new preliminary FIRM. Model 4 uses only the 70% core observations of the dataset. Model 5 uses a larger control group than just the 500 meter buffer. All observations of this bigger control group are in a 0% flood risk zone on the old flood risk map as well as on the new flood risk map.

Manhattan	(6)	(7)	(8)	(9)
Treat 0% to 1%	0.127	0.028	0.048	0.014
	[0.107]	[0.117]	[0.124]	[0.099]
Treat 1% stays 1%	0.174	0.114	0.147	-0.088
	[0.191]	[0.220]	[0.215]	[0.016]
Post map	-0.101*	-0.099	-0.100	-0.091
	[0.061]	[0.061]	[0.061]	[0.058]
Post Sandy	0.130**	0.066	0.136**	0.072
	[0.065]	[0.045]	[0.067]	[0.069]
Placebo year before	0.004	-0.034	-0.026	-0.055
Sandy	[0.089]	[0.098]	[0.094]	[0.062]
(Treat 0% to 1%	-0.073	-0.099	-0.084	-0.055
* Placebo)	[0.056]	[0.065]	[0.072]	[0.062]
(Treat 1% stays 1%	0.041	-0.119	-0.073	0.026
* Placebo)	[0.073]	[0.074]	[0.101]	[0.105]
(Treat 0% to 1%	0.133**	0.017	0.091	0.026
* Post Sandy)	[0.063]	[0.108]	[0.150]	[0.128]
(Treat 1% stays 1%	0.059		0.064	-0.010
* Post Sandy)	[0.056]		[0.056]	[0.059]
(Treat 0% to 1%	0.193		0.110	0.138
* Post map)	[0.103]		[0.112]	[0.109]
(Treat 1% stays 1%	0.183		0.152	0.145
* Post map)	[0.092]		[0.120]	[0.103]
Trend Control		0.017***	0.015***	0.0134***
		[0.003]	[0.003]	[0.003]
Trend Treat 0% to 1%		0.023***	0.020***	0.018***
		[0.005]	[0.005]	[0.005]
Trend 1% stays 1%		0.021***	0.017***	0.018
		[0.004]	[0.005]	[0.004]
Age				-0.002**
				[0.001]
Observations	72964	72964	72964	58288
R-squared	0.439	0.439	0.439	0.521
FE level	Block	Block	Block	Block
Clustered S.E. level	Block	Block	Block	Block
Number of clusters	598	598	598	576
Controlled for building type	No	No	No	Yes
Type of buildings	All	All	All	All

Table 16. Robustness checks Manhattan. Models 6, 7, 8 and 9. Model 6 includes a placebo effect for the year before Sandy. Model 7 includes group specific trends. Model 8 includes both the placebo effect and group specific trends. Model 9 includes both the placebo effect and group specific trends, while also controlling for age and building type.