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An Empirical Analysis of the Local Weathers' Effect on Dwelling Prices

Håkon Grønvold & Kristoffer Gulestø
Supervisor: Maximilian Rohrer

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Abstract

Intuition and psychological evidence predict that pleasant weather is associated with an upbeat mood, and empirical research demonstrates that mood influences decision-making. This thesis investigates the effect of local weather on the selling price of dwellings sold in Oslo. The observed weather at the hour of the house viewing and auction are used to examine if potential homebuyers' moods are affected to such an extent that it changes the sales price. We find that the weather has systematically altered dwelling sales prices in Oslo, and the results are significant both statistically and economically. The granularity of the weather and housing data combined with the model specification allows us to claim a causal relationship between local weather and dwelling prices.

Keywords: Behavioral finance, real estate pricing, hedonic model, rationality, mood, weather.
JEL Classification: G41, R31.

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Håkon Grønvold and Kristoffer Gulestø

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1 Introduction

In a rational world, the weather should not affect dwelling prices. However, psychological evidence document that there is a connection between weather and mood[1]. The change in mood caused by the weather will have an impact on human behavior. Although it is not surprising that mood affects human behavior, it is less clear which way mood can exert such influence. Research from behavioral economics reveals that mood influences decision-making and the use of heuristics[2]. It is therefore reasonable that weather could affect decision making through mood. In line with this, studies in finance document that local weather has systematically affected stock markets around the world[3], but to our knowledge, the weather-effect remains untested in the housing market.

Our contribution is two parted. First, we investigate the effect of local weather on dwelling sales prices in Oslo. We hypothesize that the weather during the house viewing will influence the mood of the participants to such an extent that it systematically affects the sales price. A bad mood corresponds with negative bias; hence, the homebuyer will be less inclined to buy the dwelling or pay less than they otherwise would. Additionally, the weather during the auction will increase the use of heuristics that are associated with bidding, where a negative mood produces more analytical and careful estimates. The weather-effect also has practical implications, as bad weather may cause a poor turnout at the house viewings and impair views from windows and balconies.

Secondly, as opposed to previously cited research on weather and financial activity[3], we use hourly weather observations instead of daily observations. The results are causal because the granular weather data allows us to measure the impact of the weather at the exact time of house viewing and auction. The weather can change several times during the day, and there is daily variation in several of the weather variables. Granular weather data allows us to capture this variation in the model. We construct a hedonic real estate regression with dwelling specific, location specific, and transaction specific variables to approximate the sales price when all else equal. To soak up market effects over time, unobserved dwelling effects, and the highly seasonal and daily patterns of the weather, we include several fixed effects variables. We account for everything that happens in the market that is unrelated to the

[1]Schwarz, N., & Clore, G. L. ,1983; Persinger, M. A., & Levesque, B. F. , 1983; Howarth, E., & Hoffman, M. S. , 1984; McAndrew, 1993; Eagles, 1994; Tietjen & Kripke, 1994; Bell, Greene, Fisher, & Baum, 2005; Denissen, Butalid, Penke, & Aken, 2008

[2]Tversky & Kahnemann, 1974; Johnson & Tversky, 1983; Thaler, 1985; Kagel & Levin, 1986; Forgas, 1995; Kahneman, 2011; Bless, Schwarz, & Kemmelmeier, 1996; Park & Banaji, 2000

[3]Saunders, 1993; Goetzmann & Zhu, 2005; Akhtari, 2011; Ødegaard, 2019

weather. When using economically intuitive weather variables with all controls fixed, the weather's effect on dwelling prices is a causal relationship. The causal results imply that the housing market is irrational, as non-fundamental information generates market mispricing. For the seller, it is difficult to exploit this mispricing since scheduling house viewings based on the weather forecast a week ahead is unlikely an effective approach. On the other hand, it is feasible for the buyer to exploit the irrationality by trying to buy dwellings that have house viewings in bad weather.

Our main finding is that local weather has systematically affected dwelling sales prices in Oslo. Bad weather, such as in rain and cloud cover, have a significantly negative impact on sales price, while good weather has a smaller but still significant positive impact on price. Most notably, rain during the first house viewing corresponds with a lowered sales price of $64,000$NOK on average. For a dwelling priced at 4MNOK, this represents a 1.6 percent decrease in price.

Several studies have documented the impact of weather conditions on economic activity. The seminal research by Saunders (1993) provides evidence that local weather systematically affected stock prices at exchanges in New York City. He found that the amount of cloud cover in the skies had a significantly negative correlation with stock prices. The mean daily change of the value-weighted New York Stock Exchange (NYSE) was 0.0305 percent in the period 1962 to 1989 according to Saunders' data. He found that a cloud cover of 20 percent or less moved the daily change to 0.0814 percent, while a full cloud cover meant a negative change of 0.0246 percent. Saunders suggests that investor psychology influences asset pricing and that his findings "cast doubt on the hypothesis that security markets are entirely rational". Hirshleifer & Shumway (2003) expand on Saunders' research by broadening the analysis to a large number of stock markets across the world and with different weather variables. They identify that the amount of sunshine is significantly associated with stock returns for several exchanges, indicating that the effect is a worldwide phenomenon. In New York City, they find that the annualized nominal market return on a sunny day is 24.8 percent versus 8.7 percent on a cloudy day. In Oslo, Ødegaard (2019) investigates if local weather in has any effect on the Oslo Stock Exchange (OSE). He hypothesizes that weather works as a proxy for mood and that traders are more optimistic in good weather. He concludes that bad weather has a significant negative impact on the OSE performance; more specifically with the variables cloud cover and windchill[4]. Ødegaard (2019) is the first to measure the relationship between windchill and stock prices.

[4]Windchill is the effective temperature as it accounts for both wind and temperature

On the other hand, some studies raise suspicion that statistically significant weather variables may be the result of spurious correlation or an exercise in data mining. Trombley (1997) replicated Saunders' (1993) study using similar data but a different methodology. He concluded that the relationship between cloud cover and NYSE returns that Saunders (1993) reported were not as clear, only seeing an effect in certain months during the last 20 out of 60 years. Also, Goetzmann & Zhu (2005) examined the effect of local weather on the trading activity in five major US cities and found no effect on individuals' propensity to buy or sell equities on cloudy days as opposed to sunny days. They do however find that NYSE spreads widen on cloudy days, and suggest that the weather-effect may influence market makers and news providers physically located in in the city of the exchange.

The housing market differs from other asset markets in that the majority of its participants are inexperienced and non-institutional. The inexperienced homebuyer is more likely misattribute weather-induced mood than the average investor in the stock market. In line with this, Akhtari (2011) finds that the weathers' impact on Dow Jones performance is stronger in the late 1990s when the stock market attracted attention. She hypothesizes that the entry of inexperienced investors during the dot-com bubble explains the strong weather-effect in this specific period. In the commercial market, Busse, Pope, Pope, & Silva-Risso (2015) find that the sale of convertible and four-wheel-drive cars are highly dependent on the weather at the time of purchase. Consequently, it is reasonable to suggest that a weather-effect can also exist in the housing market, and even be more persistent than in the stock market.

2 Hypothesis Development

The findings from weather research on the stock market and literature from behavioral economics motivates us to investigate the weather-effect on the housing market; our research question is:

Does the observed local weather at the time of house viewing and auction have a causal effect on the selling price of dwellings sold in Oslo?

Weather will differ in time and region. Prices will also differ in time and regions. However, we use weather data at the granularity where prices cannot differ. The market will go up and down; it might be booming a month, a week, or even on a given day, but not at a specific hour. The hedonic model control for differences in the sales price based on attributes of the dwelling. We control for years, month-of-year, week-of-year, day-of-week, and time-of-day fixed effects capture seasonality and price variation over time. Also, we use location fixed effects and geospatial variables to correct for unobserved market and location effects. From there, we create economically reasonable and creative weather variables and borrow the windchill variable from Ødegaard (2019). Placebo tests with the weather in Tromsø on dwelling prices in Oslo are performed to ensure that the results are not due to spurious correlation. We test that there is no correlation between the weather Tromsø and Oslo. Henceforth, the placebo test supports causal inference between local weather and dwelling prices.

In order to underpin our results, we measure the impact of bad weather at *both* the house viewings and find a significant negative effect on price with great magnitude. In the next to last analysis, we substitute the dependent price variable with a price-to-asking price ratio to measure the weather-effect on overpricing (or underpricing) relative to the asking price. Lastly, we measure the effect of weather on "time-on-market" by changing the dependent variable to measure how long the dwelling stays unsold.

2.1 The Dwelling Transaction

Real estate brokerage firms mainly conduct the sale of dwellings in Norway. The broker representing the firm is responsible for creating the advertisement and prospect, in addition to setting up the house viewing. At the day of the viewing, interested parties meet up to inspect the dwelling and ask questions. In our data, there are only observations with two house viewings, and we observe that 75 percent of the first house viewings are on Sundays.

The second house viewing is distributed more differently, with 50 percent of the observations on Monday, while Tuesday holds 20 percent. Since the day of the house viewings varies, we want to control for this in the regression. Therefore we include "day-of-the-week" fixed effects to control for any unobserved heterogeneity between the different days of the week. To account for any variation on the different times of day to conduct viewings, we use a "time-of-day" fixed effect. Similar controls have been used in related literature. For example, Saunders (1993) includes a Monday dummy to account for the phenomenon of significantly lower returns on Mondays, also known as the weekend effect (French, 1980).

In the morning of the first business day following the second viewing, interested parties can start placing bids. However, the real estate broker is not allowed to inform the seller of any bids that expire before noon the first business day after the last viewing (Norges Eiendomsmeglerforbund, 2014). The Norwegian Consumer Council writes that the auction usually concludes by noon (Forbrukerrådet, 2013), and we corroborated this with brokers in Oslo. The time from 11:00 to 12:00 is the pinnacle of the bidding process, with much information going back and forth between the broker and bidders. Therefore, in the auction analysis, we use the observed weather at 11:00 to measure if the weather during the auction has an impact on the dwelling sales price.

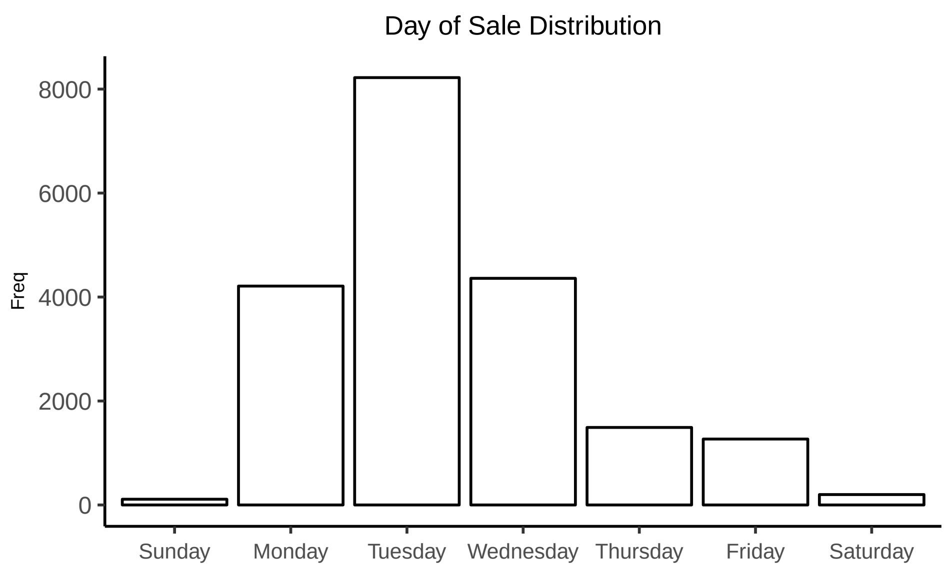

Figure 1: *Day of Sale Distribution in Oslo from 1/1/13 to 31/12/18. Day of Sale is defined as the day the dwelling is sold.*

The average time from the first viewing to the day of sale is 2.7 days. Figure 1 depicts the day of the week that the dwelling is sold, and most dwellings are sold on Tuesdays. In addition to the previously mentioned controls, we use a "day-of-sale" fixed effect to account for any variation between the different selling days.

One risk is that brokers could sell expensive dwellings on days that are forecasted to be sunny. This would create bias in our results since the broker would work as an instrument for selling expensive dwellings on sunny days. In order to have causal results, the weather must be exogenous. On average, it takes 7.3 days from the finn-ad is published to the first house viewing. Hu & Skaggs (2009) find that the historical accuracy of six to ten-day precipitation forecasts are about 40 percent. It is therefore difficult for brokers to schedule house viewings based on the weather forecast. We corroborate this with Frode Furuhovde, which is responsible for sales and operations at the real estate brokerage firm Privatmegleren. The brokers at Privatmegleren do not plan house viewings based on weather forecasts. Considering this and the fact that 75 percent of the first house viewings are on Sundays, the weather is exogenous.

2.2 Behavioral Economics

The existence of a weather-effect implies that the housing market is not rational. Shiller (2015) argues that the housing market lacks rationality, as its participants are predominantly non-professionals, and there is no practical way to bet against bubble-level prices. The following part will consist of three sections. First, we provide the empirical background that individuals might not always behave rationally, and that cognitive biases and heuristics play a large role in the lack of rationality. Secondly, we explore how weather can affect mood. Lastly, we analyze how mood and sentiment can affect decision-making. Using this train of thought, we can deduct that local weather should have an economically intuitive effect on the selling price of dwellings.

2.2.1 Rationality and Heuristics

The belief that individuals behave rationally is the crux of traditional economic theory and the efficient market hypothesis. *Homo economicus* - a term used for the consistently rational individual driven by self-interest. However, Simon (1957) challenges the notion of human rationality. He coined the term "bounded rationality", which is the idea that there are limitations in our cognitive ability to process information, limitations in available information, and limitations in time. Behavioral economists suggest that the situational context influences behavior and that behavior fluctuates over time and space (Cialdini, 2018). In the housing context, much information will overwhelm the homebuyers if they lack experience and time.

Buying a home is a critical moment. For most people, it is the most significant investment of their lifetime. Ergo, this should be a rational decision. Daniel Kahneman uses a dual-system framework to explain why decision-making is not always rational. System 1 is the brain's fast, automatic, and experience-based approach, while system 2 is slower, more reflective, and analytical Kahneman (2011). The decision to buy a home, or place a bid should be a task for the slow and logical system 2, but as Kahneman describes, system 2 is very much influenced by the fast and unconscious system 1.

There are several cognitive biases and heuristics associated with system 1 and fast thinking. For the scope of this thesis, we will use some examples relating to the decision to buy and the bidding process.

One of the universal heuristics is availability, which is a mental bias that makes the decision maker perceive the possibility of a given outcome as more likely when they have an example of it readily available (Tversky & Kahneman, 1974). For instance, one may assess the housing market as very lucrative if an acquaintance recently sold their dwelling with large profits. From the same publication, Tversky & Kahneman (1974) discuss the implication of anchoring, which is that people make estimates depending on an initial value, or starting point. Different starting points yield different estimates. To explore this effect, we run an additional analysis with the weather's effect on overpricing (or underpricing), where the asking price is the anchor.

Also, humans often think of value in relative terms as opposed to absolute terms. This heuristic is a type of mental accounting, which sets to explain how we categorize and evaluate economic outcomes (Thaler, 1985). For example, in the auction, bidding an extra $25,000$NOK over the budget might seem like a drop in the ocean when buying a 4MNOK home. On the one hand, this is only a 0.625 percent increase from 4MNOK. On the other hand, this sum represents the annual saving per year for the average Norwegian person (Halvorsen, 2011). In addition, where the money comes from is another mental accounting bias that can affect willingness to pay. The use of credit instead of hard-earned money can increase overspending (Cooper, 2010). In one study, professors at Massachusetts Institute of Technology experimented with their MBA students and found that using a credit card as opposed to cash as much as doubled the students' willingness to pay (Prelec & Simester, 2001).

Dwelling auctions happen at a fast pace, and this forces buyers to make hasty decisions. Buyers may end up making irrationally high bids when eager to "seal the deal". This concept is known as the “winner’s curse” (Galinsky, Ku, & Murnighan, 2006; Heyman, Orhun, & Ariely, 2004; Kagel & Levin, 1986; Ku, Malhorta, & Murnighan, 2005). Under pressure, buyers are more likely to be affected by mood, which could potentially aggravate the winner’s curse problem. Bazerman & Samuelson (1983) provide a typical example of the winner’s curse where they auctioned off a jar containing an unknown number of coins to their students. Some students tried to make a profit buy bidding below their estimates of coins in the jar. The winner was still the student who had the most optimistic estimate and overpaid the most. The bottom line of the winner’s curse is that the winning bidder ends up paying more than the item is worth. Roll (1986) show that overconfident managers tend to overbid when acquiring other corporations. Two factors affect the magnitude and likelihood on the winner’s curse: the degree of competition between the potential buyers, and the degree of opinion concerning the auctioned item (Bazerman & Samuelson, 1983; Capen, Clapp, & Campbell, 1971).

2.2.2 Weather and Mood

Literature from psychology shows that the weather influences human behavior and mood. Schwarz & Clore (1983) found that people rate their life satisfaction higher on sunny days as opposed to cloudy days. Additionally, they found that external stimuli, such as sunny weather will often cancel out a bad mood. Persinger & Levesque (1983) reported a variation of 30 to 60 percent in daily mood scores when testing different types of weather factors on mood. In a comprehensive study by Howarth & Hoffman (1984), humidity, temperature, and amounts of sunshine have the most considerable influence on mood. McAndrew (1993) showed that the lack of sunlight makes people feel melancholic and upset. Also, the lack of daylight and sunshine can coincide with depression Eagles (1994) and suicide (Tietjen & Kripke, 1994). Bell, Greene, Fisher, & Baum (2005) found that individuals demonstrate different behaviors when is it extremely hot or cold. For instance, crime increases when temperatures are very high (Asher, 2018). The Federal Bureau of Investigations in the US even lists intense heat as a leading catalyst to violent crimes (Gamble & Hess, 2012). Denissen, Butalid, Penke, & Aken (2008) showed that bad weather such as low temperatures, high winds, and lack of sunlight had a significantly negative effect on mood.

2.2.3 Mood and Decision-Making

As mentioned in the previous section, is it widely accepted that weather affects peoples' mood. Building on this, we will now discuss how mood can affect decision-making. Individuals can misattribute weather-induced mood in the decision-making process. People in positive moods tend to make more optimistic decisions, whereas people in bad moods make more pessimistic decisions (Johnson & Tversky, 1983). Forgas (1995) found that mood is most strongly affecting judgment when people lack accurate information. Kahneman (2011) establishes that good mood loosens control over the analytical system 2, making people more creative, but also less vigilant and more prone to logical errors. He argues that this is an evolutionary trait. A good mood signals that things are going well; we are safe and can let our guard down. On the other hand, a bad mood might mean there is a threat, and more caution is required. In line with Kahneman's research, Bless, Schwarz, & Kemmelmeier (1996) and Park & Banaji (2000) found that a good mood increases the chances of relying on heuristics when making decisions, while a bad mood makes individuals more prone to process information in a logical and bottom-up way.

In light of this, bad weather during the house viewing will result in a declined mood of the potential homebuyers. They will look at the decision to buy more negatively, and if deciding how much to bid, they will come up with a more analytical and cautious estimate; resulting in a lower selling price. On the other hand, good weather will result in a better mood and the increased use of heuristics, which will have an opposite effect on the selling price.

In addition to weather-induced mood affecting decision-making, the weather will have more intuitive and practical effects in the real estate context. For one, general mood is affected by weather, and this will cause homebuyers to perceive the dwelling differently depending on their mood. Secondly, dwellings with a beautiful view, balcony or other recreational areas could have a bigger weather-effect. For example, stepping on to a balcony with views over the fjord of Oslo on a sunny day will likely trigger positive emotions. Third, lousy weather can make people less willing to bother going to the viewing, resulting in lower attendance. Horanont, Phithakkitnukoon, Leong, Sekimoto, & Shibasaki (2013) provide evidence from Tokyo that people's activities are affected by the weather. Using mobile GPS data, they found that the farther away someone is from a train station, the higher the effect of weather pattern on the choice of activities. In some extreme cases, it might even be physically challenging to go out if the weather is terrible.

3 Methodology

The hedonic regression method values a heterogeneous good in a segmented market by its individual attributes or characteristics. It measures the relative impact of the attributes that affect the price of a good. In the real estate context, these characteristics can include attributes of both the dwelling itself and the location of the dwelling (Haan & Diewert, 2013). Examples of characteristics can be lot size, the number of bedrooms, and proximity to the city center. Hedonic modeling is widely used in mass appraisal of real estate, but also in the valuation of non-market effects (such as weather) that can contribute to the price of the dwelling (Anselin & Lozano-Gracia, 2009).

It is preferable to use categorical variables over continuous variables in hedonic regression. Rather than having one continuous variable with number of bedrooms, we transform it into several dummy variables. This approach has greater flexibility as it allows for the effect of having an extra bedroom to differ depending on the initial number of bedrooms (Hill, 2013). Categorical variables will also allow the impact of non-linearity. For example, the value of the dwelling decreases when the building ages. However, older residences may have a premium in the same way as antique furniture; the value starts increasing at some point in age. In other words, it has a convex price curve. The increased flexibility of dummy variables does come at a price of fewer degrees of freedom. However, when working with a dataset with a large number of observations, the dummy variable approach is still preferable (Hill, 2013).

Shiller (2008) criticizes hedonic regression by saying there are too many possible explanatory variables to use. We mostly adopt hedonic variables used by previous research, and find a similar adjusted R-squared compared to these publications. At some point in the process, adding trivial variables such as “alluring words” used by the broker in the finn-ad yielded diminishing explanatory power. Another issue is omitted variables bias, as there will always be effects that are hard to measure. Examples of this are the level of maintenance or the amount of received sunlight on the balcony. A solution for the omitted variable problem is including location variables (Hill, 2013), either by district fixed effects, or geospatial variables with distance to schools, kindergartens or train stations. This will correct for omitted variable bias since neighborhoods share many price-determining factors. Prices and characteristics of dwellings closer together are usually more similar than those dwellings farther apart.

4 Data

Eiendomsverdi AS has provided essential data to this thesis.[5] In addition to the transaction data, we downloaded weather data from the Norwegian Meteorological Institue[6] database, Frost. From Oslo Municipality[7] we acquired postal codes for each district.

4.1 Data Sources

Eiendomsverdi AS follows and registers the activity in the Norwegian housing market daily. Their database includes every property transaction in Norway and contains information on sales price, dwelling-specific information, and the relevant finn.no advertisement. Eiendomsverdi provides services to banks, real estate agencies and public enterprises (Eiendomsverdi, 2018). Access to their database was through a web application, and retrieving the amounts of data from the web application and finn-ads manually would have been a time-consuming task. Therefore, we automated this process with robotic process automation that went into every single transaction in the web application, then inspecting the finn.no-ad and retrieving relevant variables, then saving the information in a data set. The development of the automation process has allowed us to collect high quality data in abundance.

Frost provides free access to Norway's archive of historical weather and climate data. The data is quality controlled and contains hourly measurements of temperature, precipitation, cloud cover and wind for various weather stations in Norway, Frost (2019). We have acquired hourly observations from Blindern weather station in Oslo and Tromsø.

In addition to Eiendomsverdi and Frost, we downloaded data from Oslo Municipality and the Norwegian Directorate of Education and Training. From the Oslo Municipality website, we have downloaded the names and addresses of all youth, upper secondary, and primary schools in the Oslo area. We collected this data to create variables with distance from each dwelling to the closest school. From the Directorate of Education and Training we have downloaded addresses and names to all kindergartens in the Oslo Municipality, with the same purpose. We collect coordinates from each dwelling, school, and kindergarten address using the Google Geolocation API. Further we compute the distance to the closest school and kindergarten from each dwelling.

[5] We would like to thank the research director of Eiendomsverdi Norge, Erling Røed Larsen

[6] In Norwegian "Metrologisk Institutt"

[7] In Norwegian "Oslo Kommune"

4.2 Dwelling Data

The data sample gathered from Eiendomsverdi's database consists of six years of dwelling transactions in Oslo between 2013 and 2018. We use this time period as it allows us to collect enough data to answer this reserach question. In addition, the data sample allows us to investigate recent market behavior. The dwellings are limited to apartments, and those defined as housing cooperative[8] and freeholder[9]. Hence, the data sample does not contain detached houses, semi-detached houses, terraced houses or leisure homes. See figure 8 in the appendix for freeholder and cooperative dwellings distribution of the dataset. Eiendomsverdi's database contains both dwelling specific and transaction specific variables, which we use in the hedonic regression analysis. Dwelling and transaction specific variables include Age of Dwelling, District, Living Area, Type of Ownership, Number of Bedrooms, Janitor/Security Service, Parking, Guest Parking, Modern, Common Laundry Room, Child-Friendly, Fire Place, Expandability, View, Parquet, Elevator and Quiet Area, Sales Price, Date of Sale, Date of House Viewing, and Time-on-Market. A list of both dwelling specific and transaction specific variables with description is given in table A1.

We gather information about the date and time of house viewings from the finn.no ads. The data at Eiendomsverdi contains postcode, but not information about city district. We have therefore matched the postcodes with the city district list from Oslo Municipality to create district fixed effects.

The original data contained $30,000$ observations. We remove $3,129$ transactions that have missing Date of Sale, Sale Price or no date of viewing. Further, we remove $3,266$ transactions that have a higher difference between Date Registered and Date of Sale than 14 days. We remove these observations because if the dwelling stays on the market for more than two weeks, there could have been more viewings than described in the finn-ad. We also exclude $2,101$ observations with missing Living Area, Age, and monthly-shared costs. Lastly, as want to look at the typical dwelling transactions in Oslo we remove the top and bottom 5 percent of sales prices from our sample, this corresponds to $2,150$ observations. The final dataset contains $19,354$ values, due to $10,646$ removed values.

[8] "Borettslag" in Norwegian

[9] "Selveier" in Norwegian

4.3 Meteorological Data

The weather data contains 52, 504 observations with four different variables: air temperature, precipitation amount, wind speed, and cloud cover. Every variable is measured hourly, except cloud cover, which is measured every third hour. Precipitation includes rain, drizzle, snow, and hail.[10] The measurement of precipitation is in millimeters, wind speed is in meters per second and temperature is in Celsius. A scale from zero to eight measures cloud cover, where eight is maximum cloud cover, and zero is no cloud cover. Table 1 describes the weather variables.

Table 1: Weather Observation Description

Weather	Description
Temperature	Mean air temperature at the observation in degrees °C. Measured two meters above ground
Precipitation	The total amount of precipitation during the last hour. Measured in millimeters.
Wind	Mean wind speed for the last hour. Measured in meters per second 10 meters above ground.
Cloud Cover	Total cloud cover in octas. Where 0 = clear sky, and 8 = completely cloudy sky.

Source: https://frost.met.no/elementtable

In total there are 52 different weather stations in Oslo. Optimally we could have gathered coordinates for every station and connected each dwelling to their closest weather station. Adding granularity to the data would increase the causality. However, Blindern is the only station in Oslo that measures all four weather variables consistently over the sample time. Therefore, we only use Blindern due to the high quality and consitency of the data. Figure 2 is a map of Oslo with the location of Blindern weather station.

[10] https://climate.ncsu.edu/edu/PrecipTypes

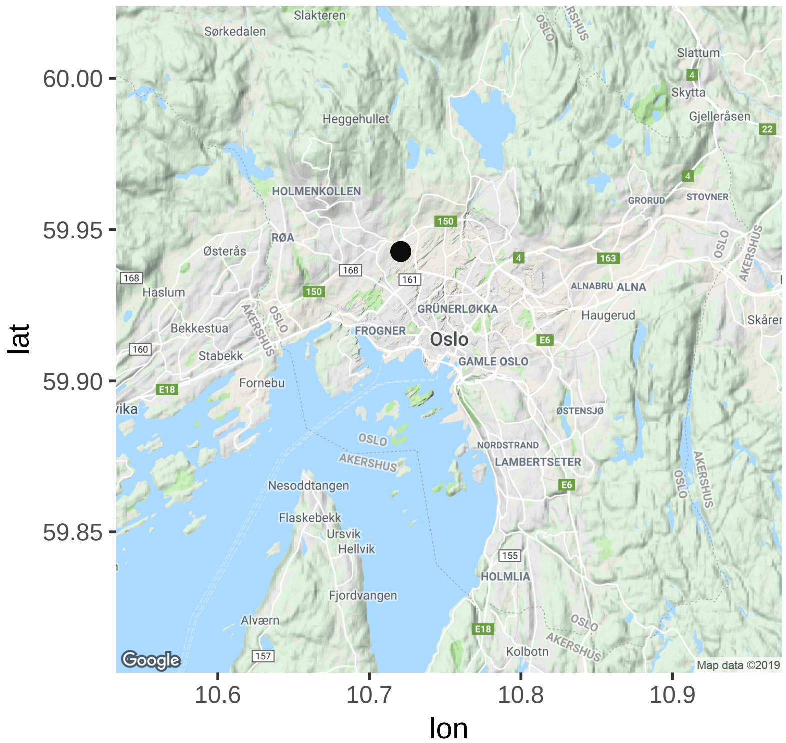

Figure 2: Map of Oslo, Black dot is the location of the weather station.

The weather varies throughout the year, whereas the four different seasons carry their specific characteristics. The temperature is at its highest during June, July, and August, and at its lowest during December, January, and February. To account for the seasonal and daily variation in the weather, we use year, month-of-year, week-of-year, day-of-week and hour-of-day fixed effects.

4.3.1 Weather Variables

Ødegaard (2019) measured a significant relationship between windchill and OSE performance in Oslo. Therefore, we hypothesize that windchill will affect dwelling prices as well. Windchill is the felt temperature on the skin. High winds and low temperatures will cause a low windchill. In other words, the temperature at higher wind speeds feels colder than it is. We use the formula from Environment Canada, as the climate in Norway and Canada has similar features. The formula for Windchill of Environment Canada[11]:

[11] https://www.canada.ca/en/environment-climate-change/services/weather-health/wind-chill-cold-weather/wind-chill-index.html

$$T_{wc} = 13.12 + 0.6215T_a - 11.37v^{+0.16} + 0.3965T_a v^{+0.16} \tag{1}$$

Where T_{wc} is the windchill index, T_a is the air temperature in °C, and v is the wind speed measured $10m$ above ground level, in km/h.

As mentioned earlier, cloud cover is measured in octas from zero to eight. Some observations of cloud cover are given as -3 or 9. This means it was not possible to measure cloud cover due to fog or blowing snow. These observations are therefore excluded. Cloud cover is only measured every third hour. We solved this by interpolating between the missing values. For example, if we have four data points between 10:00 and 13:00: 2, *NA*, *NA* and 5. The interpolation will return: 2, 3, 4 and 5. Data points with more than two *NA's* between each observation are not interpolated.

We want to investigate the impact of precipitation during the auction hour and house viewing. We hypothesize that *if* precipitation is present during the auction or house viewing is more critical than the *amount* of precipitation. For example, an increase from 0.0 to 0.1 millimeter has a more significant impact on mood than an increase from 3.0 to 3.1. Hence, the variable for precipitation is specified as a dummy variable, which is 1 if there is precipitation, and 0 otherwise.

We create dummies which measures how "extreme weather" may impact the mood of participants. Extreme weather is defined as the weather that only takes place at the upper and lower 5 percent of the time. The variables include extremely high temperatures (5 percent warmest days), extremely low temperatures, and extreme windchill.

The weather is inherently autocorrelated. So we are also investigating how sudden changes in weather may impact dwelling prices. Since temperature and windchill are highly dependent on the time of day, we cannot reasonably create averages for the previous day, so we use the hourly observation 24 hours before the relevant event. We define sudden change for different weather variables as dummy variables. For air temperature, we create a dummy that is equal to 1 if the temperature is five or more degrees colder than at the same time the previous day. We did the same for windchill. Sudden change in precipitation get the value of 1 if there was no precipitation the day before, but there is at the event. Sudden change in cloud cover is defined as a negative change of 5 or more octas from the mean cloud cover the previous day. The results of the sudden change analysis can be found in section A.5 in the appendix.

The number of observations in the various regressions are different. Some house viewings do not start on the hour, and since our weather data are hourly, this does not match. We could have rounded the times to the closest hour (for example 13:20 to 13:00), but this could affect causality. Since causality is an incredibly important factor in solving our research question, we decided only to use the house viewings that starts on the hour when analyzing the weather-effect on price during house viewing.

The dataset in the auction analysis has $19,354$ observations; none of them are excluded since all auctions start at 11:00. The first house viewing dataset has $13,227$ observations since $6,547$ are excluded. The second house viewing dataset has $12,771$ observations, and the dataset for both house viewings contains $9,271$.

4.4 Descriptive Statistics

We present descriptive statistics for the general dataset. In the matrix in Table 2, we observe no correlation between weather variables and price. Correlation matrices for each dataset used in the analysis are given in section A.2 in the appendix.

Table 2: Correlation Matrix, Full Dataset

	Price	Temperature	Precipitation	Windchill	Cloud Cover
Price	1	-0.009	-0.022	-0.014	-0.011
Temperature	-0.009	1	-0.043	0.990	-0.336
Precipitation	-0.022	-0.043	1	-0.048	0.242
Windchill	-0.014	0.990	-0.048	1	-0.353
Cloud Cover	-0.011	-0.336	0.242	-0.353	1

Descriptive statistics in table 3 depicts that the highest dwelling sales price is $5,750,000$NOK and lowest is $2,400,000$NOK. The small gap is due to winsorization of the dwelling data, where we remove the top and bottom 5 percent of the sales prices. Cloud Cover has fewer observations than the other variables due to missing values. Descriptive statistics for each dataset used in the analysis are given in section A.2 in the appendix.

Table 3: Descriptive Statistics, Full Dataset

Statistic	N	Mean	St. Dev.	Min	1st Qu.	3rd Qu.	Max
Price	19,774	3,610,319	703,312	2,400,000	3,100,000	4,025,000	5,750,000
Temperature	19,774	9.970	8.201	−12.600	3.700	17.000	29.800
Precipitation	19,774	0.091	0.367	0	0	0	5
Windchill	19,774	8.738	9.598	−18.322	1.200	16.895	32.261
Cloud Cover	19,113	5.626	2.287	0.000	4.000	8.000	8.000

Figure 3 illustrate the distribution of the price and the weather variables. 97.5 percent of the precipitation observations are equal to zero, and we can see a strong positive skew in the precipitation distribution. Cloud cover has a strong negative skew as most observations are equal to eight. Dwelling price has a weak positive skew.

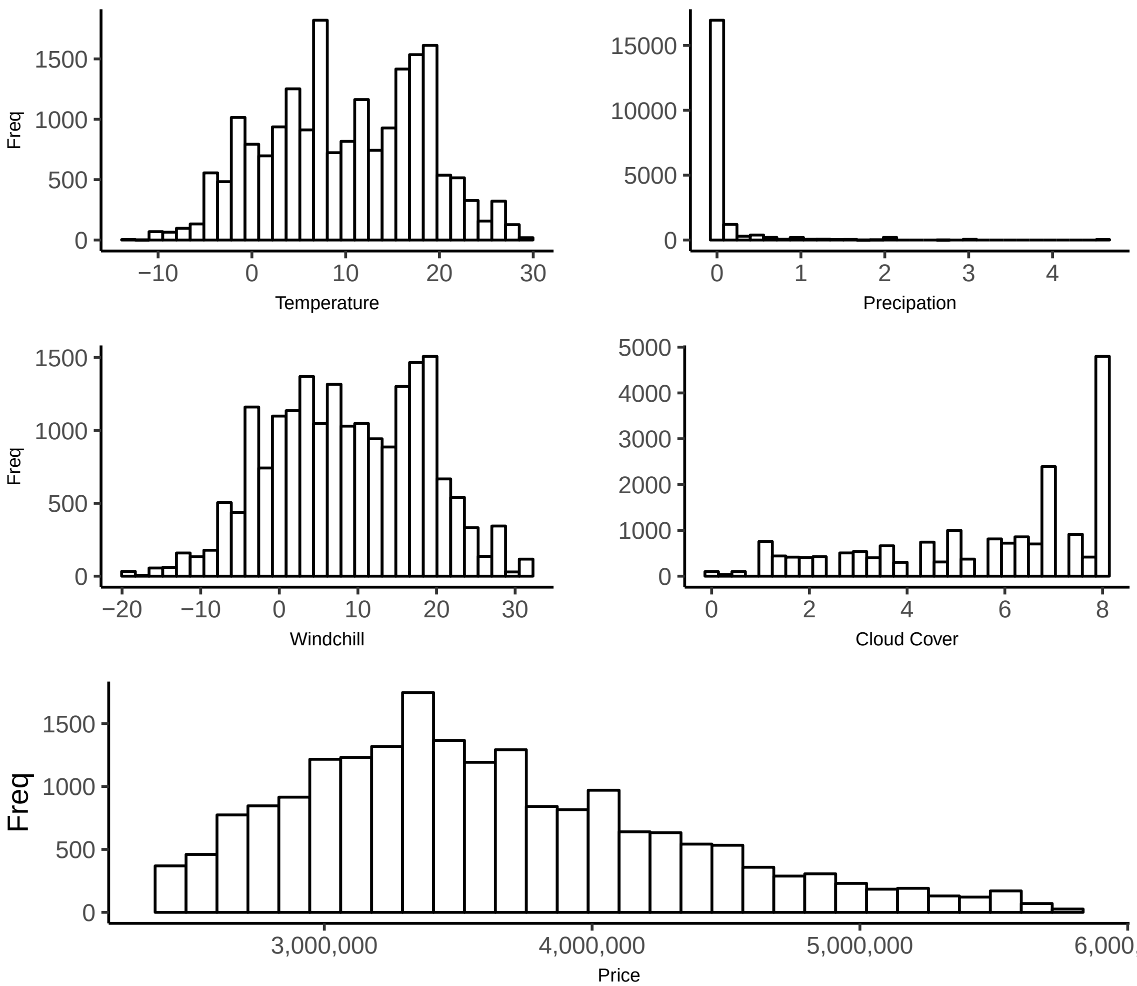

Figure 3: *Distribution of Price and Weather Variables from 1/1/13 to 31/12/18. First row is the distribution of temperature and precipitation, second row is the distribution of windchill and cloud cover and the third row is the distribution of price.*

Figure 4 is the distribution of house viewings. For the first house viewing, most take place on Sundays. Additionally, we see that most first house viewings are at 13:00, which makes sense as most people are not working on Sundays. For the second house viewing, most take place on Mondays. We see that the second viewings are normally at 17:00. As explained earlier auction day takes place the first business day after the second house viewing, this means that most transactions in our dataset happen within a time frame of three days.

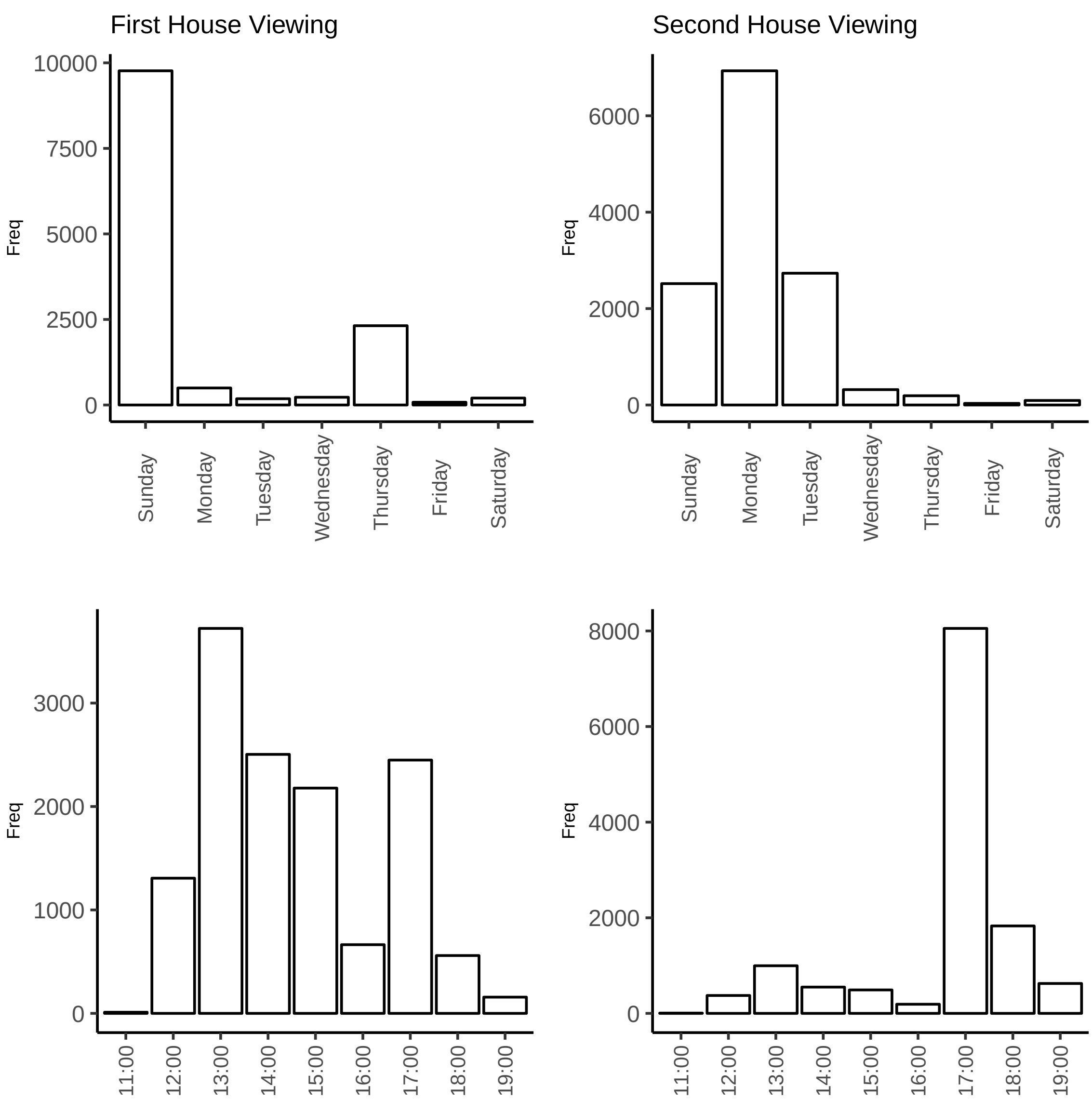

Figure 4: *Distribution of House Viewings from 1/1/13 to 31/12/18. Top row is distribution of days, and the second row is the distribution of time.*

5 Emperical Results

We present the results and analysis of the weathers impact on auction day, first and second house viewing in three separate regressions. Further, we present a regression where we measure the effect of bad weather at *both* of the house viewings. Lastly, we investigate the effect of sudden change in the weather.

Our basic methodology is to estimate a hedonic housing price model based on the following empirical specification and variable definitions:

$$p_{it} = \beta_0 + \beta_1 w_{it} + \mu_i + \gamma_t + \eta_i + \epsilon_{it} \tag{2}$$

Where $w_{i,t}$ denotes: Windchill, Cloud Cover, and a dummy for precipitation. μ_d is the district specific fixed effects, γ_t are the yearly, monthly, weekly, and hourly fixed effects, and η_c are the specific property characteristics. See full list in table A1. $\epsilon_{i,t}$ is the error term. We expect the coefficients of $w_{i,t}$ to be positive for windchill, as higher felt temperature is believed to increase mood. We expect precipitation and cloud cover coefficients to be negative, as rain and cloudy weather will likely worsen the mood of the participants.

We are interpreting temperature as a non-linear function for mood, as we hypothesize higher temperatures affects mood positively up to a certain point. At very high temperatures we have two theories; it is so warm that temperature has a negative effect on mood, or that is is so warm that people would instead enjoy the beautiful weather than attending the house viewing. Specification of temperature:

$$p_{it} = \beta_0 + \beta_1 temp_{it} + \beta_2 temp_{it}^2 + \mu_i + \gamma_t + \eta_i + \epsilon_{it} \tag{3}$$

We include districts fixed effects to control for unobserved heterogeneity *between* the different districts in Oslo. The sales price can be affected by unobservable variables that systematically vary across the districts in Oslo. We have included multiple dwelling-specific variables and location-specific variables in the hedonic regression, but there will always be the danger of omitted variable bias when working with observation data.

We also cluster the standard errors on districts in Oslo. It is acceptable to use both fixed effects and clustered standard errors. Clustered errors are accounting for situations where unobserved components *within* the districts are correlated. We account for districts fixed effects, but there may be some unexplained variation in the sales price that correlates over time.

We find that 81 percent of the variation in temperature is caused by time effects. We include yearly, monthly, weekly, and hourly fixed effects to control for weather seasonality. The time fixed effects also control for any seasonal variation and growth in the real estate market. See table A1 in the Appendix for all control variables used in the regression. We can see from figure 3 that prices are quite normally distributed, we can therefore not see any reason to log-transform our dependent variable. We have done a VIF-test[12] for multicollinearity. All variables have a VIF-value less than 5; hence multicollinearity is not a problem in the analysis.

[12] Variance Inflation Factor

5.1 The Weather's Effect on Dwelling Sales Price at the Auction

Table 4: Auction Regression Results

	Dependent variable:			
	Price			
	(1)	(2)	(3)	(4)
Air Temperature	$-3{,}394.0^{***}$			
	(508.1)			
Air Temperature^2	180.5^{***}			
	(30.7)			
Windchill		-694.0		
		(457.7)		
Precipitation			$-9{,}080.8^{***}$	
			(3,482.1)	
Cloud Cover				$-1{,}744.6^{**}$
				(784.1)
Controls	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clusters S.E.	Districts	Districts	Districts	Districts
Observations	19,774	19,774	19,774	19,113
Adjusted R^2	0.677	0.677	0.677	0.680

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18. The fourth regression has less observations than 1, 2, and 3, due to missing values of the interpolated cloud cover. Air temperature, Windchill, and Cloud Cover are continous variables. Precipitation is a dummy variable equal to 1 if there is precipitation present at the house viewing, and 0 otherwise. Time fixed effects are yearly, monthly, and weekly at the date of the auction day. Property and transaction specific controls includes districs. Full list are given in table A1 in the appendix.

Temperature and Temperature^2 are both significant at a 1% level. We expected the coefficient of Temperature to be negative, as we expected that higher temperatures increases mood to a certain point, where people would rather enjoy the heat then participate in the house viewing. However, according to Dr. George Tselioudis at NASA Goddard Institute for Space Studies[13], cloud covers' effect on temperature turns out to be seasonal dependent. During

[13] https://www.giss.nasa.gov/research/briefs/tselioudis_01/

winter more cloud cover causes higher temperatures, as clouds block heat from escaping into space. During the summer months' cloud cover has the opposite effect on temperature. More clouds cause lower temperatures, as clouds block heat from entering the atmosphere. In our model temperature could be interpreted as a proxy for cloud cover, where lower temperatures during winter is a result of less cloud cover, and higher temperatures during summer are due to less cloud cover. This might explain the coefficient of the second-degree polynomial.

Without a intercept we cannot reasonably interpret the temperature function. We can only observe the curvature of the function. To confirm the curvature of the second-degree polynomial function we regress temperature intervals on price, see A20 in the Appendix. We find that the curvatures are similar, which amplifies our belief that temperature works as a proxy for cloud cover.

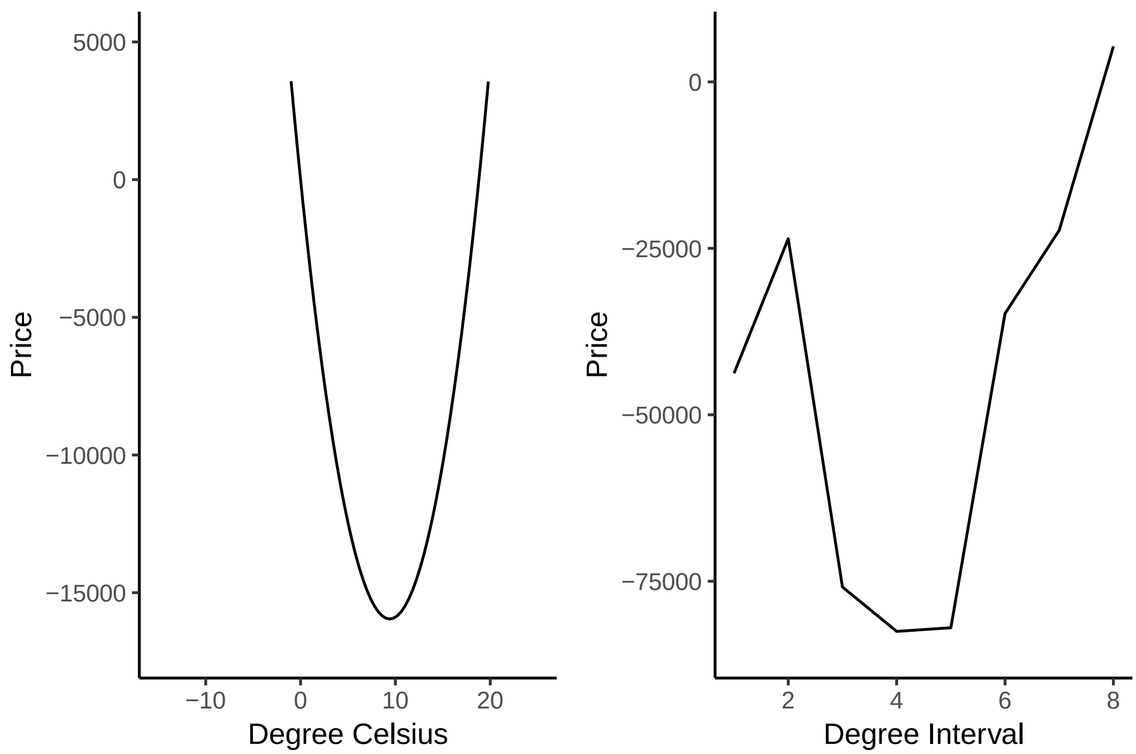

Figure 5: *Plot of Temperature Function. First column of the figure is the temperature function estimated by the regression analysis in table 4. The second column is a plot of degree intervals estimated in table A20.*

Windchill is not statistically significant. Precipitation is statistically significant at a 1% level, and cloud cover at a 5% level. If there is precipitation present during the auction hour, the price is reduced by $-9,080.8$NOK, and a unit increase in cloud cover reduces the price by

$-1,744.6$NOK.

A possible explanation for these effects could be the tension and stress one feels when participating in an auction with a considerable amount of money makes people vulnerable. We know decision-making is affected by our emotional state and mood (Johnson & Tversky, 1983), and as Denissen et al. (2008) proves, “bad” weather negatively affects mood. Mood affects the use of heuristics in decision-making; more specifically, a negative mood will decrease the use of heuristics, making the person think more analytically. The findings from our auction regression corroborate with theory from the field of behavioral economics, as a bad mood is consistent more cautious and analytical estimates. These findings indicate that bad weather, precipitation and cloud cover affect the dwelling prices through the auction participants’ mood.

5.2 The Weather's Effect on Dwelling Sales Price at the First House Viewing

Table 5: First House Viewing Regression Results

	Dependent variable:			
	Price			
	(1)	(2)	(3)	(4)
Air Temperature	$-2{,}206.6^{**}$			
	(875.1)			
Air Temperature^2	142.4^{***}			
	(31.0)			
Windchill		609.2^{*}		
		(333.0)		
Precipitation			$-63{,}982.8^{***}$	
			(4,471.3)	
Cloud Cover				$-1{,}119.1^{**}$
				(558.7)
Controls	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clusters S.E.	Districts	Districts	Districts	Districts
Observations	13,505	13,505	13,505	13,353
Adjusted R^2	0.670	0.670	0.670	0.669

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18. The fourth regression has less observations than 1, 2, and 3, due to missing values of the interpolated cloud cover. Air temperature, Windchill, and Cloud Cover are continous variables. Precipitation is a dummy variable equal to 1 if there is precipitation present at the house viewing, and 0 otherwise. Time fixed effects are yearly, monthly, and weekly at the date of the first house viewing. Property and transaction specific controls includes districs. Full list are given in table A1 in the appendix.

The temperature function is statistically significant. The convex curvature is consistent with the results in the auction analysis, and suggests that temperature is a proxy for cloud cover for the first house viewing as well. Windchill is significant at a 10% level. A one degree increase in windchill increases the price by 609.2NOK. Participants will travel to the house viewing and home afterward. So their mood could be affected by cold temperatures on their way to the house viewing.

Precipitation is statistically significant at a 1% level, and cloud cover at 5% level. A unit increase in cloud cover during house viewing reduces the price by $-1,119.1$NOK, and precipitation during house viewing reduces the price by $-63,982.8$NOK, which corresponds to a 1.6 percent reduction in the price of a 4MNOK dwelling.

A possible explanation of this phenomenon could be that the impression people get of the dwelling at the house viewing are worsened when the weather is particularly bad. This effect may be due to less natural light, or just a bad mood. If the dwelling has a beautiful view on a sunny day, the view would most likely not be the same with precipitation and cloudy weather. Participants have undoubtedly seen pictures of a beautiful view in the advertisement and have high expectations. Due to bad weather during the house viewing the view may not live up to the expectations. This feeling could impact the impression, and extinguish interest. Another and more straightforward explanation could be that fewer people attend house viewings in bad weather, simply because they do not want to go outside in the rain.

5.3 The Weather's Effect on Dwelling Sales Price at the Second House Viewing

Table 6: Second House Viewing Regression Results

	Dependent variable:			
	Price			
	(1)	(2)	(3)	(4)
Air Temperature	$-3{,}598.4^{***}$			
	(677.1)			
Air Temperature^2	279.1^{***}			
	(34.6)			
Windchill		621.7^{*}		
		(373.4)		
Precipitation			$-15{,}243.3^{***}$	
			(4,107.2)	
Cloud Cover				240.5
				(562.3)
Controls	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clusters S.E.	Districts	Districts	Districts	Districts
Observations	13,062	13,062	13,062	12,662
Adjusted R^2	0.672	0.672	0.672	0.671

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. The event window is between 1/1/13 and 31/12/18. The fourth regression has less observations than 1, 2, and 3, due to missing values of the interpolated cloud cover. Air temperature, Windchill, and Cloud Cover are continous variables. Precipitation is a dummy variable equal to 1 if there is precipitation present at the house viewing, and 0 otherwise. Time fixed effects are yearly, monthly, and weekly at the date of the second house viewing. Property and transaction specific controls includes districs. Full list are given in table A1 in the appendix.

We find that the results from the second house viewing are generally weaker compared to the first viewing. We do not have data on viewing attendance, but discussions with several brokers indicate that attendance is higher at the first house viewing. As most second viewings are scheduled to Mondays, people are occupied with everyday chores. We suspect weaker results are due to lower attendance.

Both temperature and squared temperature is significant at a 1% level, and with coefficients of $-3,598.4$NOK and 279.1NOK, respectively. Windchill is only significant at a 10% level, and a degree Celsius increase in windchill corresponds with an increased price of 621.7NOK on average, also similar to the first viewing. The precipitation dummy is significant at the 1% level, but has a lot less force, going from $-63,982.8$NOK at the first viewing to $-15,243.3$NOK in the second. Such significant gaps in the two days in house viewing might be of concern, but we point to the argument of weaker attendance. Cloud cover is not significant at any levels at the second house viewing.

5.4 The Weather's Effect on Dwelling Sales Price at both the House Viewings

In this regression, we combine the two days of house viewings to observe the effect of bad weather both days. We constructed dummies of our weather variables, so if the weather is terrible at both days, it gets the value of 1, and 0 otherwise. Our motivation for this is that the coefficients of the variables should increase when both days of viewing has bad weather.

Table 7: Both House Viewings

	Dependent variable:			
	Price			
	(1)	(2)	(3)	(4)
Extreme Temperature	9,295.7			
	(20,104.2)			
Extreme Windchill		−5,749.9		
		(3,884.2)		
Precipitation			$-68{,}624.4^{***}$	
			(11,878.8)	
Max Cloud Cover				$-16{,}930.1^{**}$
				(8,175.9)
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clustered S.E.	Districts	Districts	Districts	Districts
Observations	9,271	9,271	9,271	9,159
Adjusted R^2	0.662	0.662	0.662	0.663

Note: *p<0.1; **p<0.05; ***p<0.01. Extreme Temperature is a dummy variable equal to 1 if there is extreme temperature at both house viewings, 0 otherwise. Extreme Windchill is a dummy variable equal to 1 if there is extreme windchill at both house viewings, 0 otherwise. Precipitation is a dummy variable equal to 1 if there is precipitation on both house viewings, 0 otherwise. Max Cloud Cover is a dummy variable equal to one if there is maximum cloud cover on both house viewings, 0 otherwise. Time fixed effects are yearly, monthly, and weekly at the date of the second house viewing. Property specific controlls includes districs. Full list are given in table A1 in the appendix.

As expected, the price effect of precipitation increases to $-68,624.4$NOK and is significant at the 1% level. The increase makes sense since the first viewing has a magnitude of $-63,982.8$NOK and the second $-15,243.3$NOK. The result corroborates with our hypothesis of higher attendance at the first viewing, as the the combined precipitation dummy is closer to that of the first one.

The variable of maximum cloud cover is significant at the 5% level. If cloud cover is at its most at both house viewings, the sales price is decreased by $16,930.1$NOK on average. A one unit increase of cloud cover at the first viewing decreases the price by $1,119.1$NOK on average, and since it is continuous, a maximum cloud cover of eight would represent a price decrease of $8,952.8$NOK. Cloud cover for the second house viewing is not significant, so we do find the discrepancy of $7,977$NOK in the results somewhat strange. Frode Furuhovde (Privatmegleren) said that interested parties often meet up at both the viewings. We hypothesize that very cloudy weather at both the viewings magnifies the effect on the participants' mood, and therefore has a more significant effect on price. It can also mean that the weather has been generally bad lately, and the participants might be feeling more down than usual.

Extreme windchill and extreme temperature are not significant. Oslo does not experience such extreme temperatures and wind speeds. The lowest temperature recorded in our sample is -16.8 degrees Celsius, and the highest is 33.1 degrees Celsius, which is very cold and warm, but not "extremely." Also, the highest gusts recorded in our sample is at 12.1 meters per second. Empirically, researchers have had more luck with extreme variables in regions with more extreme weather. Chang, Nieh, Yang, & Yang (2006) find that temperature in Taiwan is significant on stock returns, and Taiwan in a warm country. Additionally, P. Keef & L. Roush (2002) find that wind speed has a significant impact on stock returns in Wellington, New Zealand, and Wellington is known to be one of the windiest cities in the world.

5.5 The Weather's Effect on Price-to-Asking Price (PAP) at the Auction

Overpricing is defined as price over listing price.

$$PAP_{i,t} = Price_{i,t}/Asking\ Price_{i,t} \tag{4}$$

A dwelling sold below its listing price means that the PAP ratio would be less than zero, and vice versa. Estimates are dependent on the initial value, also known as anchoring (Tversky & Kahneman, 1974). As a supplementary analysis, we investigate the weathers' effect on PAP, and anchoring in practice. The frequency distribution table depicts that most dwellings are sold at asking price, that is, $PAP_{i,t} = 1$. We observe that dwellings are more often sold above ask price than below ask price, i.e. $PAP_{i,t} > 1$. In 2016, the Norwegian Consumer Authority[14] investigated over a thousand dwelling transactions in Oslo and found that real estate brokers strategically underprice[15] (Wig, 2016). We cannot rule out that strategic underpricing might influence the results.

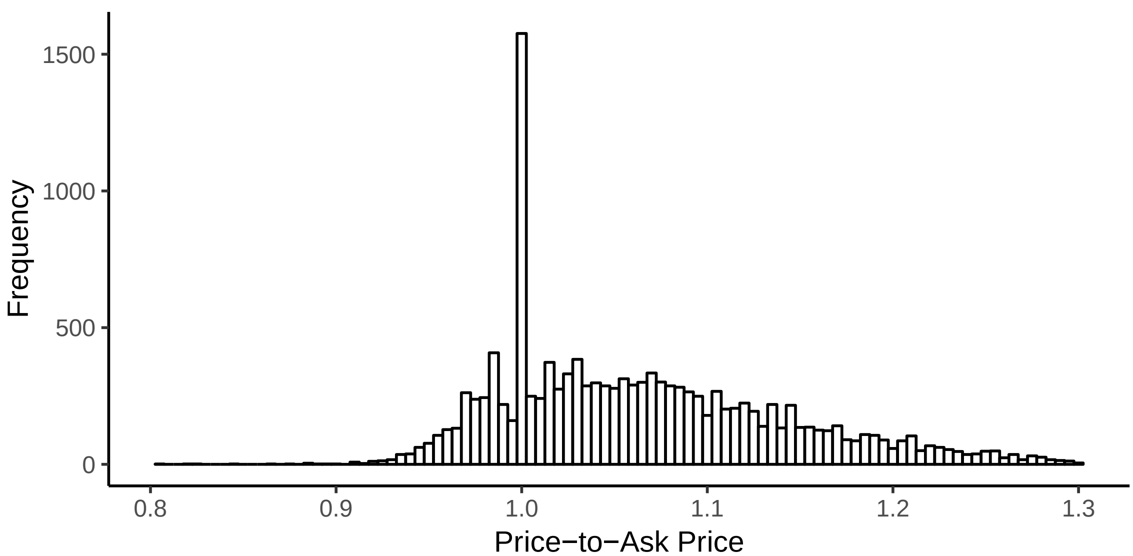

Figure 6: *Price-to-Ask Price Frequency Distribution of Dwellings in Oslo from 1/1/13 to 31/12/18.*

[14]Forbrukertilsynet
[15]In Norwegian "Lokkeprise"

Table 8: Overpricing Auction

	Dependent variable:			
	PAP			
	(1)	(2)	(3)	(4)
Air Temperature	−0.0004			
	(0.0005)			
Air Temperature^2	0.00004*			
	(0.00002)			
Windchill		0.0002		
		(0.0002)		
Precipitation			−0.003**	
			(0.001)	
Cloud Cover				−0.001***
				(0.0001)
Controls	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clusters S.E.	Districts	Districts	Districts	Districts
Observations	19,773	19,773	19,773	19,112
R^2	0.263	0.262	0.262	0.262
Adjusted R^2	0.258	0.257	0.257	0.257

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18. The fourth regression has less observations than 1, 2, and 3, due to missing values of the interpolated cloud cover. Air temperature, Windchill, and Cloud Cover are continous variables. Precipitation is a dummy variable equal to 1 if there is precipitation present at the house viewing, and 0 otherwise. Time fixed effects are yearly, monthly, and weekly at the date of the auction. Property and transaction specific controls includes districs.

Precipitation is significant a 5% level and the coefficient indicates that if there are precipitation during auction the ratio will decrease by 0.3% on average. This corresponds to a 12.000NOK decrease in price to a listing price of 4MNOK. Cloud cover is significant at a 1% level, and an octa increase in cloud cover indicates a 0.1% decrease in price over listing price on average. This corresponds to 4000NOK decrease per increase in cloud cover for a dwelling with a listing price of 4MNOK.

5.6 The Weather's Effect on Time-on-Market (TOM) at the First House Viewing

Time-on-Market (TOM) is defined as number of days between the date registered for sale and the sales date.

$$TOM_{i,t} = Sales\ Date_{i,t} - \ Registered\ Date_{i,t} \tag{5}$$

TOM has a mean of 21.06 and a median of 10. As TOM is not normally distributed, we log-transform TOM to make a log-normal distribution. The log-transformed TOM has a mean of 2.59 and a median of 2.30.

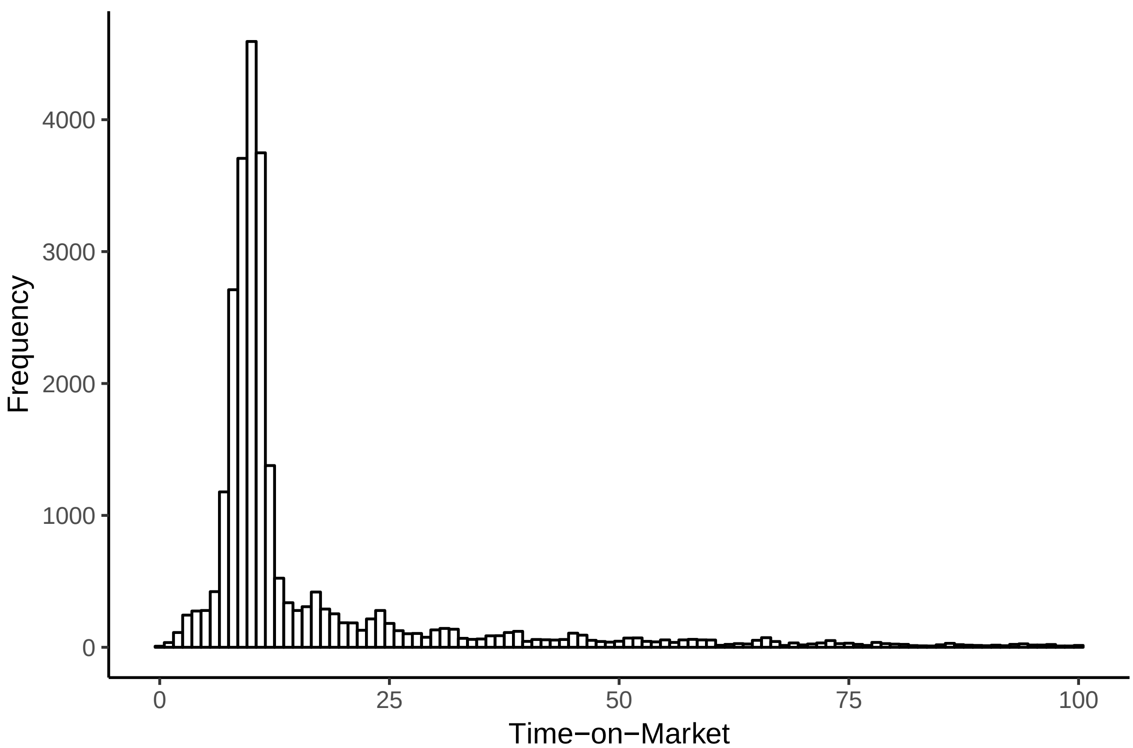

Figure 7: *Time-on-Market Frequency Distribution of Dwellings in Oslo from 1/1/13 to 31/12/18. We exclude observations larger than 100 days, due to graphical convenience.*

Table 9: Time-on-Market First House Viewing

	Dependent variable:			
	$log(TOM)$			
	(1)	(2)	(3)	(4)
Air Temperature	-0.007^{*}			
	(0.004)			
Air Temperature^2	0.0002^{*}			
	(0.0001)			
Windchill		-0.001		
		(0.002)		
Precipitation			0.059^{*}	
			(0.036)	
Cloud Cover				0.004
				(0.004)
Controls	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clusters S.E.	Districts	Districts	Districts	Districts
Observations	17,844	17,844	17,844	17,638
Adjusted R^2	0.132	0.131	0.132	0.133

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18. Time fixed effects are yearly, monthly, and weekly at the date of the sold date. Property and transaction specific controls includes districs. Full list are given in table A1 in the appendix.

The non-linear air temperature function is significant on a 10% level with equal curvature to the previous results. Precipitation is significant at a 10% level, and the coefficient indicates that if there are precipitation present at the first house viewing, the dwellings time on the market will increase with 5.9% on average. We observe no significance in windchill and cloud cover. The weathers' effects on TOM for auction and the second house viewing are given in the appendix.

6 Discussion

Precipitation during the auction implies a lowered sales price of $9,080.8$NOK, while precipitation during the first house viewing lowers the price by of $63,982.8$NOK on average. The difference indicates that precipitation during the first house viewing is a more substantial driver on price. A possible explanation for this difference can be the impression people get of the dwelling, and the experience of attending the house viewing is more critical for sales price than mood itself; as we expect weather on auction day only to affect the bidders' mood rather than the impression of the dwelling.

The house viewing analysis is more ambiguous, as it accounts for more factors than the auction analysis. It captures the weather-induced mood from leaving your home to travel to the house viewing, possibly in the pouring rain. It also captures your mood during the house viewing, which will affect the impression you get of the dwelling. Additionally, bad weather will obstruct beautiful views from windows and balconies; and even the practical aspect of showing up at the house viewing. Loads of rainfall will likely make people think twice about bothering to attend the house viewing, and a lower attendance will likely lower the sales price. All these factors may be the reason for the large price-effect difference between the house viewing and the auction.

We substantiate this argument by looking at the windchill variable. Windchill is statistically significant in the first house viewing analysis, but not in the auction analysis. This could be because people are usually indoors at work or home while bidding, and will therefore not feel the effective temperature. However, when traveling to the house viewing the participants will feel the windchill, and very low windchill might even prevent people from going outside.

Cloud cover has a bigger and more significant coefficient in the auction analysis than in the first house viewing analysis. We have two explanations for this. First, people in Oslo are used to cloudy weather, and this does not stop people from going outside, while precipitation is not ordinary. See relevant weather statistics in figure 3. Second, cloud cover likely affects the impression and experience of attending the house viewing to a smaller degree, while it has a bigger impact on mood. The lack of sunshine has affected peoples' mood and hence also market returns (Hirshleifer & Shumway, 2003; Saunders, 1993). Fewer hours of sunshine also coincide with depression (Eagles, 1994). We hypothesize that mood is more important during the auction, as mood affects decision-making and increases the use of heuristics that are associated with bidding.

Since we suspect the non-linear temperature function is a proxy for cloud cover, we derive it so we can learn some more about it. The non-linear function for auction has a global minimum at 7.5 degrees Celsius, which corresponds to a -10.561NOK reduction in price on average. For the first house viewing the global minimum is 6.3 degrees Celsius, this corresponds to a -5.512NOK reduction in price. Comparing this to the significant cloud cover coefficient for both regressions these results look reasonable. It is also likely to think that there is a lot of cloud cover in Oslo at these temperatures. These results also substantiate that cloud cover during auction has a greater impact on sales price than during first house viewing since the price reduction is larger at the global minimum of the auction temperature function.

For the general analysis, which looks at both house viewings, we observe strong coefficients on precipitation and cloud cover. As Frode Furuhovde said, interested participants often show up on both house viewings. A reason for this could be that these potential homebuyers might want to be sure of their valuation of the dwelling before the bidding starts. A possible reason for the strong coefficients could be that the negative impression participants get at the first house viewing due to bad weather is confirmed if there is bad weather on the second house viewing as well; hence their valuation of the dwelling decreases.

6.1 Are the Results a Statistical Artifact?

The results show that there is a statistical relationship between weather variables and sales prices of dwellings, but is it an economically significant relationship? To conclude from this, we use two alternative hypotheses given by Saunders (1993), efficient markets or behavioral explanations. If markets are efficient, prices of dwellings in Oslo should not be affected by the weather. Secondly, the mood of market participants is affected by the weather, which again affects their valuation and interest of the specific dwelling.

We find a significant correlation between weather variables and dwelling prices, so one could believe that we reject the efficient market hypothesis and accept that there are behavioral explanations. However, some research on the weather's effect on stock prices has concluded with the effect being due to spurious correlation (Goetzmann & Zhu, 2005; Trombley, 1997).

One can never answer this question entirely, but a standard method of assessing the robustness of a model is by doing a *placebo test*. A placebo test aims to demonstrate that an effect does not exist where it "should not" exist. One way to do a placebo test is by replacing the explanatory variables with some alternative variables that should be less connected with what we are testing. We collect weather data for the city of Tromsø, which is 1,149 kilometers away from Oslo, and construct the same weather variables only with Tromsø data. Tromsø is located far north in Norway, and has a coastal climate, as opposed to Oslo. The correlation between the weather in Oslo and Tromsø can be found in the matrix in appendix A19. It shows no correlation between the weather in Oslo and Tromsø, with exception to temperature. For those reasons, it serves as a appropriate placebo test.

We do placebo tests for all the regressions, and find less cases of significance. The exception being precipitation which is significant in all tests except for the first house viewing. However, one cannot reasonably interpret the variables as they have a positive sign. In other words, its interpretation is that rain in Tromsø *increases* the dwelling sales price in Oslo. A possible explanation could be that there is a negative correlation between precipitation on Oslo and Tromsø, but this is not true. Another possible explanation could be an unobserved third variable that affects precipitation in both Oslo and Tromsø or an unobserved variable that affects the weather and the real estate market. One driver that is well known to affect the real estate market is seasonality, but we already accounted for seasonality in the model.

Cloud cover is significant in the placebo test of the first house viewing, implying that more cloud cover in Tromsø affects the price positively. All in all, we observe a lot fewer cases of significance, with signs that give no economic intuition. Placebo tests for regression 1, 2, 3 and 4 are given in section A.6 the appendix.

As we argue for a behavioral explanation, we should ideally have gathered data about attendance at house viewings. Then we could have tested if attendance at house viewings are lower on days with ‘’bad weather”, as we suspect the weather variables works as an instrument for both the house viewing attendance and mood. We must look to the actors of the real estate market when assessing behavioral explanations. Previously we have discussed how the participants of the real estate market are largely non-professionals. We have referenced empirical evidence that the weather’s effect on stock markets is greater at times where it attracted more attention Akhtari (2011), and therefore attracted more inexperienced investors. Therefore, the weather-effect is more significant on inexperienced investors.

A body of clinical and empirical research shows that mood does affect our decision-making (Denissen et al., 2008; Howarth & Hoffman, 1984; McAndrew, 1993; Persinger & Levesque, 1983; Schwarz & Clore, 1983), and this makes sense intuitively as well. Further, a good mood is associated with optimistic decisions and fast thinking, and bad mood with pessimistic decisions and slower, analytical thinking (Johnson & Tversky, 1983; Kahneman, 2011). Therefore, bad weather will cause homebuyers to think more carefully about whether to buy and how much to bid. In addition, homebuyers will likely perceive the dwelling in a more negative light when the weather is bad. Irrational human behavior is a fundamental explanation for our strong weather-effect results and that the results make sense economically and intuitively.

Lastly, we discuss the strong coefficients. In a booming market, sales happen fast, and decision makers are more prone to be affected by non-fundamental information. Also, the "hot hand fallacy" is the notion that success in the past implies continued success. Gilovich, Vallone, & Tversky (1985) investigate the hot hand fallacy in baseball, which is the belief that a baseball players' chance of hitting a shot is higher following a hit on the previous shot. They found no correlation between the outcome of successive shots. The Oslo housing market has experienced considerable growth in the last three decades. The sample period from 2013 to 2018 captures a booming market, especially in 2015 and 2016, which combined had a growth of almost 33 percent in Oslo. In 2017. According to the hot hand fallacy, this will aggravate the belief of continued growth and over-optimism. Along the same lines, Akhtari (2011) found that the weather-effect was stronger on Dow Jones performance in the build-up of the dot-com bubble. We speculate that the significant and robust effect of the weather might be partly due to the booming market and that the already irrational housing market could amplify the irrational weather-effects.

7 Conclusion

Previous studies on financial markets documents that weather-induced mood can explain variation in investment outcomes such as stock prices and liquidity. In this thesis, we investigate the weather's effect on dwelling sales price between 2013 and 2018 in Oslo. We construct a hedonic real estate model to estimate how the weather-effect contributes to the sales price of a dwelling. We analyze the impact of weather during auction hour, the first house viewing and the second house viewing separately. Further, we analyze the impact of bad weather at both the house viewings, and lastly the effect of sudden changes in weather.

First, we find that the local weather at the time of house viewing and the time of auction have significantly altered sales prices. We find that the negative effect of bad weather, such as precipitation and cloud cover has the greatest impact on the sales price. The temperature has a significant effect on both auction on house viewing but works as a proxy for cloud cover. We also find that windchill has a significant negative effect on the first house viewing, but not on auction and the second house viewing. We argue this is due to lower attendance on the second house viewing, and that windchill does not affect mood during the auction hour, as people are usually inside when bidding.

Our results are consistent with research on the weather and its effect on stock markets. The findings are also consistent with literature from psychology, that individuals misattribute mood induced by non-decision-relevant factors as information in their decision-making process. To our knowledge, this study is the first to investigate the effect of weather-induced mood on dwelling sales price.

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A Appendix

A.1 List of Variables Used in the Analysis

Table A1: Explanation of Variables Used in the Analysis

Variables	Explanation
Quiet Area	The dwelling is in a quiet area
Elevator	There is an elevator in the builing
Parquet	There is parquet on the floor
View	The dwelling as a view
Expandability	There is a possibility to expand the living area of the dwelling.
Fire place	There is a fireplace in the dwelling
Child-friendly	The dwelling is in a child-friendly area
Common Laundry Room	Common Laundry for all apartments
Modern	The dwelling is refurbised later than 2010
Parking	The dwelling has its own parking space
Guest Parking	The dwelling has its own guest parking space
Janitor/Security Service	The dwelling has Janior or Security Service
Bedroom	Number of bedrooms in the dwelling
Type of Ownership	Housing cooperative or Freeholder
Living Area	Measure of area for primary use
Age	The age of the dwelling
Distance to School	Distance to the closest School
Distance to Kindergarten	Distance to the closest Kindergarten
District	In which district the dwelling is located. Could be either: Bjerke, Gamle Oslo, Grorud, Nordstrand, Sagene, Østensjø, Søndre Nordstrand, Stovner, Vestre Aker, Frogner, Nordre Aker, Alna, St.Hanshaugen or Ullern.

A.2 Descriptive Statistics

A.2.1 Auction

Table A2: Descriptive Statistics, Auction

Statistic	N	Mean	St. Dev.	Min	1st Qu.	3rd Qu.	Max
Price	19,774	3,610,319	703,312	2,400,000	3,100,000	4,025,000	5,750,000
Temperature	19,774	9.970	8.201	−12.600	3.700	17.000	29.800
Precipitation	19,774	0.091	0.367	0	0	0	5
Windchill	19,774	8.738	9.598	−18.322	1.200	16.895	32.261
Cloud Cover	19,113	5.626	2.287	0.000	4.000	8.000	8.000

Table A3: Correlation Matrix, Auction

	Price	Temperature	Precipitation	Windchill	Cloud Cover
Price	1	-0.009	-0.022	-0.014	-0.011
Temperature	-0.009	1	-0.043	0.990	-0.336
Precipitation	-0.022	-0.043	1	-0.048	0.242
Windchill	-0.014	0.990	-0.048	1	-0.353
Cloud Cover	-0.011	-0.336	0.242	-0.353	1

A.2.2 First House Viewing

Table A4: Descriptive Statistics, First House Viewing

Statistic	N	Mean	St. Dev.	Min	1st Qu.	3rd Qu.	Max
Price	13,273	3,598,790	699,853.6	2,400,000	3,100,000	4,000,000	5,750,000
Temperature	13,273	10.612	8.546	−12.600	3.600	17.200	30.400
Precipitation	13,273	0.080	0.368	0	0	0	9
Windchill	13,273	11.387	9.110	−15.675	3.975	18.329	32.841
Cloud Cover	13,122	5.338	2.425	−3.000	3.000	7.667	8.000

Table A5: Correlation Matrix, First House Viewing

	Price	Temperature	Precipitation	Windchill	Cloud Cover
Price	1	0.003	-0.019	0.002	0.003
Temperature	0.003	1	-0.021	0.994	-0.190
Precipitation	-0.019	-0.021	1	-0.021	0.193
Windchill	0.002	0.994	-0.021	1	-0.199
Cloud Cover	0.003	-0.190	0.193	-0.199	1

A.2.3 Second House Viewing

Table A6: Descriptive Statistics, Second House Viewing

Statistic	N	Mean	St. Dev.	Min	1st Qu.	3rd Qu.	Max
Price	13,062	3,608,003	708,345	2,400,000	3,100,000	4,022,500	5,750,000
Temperature	13,062	10.024	8.520	−14.100	3.400	16.900	30.500
Precipitation	13,062	0.080	0.370	0	0	0	7
Windchill	13,062	10.786	9.123	−15.100	3.521	18.044	32.924
Cloud Cover	12,662	5.394	2.484	−3.000	3.333	7.667	8.000

Table A7: Correlation Matrix, Second House Viewing

	Price	Temperature	Precipitation	Windchill	Cloud Cover
Price	1	-0.017	-0.021	-0.022	0.032
Temperature	-0.017	1	-0.014	0.993	-0.248
Precipitation	-0.021	-0.014	1	-0.016	0.194
Windchill	-0.022	0.993	-0.016	1	-0.268
Cloud Cover	0.032	-0.248	0.194	-0.268	1

A.3 Price-to-Asking Price (PAP)

A.3.1 PAP - First House Viewing

Table A8: PAP - First House Viewing

	Dependent variable:			
	Overpricing			
	(1)	(2)	(3)	(4)
Air Temperature	0.001			
	(0.0005)			
Air Temperature2	−0.00000			
	(0.00002)			
Windchill		0.0004*		
		(0.0002)		
Precipitation			−0.001	
			(0.004)	
Cloud Cover				−0.001*
				(0.0005)
Controls	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clusters S.E.	Districts	Districts	Districts	Districts
Observations	13,505	13,505	13,505	13,353
Adjusted R^2	0.250	0.249	0.250	0.250

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18. Temperature is a dummy variable that is 1 if the temperature is 5 or more degrees colder than at the same time the previous day, 0 otherwise. Windchill is a dummy variable that is 1 if the windchill is 5 or more degrees colder than at the same time the previous day, 0 otherwise. Precipitation is a dummy variable equal to 1 if there was no precipitation the day before, but there is at the event. Cloud Cover is a dummy variable equal to 1 if the cloud cover is 5 or more octas than the previous day, 0 otherwise. Time fixed effects are yearly, monthly, and weekly at the date of the first house viewing. Property specific controlls includes districs.

A.3.2 PAP - Second House Viewing

Table A9: PAP - Second House Viewing

	Dependent variable:			
	Overpricing			
	(1)	(2)	(3)	(4)
Air Temperature	0.0002			
	(0.001)			
Air Temperature2	0.00003*			
	(0.00002)			
Windchill		0.001***		
		(0.0002)		
Precipitation			−0.006***	
			(0.002)	
Cloud Cover				−0.002***
				(0.0003)
Controls	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clusters S.E.	Districts	Districts	Districts	Districts
Observations	13,061	13,061	13,061	12,661
Adjusted R^2	0.248	0.248	0.247	0.247

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18. Temperature is a dummy variable that is 1 if the temperature is 5 or more degrees colder than at the same time the previous day, 0 otherwise. Windchill is a dummy variable that is 1 if the windchill is 5 or more degrees colder than at the same time the previous day, 0 otherwise. Precipitation is a dummy variable equal to 1 if there was no precipitation the day before, but there is at the event. Cloud Cover is a dummy variable equal to 1 if the cloud cover is 5 or more octas than the previous day, 0 otherwise. Time fixed effects are yearly, monthly, and weekly at the date of the second house viewing. Property specific controlls includes districs.

A.4 Time-on-Market (TOM)

A.4.1 TOM - Auction

Table A10: Time-on-Market Auction

	Dependent variable:			
	log(*Days*)			
	(1)	(2)	(3)	(4)
Air Temperature	−0.005			
	(0.004)			
Air Temperature2	0.0003*			
	(0.0002)			
Windchill		0.002**		
		(0.001)		
Precipitation			−0.025***	
			(0.008)	
Cloud Cover				−0.0004
				(0.002)
Controls	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clusters S.E.	Districts	Districts	Districts	Districts
Observations	19,448	19,448	19,448	18,782
Adjusted R^2	0.133	0.133	0.133	0.133

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18. The fourth regression has less observations than 1, 2, and 3, due to missing values of the interpolated cloud cover. Air temperature, Windchill, and Cloud Cover are continous variables. Precipitation is a dummy variable equal to 1 if there is precipitation present at the house viewing, and 0 otherwise. Time fixed effects are yearly, monthly, and weekly at the date of the auction. Property and transaction specific controls includes districs. Full list are given in table A1 in the Appendix.

The precipitation coefficient is negative, which means that if there is precipitation present during the auction hour the time on market will decrease. Intuitively one would think that precipitation should increase the dwellings' time on the market, but during the auction we also have to account for the sellers' mood. If the weather is particularly “bad”" during the auction, the seller might be willing to accept a lower bid, hence the time on market will decrease. Also, the weather during the auction will have a bigger effect on price than TOM, as most participants already have decided whether they want to buy or not, but not how much they will end up paying.

A.4.2 TOM - Second House Viewing

Table A11: Time-on-Market Second House Viewing

	Dependent variable:			
	$log(TOM)$			
	(1)	(2)	(3)	(4)
Air Temperature	-0.008^{**}			
	(0.003)			
Air Temperature^2	-0.00003			
	(0.0001)			
Windchill		-0.007^{***}		
		(0.002)		
Precipitation			0.073^{***}	
			(0.023)	
Cloud Cover				0.009^{*}
				(0.005)
Controls	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clusters S.E.	Districts	Districts	Districts	Districts
Observations	17,110	17,110	17,110	16,560
Adjusted R^2	0.128	0.128	0.127	0.123

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18. The fourth regression has less observations than 1, 2, and 3, due to missing values of the interpolated cloud cover. Air temperature, Windchill, and Cloud Cover are continous variables. Precipitation is a dummy variable equal to 1 if there is precipitation present at the house viewing, and 0 otherwise. Time fixed effects are yearly, monthly, and weekly at the date of the first house viewing. Property and transaction specific controls includes districs. Full list are given in table A1 in the Appendix.

A.5 Sudden Changes

A.5.1 Sudden Changes - Auction

Table A12: Sudden Changes - Auction

	Dependent variable:			
	Price			
	(1)	(2)	(3)	(4)
Temperature	25,965.2			
	(16,636.430)			
Windchill		−9,568.5		
		(10,494.6)		
Precipitation			768.9	
			(10,233.0)	
Cloud Cover				−10,431.9
				(12,606.0)
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clusters S.E.	Districts	Districts	Districts	Districts
Observations	19,774	19,774	19,774	19,112
Adjusted R^2	0.677	0.677	0.677	0.680

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18. Temperature is a dummy variable that is 1 if the temperature is 5 or more degrees colder than at the same time the previous day, 0 otherwise. Windchill is a dummy variable that is 1 if the windchill is 5 or more degrees colder than at the same time the previous day, 0 otherwise. Precipitation is a dummy variable equal to 1 if there was no precipitation the day before, but there is at the event. Cloud Cover is a dummy variable equal to 1 if the cloud cover is 5 or more octas than the previous day, 0 otherwise. Time fixed effects are yearly, monthly, and weekly at the date of the second house viewing. Property specific controlls includes districs. Full list are given in table A1 in the Appendix.

A.5.2 Sudden Changes - First House Viewing

We hypothesize that if the weather is bad today, and it was good yesterday, then the negative impact on mood will be greater than just bad weather isolated. Empirically, the negative effect of bad weather has a more considerable influence on a person's mood than the positive mood-effect caused by good weather. That is why we chose to test the sudden negative change in weather.

Table A13: Sudden Changes - First House Viewing

	Dependent variable:			
	Price			
	(1)	(2)	(3)	(4)
Temperature	28,368.8			
	(38,732.5)			
Windchill		31,058.0		
		(31,978.3)		
Precipitation			8,954.9	
			(10,125.8)	
Cloud Cover				$-13{,}125.8^{*}$
				(7,126.0)
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clustered S.E.	Districts	Districts	Districts	Districts
Observations	13,227	13,227	13,227	13,064
Adjusted R^2	0.671	0.671	0.671	0.670

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18. Temperature is a dummy variable that is 1 if the temperature is 5 or more degrees colder than at the same time the previous day, 0 otherwise. Windchill is a dummy variable that is 1 if the windchill is 5 or more degrees colder than at the same time the previous day, 0 otherwise. Precipitation is a dummy variable equal to 1 if there was no precipitation the day before, but there is at the event. Cloud Cover is a dummy variable equal to 1 if the cloud cover is 5 or more octas than the previous day, 0 otherwise. Time fixed effects are yearly, monthly, and weekly at the date of the second house viewing. Property specific controlls includes districs. Full list are given in table A1 in the Appendix.

We find generally weak results on a sudden change in the weather. Cloud cover is the only significant variable with a level of 10%. An increase in cloud cover of five octas will have the price effect of $-13,125.8$NOK on the sales price. In general, our results mean that the effect of sudden weather change is much weaker than we anticipated.

A.5.3 Sudden Changes - Second House Viewing

Table A14: Sudden Changes - Second House Viewing

	Dependent variable:			
	Price			
	(1)	(2)	(3)	(4)
Temperature	−7,085.2			
	(25,094.4)			
Windchill		11,752.8		
		(16,528.9)		
Precipitation			4,557.9	
			(5,540.0)	
Cloud Cover				17,201.5
				(18,666.2)
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clustered S.E.	Districts	Districts	Districts	Districts
Observations	12,771	12,771	12,771	12,366
Adjusted R^2	0.674	0.674	0.674	0.674

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18. Temperature is a dummy variable that is 1 if the temperature is 5 or more degrees colder than at the same time the previous day, 0 otherwise. Windchill is a dummy variable that is 1 if the windchill is 5 or more degrees colder than at the same time the previous day, 0 otherwise. Precipitation is a dummy variable equal to 1 if there was no precipitation the day before, but there is at the event. Cloud Cover is a dummy variable equal to 1 if the cloud cover is 5 or more octas than the previous day, 0 otherwise. Time fixed effects are yearly, monthly, and weekly at the date of the second house viewing. Property specific controlls includes districs. Full list are given in table A1 in the Appendix.

A.6 Placebo Tests

A.6.1 Placebo Test - Auction

Table A15: Placebo Tests - Auction

	Dependent variable:			
	Price			
	(1)	(2)	(3)	(4)
Air Temperature	−1,508.3			
	(1,015.3)			
Air Temperature^2	94.4***			
	(27.1)			
Windchill		289.1		
		(294.2)		
Precipitation Dummy			20,134.8***	
			(5,477.4)	
Cloud Cover				−278.5
				(639.1)
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clustered S.E.	Districts	Districts	Districts	Districts
Observations	19,778	19,778	19,778	19,092
Adjusted R^2	0.676	0.676	0.676	0.677

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18. The fourth regression has less observations than 1, 2, and 3, due to missing values of the interpolated cloud cover. Temperature, Windchill, and Cloud Cover are continous variables. Precipitation is a dummy variable equal to one if there is precipitation present at the auction, 0 otherwise. Time fixed effects are yearly, monthly, and weekly at the date of the first house viewing. Property specific controlls includes districs. Full list are given in table A1 in the Appendix.

A.6.2 Placebo Test - First House Viewing

Table A16: Placebo Tests - First House Viewing

	Dependent variable:			
	Price			
	(1)	(2)	(3)	(4)
Air Temperature	−1,879.9			
	(1,505.6)			
Air Temperature^2	−57.4			
	(74.8)			
Windchill		230.6		
		(293.7)		
Precipitation Dummy			10,143.1	
			(9,021.5)	
Cloud Cover				3,319.9**
				(1,452.6)
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clustered S.E.	Districts	Districts	Districts	Districts
Observations	13,507	13,507	13,507	12,951
Adjusted R^2	0.669	0.669	0.669	0.671

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18. The fourth regression has less observations than 1, 2, and 3, due to missing values of the interpolated cloud cover. Temperature, Windchill, and Cloud Cover are continous variables. Precipitation is a dummy variable equal to one if there is precipitation present at the auction, 0 otherwise. Time fixed effects are yearly, monthly, and weekly at the date of the first house viewing. Property specific controlls includes districs. Full list are given in table A1 in the Appendix.

A.6.3 Placebo Test - Second House Viewing

Table A17: Placebo Tests - Second House Viewing

	Dependent variable:			
	Price			
	(1)	(2)	(3)	(4)
Air Temperature	1,039.1			
	(761.1)			
Air Temperature^2	-23.5			
	(41.867)			
Windchill		408.5		
		(465.1)		
Precipitation Dummy			13,927.3***	
			(5,202.7)	
Cloud Cover				2,523.6***
				(920.8)
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clustered S.E.	Districts	Districts	Districts	Districts
Observations	13,081	13,081	13,081	12,748
Adjusted R^2	0.671	0.671	0.671	0.671

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18. The fourth regression has less observations than 1, 2, and 3, due to missing values of the interpolated cloud cover. Temperature, Windchill, and Cloud Cover are continous variables. Precipitation is a dummy variable equal to one if there is precipitation present at the auction, 0 otherwise. Time fixed effects are yearly, monthly, and weekly at the date of the second house viewing. Property specific controlls includes districs. Full list are given in table A1 in the Appendix.

A.6.4 Placebo Test - House Viewing in General

Table A18: Placebo Test - Both House Viewings

	Dependent variable:			
	Price			
	(1)	(2)	(3)	(4)
Extreme Temperature	27,970.6			
	(23,385.6)			
Extreme Windchill		−672.9		
		(23,718.1)		
Precipitation			35,858.3**	
			(15,099.5)	
Max Cloud Cover				35,598.8*
				(18,328.9)
Time F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
Clustered S.E.	Districts	Districts	Districts	Districts
Observations	9,291	9,291	9,291	9,179
Adjusted R^2	0.664	0.664	0.664	0.663

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18. Extreme Temperature is a dummy variable equal to 1 if there is extreme temperature at the time of the event, 0 otherwise. Extreme windchill is a dummy variable equal to 1 if there is extreme windchill at the time of the event, 0 otherwise. Precipitation is a dummy variable equal to one if there is precipitation on both house viewings. Max Cloud Cover is a dummy variable equal to one if there is maximum cloud cover on both house viewings. Time fixed effects are yearly, monthly, and weekly at the date of the second house viewing. Property specific controlls includes districs.

A.6.5 Correlation Matrix Weather Variables

	Precipitation Oslo	Temperature Oslo	Cloud Cover Oslo	Windchill Oslo	Precipitation Tromso	Temperature Tromso	Cloud Cover Tromso	Windchill Tromso
Precipitation Oslo	1.000	0.018	0.159	0.013	−0.025	0.048	−0.034	0.052
Temperature Oslo	0.018	1.000	−0.126	0.991	−0.010	0.816	0.109	0.822
Cloud Cover Oslo	0.158	−0.126	1.000	−0.144	−0.066	−0.064	−0.103	−0.057
Windchill Oslo	0.013	0.992	−0.144	1.000	0.000	0.818	0.121	0.823
Precipitation Tromso	−0.025	−0.010	−0.066	0.000	1.000	−0.020	0.158	−0.036
Temperature Tromso	0.048	0.816	−0.064	0.818	−0.020	1.000	0.095	0.984
Cloud Cover Tromso	−0.034	0.109	−0.103	0.121	0.158	0.095	1.000	0.056
Windchill Tromso	0.052	0.822	−0.057	0.823	−0.036	0.984	0.056	1.000

Table A19: Correlation Matrix Weather Oslo and Tromsø

A.7 Distribution of Owner types

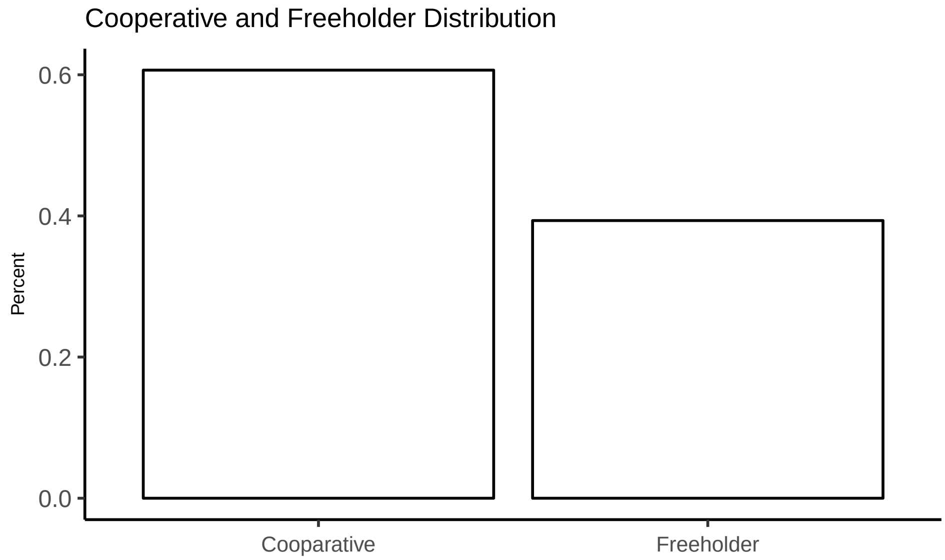

Figure 8: *Distribution of Owner Types for Dwellings in Oslo from 1/1/13 to 31/12/18. Distribution is given is percent.*

A.8 Temperature Interval Regression

Table A20: Temperature Interval Regression

	Dependent variable:
	Price
−10 to −5	−43,760.0
	(33,747.5)
−5 to 0	−23,554.1
	(28,871.7)
0 to 5	−75,873.9**
	(29,772.5)
5 to 10	−82,541.2***
	(29,090.0)
10 to 15	−81,988.7***
	(26,366.1)
15 to 20	−34,784.8
	(26,090.8)
20 to 25	−22,286.3
	(27,602.3)
25 to 30	5,333.5
	(29,727.3)
Time F.E.	Yes
District F.E.	Yes
Clustered S.E.	Districts
Observations	19,354
Adjusted R^2	0.678

Note: *p<0.1; **p<0.05; ***p<0.01. The event window is between 1/1/13 and 31/12/18.